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Benedikt Fleischmann

# Asset Allocation under the Influence of Long-Run Relations

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# Chapter 1

# Research Objectives, Methods and Scientific Contributions

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

Most of the empirical studies falsify the inflation-hedging hypothesis of stocks and real estate, but they typically establish their research methods on quarterly to annual returns and, therefore, contrast with the fact that most investors have much longer investment horizons. Additionally, the perverse inflation-hedging characteristics of stocks and real estate run contrary to the general economic theory that these assets should be a good hedge against inflation. The residual claims of the investors are the cash flows and retained earnings, and these are derived from real assets.

In our paper *'Inflation-Hedging, Asset Allocation and the Investment Horizon'*, my coauthors, Christian Rehring and Steffen Sebastian, and I link the inflation-hedging analysis to the mixed asset allocation analysis focusing on the role of the investment horizon for a buy-and-hold investor. Using a vector auto-regression (VAR) for the UK market, we estimate correlations of nominal returns with inflation to analyze how the inflation-hedging abilities of cash, bonds, stocks and direct commercial real estate change with the investment horizon. In doing so, we find that the inflation-hedging characteristics of all assets improve with the investment horizon. Cash is clearly the best inflation hedge at short and medium horizons. For long horizons, direct real estate hedges unexpected inflation as well as cash. These results have implications for the difference between the term structures of annualized volatilities of real versus nominal returns, and ultimately for portfolio choice. While cash is very attractive for short-horizon investors, it is much less attractive at medium and long horizons. The allocation to real estate is strongly increasing with the investment horizon; due to the favorable inflation-hedging abilities, real estate is more attractive for an investor concerned about inflation. Bonds are less attractive for an investor taking into account inflation. 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 respectively providing information about the inflation-hedging qualities of the single assets in a portfolio context. The differences between the real and nominal asset allocation results can be substantial.

## Modeling Asset Price Dynamics under a Multivariate Cointegration Framework

The stationary vector autoregressive (VAR) model is a popular framework for modeling long-run asset price dynamics in the empirical finance research. This approach allows to study the interactions between asset prices and economic state variables as well as the pulling and pushing forces going through certain economic channels. However, the stationary VAR approach ignores important additional information as it does not consider the presence of common long-run relations between the assets and state variables. Under cointegration, deviations of the long-term comovement of the variables cause predictable backward movements.

Therefore, in our paper *'Modeling Asset Price Dynamics under a Multivariate Cointegration Framework'*, my coauthor, Tim Koniarski, and I contribute to the literature by comparing the stationary VAR and the VEC approach with respect to their modeled short and long-run behavior, where both models include the same set of investable assets (T-bills, stocks and bonds) and common state variables that have been shown to predict returns (dividend-price ratio, term spread and inflation).

Starting from a VAR representation, we find strong evidence for common stochastic trends between the levels of the six variables. The cointegration rank test indicates four cointegration relations among the level variables. While the standard VAR model captures only the long-run dynamics of stationary data, the VEC model takes into account information about the four cointegration relations and is able to distinguish between short and long-run effects. The estimation results show a more than two times higher adjusted $R^2$ for the risk premia of stocks and bonds for the VEC. These increases already show the importance of incorporating common long-run effects in the analysis of asset price dynamics. This motivates a further comparison of the long-run dynamics implied by the VAR and VEC, depending on the time horizon, by investigating the variance decompositions of real and nominal asset returns. Therefore, we examine the various risk components of the returns, their interactions and sources. We find substantial differences between the two models with respect to the term structure of risk. The VEC shows a much higher correlation between the risk premia and real interest rate in short and medium horizons as well as a much more negative correlation between the risk premia and inflation in the long run. As a further finding, the volatilities of nominal returns are significantly lower under cointegration over all horizons. Turning to real terms, we find the same evidence for stock returns and, moreover, the term structure of T-bills appears roughly flat compared to the mean-averting structure of the stationary VAR. The latter result indicates a strong common stochastic trend between nominal T-bills and inflation. Finally, these differences in the risk structure influence the optimal portfolio choice. Under cointegration the global minimum variance portfolio of real (nominal) returns is much more tilted towards T-bills (bonds). In the VEC, a less risk-averse investor has a much higher equity exposure as the investment horizon lengthens and even leverages the position in the very long run. This behavior is borne by a decreasing bond position compared to the VAR model.

# Do Stock Prices and Cash Flows Drift Apart? The Influence of Macroeconomic Proxies

Several studies in the predictability literature use variables such as the dividend-price ratio and earnings-price ratio to forecast stock returns. According to theory, stock prices are the discounted future cash flows and, therefore, should move around their fundamentals (dividends and earnings) in the long run. Hence, it is generally assumed that prices and cash flows are cointegrated one-for-one or, alternatively, that the dividend-price ratio and earnings-price ratio are stationary variables, since otherwise the conventional $t$-statistics lead to wrong conclusions about the evidence of return predictability.

In our paper *'Do Stock Prices and Cash Flows Drift Apart? The Influence of Macroeconomic Proxies'*, my coauthor, Tim Koniarski, and I extend the loglinear Campbell and Shiller (1988a) model to investigate the influences of macroeconomic variables (inflation, short-term interest rates, government and corporate bond yields) on stock prices and cash flows (dividends and earnings) and, consequently, the implied impacts on total stock returns. The versatile model setup enables us to test the validity of the stationarity of the dividend-price ratio in a multivariate framework. Moreover, in the same way we also examine the stationarity of further financial ratios such as dividend-earnings, earnings-price, real short-interest rates, term spread and credit spread, which are additionally used in the predictability literature. Our tests show that dividend-earnings and the term spread most likely are stationary or, alternatively, that the underlying variables have the same stochastic trends, whereas the null hypothesis of stationarity is rejected for the remaining ratios. Additionally, we find inflation to have a strong impact on the equity market. While other papers often consider returns, prices and dividends in real terms to avoid inflation effects and assume that inflation influences equity market variables identically, we show a negative linkage between nominal prices and inflation and nominal cash flows to be positively associated to inflation in the long run. Thus, nominal total stock returns are reduced by inflation shocks in the short term, but recover for long time horizons. This result connects the contrary findings of Fama and Schwert (1977) and Boudoukh and Richardson (1993), and enforces the findings of my first paper

*'Inflation-Hedging, Asset Allocation and the Investment Horizon'*. Moreover, we find that interest rates play a similar role for all equity market variables. Although prices, dividends and earnings are reduced by rising interest rates, the magnitude is much more pronounced for cash flows than for stock prices. Finally, while for corporate bond yields we find large positive effects on the equity market, the influences of the government bond yields are negative.

# Chapter 2

# Inflation-Hedging, Asset Allocation and the Investment Horizon

This paper is the result of a joint project with *Christian Rehring* and *Steffen Sebastian.*


## Abstract

Focusing on the role of the investment horizon, we analyze the inflation-hedging abilities of stock, bond, cash and direct real estate investments. Based on vector autoregression for the UK market, we find that the inflation-hedging characteristics of all assets improve with the investment horizon. For long horizons, direct real estate seems to hedge unexpected inflation as well as cash. This has important implications for the risk structure of real versus nominal returns of the assets depending on the investment horizon, and ultimately for portfolio choice. Switching from nominal to real returns, real estate becomes more attractive with very high long-term allocations. In contrast, bonds are less attractive for an investor taking inflation into account.

## 2.1 Introduction

The monetary base has grown considerably in many economies as a reaction to the recent 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. While persistency makes the level of inflation well predictable in the short run, this effect turns upside down in the long term, making inflation a key variable for long-term portfolio decisions. Accordingly, assets that hedge inflation are desirable for private investors who are concerned about the purchasing power of their investments as well as for institutional investors whose liabilities are linked to inflation (such as pension funds). 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).

Most of the empirical studies falsify the inflation-hedging hypothesis of stocks and real estate, but they typically use quarterly or annual returns. The perverse inflation-hedging characteristics run contrary to the general economic theory that assets should be a good hedge against inflation due to the fact that they are claims to cash-flows derived from real assets. However, studies based on quarterly or annual returns contrast 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 and inflation-hedging abilities depend on the investment horizon. The asset classes which are usually considered for a mixed asset allocation optimization are cash, bonds and stocks. But real estate is a further important asset class as it offers performance and diversification benefits. Moreover, practitioners often regard real estate investments to be a good inflation hedge. Direct real estate has high transaction costs, inducing substantial horizon effects in periodic expected returns (e.g. Collet, Lizieri, and Ward, 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, Lizieri, and Ward, 2003; Fisher and Young, 2000).

In this paper, we link the inflation-hedging analysis to the mixed asset allocation analysis focusing on the role of the investment horizon for a buy-and-hold investor. Using a vector auto-regression (VAR) for the UK market, we estimate correlations of nominal returns with inflation to analyze how the inflation-hedging abilities of cash, bonds, stocks and direct commercial real estate change with the investment horizon.[1] In doing so, we find that the inflation-hedging characteristics of all assets improve with the investment horizon. These 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 respectively providing information about the inflation-hedging qualities of the single assets in a portfolio context.

The remainder of the paper 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 and discuss the inflation-hedging abilities of the assets. The asset allocation problem is examined in the next section, again distinguishing between nominal and real returns. Finally, the main findings are summarized.

## 2.2 Literature Review

Our paper contributes to two strands of literature: inflation-hedging and strategic asset allocation. Both fields are studied over different investment horizons, because long-term results can differ tremendously from short-term results.

The inflation-hedging literature starts with Bodie (1976), Jaffe and Mandelker (1976) and Fama and Schwert (1977). They find 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

[1] 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.

other countries. Bonds and bills provide a hedge against expected inflation, but not against unexpected inflation. Studies using the Fama and Schwert methodology and 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, Chen, and Thibodeau, 1984; Hartzell, Hekman, and Miles, 1987; Gyourko and Linneman, 1988; Rubens, Bond, and Webb, 1989). Examining the UK market, Limmack and Ward (1988) 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.

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 have motivated research in 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. Hoesli, Lizieri, and MacGregor (2008), Luintel and Paudyal (2006) 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, Lizieri, and MacGregor (2008) 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, while the long-term link to unexpected inflation is often negative. Luintel and Paudyal (2006) confirm the positive long-term relationship between UK stocks and inflation. Schätz and Sebastian (2009) 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, Lizieri, and MacGregor (2008), 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 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) find US stocks to hedge unexpected inflation in the very long-run (at the 50-year horizon). Hoevenaars, Molenaar, Schotman, and Steenkamp (2008) calculate correlations between 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.

While the empirical evidence is not unambiguous, the general picture emerges is that the inflation-hedging abilities of assets improve with the investment horizon. Nevertheless, there is no evidence about the long-term inflation-hedging abilities of direct real estate in a VAR framework.

Of course, the different inflation-hedging characteristics of the assets have portfolio implications. Intuitively, a highly positive correlation of nominal returns with inflation decreases the volatility of real returns on the asset. Hence, the better the inflation-hedging ability of the asset, the more attractive it is for an investor concerned about real returns. Schotman and Schweitzer (2000) show that when the investor is concerned 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 varying over the investment horizon.

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 strong mean reversion, bonds exhibit slight mean reversion, whereas cash returns are mean averting. Thus, there are huge horizon effects in optimal portfolio compositions. In addition to stocks, bonds and cash investments, Fugazza, Guidolin, and Nicodano (2007) consider European property shares, Fugazza, Guidolin, and Nicodano (2009) consider US REITs, whereas MacKinnon and Al Zaman (2009) consider US direct real estate.[2] While Fugazza, Guidolin, and Nicodano (2007) find property shares and REITs important in an investor's portfolio, MacKinnon and Al Zaman (2009) weaken their result if an investor has access to the direct property market. Hoevenaars, Molenaar, Schotman, and Steenkamp (2008) and Amenc, Martellini, Milhau, and Ziemann (2009) analyze the US market including securitized real estate as an asset class. Hoevenaars, Molenaar, Schotman, and Steenkamp (2008) 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. Rehring (2012) studies the role of direct real estate in a mixed-asset portfolio over different investment horizons for the UK market. Considering transaction costs, he finds direct real estate to be important if the investor has a long horizon.

Analyzing the UK market, we follow the studies using a VAR approach. 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 show the impact of the differing inflation-hedging abilities of the assets in a portfolio.

## 2.3 VAR Model and Data

### 2.3.1 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

[2] Hoevenaars, Molenaar, Schotman, and Steenkamp (2008) and Amenc, Martellini, and Ziemann (2009) extend the long-term asset allocation analysis based on VAR estimates to an asset-liability context, modeling the dynamics of liabilities of institutional investors.

returns. Assume that a VAR(1) model captures the dynamic relationships between asset returns and the additional state variables:

$$\boldsymbol{z}_{t+1} = \boldsymbol{\Phi}_0 + \boldsymbol{\Phi}_1 \boldsymbol{z}_t + \boldsymbol{\nu}_{t+1}. \tag{2.1}$$

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 $(3 \times 1)$ 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 realized inflation $i_{t+1}$, and three other state variables stacked in the $(3 \times 1)$ vector $\boldsymbol{s}_{t+1}$ (the cap rate, the dividend yield and the yield spread). Thus,

$$\boldsymbol{z}_{t+1} = \begin{pmatrix} n_{0,t+1} \\ \boldsymbol{x}_{t+1} \\ i_{t+1} \\ \boldsymbol{s}_{t+1} \end{pmatrix} \tag{2.2}$$

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

$$\boldsymbol{\nu}_{t+1} \sim IIDN(\boldsymbol{0}, \boldsymbol{\Sigma}_\nu) \text{ with } \boldsymbol{\Sigma}_\nu = \begin{pmatrix} \sigma_0^2 & \boldsymbol{\sigma}_{0x} & \sigma_{0i} & \boldsymbol{\sigma}_{0s} \\ \boldsymbol{\sigma}_{0x} & \boldsymbol{\Sigma}_{xx} & \boldsymbol{\sigma}_{ix} & \boldsymbol{\Sigma}_{sx} \\ \sigma_{0i} & \boldsymbol{\sigma}_{ix} & \sigma_i^2 & \boldsymbol{\sigma}_{is} \\ \boldsymbol{\sigma}_{0s} & \boldsymbol{\Sigma}_{sx} & \boldsymbol{\sigma}_{is} & \boldsymbol{\Sigma}_{ss} \end{pmatrix}. \tag{2.3}$$

The matrix $\boldsymbol{\Sigma}$ consists of the following block structure: the variance of nominal cash return shocks, $\sigma_0^2$, the covariance-matrix of excess return shocks, $\boldsymbol{\Sigma}_{xx}$, the variance of inflation shocks, $\sigma_i^2$, and the covariance-matrix of the residuals of the state variables, $\boldsymbol{\Sigma}_{ss}$. 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, $\sigma_{0i}$, 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, $\boldsymbol{\Sigma}_{sx}$, and the vector of covariances between inflation shocks and shocks to the state variables, $\boldsymbol{\sigma}_{is}$.

### 2.3.2 Data

The results are based on an annual dataset from 1956 to 2010 (55 observations) for the UK market, the Appendix 2.A.1 provides more details on the data used. As noted above, cash (T-bills), direct commercial real estate, stocks and long-term government bonds (gilts) 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. For direct real estate returns we 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; Plazzi, Torous, and Valkanov, 2010; Rehring, 2012).

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 2010 are based on IPD's long-term index. Returns from 1956 to 1970 are from Scott (1996).[3] 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).[4] Key, Zarkesh, and Haq (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. Additionally the use of annual frequency avoid the stale appraisal problem. Real estate returns are unsmoothed using the approach of Barkham and Geltner (1994) because the original smoothed

[3]Note that due to the unsmoothing procedure for real estate returns, one additional observation is needed as shown in Appendix 2.A.2 .

[4]For comparison, the widely-used NCREIF Property Index (NPI) for the U.S. was based on only 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).

returns would understate the true short-term volatility. Appendix 2.A.2 provides details about the unsmoothing procedure and Appendix 2.A.3 reports robustness checks with regard to the unsmoothing parameters.

Table 2.1 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, while bonds have a mean excess return with regard to cash of only 1% p.a., but additionally bond returns are quite volatile so that the Sharpe ratio is low. Direct 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 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.

### 2.3.3 VAR Estimates

The results of the VAR(1), estimated by OLS, are given in Table 2.2. Panel A reports the estimated coefficients. In parentheses below are the standard errors. The last column shows the $R^2$ and the $F$-statistics of the joint significance in brackets below. Panel B contains the standard deviations (diagonal) and correlations (off-diagonals) of the VAR residuals. Appendix 2.A.4 provides several VAR specification tests and suggests an adequate fulfillment of the statistical assumptions.

The $F$-test of joint significance in Panel A indicates 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, Goetzmann, and Rouwenhorst, 1999; Quan and Titman, 1999). Confirming previous studies, real estate returns can also be predicted by

Table 2.1: Summary Statistics

| | Mean | Standard deviation | Sharpe Ratio | Min | Max | Auto-correlation |
|---|---|---|---|---|---|---|
| *Returns* | | | | | | |
| Nominal return on cash ($r_{nom}$) | 7.32% | 3.34% | | 0.50% | 15.70% | 0.82 |
| Excess return on real estate ($x_{re}$) | 3.48% | 15.17% | 0.25 | -56.95% | 26.65% | 0.01 |
| Excess return on stocks ($x_{st}$) | 6.89% | 23.42% | 0.29 | -81.38% | 81.09% | -0.13 |
| Excess return on bonds ($x_{bo}$) | 0.91% | 11.30% | 0.08 | -28.35% | 29.72% | -0.10 |
| *State variables* | | | | | | |
| Log inflation ($infl$) | 5.53% | 4.37% | | 0.01% | 22.01% | 0.76 |
| Log cap rate ($cr$) | -2.84 | 0.23 | | -3.44 | -2.28 | 0.64 |
| Log dividend yield ($dy$) | -3.15 | 0.30 | | -3.86 | -2.15 | 0.71 |
| Log yield spread ($ys$) | 0.43% | 1.62% | | -4.34% | 4.37% | 0.45 |

*Notes:* This table shows summary statistics for the variables included in the VAR model over the sample 1956–2010. Autocorrelation refers to the first-order autocorrelation. The mean log returns are adjusted by one half of the return variance to reflect log mean returns.

Table 2.2: VAR Estimation Results

| Panel A | | Coefficients of the lagged variables | | | | | | | | $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|
| | Const. | $r_{nom,t}$ | $x_{re,t}$ | $x_{st,t}$ | $x_{bo,t}$ | $infl_t$ | $cr_t$ | $dy_t$ | $ys_t$ | $[F-stat.]$ |
| $r_{nom,t+1}$ | -0.01 | 0.82*** | 0.05*** | 0.01 | -0.06*** | 0.08 | -0.01 | 0.01 | -0.25* | 88.9% |
| | (0.04) | (0.08) | (0.02) | (0.01) | (0.02) | (0.06) | (0.01) | (0.01) | (0.13) | [45.9***] |
| $x_{re,t+1}$ | 0.79* | -0.48 | 0.13 | -0.02 | 0.25 | -0.21 | 0.18* | 0.07 | 3.04** | 33.2% |
| | (0.43) | (0.91) | (0.20) | (0.11) | (0.21) | (0.71) | (0.10) | (0.08) | (1.41) | [2.9**] |
| $x_{st,t+1}$ | 2.14*** | -0.09 | -0.08 | -0.01 | 0.26 | -0.94 | 0.26 | 0.41*** | 2.12 | 39.2% |
| | (0.63) | (1.34) | (0.29) | (0.16) | (0.3) | (1.04) | (0.16) | (0.12) | (2.07) | [3.7***] |
| $x_{bo,t+1}$ | 0.63** | 0.72 | 0.07 | -0.04 | -0.21 | 0.29 | 0.24*** | 0.00 | 1.46 | 34.3% |
| | (0.32) | (0.67) | (0.15) | (0.08) | (0.15) | (0.52) | (0.08) | (0.06) | (1.04) | [3.0***] |
| $infl_{t+1}$ | -0.07 | 0.16 | 0.05 | -0.05*** | -0.06* | 0.65*** | -0.03* | 0.01 | 0.53** | 79.7% |
| | (0.07) | (0.15) | (0.03) | (0.02) | (0.03) | (0.12) | (0.02) | (0.01) | (0.23) | [22.5***] |
| $cr_{t+1}$ | -1.34** | 0.47 | -0.22 | -0.07 | -0.12 | 0.36 | 0.66*** | -0.11 | -3.96** | 56.6% |
| | (0.55) | (1.16) | (0.25) | (0.14) | (0.26) | (0.90) | (0.14) | (0.11) | (1.79) | [7.5***] |
| $dy_{t+1}$ | -2.17*** | 0.12 | 0.09 | 0.09 | -0.37 | 0.59 | -0.37** | 0.66*** | -0.88 | 64.1% |
| | (0.65) | (1.37) | (0.3) | (0.17) | (0.31) | (1.06) | (0.16) | (0.13) | (2.12) | [10.3***] |
| $ys_{t+1}$ | 0.02 | -0.07 | -0.01 | -0.03** | 0.02 | 0.11 | 0.01 | 0.00 | 0.38** | 37.4% |
| | (0.05) | (0.1) | (0.02) | (0.01) | (0.02) | (0.08) | (0.01) | (0.01) | (0.15) | [3.4***] |

*Continued*

*Continued*

Panel B

| | $r_{nom}$ | $x_{re}$ | $x_{st}$ | $x_{bo}$ | $infl$ | $cr$ | $dy$ | $ys$ |
|---|---|---|---|---|---|---|---|---|
| $r_{nom}$ | (1.21%) | -16.36% | -12.89% | -24.23% | 54.13% | 14.63% | 16.63% | -39.98% |
| $x_{re}$ | | (13.44%) | 53.82% | 16.99% | -3.24% | -97.42% | -52.56% | -21.36% |
| $x_{st}$ | | | (19.79%) | 43.63% | -11.80% | -53.39% | -95.57% | -18.59% |
| $x_{bo}$ | | | | (9.92%) | -49.96% | -15.50% | -46.07% | -3.27% |
| $infl$ | | | | | (2.19%) | 4.59% | 15.10% | -4.72% |
| $cr$ | | | | | | (17.09%) | 52.75% | 22.86% |
| $dy$ | | | | | | | (20.24%) | 20.45% |
| $ys$ | | | | | | | | (1.45%) |

*Notes:* The Table reports the estimation results of the VAR based on annual data from 1956 to 2010. Panel A shows the VAR coefficients. The standard errors are given in parentheses; the symbols *, ** and *** denote significance at the 10, 5 and 1% level, respectively. The rightmost column contains the $R^2$-values and the $F$-statistics of joint significance in brackets with the levels of statistical significance. Panel B shows results regarding the covariance matrix of residuals, where standard deviations are on the diagonal in parentheses and correlations are off the diagonal.

the cap rate.[5] 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 in Panel B of Table 2.2, we see that excess stock and direct real estate return residuals are almost perfectly negatively correlated with shocks to the corresponding 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.

## 2.4 Horizon Effects in Risk and Return for Nominal and Real Returns

### 2.4.1 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,

[5]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 paper with the excess return on property shares (UK Datastream real estate total return index) as an additional state variable for the period 1966 to 2010. The main results are similar to those reported in this paper. To make use of the additional observations and to avoid proliferation of the VAR parameters, the eight-variable VAR is used.

2004):

$$\frac{1}{k}Var\left(\boldsymbol{z}_{t+1}+\cdots+\boldsymbol{z}_{t+k}\right)\right) = \frac{1}{k}\Big[\boldsymbol{\Sigma}_\nu + (\boldsymbol{I}+\boldsymbol{\Phi}_1)\,\boldsymbol{\Sigma}_\nu\,(\boldsymbol{I}+\boldsymbol{\Phi}_1)' + \left(\boldsymbol{I}+\boldsymbol{\Phi}_1+\boldsymbol{\Phi}_1^2\right)\boldsymbol{\Sigma}_\nu\left(\boldsymbol{I}+\boldsymbol{\Phi}_1+\boldsymbol{\Phi}_1^2\right)' + \cdots + \left(\boldsymbol{I}+\boldsymbol{\Phi}_1+\cdots+\boldsymbol{\Phi}_1^{(k-1)}\right)\boldsymbol{\Sigma}_\nu\left(\boldsymbol{I}+\boldsymbol{\Phi}_1+\boldsymbol{\Phi}_1^{(k-1)}\right)'\Big], \tag{2.4}$$

where $\boldsymbol{I}$ is the $(8\times8)$ 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:

$$\boldsymbol{M}_n = \begin{bmatrix} 1 & \boldsymbol{0}_{1\times3} & 0 & \boldsymbol{0}_{1\times3} \\ \boldsymbol{\iota}_{3\times1} & \boldsymbol{I}_{3\times3} & \boldsymbol{0}_{3\times1} & \boldsymbol{0}_{3\times3} \\ 0 & \boldsymbol{0}_{1\times3} & 1 & \boldsymbol{0}_{1\times3} \end{bmatrix}. \tag{2.5}$$

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

$$\frac{1}{k}Var\begin{bmatrix} n_{0,t+k}^{(k)} \\ \boldsymbol{n}_{t+k}^{(k)} \\ i_{t+k}^{(k)} \end{bmatrix} = \frac{1}{k}\boldsymbol{M}_n Var\left(\boldsymbol{z}_{t+1}+\cdots+\boldsymbol{z}_{t+k}\right)\boldsymbol{M}_n'. \tag{2.6}$$

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

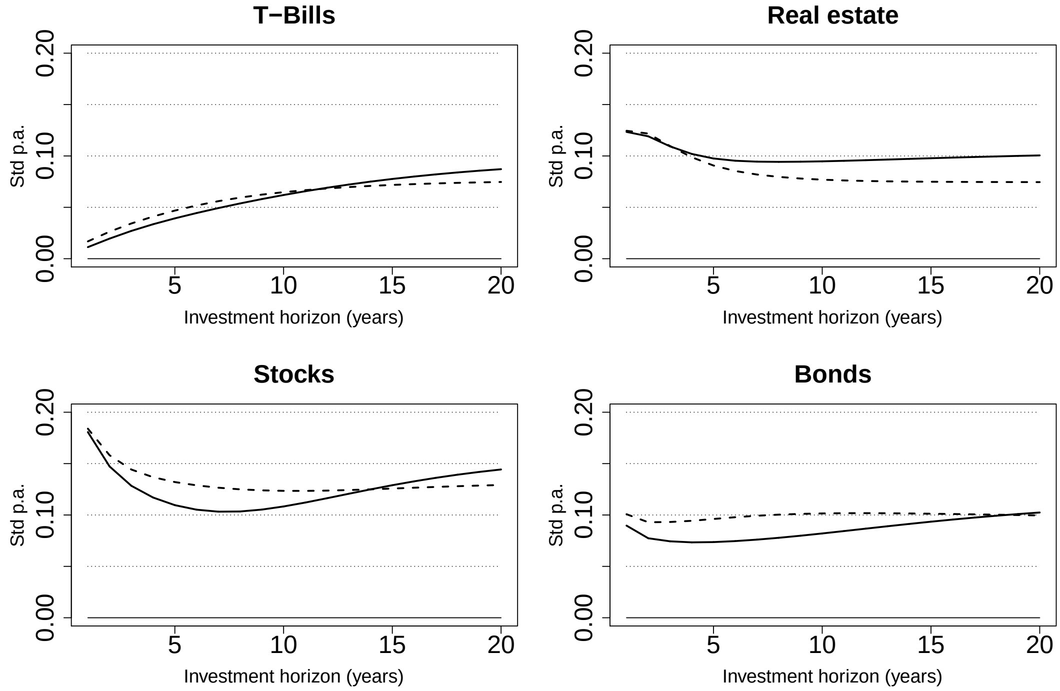
$$\boldsymbol{M}_r = \begin{bmatrix} \boldsymbol{I}_{4\times4} & -\boldsymbol{1}_{4\times1} \\ \boldsymbol{0}_{1\times4} & 1 \end{bmatrix}, \tag{2.7}$$

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

$$\frac{1}{k}Var\begin{bmatrix} r_{0,t+k}^{(k)} \\ \boldsymbol{r}_{t+k}^{(k)} \\ i_{t+k}^{(k)} \end{bmatrix} = \frac{1}{k}\boldsymbol{M}_r Var\begin{bmatrix} n_{0,t+k}^{(k)} \\ \boldsymbol{n}_{t+k}^{(k)} \\ i_{t+k}^{(k)} \end{bmatrix}\boldsymbol{M}_r', \tag{2.8}$$

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

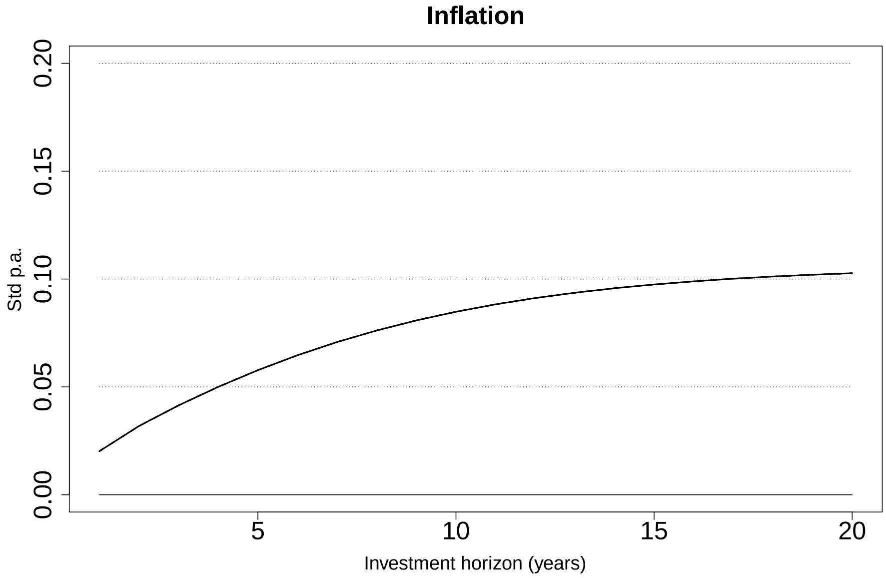
Figure 2.1: Conditional Standard Deviations of the Assets




*Notes:* The figure shows the annualized conditional standard deviations of real and nominal returns of the four assets depending on the investment horizon (years). Nominal returns are represented by solid lines, real returns by dashed lines.

The annualized standard deviations for nominal and real returns of the four asset classes, depending on the investment horizon, are shown in Figure 2.1. Due to return persistency, the periodic long-term return volatility of real cash 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 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 but long investment horizons. 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

Figure 2.2: Conditional Standard Deviation of the Inflation




*Notes:* The figure shows the annualized conditional standard deviation of the inflation rate depending on the investment horizon (years).

(2005), except that they find that real bond returns are slightly mean reverting. Nominal and real returns on direct 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 between the excess returns and the lagged market yield (dividend yield and cap rate respectively) and the high negative correlation of return shocks and market yield shocks. If prices are decreasing unexpectedly, 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 positive shocks to the dividend yield (cap rate) and high dividend yield (cap rate) predict high returns for the future. The annualized $k$-period standard deviation of inflation shocks is shown in Figure 2.2. We see that due to the persistence of inflation, the periodic long-term volatility of inflation is much larger than the short-term volatility.

### 2.4.2 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, stock and bond investments, stacked in the $(3 \times 1)$ vector $\boldsymbol{c}$, the approximation to the nominal $k$-period portfolio return is:

$$n_{p,t+k}^{(k)} = n_{0,t+k}^{(k)} + \boldsymbol{\alpha}'(k)\left(\boldsymbol{x}_{t+k}^{(k)} - \boldsymbol{c}\right) + \frac{1}{2}\boldsymbol{\alpha}'(k)\left[\boldsymbol{\sigma}_x^2(k) - \boldsymbol{\Sigma}_{xx}(k)\boldsymbol{\alpha}(k)\right], \tag{2.9}$$

where $\boldsymbol{\alpha}(k)$ is the $(3\times1)$ vector containing the asset weights, except for the weight on cash, with regard to a $k$-period investment, and $\boldsymbol{\sigma}_x^2(k) = diag\left[\boldsymbol{\Sigma}_{xx}(k)\right]$. Subtracting the $k$-period inflation rate $i_{t+k}^{(k)}$ yields the real portfolio return:

$$r_{p,t+k}^{(k)} = n_{0,t+k}^{(k)} + \boldsymbol{\alpha}'(k)\left(\boldsymbol{x}_{t+k}^{(k)} - \boldsymbol{c}\right) + \frac{1}{2}\boldsymbol{\alpha}'(k)\left[\boldsymbol{\sigma}_x^2(k) - \boldsymbol{\Sigma}_{xx}(k)\boldsymbol{\alpha}(k)\right] - i_{t+k}^{(k)}. \tag{2.10}$$

From Equations (2.9) and (2.10) one can calculate the conditional $k$-period variance of the portfolio return as:

$$Var\left(n_{p,t+k}^{(k)}\right) = \boldsymbol{\alpha}'(k)\boldsymbol{\Sigma}_{xx}(k)\boldsymbol{\alpha}(k) + \sigma_0^2(k) + 2\boldsymbol{\alpha}'(k)\boldsymbol{\sigma}_{0x}(k), \tag{2.11}$$

and

$$\begin{aligned} Var\left(r_{p,t+k}^{(k)}\right) = {} & \boldsymbol{\alpha}'(k)\boldsymbol{\Sigma}_{xx}(k)\boldsymbol{\alpha}(k) + \sigma_0^2(k) + 2\boldsymbol{\alpha}'(k)\boldsymbol{\sigma}_{0x}(k) \\ & + \sigma_i^2(k) - 2\sigma_{0i}(k) - 2\boldsymbol{\alpha}'(k)\boldsymbol{\sigma}_{ix}(k). \end{aligned} \tag{2.12}$$

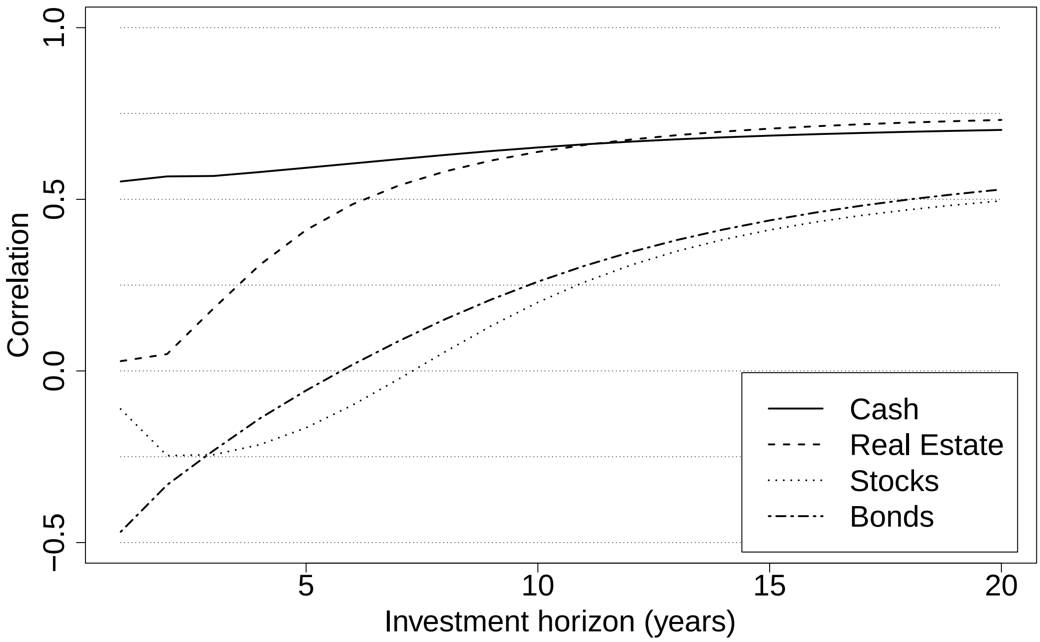
Assuming a 100% investment in the respective asset, Equations (2.11) and (2.12) are the formulas for the variance of asset returns. The variance of the nominal return on an asset differs from the variance of the real return on the asset by the last three terms in Equation (2.12). The first of the three terms says that for all assets the real return volatility is higher than the nominal return volatility due to the variance of inflation shocks. 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, $\sigma_{0i}$, is positive, this decreases the volatility of real cash returns. For the analysis of the other assets it is helpful to note that:

$$-2\sigma_{0i}(k) - 2\boldsymbol{\alpha}'(k)\boldsymbol{\sigma}_{ix}(k) = -2\boldsymbol{\alpha}'(k)\boldsymbol{\sigma}_{in}(k) - 2\left(1 - \boldsymbol{\alpha}'(k)\boldsymbol{\iota}\right)\sigma_{0i}(k), \qquad (2.13)$$

where $\boldsymbol{\sigma}_{in}$ is the vector of covariances between inflation shocks and shocks to the nominal returns on real estate, stocks and bonds. The last term on the right hand side of Equation (2.13) 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. 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 2.3. 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, direct 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.

There are theoretical arguments supporting this empirical evidence. Fama and Schwert (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 paper, 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 being 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) hypothe-

Figure 2.3: Conditional Correlations of Asset Returns and Inflation




*Notes:* The figure shows conditional correlations of nominal returns and inflation depending on the investment horizon (years).

sis, 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 mispricing 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.

### 2.4.3 The Term Structure of Expected Returns

From Equations (2.9) and (2.11) one can calculate the $k$-period log expected nominal portfolio return as:

$$E\left(n_{p,t+k}^{(k)}\right) + \frac{1}{2}Var\left(n_{p,t+k}^{(k)}\right) = E\left(n_{0,t+k}^{(k)}\right) + \frac{1}{2}\sigma_0^2(k) + \boldsymbol{\alpha}'\Big[E\left(\boldsymbol{x}_{t+k}^{(k)} - \boldsymbol{c}\right) + \frac{1}{2}\boldsymbol{\sigma}_x^2(k) + \boldsymbol{\sigma}_{0x}(k)\Big]. \quad (2.14)$$

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 $E\left(n_{0,t+k}^{(k)}\right) = k\bar{n}_0$ , where $\bar{n}_0$ denotes the sample average of log nominal cash returns. Similarly, we assume for the vector of log excess returns: $E\left(\boldsymbol{x}_{t+k}^{(k)}\right) = k\bar{\boldsymbol{x}}$. 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 paper, 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%. Bid-ask spreads of government bonds are typically tiny; total round-trip transaction costs for bonds are assumed to be 0.1%. Transaction costs for buying and selling direct real estate encompass professional fees and the transfer tax. We assume round-trip transaction costs for direct real estate of 7%. For a more extensive discussion about transaction costs of UK direct real estate we refer to Rehring (2012). The assumed round-trip transaction costs enter the vector $\boldsymbol{c}$ in continuously compounded form.

Table 2.3: Term Structure of Expected Returns

| | Expected Returns p.a. | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Real Returns | | | | Nominal Returns | | | |
| Investment Horizon | 1 | 5 | 10 | 20 | 1 | 5 | 10 | 20 |
| T-Bills | 1.8% | 1.9% | 2.0% | 2.1% | 7.3% | 7.4% | 7.5% | 7.7% |
| Real Estate | -1.6% | 3.4% | 3.8% | 4.1% | 3.8% | 8.9% | 9.6% | 10.1% |
| Stocks | 6.9% | 6.7% | 6.8% | 7.2% | 12.4% | 12.2% | 12.3% | 12.8% |
| Bonds | 2.5% | 2.5% | 2.6% | 2.6% | 8.0% | 7.9% | 8.1% | 8.2% |

*Notes:* The table shows annualized expected real and nominal returns depending on the investment horizon (years). These follow from Equations (2.14) and (2.15), 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 7.0% for real estate, 1.0% for stocks and 0.1% for bonds.

The $k$-period expected real portfolio return can be calculated from Equations (2.10) and (2.12) as:

$$\begin{aligned} E\left(r_{p,t+k}^{(k)}\right) + \frac{1}{2}Var\left(r_{p,t+k}^{(k)}\right) = {} & E\left(n_{0,t+k}^{(k)}\right) + \frac{1}{2}\sigma_0^2(k) - E\left(i_{t+k}^{(k)}\right) + \frac{1}{2}\sigma_i^2(k) \\ & + \boldsymbol{\alpha}'\left[E\left(\boldsymbol{x}_{t+k}^{(k)} - \boldsymbol{c}\right) + \frac{1}{2}\boldsymbol{\sigma}_x^2(k) + \boldsymbol{\sigma}_{0x}(k)\right] \\ & - \sigma_{0i}(k) - \boldsymbol{\alpha}'\boldsymbol{\sigma}_{0x}(k), \end{aligned} \quad (2.15)$$

where $E\left(i_{t+k}\right) = k\bar{i}$, the $k$-period expected log inflation and $\frac{1}{2}\sigma_i^2(k)$, one-half of the cumulative variance of 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 Table 2.3.

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 direct real estate return, which increases strongly with the investment horizon, whereas the periodic expected returns on the other assets are roughly constant.

## 2.5 Horizon-Dependent Portfolio Optimizations

### 2.5.1 Mean-Variance Optimization

Campbell and Viceira (2002, 2004) provide the formula for the solution to the mean-variance problem. The optimization problem for nominal return is defined as:

$$\max_{\boldsymbol{\alpha}(k)} E\left(n_{p,t+k}^{(k)}\right) + \frac{1}{2}(1-\gamma)\,Var\left(n_{p,t+k}^{(k)}\right). \tag{2.16}$$

Augmented by transactions, we get the closed-form solution without any restrictions as:

$$\boldsymbol{\alpha}(k) = \frac{1}{\gamma}\boldsymbol{\Sigma}_{xx}^{-1}(k)\left[E\left(\boldsymbol{x}_{t+k}^{(k)} - \boldsymbol{c}\right) + \frac{1}{2}\boldsymbol{\sigma}_x^2(k)\right] + \left(1-\frac{1}{\gamma}\right)\left[-\boldsymbol{\Sigma}_{xx}^{-1}(k)\boldsymbol{\sigma}_{0x}(k)\right], \tag{2.17}$$

where $\gamma$ is the coefficient of relative risk aversion. $\boldsymbol{\alpha}(k)$ is a combination of two portfolios and the mixture depends on the investors risk aversion. The first portfolio:

$$\boldsymbol{\Sigma}_{xx}^{-1}(k)\left[E\left(\boldsymbol{x}_{t+k}^{(k)} - \boldsymbol{c}\right) + \frac{1}{2}\boldsymbol{\sigma}_x^2(k)\right] \tag{2.18}$$

is the *growth optimal* portfolio, the second portfolio is the *global minimum variance* portfolio and is the solution for an extreme risk averse investor ($\gamma \to \infty$):

$$-\boldsymbol{\Sigma}_{xx}^{-1}(k)\boldsymbol{\sigma}_{0x}(k). \tag{2.19}$$

Formula (2.17) applies directly to the mean-variance problem for nominal returns. The solution to the mean-variance problem for real returns differs from Equation (2.17) only by the definition of the global minimum variance portfolio, which is for real returns:

$$-\boldsymbol{\Sigma}_{xx}^{-1}(k)\left(\boldsymbol{\sigma}_{0x}(k) - \boldsymbol{\sigma}_{ix}(k)\right). \tag{2.20}$$

We analyze two portfolios. One portfolio is the global minimum variance portfolio. The second portfolio represents a less risk-averse investor. Campbell and Viceira calculate a "tangency-portfolio" assuming the existence of 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 cash, bonds, stocks and direct real estate for a specific coefficient of relative risk aversion; we choose $\gamma = 10$. The necessary statistics can be calculated by applying appropriate selection matrices to Equations (2.6) and (2.8). We rule out short-selling in both cases of the optimization. To get deeper insight into the shift effects we additionally calculate the portfolios for a non real estate investor denoted as base case.[6]

### 2.5.2 Results

Table 2.4 shows the two cases with optimal portfolio allocations for investment horizons of up to twenty years. Panel A reports the composition of the global minimum variance (GMV) portfolio for optimizations based on real and nominal returns. In the base case a very risk-averse investor holds all (real returns) or most (nominal returns) of his money in cash because it is the least risky investment in nominal as well as in real terms over all investment horizons. Bonds are more attractive in nominal than in real terms. Based on the optimizations for nominal returns, the weight increases from around 3% at the one-year horizon to 16% at the twenty-year horizon, whereas the weight is zero 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 zero weight at long investment horizons.

Considering direct real estate as an additional asset the weight assigned to real estate is increasing with the investment horizon. The differences between the term structures of risk 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 up to 15% 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 (35%) and long horizons (50%). Since the allocations for stocks and bonds remain nearly unchanged compared to the base case, the amount shifted to real estate arises mainly from a decreased cash allocation.

[6] We use the estimated VAR coefficients for the calculation and restrict the real estate weight to zero. Otherwise the results can be changed by different VAR estimates.

Table 2.4: Portfolio Calculations

| Panel A | Global Minimum Variance Portfolio | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Real Returns | | | | Nominal Returns | | | |
| Investment Horizon | 1 | 5 | 10 | 20 | 1 | 5 | 10 | 20 |
| *Base Case* | | | | | | | | |
| T-Bills | 1.00 | 1.00 | 1.00 | 1.00 | 0.97 | 0.81 | 0.77 | 0.85 |
| Stocks | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.06 | 0.04 | 0.00 |
| Bonds | 0.00 | 0.00 | 0.00 | 0.00 | 0.03 | 0.13 | 0.19 | 0.15 |
| *Direct Real Estate Investor* | | | | | | | | |
| T-Bills | 0.99 | 0.84 | 0.65 | 0.50 | 0.96 | 0.77 | 0.72 | 0.69 |
| Real Estate | 0.01 | 0.16 | 0.35 | 0.50 | 0.01 | 0.04 | 0.05 | 0.15 |
| Stocks | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.05 | 0.04 | 0.00 |
| Bonds | 0.00 | 0.00 | 0.00 | 0.00 | 0.03 | 0.13 | 0.20 | 0.16 |

| Panel B | Optimal Portfolio Holdings for $\gamma = 10$ | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Real Returns | | | | Nominal Returns | | | |
| Investment Horizon | 1 | 5 | 10 | 20 | 1 | 5 | 10 | 20 |
| *Base Case* | | | | | | | | |
| T-Bills | 0.86 | 0.73 | 0.60 | 0.47 | 0.85 | 0.56 | 0.33 | 0.42 |
| Stocks | 0.14 | 0.27 | 0.40 | 0.41 | 0.15 | 0.44 | 0.54 | 0.32 |
| Bonds | 0.00 | 0.00 | 0.00 | 0.12 | 0.00 | 0.00 | 0.13 | 0.26 |
| *Direct Real Estate Investor* | | | | | | | | |
| T-Bills | 0.86 | 0.48 | 0.00 | 0.00 | 0.85 | 0.43 | 0.00 | 0.00 |
| Real Estate | 0.00 | 0.29 | 0.66 | 0.75 | 0.00 | 0.15 | 0.36 | 0.64 |
| Stocks | 0.14 | 0.24 | 0.34 | 0.25 | 0.15 | 0.42 | 0.50 | 0.24 |
| Bonds | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.15 | 0.13 |

*Notes:* The table shows optimal portfolio compositions for real and nominal returns depending on the investment horizon (years).

Panel B of Table 2.4 reports the portfolio allocations for an investor with risk aversion of $\gamma = 10$. As noted above, we consider stocks, bonds, cash, and real estate in comparison to the base case where the investor is restricted to stocks, bonds, and cash. In addition to risk statistics, 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. Due to the low expected return on real estate and the high volatility of stock returns, cash is the asset with the highest allocation at short horizons. The weight assigned to cash is strongly decreasing with the investment horizon. As in the GMV portfolio, direct 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. For a direct real estate investor the weight increases to 75% for real returns and to 64% for nominal returns at the twenty-year horizon, while the biggest differences between real and nominal real estate allocations is at the medium horizon (30 percentage points). For the optimization based on nominal returns, the allocation to stocks shows a hump-shaped structure with highest allocations (up to 54%) at intermediate horizons in both cases. For optimizations based on real returns, the allocations to stocks are smaller at medium horizons and the downward tilts for long horizons are less strong due to the strong mean reversion effect of real stock returns. The term structure of real bond returns is roughly flat and on a higher level than cash and real estate combined with a low expected return. Thus, bonds are of low importance in a portfolio based on real terms. 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. Compared to the base case, direct real estate crowds out stocks, bonds and particularly cash.

## 2.6 Conclusion

Focusing on the role of the investment horizon, we analyze the inflation-hedging abilities of stock, bond, cash, and direct real estate investments, and the implications of the inflation-hedge results for portfolio choice. Based on a vector autoregression for the UK market we find that the inflation-hedging characteristics of all assets analyzed improve with the investment horizon. Cash is clearly the best inflation hedge at short and medium horizons. For long horizons, direct real estate hedges unexpected inflation as well as cash. This has implications for the difference between the volatility of real returns versus the 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. This has implications for portfolio choice. When the investor does not have access to direct real estate, cash is a very attractive asset class with higher allocations when the optimization is based on real instead of nominal returns. When direct real estate is an available asset, cash is much less attractive at medium and long horizons. The allocation to real estate is strongly increasing with the investment horizon; due to the favorable inflation-hedging abilities, real estate is more attractive for an investor concerned about inflation. Bonds are less attractive for an investor taking into account inflation. Switching from nominal to real returns, the allocation to stocks is increasing at medium horizons, but decreasing at long horizons. The differences between the asset allocation results can be substantial. Hence, 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.

## 2.A Appendix

### 2.A.1 Data

Table 2.5 contains information on the data.

Table 2.5: Data Information

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

### 2.A.2 Calculation of the Desmoothed Real Estate Returns

The real estate total return and cap rate series are calculated as follows: 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

$$g_t = \frac{g_t^* - (1-a)g_{t-1}^*}{a}, \tag{2.21}$$

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. 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 $(CV)_t$: $Inc_t = IR_t \times CV_{t-1}$. New income returns are computed with regard to the unsmoothed capital value index: $IRU_t = \frac{Inc_t}{UCV_{t-1}}$. 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 $CR_t = \frac{IRU_t}{UCV_t}$.

### 2.A.3 Robustness Regarding Different Unsmoothing Parameters

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: $\alpha = 0.50$ and $\alpha = 0.75$. The results are presented in Table 2.6. For comparison, the results obtained from the assumption made so far ($\alpha = 0.625$) 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 ($\alpha = 0.50$), the one-year volatility is about 15%. In contrast, when the original returns are assumed to exhibit relatively little smoothing ($\alpha = 0.75$),

Table 2.6: Results Regarding Different Unsmoothing Parameters

| Investment Horizon (years) | 1 | | | 5 | | | 10 | | | 20 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Smoothing Parameter $\alpha$ | 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 | -1.0% | -1.6% | -1.9% | 3.6% | 3.4% | 3.3% | 4.2% | 3.9% | 3.7% | 4.5% | 4.1% | 4.2% |
| Nominal return | 4.4% | 3.8% | 3.5% | 9.3% | 9.0% | 8.9% | 9.8% | 9.7% | 9.6% | 10.2% | 10.1% | 10.0% |
| *Conditional standard deviation of real estate returns p.a* | | | | | | | | | | | | |
| Real return | 15.5% | 12.4% | 10.3% | 10.2% | 9.1% | 8.4% | 8.3% | 7.7% | 7.3% | 7.7% | 7.5% | 7.3% |
| Nominal return | 15.4% | 12.3% | 10.2% | 10.7% | 9.7% | 9.2% | 9.9% | 9.5% | 9.3% | 10.2% | 10.0% | 9.9% |
| *Conditional correlation of inflation and real estate returns* | | | | | | | | | | | | |
| Nominal return | 0.00 | 0.03 | 0.06 | 0.35 | 0.41 | 0.45 | 0.60 | 0.64 | 0.66 | 0.72 | 0.73 | 0.74 |
| *Real estate weight at global minimum variance portfolio* | | | | | | | | | | | | |
| Real return | 0.01 | 0.01 | 0.02 | 0.13 | 0.16 | 0.18 | 0.29 | 0.35 | 0.38 | 0.44 | 0.50 | 0.54 |
| Nominal return | 0.01 | 0.01 | 0.01 | 0.04 | 0.04 | 0.05 | 0.04 | 0.05 | 0.05 | 0.12 | 0.15 | 0.18 |
| *Real estate weight at portfolio with* $\gamma = 10$ | | | | | | | | | | | | |
| Real return | 0.00 | 0.00 | 0.00 | 0.24 | 0.29 | 0.32 | 0.57 | 0.66 | 0.67 | 0.74 | 0.75 | 0.75 |
| Nominal return | 0.00 | 0.00 | 0.00 | 0.13 | 0.15 | 0.18 | 0.32 | 0.36 | 0.37 | 0.62 | 0.64 | 0.65 |

*Notes:* This table shows results for three parameters $\alpha$ used to unsmooth real estate returns and four investment horizons. Results are obtained from re-estimated VAR's where the real estate excess return and cap rate series are based on the alternative assumptions.

the one-year volatility is only 10.3%. However, the longer the investment horizon, the smaller this difference is. Due to the Jensen's inequality adjustment, expected returns are higher for $\alpha = 0.5$; 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 ($\alpha = 0.5$) 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.

### 2.A.4 Misspecification Tests

This appendix presents the specification tests of our VAR model. We perform a VAR order selection and test the residual for autocorrelation, nonnormality and heteroskedasticity. Table 2.7 reports the results of the VAR order selection. Based on the Hannan & Quinn and Schwarz criterion the optimal leg length of the VAR is one.

Table 2.7: VAR Order Selection

| | Lag length | | | |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| AIC(n) | -26.799 | -27.037 | -26.975 | **-27.427*** |
| HQ(n) | **-24.171*** | -22.073 | -19.675 | -17.793 |
| SC(n) | **-25.783*** | -25.117 | -24.152 | -23.702 |

Table 2.8 reports the results of the multivariate residual tests. We first test for residual autocorrelation using the Portmanteau test and the Breusch-Godfrey-$LM$ test with the small sample correction by Edgerton and Shukur (1999). Both tests have the null of no autocorrelation up to $h$th order residual autocorrelation whereas the Portmanteau test has been found to have greater power for larger $h$ and the Edgerton and Shukur test for low order residual autocorrelation (small $h$). Therefore, we calculate the $Q$-statistics for 8th, 12th and 16th order for the Portmanteau and the $FLM$-statistic for 4th order for the Edgerton and Shukur test.

Table 2.8: Residual Tests

| | Results | | |
|---|---|---|---|
| Test | Test statistic | Appr. distrubution | $p$-value |
| $Q_8$ | 484.84 | $\chi^2(448)$ | 0.111 |
| $Q_{12}$ | 702.755 | $\chi^2(704)$ | 0.506 |
| $Q_{16}$ | 897.234 | $\chi^2(960)$ | 0.926 |
| $FLM_4$ | 1.001 | $F(256, 63)$ | 0.513 |
| $LJB_{Skew}$ | 8.975 | $\chi^2(8)$ | 0.481 |
| $LJB_{Kurt}$ | 6.621 | $\chi^2(8)$ | 0.344 |
| $LJB_{Both}$ | 15.596 | $\chi^2(16)$ | 0.58 |
| $MARCH_{LM}(1)$ | 1296.784 | $\chi^2(1296)$ | 0.489 |
| $W_{nocrossterms}$ | 584.618 | $\chi^2(576)$ | 0.393 |

Next we look for non-normality in the residuals using the multivariate extension of the Jarque-Bera test and examine the null of normal skewness, kurtosis and the joint of both represented by the $LJB$-statistics. In the last part of table 2.8 we test to neglect conditional and general heteroskedasticity with the multivariate $ARCH - LM$ and White test, both tests have the null of homoskedasticity. All of these tests cannot reject their null hypothesis to the common 5% level and hence the first order VAR is well specified.

# Chapter 3

# Modeling Asset Price Dynamics under a Multivariate Cointegration Framework

This paper is the result of a joint project with *Tim Koniarski*.


## Abstract

We show that allowing for cointegration within a vector autoregressive (VAR) framework yields important implications for modeling the asset price dynamics of T-bills, stocks and bonds over all investment horizons. While the stationary VAR approach ignores common stochastic trends of the included variables, the vector error correction (VEC) model captures these common long-run relations and their predictable restorations. We find interesting differences in the term structure of risk of the VEC compared to the traditional VAR. There is a strong positive link between risk premia and real interest rates in the short term and a much more negative and longer-lasting impact of inflation on excess stock and bond returns. Incorporating cointegration significantly shifts downward nominal stock and bond volatilities and incorporates inflation as the driving component of nominal interest rates, which results in a flat risk structure of real interest rates. For an extreme risk-averse investor, the optimal real (nominal) return portfolio is much more tilted towards T-bills (bonds).

## 3.1 Introduction

In recent empirical finance research, the stationary vector autoregressive (VAR) model is a popular framework for modeling long-run asset price dynamics.[1] In the multi-horizon context, the VAR has some convenient advantages compared to the simple regression model. First, this approach makes it possible to study the interactions between asset prices and economic state variables as well as the pulling and pushing forces going through certain economic channels. Second, long-term effects can easily be explored by iteratively calculating multi-period forecasts. Hence, the model estimated by short-run dynamics is able to capture long-horizon behavior. Third, while simple long-horizon regressions are often criticized due to their statistical properties (biased $t$-statistics), the VAR shows no econometric issues with respect to long-run forecasts. Therefore, the VAR setup is often used to account for predictability and to capture time-varying investment opportunities of stocks and bonds simultaneously.

However, we argue that the stationary VAR approach ignores important additional information as it does not consider the presence of common long-run relations between the assets and state variables. Deviations in the long-term comovement of the variables cause predictable backward movements. These cointegration effects can be incorporated into an extension of the VAR model, the vector error correction (VEC) model. Allowing for cointegration yields important implications for the interdependencies among the variables at all horizons. We observe a significant change in the horizon-dependent risk structure of the asset returns and ultimately that the optimal portfolio rules are substantially different from the stationary VAR model.

The framework of cointegration and error correction has been used in several other studies and goes back to Granger (1981) and Engle and Granger (1987). Campbell and Shiller (1987) test cointegration between dividends and stock prices as well as long-term bond yields and short-term interest rates. They detect the dividend-

[1] Some examples of authors using the VAR methodology to account for predictability and horizon effects of asset returns include: Campbell and Shiller (1988a,b); Campbell (1991); Campbell and Ammer (1993); Kandel and Stambaugh (1996); Barberies (2000); Campbell, Chan, and Viceira (2003); Campbell and Viceira (2005); Hoevenaars, Molenaar, Schotman, and Steenkamp (2008); Jurek and Viceira (2011).

price ratio and term spread to be stationary and restoring to their means, while the deviations can be quite persistent. Nasseh and Strauss (2000) find significant cointegration relations between stock prices and macroeconomic variables in six European countries. Other academic researchers emphasize a long-run relationship between consumption and dividends containing important information about the variances and means of cash flows and, by implication, their returns (Bansal, Gallant, and Tauchen, 2007; Hansen, Heaton, and Li, 2008; Bansal, Dittmar, and Kiku, 2009; Bansal and Kiku, 2011). Bansal, Dittmar, and Kiku (2009) and Bansal and Kiku (2011) incorporate this error correction information into the VAR framework (EC-VAR) and conclude that the dynamics are better captured compared to the traditional VAR. As a consequence, the risk premium and the term structure of risk can be distorted by neglecting cointegration. Furthermore, Lettau and Ludvigson (2001) and Lettau and Ludvigson (2005) motivate cointegration between consumption, labor income and financial wealth (*cay*). They find that *cay* outperforms popular stock return predictors such as the dividend-price ratio for short as well as long horizons. Hence, cointegration can handle the deviation of asset prices from the fundamental equilibrium in boom and bust cycles and predict their restorations.

These findings motivate an extension of the stationary VAR model by cointegration and the integration of common long-run relationships into a long-run asset pricing analysis. If the time series used in the traditional VAR are differenced in order to obtain stationarity, their stochastic trends are eliminated. Although this procedure is quite common, it is disadvantageous for cointegrated variables and always leads to a distortion of the relationships between the variables analyzed. However, the magnitude and the direction of this bias remain unclear and depend on the investment horizon.

Therefore, we contribute to the literature by comparing the stationary VAR and the VEC model with respect to their modeled short- and long-run behavior, where both models include the same set of investable assets (T-bills, stocks and bonds) and common state variables that have been shown to predict returns (dividend-price ratio, term spread and inflation).[2] Starting from a VAR representation, we find strong

[2] A large amount of literature documents predictability, see for example: Campbell and Shiller (1988a,b); Fama and French (1988, 1989); Hodrick (1992); Campbell and Vuolteenaho (2004a);

evidence for common stochastic trends between the levels of the six variables. The cointegration rank test indicates four cointegration relations among the level variables on a 5% significance level. While the standard VAR model captures only the long-run dynamics of stationary data, the VEC model takes into account information about the four cointegration relations and is able to distinguish between short and long-run effects. The estimation results show a more than two times higher adjusted $R^2$ for the risk premia of stocks and bonds for the VEC. These increases already show the importance of incorporating common long-run effects in the analysis of asset price dynamics. This motivates a further comparison of the long-run dynamics implied by the VAR and VEC, depending on the time horizon, by investigating the variance decompositions of real and nominal asset returns. Therefore, we examine the various risk components of the returns, their interactions and sources. We find substantial differences between the two models with respect to the term structure of risk. The VEC shows a much higher correlation between the risk premia and real interest rate in short and medium horizons as well as a much more negative correlation between the risk premia and inflation in the long run. As a further finding, the volatilities of nominal returns are significantly lower over all horizons under cointegration. Turning to real terms, we find the same evidence for stock returns and, moreover, the term structure of T-bills appears roughly flat compared to the mean-averting structure of the stationary VAR. The latter result indicates a strong common stochastic trend between nominal T-bills and inflation. Finally, these differences in the risk structure influence the optimal portfolio choice. Under cointegration and extreme risk aversion, the optimal real (nominal) return portfolio is much more tilted towards T-bills (bonds). In the VEC, a less risk-averse investor has a much higher equity exposure as the investment horizon lengthens and even leverages the position in the very long run. This behavior is borne by a decreasing bond position compared to the VAR model.

Campbell and Viceira (2005); Jurek and Viceira (2011). However, the evidence of predictability is not unambiguous, especially in the short run. Several authors mention the poor out-of-sample predictability of stock returns. A critical discussion of out-of-sample predictability is given by Goyal and Welch (2008).

The remainder of the paper is organized as follows: In the next section, we describe the methodology of a VAR model, extend it to a VEC model, derive the horizon-dependent variance-covariance matrices for both models and outline the portfolio problem. The third section introduces the data, examines the time series properties for further investigations and presents the results of our empirical short and long-run analysis. Finally, Section 4 summarizes the main findings.

## 3.2 Methodology

In this section, we introduce the VAR and VEC models capturing the return dynamics of the assets analyzed first. Starting with the commonly used VAR methodology, we extend this framework to a VEC model for analyzing integrated and cointegrated time series. Additionally, the VEC allows us to explicitly distinguish between short- and long-run effects in the dynamic system. Second, the predictable return components have important implications for the investment horizon-dependent risk structure of the assets, and ultimately for the portfolio choice. Finally, the risk structure modeled by multi-period conditional variances and the portfolio choice problem are derived.

### 3.2.1 VAR Specification

Let $\Delta \mathbf{z_t}$ be a vector that includes $n_a + 1$ log asset returns and $n_s$ additional log state variables that have been identified to predict returns. In the specification of this study, $r_{0,t}$ denotes our benchmark asset, while $\mathbf{x}_t = \mathbf{r}_t - \boldsymbol{\iota} r_{0,t}$ are the $n_a$ excess returns of the other asset returns, $\mathbf{r}_t$, relative to the benchmark (where $\boldsymbol{\iota}$ is a vector of $n_a$ ones) and $\boldsymbol{s}_t$ contains the $n_s$ predictors. Thus:

$$\Delta \mathbf{z}_t = \begin{pmatrix} r_{0,t} \\ \mathbf{x}_t \\ \mathbf{s}_t \end{pmatrix} \tag{3.1}$$

is of order $((1 + n_a + n_s) \times 1)$. Assume that a VAR model of order $p$ captures the dynamic relationships between the $n = 1 + n_a + n_s$ asset returns and the state variables:

$$\Delta \mathbf{z}_t = \boldsymbol{\mu} + \mathbf{B}_1 \Delta \mathbf{z}_{t-1} + \cdots + \mathbf{B}_p \Delta \mathbf{z}_{t-p} + \mathbf{u}_t, \tag{3.2}$$

where the $\mathbf{B}_j$s are the $(n \times n)$ coefficient matrices, $\boldsymbol{\mu}$ is a $(n \times 1)$ vector of constants and $\mathbf{u}_t = (u_{1t}, ..., u_{nt})'$ is an error term. The shocks $\mathbf{u}_t$ are assumed to be $IID$ with time-invariant zero means and variance-covariance matrix $\boldsymbol{\Sigma}_u$.

This standard VAR approach is an established framework for modeling asset return distributions at various investment horizons (see Kandel and Stambaugh, 1996; Barberies, 2000; Campbell, Chan, and Viceira, 2003; Campbell and Viceira, 2005; Jurek and Viceira, 2011). The variables (returns, rates and first differences of indices) in $\Delta \mathbf{z}_t$ are assumed to be stationary, i.e. integrated of order zero ($I(0)$) or, alternatively, to have no stochastic trends. But $\Delta \mathbf{z}_t$ can be transformed to a level vector $\mathbf{z}_t$ to obtain important additional information for its joint long-run behavior. In this case the variables have a strong link among each other and the VAR of the first differences is not the most beneficial framework, since it can distort these relationships (Lütkepohl, 2005, pp. 243–244).

### 3.2.2 VEC Specification

Although a VAR($p$) model is generally able to handle $\mathbf{z}_t$ with stochastic trends, it is not the most adequate form in our context because the variables of interest are $\Delta \mathbf{z}_t$. However, we can rewrite the level VAR($p$):

$$\mathbf{z}_t = \boldsymbol{\mu} + \mathbf{A}_1 \mathbf{z}_{t-1} + \cdots + \mathbf{A}_p \mathbf{z}_{t-p} + \mathbf{u}_t \tag{3.3}$$

to an unrestricted VEC model of order $p-1$ by subtracting both sides of Equation (3.3) with $\mathbf{z}_{t-1}$:

$$\Delta \mathbf{z}_t = \boldsymbol{\mu} + \boldsymbol{\Pi} \mathbf{z}_{t-1} + \boldsymbol{\Gamma}_1 \Delta \mathbf{z}_{t-1} + \cdots + \boldsymbol{\Gamma}_{p-1} \Delta \mathbf{z}_{t-p+1} + \mathbf{u}_t, \tag{3.4}$$

where $\boldsymbol{\Pi} = -(\mathbf{I} - \mathbf{A}_1 - \cdots - \mathbf{A}_p)$ and $\boldsymbol{\Gamma}_j = -(\mathbf{A}_{j+1} + \cdots + \mathbf{A}_p)$ for $j = 1, ..., p-1$. As can be seen in Equation (3.4), matrix $\boldsymbol{\Pi}$ summarizes the long-run effects, and the short-run effects remain in the $\boldsymbol{\Gamma}_j$s. While the $\boldsymbol{\Gamma}_j$s are full rank matrices, $\boldsymbol{\Pi}$ must have reduced rank, otherwise a logical inconsistency would occur.[3]

Since we want to account for not only stochastic trends, but also for cointegration relationships, we apply the cointegration-rank test (Johansen, 1988, 1991) to determine the number $r < n$ of cointegration relations. This procedure, based on likelihood ratios, tests whether there is a significant difference between the likelihood of the unrestricted model in Equation (3.4) and the likelihood of a model with $\boldsymbol{\Pi}_r$ restricted to rank $r$. Hence, stepwise testing indicates the number of cointegration relations $r$, which is the most restrictive model without obtaining a significantly different likelihood. After obtaining $r$, we calculate the decomposition of $\boldsymbol{\Pi}_r = \boldsymbol{\alpha}\boldsymbol{\beta}'$, where $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are $(n \times r)$ matrices, which leads to the reduced rank system:

$$\Delta \mathbf{z}_t = \boldsymbol{\mu} + \boldsymbol{\alpha}\boldsymbol{\beta}'\mathbf{z}_{t-1} + \boldsymbol{\Gamma}_1 \Delta \mathbf{z}_{t-1} + \cdots + \boldsymbol{\Gamma}_{p-1}\Delta \mathbf{z}_{t-p+1} + \boldsymbol{\nu}_t, \tag{3.5}$$

as shown in Johansen (1996). The matrix $\boldsymbol{\beta}$ contains the cointegration relations, $\boldsymbol{\alpha}$ is a matrix of loadings and $\boldsymbol{\nu}_t$ is an error term, which is assumed to be $IID$ with zero means and variance-covariance matrix $\boldsymbol{\Sigma}_\nu$. Note that in case of $r = 0$, i.e. $n$ independent stochastic trends and no cointegration, the matrix $\boldsymbol{\Pi}_r = \mathbf{0}$ and the VEC($p-1$) in Equation (3.5) equals a VAR($p-1$) as in Equation (3.2). Otherwise the VEC outperforms the VAR in differences, because taking into account cointegration relations leads to an increase in the likelihood.

### 3.2.3 Horizon Dependent Variance-Covariance

We investigate the long-run dynamics implied by the stationary VAR and the VEC by examining the term structure of risk and the horizon-dependent variance decompositions of the asset returns analyzed. The risk statistics are based on the covariance matrix of the residuals, i.e. we take into account return predictability. In the following section, we derive the conditional $k$-period variance-covariance matrices.

[3] Assuming $\mathbf{z}_t \sim I(1)$, $\Delta\mathbf{z}_t \sim I(0)$ and considering $\boldsymbol{\Pi} = \mathbf{I}$, the stationary variable $\Delta\mathbf{z}_t$ on the left-hand side of Equation (3.4) would be equal to the sum of stationary variables $\boldsymbol{\Gamma}_j\Delta\mathbf{z}_{t-j}$s and a non-stationary term $\mathbf{z}_{t-1}$ (Juselius, 2006, chap. 5).

For the VAR model, the conditional $k$-period variance-covariance matrix, scaled by the investment horizon, is calculated as follows (see e.g. Campbell and Viceira, 2004):

$$\begin{aligned}\frac{1}{k}Var\left(\Delta\mathbf{z}_{t+1}+\cdots+\Delta\mathbf{z}_{t+k}\right) &= \frac{1}{k}Var\left(\mathbf{z}_{t+k}-\mathbf{z}_{t}\right)=\frac{1}{k}Var\left(\mathbf{z}_{t+k}\right)\\ &= \frac{1}{k}\mathbf{M}'\Big[\boldsymbol{\Sigma}+\left(\mathbf{I}+\mathbf{B}\right)\boldsymbol{\Sigma}\left(\mathbf{I}+\mathbf{B}\right)'\\ &\quad+\left(\mathbf{I}+\mathbf{B}+\mathbf{B}^2\right)\boldsymbol{\Sigma}\left(\mathbf{I}+\mathbf{B}+\mathbf{B}^2\right)'+\cdots\\ &\quad+\left(\mathbf{I}+\mathbf{B}+\cdots+\mathbf{B}^{(k-1)}\right)\boldsymbol{\Sigma}\left(\mathbf{I}+\mathbf{B}+\cdots+\mathbf{B}^{(k-1)}\right)'\Big]\mathbf{M},\end{aligned} \tag{3.6}$$

where:

$$\mathbf{B}=\begin{pmatrix}\mathbf{B}_1 & \mathbf{B}_2 & \mathbf{B}_3 & \cdots & \mathbf{B}_p\\ \mathbf{I} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0}\\ \mathbf{0} & \mathbf{I} & \ddots & & \vdots\\ \vdots & \ddots & \ddots & \mathbf{0} & \vdots\\ \mathbf{0} & \cdots & \mathbf{0} & \mathbf{I} & \mathbf{0}\end{pmatrix},\ \boldsymbol{\Sigma}=\begin{pmatrix}\boldsymbol{\Sigma}_u & \mathbf{0} & \cdots & \mathbf{0}\\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0}\\ \vdots & \ddots & \ddots & \vdots\\ \mathbf{0} & \cdots & \cdots & \mathbf{0}\end{pmatrix},\ \mathbf{M}=\begin{pmatrix}\mathbf{I}\\ \mathbf{0}\\ \vdots\\ \mathbf{0}\end{pmatrix} \tag{3.7}$$

and $\mathbf{I}$ is the $(n\times n)$ identity matrix and $\mathbf{0}$ is a $(n\times n)$ matrix filled with zeros.

For the VEC model, we start by retransforming the VEC$(p-1)$ in Equation (3.5) to a VAR$(p)$ in Equation (3.3) by setting $\boldsymbol{\Pi}_r=\boldsymbol{\alpha}\boldsymbol{\beta}'=-(\mathbf{I}-\mathbf{A}_1-\cdots-\mathbf{A}_p)$ and $\boldsymbol{\Gamma}_j=-(\mathbf{A}_{j+1}+\cdots+\mathbf{A}_p)$ for $j=1,...,p-1$. Afterwards, we write the VAR$(p)$ in a VAR(1) representation, where $\mathbf{A}$ is of the same structure as $\mathbf{B}$ in Equation (3.7), replacing the $\mathbf{B}_j$s by the $\mathbf{A}_j$s and derive $\mathbf{z}_{t+k}$ for this VAR(1):

$$\mathbf{z}_{t+k}=\mathbf{c}+\mathbf{A}^{k-1}\boldsymbol{\nu}^*_{t+1}+\mathbf{A}^{k-2}\boldsymbol{\nu}^*_{t+2}+\cdots+\mathbf{A}\boldsymbol{\nu}^*_{t+k-1}+\boldsymbol{\nu}^*_{t+k},$$

where $\mathbf{c}$ includes all deterministic components and $\boldsymbol{\nu}^*_{t+j}=(\boldsymbol{\nu}_{t+j},\mathbf{0},...,\mathbf{0})'$. Finally, we obtain the conditional $k$-period variance-covariance matrix of the VEC$(p-1)$, scaled by the investment horizon:[4]

$$\frac{1}{k}Var\left(\mathbf{z}_{t+k}\right)=\frac{1}{k}\mathbf{M}'\left[\mathbf{A}^{k-1}\boldsymbol{\Sigma}^*\left(\mathbf{A}^{k-1}\right)'+\mathbf{A}^{k-2}\boldsymbol{\Sigma}^*\left(\mathbf{A}^{k-2}\right)'+\cdots+\mathbf{A}\boldsymbol{\Sigma}^*\mathbf{A}'+\boldsymbol{\Sigma}^*\right]\mathbf{M}, \tag{3.8}$$

[4]Some elements of the variance-covariance matrix of a non-stationary VAR in levels diverge as the horizon $k\to\infty$. However, in case of cointegrated variables, the elements of the VEC variance-covariance matrix can be bounded (Lütkepohl, 2005, pp. 258–262).

where $\mathbf{\Sigma}^*$ is of the same structure as $\mathbf{\Sigma}$ in Equation (3.7) replacing the $\mathbf{\Sigma}_u$ by the $\mathbf{\Sigma}_\nu$.

The investigation and comparison of the long-run dynamics implied by the VAR and VEC models are then based on decompositions of the conditional $k$-period variance of the assets analyzed.[5] The elements of these decompositions are extracted by appropriate selector vectors and matrices applied to $\frac{1}{k}Var\left(\mathbf{z}_{t+k}\right)$, as reported in Campbell and Viceira (2004) for the VAR.

### 3.2.4 Portfolio Choice Problem

Besides analyzing the term structure of risk, we additionally determine the optimal $k$-period mean-variance portfolios of a buy-and-hold investor. For this purpose we use the loglinear approximation of the $k$-period portfolio return introduced by Campbell and Viceira (2002) and used in Campbell and Viceira (2004, 2005), which is given by:

$$r_{p,t+k}^{(k)} = r_{0,t+k}^{(k)} + \boldsymbol{\omega}'(k)\mathbf{x}_{t+k}^{(k)} + \frac{1}{2}\boldsymbol{\omega}'(k)\left(\boldsymbol{\sigma}_x^2(k) - \mathbf{\Sigma}_{xx}(k)\boldsymbol{\omega}(k)\right), \tag{3.9}$$

where $\boldsymbol{\omega}(k)$ is the $(n_a \times 1)$ vector containing the asset weights, except the weight on the benchmark, with regard to a $k$-period investment. In Equation (3.9), $\boldsymbol{\sigma}_x^2(k)$ and $\mathbf{\Sigma}_{xx}(k)$ are obtained by decomposing $\frac{1}{k}Var\left(\mathbf{z}_{t+k}\right)$ into the following block structure:

$$\frac{1}{k}Var\left(\mathbf{z}_{t+k}\right) = \begin{pmatrix} \sigma_0^2(k) & \boldsymbol{\sigma}_{0x}'(k) & \boldsymbol{\sigma}_{0s}'(k) \\ \boldsymbol{\sigma}_{0x}(k) & \mathbf{\Sigma}_{xx}(k) & \mathbf{\Sigma}_{xs}(k) \\ \boldsymbol{\sigma}_{0s}(k) & \mathbf{\Sigma}_{xs}(k) & \mathbf{\Sigma}_{ss}(k) \end{pmatrix} \tag{3.10}$$

and defining $\boldsymbol{\sigma}_x^2(k) = \operatorname{diag}\left(\mathbf{\Sigma}_{xx}(k)\right)$. The $(n_a \times n_a)$ matrix $\mathbf{\Sigma}_{xx}(k)$ denotes the $k$-period covariance matrix of excess returns, the $(n_a \times 1)$ vector $\boldsymbol{\sigma}_{0x}(k)$ contains the $k$-period covariances between benchmark asset and excess returns, and $\sigma_0^2(k)$ is the $k$-period variance of the benchmark asset. The remaining components, $\boldsymbol{\sigma}_{0s}(k)$, $\mathbf{\Sigma}_{xs}(k)$ and $\mathbf{\Sigma}_{ss}(k)$, are covariances involving the state variables. From Equation

[5] For example, as the 90-day nominal T-bill, $(nTb)$, is equal to the real T-bill, $(rTb)$, plus the inflation $(infl)$, the $k$-period variance of the 90-day nominal T-bill can be decomposed as: $Var(nTb_{t+k}) = Var(rTb_{t+k}) + 2Cov(rTb_{t+k}, infl_{t+k}) + Var(infl_{t+k})$.

(3.9) one can calculate the conditional $k$-period variance of the log portfolio return as:

$$Var\left(r_{p,t+k}^{(k)}\right) = \boldsymbol{\omega}'(k)\boldsymbol{\Sigma}_{xx}(k)\boldsymbol{\omega}(k) + \sigma_0^2(k) + 2\boldsymbol{\omega}'(k)\boldsymbol{\sigma}_{0x}(k), \tag{3.11}$$

and the $k$-period log expected portfolio return as:

$$\begin{aligned} E\left(r_{p,t+k}^{(k)}\right) + \frac{1}{2}Var\left(r_{p,t+k}^{(k)}\right) = E\left(r_{0,t+k}^{(k)}\right) + \frac{1}{2}\sigma_0^2(k) \\ + \boldsymbol{\omega}'(k)\left(E(\mathbf{x}_{t+k}^{(k)}) + \frac{1}{2}\boldsymbol{\sigma}_x^2(k) + \boldsymbol{\sigma}_{0x}(k)\right). \end{aligned} \tag{3.12}$$

Equation (3.12) shows how to calculate the approximation of the cumulative log expected portfolio return. 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 depends on the horizon. 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 benchmark return, it holds that $E\left(r_{0,t+k}^{(k)}\right) = k\bar{r}_0$ , where $\bar{r}_0$ denotes the sample average of log benchmark return. Similarly, we assume for the vector of log excess returns that: $E\left(\mathbf{x}_{t+k}^{(k)}\right) = k\bar{\mathbf{x}}$. 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.

Campbell and Viceira (2002, 2004) provide the formula for the solution to the mean-variance problem. They assume an investor with power utility function, i.e. CRRA preferences. Thus, the optimization problem is defined as:

$$\max_{\boldsymbol{\omega}(k)} E\left(r_{p,t+k}^{(k)}\right) + \frac{1}{2}(1-\gamma)\,Var\left(r_{p,t+k}^{(k)}\right), \tag{3.13}$$

and the closed-form solution without any restrictions follows as:

$$\boldsymbol{\omega}(k) = \frac{1}{\gamma}\boldsymbol{\Sigma}_{xx}^{-1}(k)\left(E\left(\mathbf{x}_{t+k}^{(k)}\right) + \frac{1}{2}\boldsymbol{\sigma}_x^2(k)\right) + \left(1-\frac{1}{\gamma}\right)\left(-\boldsymbol{\Sigma}_{xx}^{-1}(k)\boldsymbol{\sigma}_{0x}(k)\right), \tag{3.14}$$

where $\gamma$ is the coefficient of relative risk aversion. $\boldsymbol{\omega}(k)$ is a combination of two portfolios and the mixture depends on the investor's risk aversion. The first portfolio:

$$\boldsymbol{\Sigma}_{xx}^{-1}(k)\left(E\left(\mathbf{x}_{t+k}^{(k)}\right) + \frac{1}{2}\boldsymbol{\sigma}_x^2(k)\right) \tag{3.15}$$

is the *growth optimal* portfolio, the second portfolio is the *global minimum variance* portfolio and is the solution for an extreme risk-averse investor ($\gamma \to \infty$):

$$-\boldsymbol{\Sigma}_{xx}^{-1}(k)\boldsymbol{\sigma}_{0x}(k). \tag{3.16}$$

## 3.3 Empirical Analysis

### 3.3.1 Data and Time Series Properties

Our empirical application is based on quarterly post-war data spanning the period 1952:Q1–2010:Q4. Thus, we start shortly after the 1951 Fed-Treasury Accord to avoid problems caused by the essentially fixed short-term nominal rates before 1952.

We use the data set from Goyal and Welch (2008)[6] and extract six time series: Stock prices of the S&P 500 Index and the 12-month moving sums of dividends paid on the S&P 500 Index, 90-day T-bill rates, long-term government bond returns as well as their yields and the inflation rates. The original source of stock prices is the Center for Research in Security Press (CRSP) and the dividends are from Robert Shiller's website. The T-bills (secondary market) are originally obtained from the Federal Reserve Bank of St. Louis (FRED). The source of the long-term government yields and return data is Ibbotson's *Stocks, Bonds, Bills and Inflation Yearbook*, and the source of the inflation rate is the Consumer Price Index (All Urban Consumers) from the Bureau of Labor Statistics.

These series are used to construct logs of the ex-post real T-bill rates, the excess stock returns (including dividends), the excess bond returns, the dividend-price ratio, the inflation rate and the term (yield) spread.[7] Table 3.1 provides the abbreviations of the variables used.

We compare a stationary VAR and a VEC model with respect to their modeled term structure of risk and asset allocation, where both models include data of the same investable assets (T-bills, stocks and bonds) and common state variables that have been shown to predict returns (dividend-price ratio, term spread and infla-

[6]We would like to thank Amit Goyal for providing an updated version of this data, which is available on his website: http://www.hec.unil.ch/agoyal/.

[7]Hereinafter we write returns and rates instead of log returns and log rates.

Table 3.1: Abbreviations

| Variable Definition | Abbreviation |
|---|---|
| Log ex-post real returns on 90-day T-bill | $d(rTb)$ |
| Log excess return on the S&P 500 index | $d(exSt)$ |
| Log excess return on the 10-year constant marturity Treasury Bond index | $d(exBo)$ |
| Log (1+S&P 500 dividend-price ratio) | $d(dp)$ |
| Log yield on a 10-year Treasury Bond minus the log yield of 90-day T-bill | $d(tms)$ |
| Log inflation rate | $d(infl)$ |

*Notes:* The table shows the abbreviations of the (differenced) variables used. The levels of the variables are the accumulated differences of the log variables and abbreviated without $d(\cdot)$.

tion). While the VAR model includes differenced variables (e.g. the stock return) shown in Table 3.1, the VEC model includes the accumulated differences of these variables, which we denote as level variables (e.g. the total stock return index). Previous research has shown that the dividend-price ratio positively forecasts future aggregate stock returns (Campbell and Shiller, 1988a,b; Fama and French, 1988, 1989; Hodrick, 1992; Goetzmann and Jorion, 1993). The term spread is a business cycle indicator and positively forecasts excess bond returns (Fama and Bliss, 1987; Fama and French, 1989; Campbell and Shiller, 1991; Campbell, Chan, and Viceira, 2003; Campbell and Vuolteenaho, 2004a; Campbell and Viceira, 2005; Jurek and Viceira, 2011). The ex-post real interest rate positively forecasts future excess stock and bond returns (Campbell, Chan, and Viceira, 2003; Campbell and Viceira, 2005; Jurek and Viceira, 2011). Moreover, we use the inflation rate instead of the commonly used ex-ante nominal interest rate (Fama and Schwert, 1977; Campbell, 1987; Glosten, Jagannathan, and Runkle, 1993; Campbell, Chan, and Viceira, 2003; Campbell and Viceira, 2005; Jurek and Viceira, 2011) because we can capture nearly the same dynamics with inflation and real interest rates as with real and nominal interest rates, but we can directly extract inflation influence. Note that all these results are based on stationary data.

Table 3.2: Descriptive Statistics

| Variable | Mean | Sd | Sharpe | Min | Max | Skew | Kurt |
|---|---|---|---|---|---|---|---|
| $d(rTb)$ | 0.28% | 0.74% | - | -1.99% | 4.00% | 0.31 | 5.82 |
| $d(exSt)$ | 1.65% | 8.02% | 0.21 | -30.80% | 19.31% | -0.88 | 4.65 |
| $d(exBo)$ | 0.48% | 5.08% | 0.09 | -19.22% | 20.10% | 0.43 | 5.36 |
| $d(dp)$ | 0.81% | 0.30% | | 0.28% | 1.54% | 0.31 | 2.55 |
| $d(tms)$ | 0.38% | 0.34% | | -0.77% | 1.11% | -0.03 | 2.87 |
| $d(infl)$ | 0.90% | 0.90% | | -3.99% | 4.19% | 0.09 | 7.03 |

*Notes:* The table reports summary statistics of the sample from 1952:Q1 to 2010:Q4 (236 data points). Mean log returns are adjusted by one half of the variance to reflect log mean (gross) returns. "Sd" denotes standard deviation, "Sharpe" denotes Sharpe ratio, "Min" denotes minimum, "Max" denotes maximum, "Skew" denotes skewness and "Kurt" denotes kurtosis of the time series.

Tables 3.2 and 3.3 provide an overview of the sample statistics and correlation of the variables used in the VAR and VEC models. We see that real T-bills have a low return and low variability. The risk premium of bonds is only about a third of the equity premium, although the standard deviation is 5.1% compared to 8% and results in a very low Sharpe ratio for bond investments. As we transform the variables to levels, we calculate the dividend-price ratio as $dp_t = ln(1 + D_t/P_t)$ instead of the normally used $dp_t = ln(D_t/P_t)$ to avoid wrong scaling effects and hence obtain a positive mean for this dividend-price "rate". At first sight, the low correlation between the risk premia of stocks and bonds indicates a good diversification potential. Furthermore, the dividend-price ratio and term spread are very persistent variables, as indicated by their high AR(1) coefficients (97.13% and 84.05%).

Since we want to account for common long-run behavior, we analyze the time-series properties of our data with respect to unit roots and cointegration. Panel A in Table 3.4 presents the results of the univariate test statistics of the augmented Dickey-Fuller test (ADF), with the null of a unit root. The tests are performed by allowing for an intercept and by setting the number of lagged differences as suggested by the Schwarz Criterion (SC) for the multivariate models (see Appendix 3.A.2 ). The non-stationarity hypothesis can be accepted for levels, but is strongly rejected for the first differences except for the dividend-price ratio, which is only rejected

Table 3.3: Simultaneous and Lagged Correlations

| Panel A | | | | | | |
|---|---|---|---|---|---|---|
| Variable | $d(rTb_t)$ | $d(exSt_t)$ | $d(exBo_t)$ | $d(dp_t)$ | $d(tms_t)$ | $d(infl_t)$ |
| $d(rTb_t)$ | 1 | 9.04% | 25.73% | 1.72% | -7.15% | -66.05% |
| $d(exSt_t)$ | | 1 | 8.33% | -8.61% | 12.11% | -17.23% |
| $d(exBo_t)$ | | | 1 | -6.51% | 20.49% | -33.70% |
| $d(dp_t)$ | | | | 1 | -23.02% | 30.25% |
| $d(tms_t)$ | | | | | 1 | -28.27% |
| $d(infl_t)$ | | | | | | 1 |

| Panel B | | | | | | |
|---|---|---|---|---|---|---|
| Variable | $d(rTb_t)$ | $d(exSt_t)$ | $d(exBo_t)$ | $d(dp_t)$ | $d(tms_t)$ | $d(infl_t)$ |
| $d(rTb_{t+1})$ | 27.76% | 10.89% | 10.43% | 3.03% | 3.12% | -6.56% |
| $d(exSt_{t+1})$ | -1.03% | 11.40% | 9.47% | 13.13% | 11.15% | -6.66% |
| $d(exBo_{t+1})$ | -2.13% | -10.76% | -5.80% | -2.06% | 18.48% | 3.46% |
| $d(dp_{t+1})$ | 1.78% | -10.76% | -9.65% | 97.13% | -25.91% | 31.53% |
| $d(tms_{t+1})$ | -4.38% | 5.19% | 23.74% | -18.83% | 84.05% | -22.43% |
| $d(infl_{t+1})$ | -7.56% | -14.31% | -21.53% | 27.59% | -32.25% | 48.36% |

*Notes:* Panel A reports simultaneous correlations between the variables: 90-day T-bill, stocks, bonds, dividend-price ratio, term spread and inflation. Panel B reports the lagged correlations of these variables with the first-order autocorrelations on the main diagonal.

on a 10% level. There is an ongoing discussion about the non-stationarity of the dividend-price ratio (see e.g. Goyal and Welch, 2003; Cochrane, 2008; Lettau and Van Nieuwerburgh, 2008). However, taking an economical position, we treat the dividend-price ratio as $I(0)$.[8]

After identifying stochastic trends in each of the level variables, we apply the Johansen trace test to determine the number of cointegration relations. The test is applied by allowing for an intercept and by setting the number of lags in the unrestricted level VAR equal to two, as suggested by the SC (see Appendix 3.A.2). The test indicates four cointegration relations at the 5% level, as shown in Panel

[8]Using the present value identity $d_t - p_t = E_t \sum \rho^{j-1}(-\Delta d_{t+j} + r_{t+j})$ derived by Campbell and Shiller (1988a), we infer the stationarity of the dividend-price ratio from the stationarity of $\Delta d_t$ and $r_t$ (as shown in Goyal and Welch, 2003).

Table 3.4: Unit Root and Cointegration Rank Test

| Panel A | Level | | | Difference | |
|---|---|---|---|---|---|
| Variable | ADF-Stat. | Lags | | ADF-Stat. | Lags |
| $rTb$ | -0.503 | 2 | $d(rTb)$ | -8.553*** | 1 |
| $exSt$ | -1.504 | 2 | $d(exSt)$ | -10.598*** | 1 |
| $exBo$ | 0.315 | 2 | $d(exBo)$ | -11.347*** | 1 |
| $dp$ | -1.487 | 2 | $d(dp)$ | -2.594* | 1 |
| $tms$ | 2.158 | 2 | $d(tms)$ | -4.103*** | 1 |
| $infl$ | -0.231 | 2 | $d(infl)$ | -6.281*** | 1 |

| Panel B | | | | |
|---|---|---|---|---|
| $H_0$ | $LR$ | 10% CV | 5% CV | 1% CV |
| $r \leq 5$ | 0.09 | 6.5 | 8.18 | 11.65 |
| $r \leq 4$ | 11.8 | 15.66 | 17.95 | 23.52 |
| $r \leq 3$ | 32.77** | 28.71 | 31.52 | 37.22 |
| $r \leq 2$ | 67.38*** | 45.23 | 48.28 | 55.43 |
| $r \leq 1$ | 106.25*** | 66.49 | 70.6 | 78.87 |
| $r = 0$ | 162.38*** | 90.39 | 85.18 | 104.2 |

*Notes:* The table reports the results of the augmented Dickey-Fuller test and the Johansen (1988) trace test. *, **, *** denote significance at the 10%, 5%, 1% levels, respectively. The augmented Dickey-Fuller test including a constant in the model is performed to test for unit root. The Johansen (1988) trace test including a constant in the model is perfomed to determine the cointegration rank. The number of lagged terms used in both tests is chosen as suggested by the SC (see Appendix 3.A.2 ).

B, meaning there are four stationary linear combinations among the level variables that have an influence on the differenced variables.[9]

### 3.3.2 Estimation Results

Since the VEC model is an extension of the stationary VAR model, we show the VAR estimation results first. Afterwards, we discuss the VEC estimates and investigate the differences of the two models with respect to the term structure of risk and optimal asset allocation.

[9]The results of the cointegration rank test can vary with the number of lags included in the VAR. However, for up to four lags in the VAR, our results remain stable around three to four relations depending on different significance levels.

Table 3.5: VAR Parameter Estimates

| Panel A | $\mathbf{A}_1$ – Coefficients of Lagged Variables | | | | | | *adj.* $R^2$ |
|---|---|---|---|---|---|---|---|
| | $d(rTb_t)$ | $d(exSt_t)$ | $d(exBo_t)$ | $d(dp_t)$ | $d(tms_t)$ | $d(infl_t)$ | ($F$-stat.) |
| $d(rTb_{t+1})$ | **0.491** | 0.009 | 0.009 | -0.096 | 0.280 | **0.284** | 11.06% |
| | [0.254,0.748] | [-0.002,0.02] | [-0.01,0.028] | [-0.495,0.302] | [-0.029,0.703] | [0.091,0.558] | (5.85) |
| $d(exSt_{t+1})$ | -1.554 | 0.102 | 0.101 | **5.673** | 1.859 | -1.473 | 4.22% |
| | [-4.557,1.488] | [-0.032,0.224] | [-0.11,0.319] | [3.475,12.663] | [-2.121,6.577] | [-4.304,1.377] | (2.717) |
| $d(exBo_{t+1})$ | **0.908** | -0.075 | -0.089 | -0.433 | **3.992** | **0.871** | 4.51% |
| | [0.053,4.084] | [-0.157,0.009] | [-0.221,0.044] | [-3.221,2.969] | [2.348,7.873] | [0.156,3.93] | (2.84) |
| $d(dp_{t+1})$ | 0.012 | -0.001 | -0.001 | **0.946** | -0.027 | 0.011 | 94.53% |
| | [-0.018,0.037] | [-0.002,0] | [-0.003,0.001] | [0.881,0.964] | [-0.071,0.008] | [-0.017,0.034] | (674.4) |
| $d(tms_{t+1})$ | 0.018 | -0.002 | 0.004 | -0.018 | **0.852** | 0.022 | 70.53% |
| | [-0.035,0.109] | [-0.005,0.001] | [-0.001,0.009] | [-0.115,0.115] | [0.731,0.934] | [-0.025,0.108] | (94.4) |
| $d(infl_{t+1})$ | **0.469** | -0.005 | -0.010 | 0.120 | -0.211 | **0.677** | 33.81% |
| | [0.143,0.667] | [-0.017,0.007] | [-0.03,0.009] | [-0.325,0.512] | [-0.665,0.105] | [0.339,0.828] | (20.9) |

*Continued*

*Continued*

Panel B

| | $\Sigma_{\mathbf{u}}$ – Residual Correlations and Standard Deviations | | | | | |
|---|---|---|---|---|---|---|
| | $d(rTb)$ | $d(exSt)$ | $d(exBo)$ | $d(dp)$ | $d(tms)$ | $d(infl)$ |
| $d(rTb)$ | (0.688%) | 10.2% | 27.3% | -10.3% | -21.0% | -94.9% |
| $d(exSt)$ | - | (7.767%) | 9.7% | -91.7% | 6.3% | -13.9% |
| $d(exBo)$ | - | - | (4.915%) | -20.5% | 8.9% | -44.7% |
| $d(dp)$ | - | - | - | (0.069%) | -9.5% | 16.6% |
| $d(tms)$ | - | - | - | - | (0.181%) | -6.4% |
| $d(infl)$ | - | - | - | - | - | (0.717%) |

*Notes:* Panel A reports coefficient estimates of the VAR $\Delta \mathbf{z}_t = \boldsymbol{\mu} + \mathbf{A}_1 \Delta \mathbf{z}_{t-1} + \mathbf{u}_t$ with variables: 90-day T-bill, stocks, bonds, dividend-price ratio, term spread and inflation. Bootstrap intervals are calculated from 10,000 paths under the assumption that the initial estimated VAR model truly generates the data process and are reported in brackets. Bold coefficients imply significance on a 5% level. The last column displays the adjusted $R^2$ and the $F$-statistic. Panel B reports the covariance structure of the residuals showing the standard deviations of the innovations on the main diagonal in parentheses and the cross-correlations above the main diagonal.

Table 3.5 presents the OLS estimates of the VAR model of order one. The number of lags is chosen according to the SC statistics (see Appendix 3.A.2 ). Panel A reports the slope coefficients and adjusted $R^2$ with bootstrapped 95% confidence intervals and $F$-statistics given in brackets and parentheses below. Since there is suspicion of autocorrelation and heteroskedasticity in the residuals, we perform a bootstrap to analyze the significance of the point estimates, as the common $t$-statistics might be biased.This bootstrap is performed under the null hypothesis that the initial estimated model truly generates the data process.[10] The coefficients indicated to be significant by the bootstrap intervals are boldfaced. Panel B shows the standard deviations of the innovations on the main diagonal and the cross-correlations above the main diagonal.

The first row in Panel A of Table 3.5 represents the prediction equation for the real T-bill rates. It shows that only the own lag and the lagged inflation have a

[10] Appendix 3.A.1 provides a more detailed description of the bootstrapping method .

significant positive influence on the real interest rate. The second and third rows correspond to the risk premia of stocks and bonds and these variables seem to be difficult to predict, as they have the lowest $R^2$s. However, the lagged dividend-price ratio has a positive significant coefficient in the excess stock equation. Excess bond returns are significantly positively explained by the real interest rate, the term spread and inflation. The last three rows represent the state variable equations and show their very persistent autoregressive behavior. Additionally, the real interest rate has a significant positive influence on the inflation rate. Turning to the covariance structure of the innovations in Panel B, we see that the innovations in risk premia are slightly positively correlated to each other and both are positively correlated with shocks to the real T-bill rates. Unexpected excess stock returns are almost perfectly negatively correlated with shocks to the dividend-price ratio. Unexpected excess bond returns are slightly positively correlated to innovations in the term spread and are negatively correlated with shocks to inflation. Moreover, unexpected inflation is almost perfectly negatively correlated with unexpected real interest rates. These findings are in line with Campbell, Chan, and Viceira (2003); Campbell and Viceira (2005); Hoevenaars, Molenaar, Schotman, and Steenkamp (2008) and Jurek and Viceira (2011).

While the standard VAR model captures only the long-run dynamics of stationary data, the VEC model takes into account information of the four cointegration relations and is able to distinguish between short- and long-run effects. The results of the reduced rank first-order VEC presented in Equation (3.5), as detected by the lag length selection criterion (see Appendix 3.A.2 ), are displayed in Table 3.6. Panel A of Table 3.6 shows the loadings $\boldsymbol{\alpha}$ for the four normalized cointegration relations $\boldsymbol{\beta}'$ displayed in Panel B. $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}'$ describe the long-run behavior of the data. The short-run effects $\boldsymbol{\Gamma}_1$, the adjusted $R^2$ and the $F$-statistics for the full system are illustrated in Panel C. In these three panels bootstrapped 95% confidence intervals are given in brackets below the coefficient estimates. The coefficients indicated to be significant by the bootstrap intervals are boldfaced. Panel D at the bottom summarizes the covariance structure of the innovations in the VEC system, where we show the standard deviation of the innovations on the main diagonal and the cross-correlations off the diagonal.

Table 3.6: VEC Parameter Estimates

Panel A

| | $\boldsymbol{\alpha}$ – Long-Run Loadings of Level Equations | | | |
|---|---|---|---|---|
| | $ect1$ | $ect2$ | $ect3$ | $ect4$ |
| $d(rTb_{t+1})$ | 0.003 [-0.065,0.03] | 0.005 [-0.013,0.018] | 0.008 [-0.045,0.056] | **-0.046** [-0.088,-0.002] |
| $d(exSt_{t+1})$ | 0.221 [-0.446,0.606] | **-0.113** [-0.355,-0.003] | **0.641** [0.077,1.272] | **0.598** [0.331,1.326] |
| $d(exBo_{t+1})$ | **0.448** [0.203,0.866] | -0.028 [-0.163,0.062] | 0.013 [-0.413,0.344] | **-0.355** [-0.768,-0.112] |
| $d(dp_{t+1})$ | -0.004 [-0.007,0.002] | 0.000 [-0.001,0.002] | -0.005 [-0.01,0] | **-0.003** [-0.009,-0.001] |
| $d(tms_{t+1})$ | **0.013** [0.002,0.027] | -0.003 [-0.007,0.001] | **0.019** [0.006,0.034] | 0.009 [-0.002,0.021] |
| $d(infl_{t+1})$ | -0.028 [-0.061,0.037] | -0.001 [-0.014,0.018] | -0.032 [-0.083,0.023] | **0.044** [0.004,0.09] |

Panel B

| | $\boldsymbol{\beta}'$ – Long-Run Level Equations | | | | | |
|---|---|---|---|---|---|---|
| | $rTb_t$ | $exSt_t$ | $exBo_t$ | $dp_t$ | $tms_t$ | $Infl_t$ |
| $ect1$ | **1** | 0 | 0 | 0 | 0.310 [-0.516,1.577] | -0.305 [-0.87,0.11] |
| $ect2$ | 0 | **1** | 0 | 0 | **-2.724** [-5.136,-0.686] | 0.216 [-0.693,1.395] |
| $ect3$ | 0 | 0 | **1** | 0 | **-1.503** [-2.56,-0.78] | 0.086 [-0.298,0.557] |
| $ect4$ | 0 | 0 | 0 | **1** | -0.504 [-1.324,0.401] | **-0.459** [-0.858,-0.024] |

*Continued*

*Continued*

Panel C

| | $\mathbf{\Gamma_1}$ – Short-Run Loading of Lagged Differences | | | | | | $adj.\ R^2$ |
|---|---|---|---|---|---|---|---|
| | $d(rTb_t)$ | $d(exSt_t)$ | $d(exBo_t)$ | $d(dp_t)$ | $d(tms_t)$ | $d(infl_t)$ | ($F$-stat.) |
| $d(rTb_{t+1})$ | 1.393 | 0.003 | **0.021** | -1.022 | 1.477 | 1.258 | 18.07% |
| | [-0.759,3.4] | [-0.01,0.014] | [0.002,0.043] | [-3.219,0.58] | [-0.625,3.513] | [-0.902,3.347] | (9.01) |
| $d(exSt_{t+1})$ | 19.244 | **0.176** | -0.021 | 7.729 | 18.284 | 19.524 | 10.30% |
| | [-4.809,43.658] | [0.039,0.31] | [-0.273,0.19] | [-14.721,27.682] | [-5.835,42.567] | [-5.064,44.401] | (3.95) |
| $d(exBo_{t+1})$ | 10.342 | -0.025 | 0.007 | -1.354 | 13.070 | 10.792 | 13.75% |
| | [-4.335,26.622] | [-0.101,0.072] | [-0.119,0.168] | [-16.539,10.667] | [-1.804,29.553] | [-4.1,27.307] | (4.38) |
| $d(dp_{t+1})$ | -0.149 | **-0.002** | 0.000 | **0.787** | -0.168 | -0.152 | 94.89% |
| | [-0.361,0.069] | [-0.003,-0.001] | [-0.002,0.002] | [0.574,0.957] | [-0.38,0.046] | [-0.367,0.069] | (3399.6) |
| $d(tms_{t+1})$ | **0.813** | 0.000 | 0.003 | -0.013 | **1.541** | **0.835** | 73.01% |
| | [0.277,1.388] | [-0.002,0.004] | [-0.003,0.008] | [-0.443,0.561] | [0.939,2.064] | [0.288,1.428] | (159.1) |
| $d(infl_{t+1})$ | -1.615 | -0.003 | **-0.023** | 1.055 | **-2.469** | -1.514 | 39.04% |
| | [-3.812,0.516] | [-0.015,0.01] | [-0.045,-0.004] | [-0.647,3.311] | [-4.629,-0.295] | [-3.77,0.653] | (49.8) |

*Continued*

*Continued*

Panel D

| | $\mathbf{\Sigma}_\nu$ – Residual Correlations and Standard Deviations | | | | | |
|---|---|---|---|---|---|---|
| | $d(rTb)$ | $d(exSt)$ | $d(exBo)$ | $d(dp)$ | $d(tms)$ | $d(infl)$ |
| $d(rTb)$ | (0.656%) | 17.6% | 26.9% | -17.1% | -19.3% | -95.2% |
| $d(exSt)$ | - | (7.467%) | 12.1% | -92.3% | -1.6% | -19.2% |
| $d(exBo)$ | - | - | (4.640%) | -21.9% | 5.9% | -43.3% |
| $d(dp)$ | - | - | - | (0.067%) | -2.2% | 21.3% |
| $d(tms)$ | - | - | - | - | (0.173%) | -7.1% |
| $d(infl)$ | - | - | - | - | - | (0.683%) |

*Notes:* Panel A, B, C report long- and short-run coefficient estimates of the VEC $\Delta \mathbf{z}_t = \boldsymbol{\mu} + \boldsymbol{\alpha}\boldsymbol{\beta}'\mathbf{z}_{t-1} + \mathbf{\Gamma}_1 \Delta \mathbf{z}_{t-1} + \boldsymbol{\nu}_t$ with the level variables: 90-day T-bill, stocks, bonds, dividend-price ratio, term spread and inflation. Bootstrap intervals are calculated from 10,000 paths under the assumption that the initial estimated VEC model truly generates the data process and are reported in brackets. Bold coefficients imply significance on a 5% level. The last column of Panel C displays the adjusted $R^2$ and the $F$-statistic. Panel D reports the covariance structure of the residuals showing the standard deviations of the innovations on the main diagonal in parentheses and the cross-correlations above the main diagonal.

To analyze the captured long-run effects, we must interpret $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}'$ simultaneously. The first row of $\boldsymbol{\beta}'$ in Panel B represents the long-run cointegration relation among the levels of real interest rates, term spread and inflation, in which only the T-bills are significant. The second and third equations provide the relations between the term spread, the inflation and the excess stock and bond return levels, respectively. Both risk premia are related *positively* to term spread and *negatively* to inflation in the long run, whereas the inflation is insignificant. Note that, for example, the second row of $\boldsymbol{\beta}'$ is read as $exSt_t = 2.724\, tms_t - 0.216\, infl_t$. However, the equations do not indicate causality in one direction, since the normalization of the variables can be rearranged. The last row of $\boldsymbol{\beta}'$ shows the cointegration equation of dividend-price, term spread and inflation. The influence of $\boldsymbol{\beta}'$ on $\Delta\mathbf{z}$ is weighted by the corresponding loadings in $\boldsymbol{\alpha}$ (Panel A). Only the fourth entry of the first row of $\boldsymbol{\alpha}$ is significant, indicating an influence of the fourth equation on real T-bills in the long run. Considering the loadings of the equity premium, we obtain three significant long-run influences leading to a positive long-run effect of the dividend-price ratio and a negative effect of inflation. The effect of term spread is canceled out due to contrary signs in the loadings. Excess bond returns are positively predicted by real interest rates and inflation. Moreover, there seems to be a negative influence of the dividend-price ratio on excess bond returns for the long term. The state variables dividend-price ratio and inflation react positively to each other, which might lead to a long-run inflation correction of stock prices. The term spread is positively affected by real interest rates and negatively by itself.

Panel C of Table 3.6 summarizes the short-run effects estimated by the VEC model. For the real interest rate equation only the lagged bond premium has a positive and significant coefficient. The row corresponding to excess stock returns shows that their own lagged returns predict stock premia positively and all other predictors are insignificant in this equation. However, none of the differenced variables has significant influence on excess bond returns in the short run. The state variables dividend-price and term spread are strongly influenced by their own lags and show a very persistent autoregressive behavior. Moreover, some short-term cross-forecasting effects can be observed for the state variables.

The covariance structure of the innovations is described in Panel D. We see that the innovations in risk premia are positively correlated to each other and with shocks to the real T-bill rates. Unexpected excess stock returns are almost perfectly negatively correlated with shocks to the dividend-price ratio. Unexpected excess bond returns are weakly positively correlated to innovations in the term spread and are negatively correlated with shocks to inflation. Moreover, unexpected inflation is almost perfectly negatively correlated with unexpected real interest rates.

Comparing the stationary VAR and the VEC model, we obtain a more than two times higher adjusted $R^2$ for predicting the risk premia of stocks and bonds.[11] These increases show the importance of incorporating common long-run effects for capturing the realized stock and bond return dynamics. Turning to the estimated coefficients, we can only compare the short-run matrix (influence of the stationary variables) with the VAR coefficients matrix. However, some interesting changes are

[11] Including two lags in the stationary VAR does not significantly increase the adjusted $R^2$ compared to the VAR(1) or capture the horizon effects of the VEC(1).

apparent. Significant predictors for real interest rates (lagged real interest rate and inflation) in the VAR become insignificant in the VEC model, while lagged excess bond returns now have a positive significant influence in the short run. The equity premium shows a momentum effect in the VEC, but in contrast to the stationary VAR, the dividend-price ratio has no significant short-term influence anymore. There are obviously no significant short-run effects for the bond premium in the VEC. Finally, it is interesting to note that the autoregressive component of the inflation disappears in the VEC model. Considering the covariance structure of the innovations, we see that the correlations differ only slightly. These different results motivate a further comparison of the long-run dynamics implied by the VAR and VEC, depending on the time horizon.

### 3.3.3 Long Horizon Effects

In the following section we analyze the $k$-period horizon effects by considering the term structure of risk, the horizon-dependent correlations and variance decompositions of real and nominal asset returns. A common option for decomposing the variance is to orthogonalize the innovations of the VAR and VEC to obtain a *clean* variance decomposition. However, since these results would strongly depend on the arrangement of the variables, we avoid this drawback and appropriately split the $k$-period return variances into components consisting of risk premium, real interest rate and inflation and integrate the arising covariance terms into our discussion.

Table 3.7 reports the term structure of risk and correlations of the real interest rate and the risk premia implied by the VAR (Panel A) and VEC (Panel B) model depending on the investment horizon (quarters) and the bootstrapped 95% confidence intervals in brackets below. All numbers are reported in percentage. The model comparison shows some important differences in the term structure. While in both models the periodic long-term return volatilities of real T-bills are higher than their short-term volatilities, the mean aversion effect is more pronounced for the VAR model, leading to a nearly 70% higher standard deviation for the 100-period horizon. This mean-aversion arises primarily from the persistent behavior of real T-bills, which is also found by Campbell and Viceira (2005). The weaker

Table 3.7: Term Structure of Risk and Correlations

| Panel A | Horizon $k$ (quarters) | | | | |
|---|---|---|---|---|---|
| VAR | 1 | 5 | 10 | 50 | 100 |
| $Sd(rTb_{t+k})$ | **0.697** | **0.840** | **0.852** | **1.081** | **1.419** |
| | [0.58,0.8] | [0.67,0.98] | [0.68,1.01] | [0.76,1.41] | [0.79,2] |
| $Sd(exSt_{t+k})$ | **7.868** | **7.993** | **7.499** | **5.251** | **4.406** |
| | [6.77,8.71] | [6.48,9.05] | [5.72,8.63] | [3.84,6.68] | [3.44,5.91] |
| $Sd(exBo_{t+k})$ | **4.979** | **4.673** | **4.682** | **3.914** | **3.123** |
| | [4.26,5.55] | [3.68,5.37] | [3.32,5.51] | [2.15,4.99] | [1.86,4.18] |
| $Cor(rTb_{t+k}, exSt_{t+k})$ | 10.195 | 17.060 | 14.943 | -7.029 | -14.019 |
| | [-11.4,30.8] | [-9.5,41.3] | [-13.4,41.4] | [-33.5,37.9] | [-46.2,41.7] |
| $Cor(rTb_{t+k}, exBo_{t+k})$ | **27.314** | 18.686 | 7.661 | -35.942 | -32.853 |
| | [8.2,44.5] | [-7.2,42.3] | [-21.7,37.1] | [-55.4,17.8] | [-56.3,22.8] |
| $Cor(exSt_{t+k}, exBo_{t+k})$ | 9.709 | 13.403 | 23.500 | 39.291 | 32.109 |
| | [-7.7,25.8] | [-13.6,37.1] | [-13.2,49.4] | [-20.7,62.6] | [-22.9,56.5] |

| Panel B | Horizon $k$ (quarters) | | | | |
|---|---|---|---|---|---|
| VEC | 1 | 5 | 10 | 50 | 100 |
| $Sd(rTb_{t+k})$ | **0.656** | **0.776** | **0.859** | **0.802** | **0.844** |
| | [0.53,0.75] | [0.58,0.86] | [0.57,0.96] | [0.39,1.01] | [0.33,1.21] |
| $Sd(exSt_{t+k})$ | **7.467** | **6.523** | **5.473** | **4.144** | **3.774** |
| | [6.28,8.16] | [4.91,7.19] | [3.83,6.12] | [2.18,4.82] | [1.74,4.60] |
| $Sd(exBo_{t+k})$ | **4.64** | **3.383** | **3.01** | **3.421** | **3.158** |
| | [3.91,5.14] | [2.61,3.9] | [2.19,3.59] | [1.46,4.13] | [1.16,4.02] |
| $Cor(rTb_{t+k}, exSt_{t+k})$ | 17.564 | **46.324** | **56.545** | 31.679 | -25.278 |
| | [-5.7,38.4] | [18.4,62.5] | [20.1,69.4] | [-44.4,69.7] | [-73.2,62.1] |
| $Cor(rTb_{t+k}, exBo_{t+k})$ | **26.925** | 23.021 | 32.564 | 25.570 | -28.702 |
| | [6.3,45.8] | [-4.6,49.1] | [-4.5,59.6] | [-54.4,68.3] | [-73.9,57.3] |
| $Cor(exSt_{t+k}, exBo_{t+k})$ | 12.090 | 19.917 | **32.712** | **78.666** | **84.570** |
| | [-5.9,28.6] | [-5.7,42.6] | [1.4,56.5] | [24.1,87.7] | [30.3,91.8] |

*Notes:* This table reports the term structure of risk and correlations of the assets implied by the VAR (Panel A) and by the VEC model (Panel B) depending on the investment horizon. Bootstrap intervals are calculated from 10,000 paths under the assumption that the initial estimated VAR or VEC model truly generates the data process and are reported in brackets. Bold coefficients imply significance on a 5% level. All numbers are reported in percentage.

mean-averting shape in the VEC is possibly caused by an offsetting influence of inflation. Turning to stocks, we expect a decrease in equity premium variation over the investment horizon due to the positive coefficient of the dividend-price ratio on stock returns and the large negative correlation between their innovations. If prices are decreasing unexpectedly, this is bad news for an investor. On the other hand, the good news is that a low realized return on stocks is usually accompanied by positive shocks to the dividend yield and high dividend yield predicts high returns for the future. The mean-reverting effect for excess stock returns is observed in both models, but risk substantially differs at medium horizons (7.5% in the VAR vs. 5.5% in the VEC at a 10-period horizon). This difference between the models is predominantly caused by a stronger mean-reversion effect of the dividend-price ratio in the VEC. Moreover, under cointegration, this effect is reinforced by the longer lasting influence of inflation.

Turning to excess bond returns, the volatilities are fairly similar under the models for very short and long horizons, but the stationary VAR overestimates the risk by about 50% at intermediate horizons. In the intervening periods the volatilities modeled by the VEC are hump-shaped with a much steeper drop until period 10 and a subsequent backward movement to the VAR term structure in the long run. The general mean-reversion behavior of the bond premium is due to the negative correlation of the shocks between the excess bond returns and inflation and weakened by a mean-averting influence of the term spread. However, in the VEC, the term spread positively affects the bond volatility only in the long run. This missing compensation leads to the steep drop in the first quarters. Turning to the asset correlations, we observe that the correlations estimated by the VAR are lower than the ones of the VEC and, according to the bootstrap intervals, not significantly different from zero for medium and long horizons. However, for the VEC model, we obtain significant positive correlations. Real T-bills and excess stock returns are significantly correlated at medium-term and peaks with 60% at a horizon of 20 periods. For the risk premia of stocks and bonds the correlation is over 80% at long horizons.

In Table 3.8 we report the variance decompositions of nominal T-bill returns implied by the VAR (Panel A) and the VEC model (Panel B), depending on the

Table 3.8: Variance Decomposition for Treasury Bills

| Panel A | Horizon $k$ (quarters) | | | | |
|---|---|---|---|---|---|
| VAR | 1 | 5 | 10 | 50 | 100 |
| $Var(nTb_{t+k})$ | **1.196** | **10.09** | **26.97** | **213.7** | **422.7** |
| | [0.62,1.90] | [4.75,15.6] | [10.9,41.6] | [32.8,348] | [37,788] |
| $Var(rTb_{t+k})$ | **11.16** | **16.22** | **16.70** | **26.87** | **46.28** |
| | [7.90,14.7] | [10.4,22.0] | [10.6,23.3] | [13.5,46.2] | [15,91] |
| $2Cov(rTb_{t+k}, infl_{t+k})$ | **-22.09** | **-31.54** | **-29.32** | 39.11 | 130.1 |
| | [-29.7,-15.3] | [-45.4,-18.4] | [-47.6,-13.3] | [-36.3,93.4] | [-32,271] |
| $Var(infl_{t+k})$ | **12.13** | **25.41** | **39.59** | **147.7** | **246.3** |
| | [8.49,16.2] | [15.9,34.2] | [21.1,55.2] | [29.9,241] | [30,468] |

| Panel B | Horizon $k$ (quarters) | | | | |
|---|---|---|---|---|---|
| VEC | 1 | 5 | 10 | 50 | 100 |
| $Var(nTb_{t+k})$ | **1** | **5.87** | **12.99** | **117.9** | **308.0** |
| | [0.54,1.54] | [2.90,8.47] | [5.48,18.8] | [14.9,171] | [17,451] |
| $Var(rTb_{t+k})$ | **9.885** | **13.84** | **16.96** | **14.80** | **16.38** |
| | [6.45,13.1] | [7.85,17.2] | [7.47,21.2] | [3.65,23.8] | [2.59,35] |
| $2Cov(rTb_{t+k}, infl_{t+k})$ | **-19.63** | **-27.74** | **-35.52** | -34.37 | 47.64 |
| | [-26.9,-12.5] | [-36.6,-14.8] | [-47.8,-13.2] | [-64.7,26.1] | [-30,112] |
| $Var(infl_{t+k})$ | **10.74** | **19.77** | **31.55** | **137.4** | **244.0** |
| | [6.90,14.7] | [11.1,25.6] | [14.3,41.4] | [13.4,181] | [12,349] |

*Notes:* This table reports the variance decompositions of nominal Treasury bill returns implied by the VAR (Panel A) and by the VEC model (Panel B) depending on the investment horizon. The first row of each panel shows the variances of nominal T-bills and is normalized to the first entry (one horizon variance) of the VEC panel. The decomposition for the $k$-period variance of the nominal Treasury bill return is $Var(nTb_{t+k}) = Var(rTb_{t+k}) + 2Cov(rTb_{t+k}, infl_{t+k}) + Var(infl_{t+k})$. Bootstrap intervals are calculated from 10,000 paths under the assumption that the initial estimated VAR or VEC model truly generates the data process and are reported in brackets. Bold coefficients imply significance on a 5% level.

investment horizon and the bootstrapped 95% confidence intervals in brackets below. This gives us further insight into the interaction of innovations of the short rates and the inflation. The results are interpreted as follows. The first row of each panel shows the variances of nominal T-bills and is normalized to the first entry (one horizon variance) of the VEC panel. The horizon-dependent variance of nominal T-bills is decomposed into the variances and covariance of the real T-bills and inflation. This normalization of the panels enables us to identify the horizon effects in the variances and covariances (column by column) and the components of the nominal

T-bills variance (row by row), as well as to ensure the comparability of the two panels. As we have already found for the real T-bills, the nominal T-bills also show a mean-averting behavior, but with a much steeper increase in volatility. Due to the risk reduction of the covariance at short and medium horizons, the components offset each other, leading to a slightly lower variation of nominal interest rates compared to the real T-bills. In the long-run, this effect turns upside down, makes nominal T-bills much more risky and is less pronounced in the VEC model. By implication, this indicates a strong common relationship between nominal T-bills and inflation in the long term. This relationship is ignored by the VAR model and leads to an overestimation of the T-bills' mean-averting behavior.

Table 3.9 reports the variance decompositions of nominal and real stock returns implied by the two models (Panel A and B), depending on the investment horizon and the bootstrapped 95% confidence intervals in brackets below. In contrast to the T-bills in Table 3.8, the variances of nominal stock returns are decomposed in more detail into variances and covariances of the equity premium, real interest rates

Table 3.9: Variance Decomposition for Stock Returns

| Panel A | Horizon (quarters) | | | | |
|---|---|---|---|---|---|
| VAR | 1 | 5 | 10 | 50 | 100 |
| $Var(nSt_{t+k})$ | **1.107** | **1.113** | **0.935** | **0.439** | **0.454** |
| | [0.82,1.35] | [0.73,1.43] | [0.55,1.24] | [0.27,0.69] | [0.23,0.81] |
| $Var(rSt_{t+k})$ | **1.143** | **1.204** | **1.06** | **0.503** | **0.354** |
| | [0.85,1.39] | [0.79,1.53] | [0.62,1.4] | [0.29,0.80] | [0.23,0.60] |
| $Var(exSt_{t+k})$ | **1.114** | **1.15** | **1.012** | **0.496** | **0.349** |
| | [0.83,1.36] | [0.75,1.47] | [0.59,1.34] | [0.26,0.78] | [0.21,0.62] |
| $2Cov(exSt_{t+k}, rTb_{t+k})$ | 0.02 | 0.041 | 0.034 | -0.014 | -0.032 |
| | [-0.02,0.05] | [-0.02,0.09] | [-0.03,0.09] | [-0.08,0.07] | [-0.14,0.08] |
| $Var(rTb_{t+k})$ | **0.009** | **0.013** | **0.013** | **0.021** | **0.036** |
| | [0.00,0.01] | [0.00,0.01] | [0.00,0.01] | [0.01,0.03] | [0.01,0.07] |
| $2Cov(rTb_{t+k}, infl_{t+k})$ | **-0.017** | **-0.025** | **-0.023** | 0.031 | 0.102 |
| | [-0.02,-0.01] | [-0.03,-0.01] | [-0.03,-0.01] | [-0.02,0.07] | [-0.02,0.21] |
| $Var(infl_{t+k})$ | **0.009** | **0.02** | **0.031** | **0.116** | **0.193** |
| | [0.00,0.01] | [0.01,0.02] | [0.01,0.04] | [0.02,0.18] | [0.02,0.36] |
| $2Cov(exSt_{t+k}, infl_{t+k})$ | -0.029 | **-0.086** | **-0.133** | -0.21 | -0.195 |
| | [-0.06,0.02] | [-0.15,-0.00] | [-0.23,-0.01] | [-0.42,0.04] | [-0.53,0.09] |

*Continued*

*Continued*

| Panel B | Horizon (quarters) | | | | |
|---|---|---|---|---|---|
| VEC | 1 | 5 | 10 | 50 | 100 |
| $Var(nSt_{t+k})$ | **1** | **0.765** | **0.523** | **0.156** | **0.156** |
| | [0.70,1.20] | [0.43,0.92] | [0.24,0.65] | [0.06,0.22] | [0.04,0.24] |
| $Var(rSt_{t+k})$ | **1.042** | **0.861** | **0.648** | **0.359** | **0.24** |
| | [0.74,1.24] | [0.48,1.04] | [0.30,0.80] | [0.09,0.48] | [0.05,0.34] |
| $Var(exSt_{t+k})$ | **1.004** | **0.766** | **0.539** | **0.309** | **0.256** |
| | [0.71,1.20] | [0.43,0.92] | [0.26,0.67] | [0.08,0.42] | [0.05,0.38] |
| $2Cov(exSt_{t+k}, rTb_{t+k})$ | 0.031 | **0.084** | **0.096** | 0.038 | -0.029 |
| | [-0.01,0.06] | [0.02,0.11] | [0.02,0.12] | [-0.03,0.07] | [-0.10,0.03] |
| $Var(rTb_{t+k})$ | **0.008** | **0.011** | **0.013** | **0.012** | **0.013** |
| | [0.00,0.01] | [0.00,0.01] | [0.00,0.01] | [0.00,0.01] | [0.00,0.02] |
| $2Cov(rTb_{t+k}, infl_{t+k})$ | **-0.015** | **-0.022** | **-0.028** | -0.027 | 0.037 |
| | [-0.02,-0.01] | [-0.02,-0.01] | [-0.03,-0.01] | [-0.05,0.02] | [-0.02,0.08] |
| $Var(infl_{t+k})$ | **0.008** | **0.015** | **0.025** | **0.108** | **0.191** |
| | [0.00,0.01] | [0.00,0.02] | [0.01,0.03] | [0.01,0.14] | [0.00,0.27] |
| $2Cov(exSt_{t+k}, infl_{t+k})$ | -0.035 | **-0.09** | **-0.122** | **-0.283** | **-0.311** |
| | [-0.06,0.01] | [-0.12,-0.02] | [-0.17,-0.03] | [-0.39,-0.01] | [-0.50,-0.00] |

*Notes:* This table reports the variance decompositions of nominal and real stock returns implied by the VAR (Panel A) and by the VEC model (Panel B) depending on the investment horizon. The first row of each panel shows the variances of nominal stock returns and is normalized to the first entry (one horizon variance) of the VEC panel. The decomposition for the $k$-period variance of the nominal stock return is $Var(nSt_{t+k}) = Var(exSt_{t+k}) + 2Cov(exSt_{t+k}, rTb_{t+k}) + Var(rTb_{t+k}) + 2Cov(rTb_{t+k}, infl_{t+k}) + Var(infl_{t+k}) + 2Cov(exSt_{t+k}, infl_{t+k})$ and that of the real stock return is $Var(rSt_{t+k}) = Var(exSt_{t+k}) + 2Cov(exSt_{t+k}, rTb_{t+k}) + Var(rTb_{t+k})$. Bootstrap intervals are calculated from 10,000 paths under the assumption that the initial estimated VAR or VEC model truly generates the data process and are reported in brackets. Bold coefficients imply significance on a 5% level.

and inflation. Again, the first row of each panel shows the variances of nominal T-bills and is normalized to the first entry of the VEC panel. The components of the last six rows sum up to the nominal return variance and the components of rows three to five sum up to the real return variance, respectively. For both models, nominal and real stock returns are mean-reverting, whereas the amount of risk reduction is much higher for the VEC model, for which the lowest nominal stock volatility is observed in the very long run. In both panels the variation of excess stock return attributes the most variation to real returns. Hence, the horizon effects of the real interest rate variation are small compared to the absolute stock variation. However, the covariation between real T-bills and excess stock returns adds a significant positive amount in the VEC at medium horizons. This effect, already mentioned by Fama and French (1989), is not significant in the stationary model. While the variances of inflation are fairly similar for the VAR and VEC over all horizons, the covariance between the equity premium and inflation is -0.1 compared to -0.16 and hence more than 50% higher under cointegration for a 100-period horizon. These covariance terms decrease the overall variances of nominal stock returns in both models and overcompensate inflation variation. The finding of a negative covariance is in line with the hypothesis of Modigliani and Cohn (1979), 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. This mispricing should eventually diminish, which would indicate the good inflation-hedging properties of stocks in the long run. However, when allowing for cointegration, stocks remain more risky in real than nominal terms.

Table 3.10 reports the variance decompositions of nominal and real bond returns implied by the two models (Panel A and B), depending on the investment horizon and the bootstrapped 95% confidence intervals in brackets below. The decomposition presented and the interpretation of this table are the same as in Table 3.9, replacing excess stocks by excess bonds. For the real bonds the risk structure decreases continuously in the VAR model, whereas the VEC model shows the hump-shaped term structure of the excess returns. While in both panels the variation of excess bond returns explains the most variation to real bond returns, the variation and covariation of real T-bills contribute only little fractions. For both models nominal bond returns are mean-reverting up to a horizon of 50 quarters for the VAR and up to 70 quarters for the VEC with a value of 1.6% and 2.5%, respectively. Afterwards, they show a mean-averting behavior. The mean-reversion of excess bond returns is initially reinforced by the negative covariances between the real interest rates and inflation and between the bond premium and inflation. The correlations of real interest rates and inflation are roughly equal and significantly negative in both models at short and medium horizons and the correlations between the bond premium and inflation remain negative and significant over all horizons. The latter effect, however, is much more pronounced in the VEC at long horizons. The variances of the inflation are fairly similar and mean-averting for the VAR and VEC over all horizons. In sum, the increase of the nominal T-bill volatility (which is calculated by $Var(rTb) + 2Cov(rTb, infl) + Var(infl)$) cannot be offset by the negative covariations between the bond risk premia and nominal T-bills (which is $2Cov(exBo, rTb) + 2Cov(exBo, infl)$) and leads to the mean-averting behavior of nominal bond returns in the very long run. Actually, 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 paper, do, however, represent 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 should improve with

Table 3.10: Variance Decomposition for Bond Returns

| Panel A | Horizon (quarters) | | | | |
|---|---|---|---|---|---|
| VAR | 1 | 5 | 10 | 50 | 100 |
| $Var(nBo_{t+k})$ | **1.149** | **0.874** | **0.737** | **0.316** | **0.653** |
| | [0.83,1.42] | [0.55,1.13] | [0.40,0.98] | [0.18,0.47] | [0.17,1.07] |
| $Var(rBo_{t+k})$ | **1.328** | **1.173** | **1.136** | **0.657** | **0.433** |
| | [0.96,1.65] | [0.73,1.55] | [0.58,1.56] | [0.25,1.05] | [0.20,0.70] |
| $Var(exBo_{t+k})$ | **1.211** | **1.067** | **1.071** | **0.749** | **0.476** |
| | [0.87,1.50] | [0.65,1.41] | [0.54,1.49] | [0.23,1.22] | [0.17,0.85] |
| $2Cov(exBo_{t+k}, rTb_{t+k})$ | **0.093** | 0.072 | 0.03 | -0.149 | -0.142 |
| | [0.02,0.16] | [-0.02,0.17] | [-0.08,0.14] | [-0.32,0.04] | [-0.37,0.05] |
| $Var(rTb_{t+k})$ | **0.024** | **0.034** | **0.035** | **0.057** | **0.098** |
| | [0.01,0.03] | [0.02,0.04] | [0.02,0.05] | [0.02,0.09] | [0.03,0.19] |
| $2Cov(rTb_{t+k}, infl_{t+k})$ | **-0.047** | **-0.067** | **-0.062** | 0.083 | 0.276 |
| | [-0.06,-0.03] | [-0.09,-0.03] | [-0.10,-0.02] | [-0.07,0.19] | [-0.06,0.57] |
| $Var(infl_{t+k})$ | **0.026** | **0.054** | **0.084** | **0.314** | **0.523** |
| | [0.01,0.03] | [0.03,0.07] | [0.04,0.11] | [0.06,0.51] | [0.06,0.99] |
| $2Cov(exBo_{t+k}, infl_{t+k})$ | **-0.158** | **-0.286** | **-0.422** | **-0.738** | **-0.579** |
| | [-0.23,-0.08] | [-0.42,-0.13] | [-0.63,-0.16] | [-1.28,-0.08] | [-1.29,-0.01] |

*Continued*

*Continued*

| Panel B | Horizon (quarters) | | | | |
|---|---|---|---|---|---|
| VEC | 1 | 5 | 10 | 50 | 100 |
| $Var(nBo_{t+k})$ | **1** | **0.461** | **0.31** | **0.15** | **0.201** |
| | [0.71,1.21] | [0.28,0.59] | [0.18,0.43] | [0.06,0.21] | [0.04,0.31] |
| $Var(rBo_{t+k})$ | **1.153** | **0.648** | **0.561** | **0.672** | **0.447** |
| | [0.80,1.42] | [0.38,0.85] | [0.29,0.77] | [0.12,0.90] | [0.07,0.67] |
| $Var(exBo_{t+k})$ | **1.052** | **0.559** | **0.443** | **0.572** | **0.487** |
| | [0.74,1.28] | [0.33,0.73] | [0.23,0.63] | [0.10,0.82] | [0.06,0.78] |
| $2Cov(exBo_{t+k}, rTb_{t+k})$ | **0.08** | 0.059 | 0.082 | 0.069 | -0.075 |
| | [0.01,0.15] | [-0.01,0.12] | [-0.01,0.15] | [-0.11,0.15] | [-0.24,0.06] |
| $Var(rTb_{t+k})$ | **0.021** | **0.029** | **0.036** | **0.031** | **0.035** |
| | [0.01,0.02] | [0.01,0.03] | [0.01,0.04] | [0.00,0.05] | [0.00,0.07] |
| $2Cov(rTb_{t+k}, infl_{t+k})$ | **-0.042** | **-0.059** | **-0.075** | -0.073 | 0.101 |
| | [-0.05,-0.02] | [-0.07,-0.03] | [-0.10,-0.02] | [-0.13,0.05] | [-0.06,0.23] |
| $Var(infl_{t+k})$ | **0.023** | **0.042** | **0.067** | **0.292** | **0.518** |
| | [0.01,0.03] | [0.02,0.05] | [0.03,0.08] | [0.02,0.38] | [0.02,0.74] |
| $2Cov(exBo_{t+k}, infl_{t+k})$ | **-0.134** | **-0.169** | **-0.243** | **-0.741** | **-0.866** |
| | [-0.21,-0.06] | [-0.25,-0.07] | [-0.36,-0.09] | [-1.02,-0.06] | [-1.33,-0.02] |

*Notes:* This table reports the variance decompositions of nominal and real bond returns implied by the VAR (Panel A) and by the VEC model (Panel B) depending on the investment horizon. The first row of each panel shows the variances of nominal bond returns and is normalized to the first entry (one horizon variance) of the VEC panel. The decomposition for the $k$-period variance of the nominal bond return is $Var(nBo_{t+k}) = Var(exBo_{t+k}) + 2Cov(exBo_{t+k}, rTb_{t+k}) + Var(rTb_{t+k}) + 2Cov(rTb_{t+k}, infl_{t+k}) + Var(infl_{t+k}) + 2Cov(exBo_{t+k}, infl_{t+k})$ and that of the real bond return is $Var(rBo_{t+k}) = Var(exBo_{t+k}) + 2Cov(exBo_{t+k}, rTb_{t+k}) + Var(rTb_{t+k})$. Bootstrap intervals are calculated from 10,000 paths under the assumption that the initial estimated VAR or VEC model truly generates the data process and are reported in brackets. Bold coefficients imply significance on a 5% level.

the investment horizon. However, the reassessment seems to be slow for both models and is stronger for the VAR and makes real returns less risky than nominal returns in the very long run. In contrast, allowing for cointegration implies a stronger risk reduction of nominal bond returns over all horizons and also significantly reduces the risk of real returns in the short term.

### 3.3.4 Asset Allocation Decisions

For a deeper analysis of the horizon effects in the term structure of risk mentioned above, we investigate the optimal mean-variance portfolio allocations of investors with various holding intervals. We analyze two types of portfolios. One portfolio is the global minimum variance (GMV) portfolio and the second portfolio represents a less risk-averse investor with a risk aversion of $\gamma = 20$. For the GMV portfolio, only risk statistics are taken into account for the optimal decision, while for the portfolio of an investor with lower risk-aversion, the term structure of expected returns is also relevant.

Table 3.11 shows four cases of GMV portfolio allocations for investment horizons of up to 25 years and bootstrapped 95% confidence intervals in brackets below. We consider VAR and VEC-based investors allocating their wealth by taking into account real and nominal returns. Panels A and B report the composition of the VAR and VEC models based on real returns. In these cases, very risk-averse investors hold most of their money in cash because it is the least risky investment in real terms over all investment horizons. However, cointegration tilts allocation toward cash in the long run. While a small negative weight is assigned to stock investments in the VEC at medium horizons due to a high positive correlation between T-bills and stocks, the weights are nearly zero under stationarity at all horizons. Starting with a negative weight, the allocations to real bonds increase with the investment horizon in both models. However, cointegration reduces bond allocation in the long run.

Panels C and D report the composition of the VAR and VEC models based on nominal returns. The different nominal term structures change optimal allocations compared to real terms. While in both models all asset weights are roughly equal up to horizon 10, they substantially differ for the longer investment horizons. The VEC-based investor shifts nearly all his wealth to bonds as the horizon increases, whereas he decreases T-bills to zero and assigns stocks a minor role in the nominal portfolio decision. The VAR-based investor diversifies more among the assets by holding 15% T-bills, 17% stocks and 68% bonds in the very long run.

Table 3.11 shows four cases of optimal portfolio allocations of investors with a risk aversion $\gamma = 20$ for investment horizons up to 25 years and bootstrapped 95% confidence intervals in brackets below. We consider a VAR and a VEC-based investor allocating his wealth by taking into account real and nominal returns. Panels A and B report the composition of the VAR and VEC model based on real returns. While

Table 3.11: Global Minimum Variance Portfolios

| Panel A | Horizon (quarters) | | | | |
|---|---|---|---|---|---|
| VAR real | 1 | 5 | 10 | 50 | 100 |
| T-bills | **1.04** | **1.05** | **1.02** | **0.91** | **0.84** |
| | [1.02,1.06] | [1.00,1.09] | [0.97,1.08] | [0.84,1.06] | [0.75,1.11] |
| Stocks | -0.01 | -0.02 | -0.02 | -0.02 | 0.01 |
| | [-0.02,0.00] | [-0.03,0.00] | [-0.04,0.01] | [-0.07,0.03] | [-0.10,0.08] |
| Bonds | **-0.04** | -0.03 | -0.01 | 0.11 | 0.14 |
| | [-0.06,-0.01] | [-0.07,0.01] | [-0.06,0.03] | [-0.03,0.17] | [-0.07,0.23] |

| Panel B | Horizon (quarters) | | | | |
|---|---|---|---|---|---|
| VEC real | 1 | 5 | 10 | 50 | 100 |
| T-bills | **1.05** | **1.08** | **1.12** | **1.06** | **0.92** |
| | [1.02,1.07] | [1.03,1.13] | [1.04,1.18] | [0.85,1.19] | [0.73,1.15] |
| Stocks | -0.01 | **-0.05** | **-0.08** | -0.06 | 0.01 |
| | [-0.02,0.00] | [-0.07,-0.02] | [-0.10,-0.02] | [-0.12,0.05] | [-0.15,0.15] |
| Bonds | **-0.04** | -0.03 | -0.04 | 0.00 | 0.07 |
| | [-0.06,-0.00] | [-0.09,0.01] | [-0.11,0.02] | [-0.13,0.15] | [-0.12,0.26] |

| Panel C | Horizon (quarters) | | | | |
|---|---|---|---|---|---|
| VAR nominal | 1 | 5 | 10 | 50 | 100 |
| T-bills | **0.97** | **0.89** | **0.80** | **0.38** | **0.15** |
| | [0.96,0.97] | [0.86,0.92] | [0.77,0.85] | [0.33,0.76] | [0.01,0.94] |
| Stocks | 0.00 | **0.01** | **0.02** | 0.06 | 0.17 |
| | [-0.00,0.00] | [0.00,0.02] | [0.00,0.04] | [-0.07,0.15] | [-0.19,0.37] |
| Bonds | **0.03** | **0.10** | **0.17** | **0.56** | 0.68 |
| | [0.01,0.03] | [0.07,0.11] | [0.12,0.20] | [0.20,0.60] | [-0.01,0.85] |

| Panel D | Horizon (quarters) | | | | |
|---|---|---|---|---|---|
| VEC nominal | 1 | 5 | 10 | 50 | 100 |
| T-bills | **0.97** | **0.91** | **0.82** | **0.41** | 0.03 |
| | [0.96,0.98] | [0.88,0.93] | [0.78,0.87] | [0.35,0.67] | [-0.01,0.74] |
| Stocks | 0.00 | -0.01 | -0.01 | 0.04 | -0.07 |
| | [-0.00,0.00] | [-0.01,0.00] | [-0.02,0.02] | [-0.08,0.16] | [-0.34,0.35] |
| Bonds | **0.03** | **0.10** | **0.19** | **0.55** | **1.03** |
| | [0.01,0.03] | [0.07,0.12] | [0.12,0.21] | [0.27,0.64] | [0.22,1.14] |

*Notes:* This table reports the four cases of GMV portfolio allocations for investment horizons of up to 25 years. Panels A and B show the portfolio compositions of the VAR and VEC models based on real returns. Panels C and D report the portfolio compositions of the VAR and VEC models based on nominal returns. Bootstrap intervals are calculated from 10,000 paths under the assumption that the initial estimated VAR or VEC model truly generates the data process and are reported in brackets. Bold coefficients imply significance on a 5% level.

Table 3.12: Optimal Portfolio Holdings for $\gamma = 20$

| Panel A | Horizon (quarters) | | | | |
|---|---|---|---|---|---|
| VAR real | 1 | 5 | 10 | 50 | 100 |
| T-bills | **0.83** | **0.84** | **0.83** | **0.64** | 0.44 |
| | [0.78,0.86] | [0.73,0.88] | [0.67,0.88] | [0.18,0.76] | [-0.08,0.63] |
| Stocks | **0.12** | **0.10** | **0.11** | **0.24** | **0.35** |
| | [0.09,0.14] | [0.07,0.15] | [0.08,0.19] | [0.16,0.41] | [0.22,0.53] |
| Bonds | **0.05** | **0.06** | **0.06** | **0.12** | **0.20** |
| | [0.02,0.08] | [0.01,0.13] | [0.00,0.16] | [0.00,0.46] | [0.05,0.62] |

| Panel B | Horizon (quarters) | | | | |
|---|---|---|---|---|---|
| VEC real | 1 | 5 | 10 | 50 | 100 |
| T-bills | **0.83** | **0.80** | **0.81** | 0.85 | 0.74 |
| | [0.76,0.85] | [0.61,0.85] | [0.47,0.89] | [-0.23,0.98] | [-0.80,0.98] |
| Stocks | **0.13** | **0.12** | **0.15** | **0.72** | **1.23** |
| | [0.10,0.16] | [0.09,0.23] | [0.12,0.38] | [0.58,1.49] | [0.88,2.53] |
| Bonds | **0.04** | **0.08** | 0.04 | -0.58 | -0.97 |
| | [0.01,0.08] | [0.00,0.20] | [-0.10,0.23] | [-1.01,0.16] | [-1.81,0.08] |

| Panel C | Horizon (quarters) | | | | |
|---|---|---|---|---|---|
| VAR nominal | 1 | 5 | 10 | 50 | 100 |
| T-bills | **0.76** | **0.68** | **0.61** | 0.11 | -0.25 |
| | [0.71,0.78] | [0.59,0.72] | [0.46,0.65] | [-0.14,0.30] | [-0.48,0.24] |
| Stocks | **0.13** | **0.13** | **0.15** | **0.32** | **0.51** |
| | [0.11,0.15] | [0.11,0.17] | [0.13,0.22] | [0.20,0.47] | [0.20,0.70] |
| Bonds | **0.11** | **0.18** | **0.24** | **0.57** | **0.74** |
| | [0.08,0.14] | [0.14,0.24] | [0.18,0.33] | [0.36,0.75] | [0.28,1.01] |

| Panel D | Horizon (quarters) | | | | |
|---|---|---|---|---|---|
| VEC nominal | 1 | 5 | 10 | 50 | 100 |
| T-bills | **0.76** | **0.62** | **0.51** | 0.20 | -0.15 |
| | [0.69,0.78] | [0.44,0.67] | [0.20,0.59] | [-0.71,0.38] | [-1.35,0.41] |
| Stocks | **0.14** | **0.16** | **0.23** | **0.82** | **1.15** |
| | [0.12,0.17] | [0.14,0.27] | [0.19,0.44] | [0.64,1.57] | [0.83,2.58] |
| Bonds | **0.11** | **0.21** | **0.27** | -0.02 | -0.01 |
| | [0.07,0.14] | [0.13,0.32] | [0.11,0.43] | [-0.53,0.57] | [-1.26,0.66] |

*Notes:* This table reports the four cases of optimal portfolio allocations of investors with a risk aversion $\gamma = 20$ for investment horizons up to 25 years. Panel A and B show the portfolio compositions of the VAR and VEC model based on real returns. Panel C and D report the portfolio compositions of the VAR and VEC model based on nominal returns. Bootstrap intervals are calculated from 10,000 paths under the assumption that the initial estimated VAR or VEC model truly generates the data process and are reported in brackets. Bold coefficients imply significance on a 5% level.

in both panels all asset weights are roughly equal up to horizon 10, they substantially differ for the longer investment horizons. In the short run, about 80% of the money is assigned to T-bills and the rest to stocks and bonds. As the holding period lengthens, the VAR-based investor shifts his T-bills allocation to stocks and bonds whereas the absolute increase is nearly twice as high for stocks than for bonds. In contrast, the VEC-based investor holds his T-bill exposure roughly constant over all investment horizons. He funds the strong increasing stock allocation with short-selling bonds resulting in a 123% stock and -97% bond position.

Panels C and D report the composition of the VAR and VEC models based on nominal returns. We see once more that the differences in optimal portfolio weights are small at short horizons. Furthermore, in both cases, the T-bills allocations strongly decrease with the investment horizon and are negative for the very long run. An alternative pattern with respect to stock and bond allocations is observed between the models. While the VAR-based investor allocates most of his wealth to bonds as the investment horizon increases, the VEC-based investor shifts his money to stocks, resulting in a leveraged equity position at a 100-period horizon and his preference toward bonds reverses as the holding period lengthens.

The differences in the optimal portfolio allocations between the stationary and the cointegrated model arise due to the different term structures of risk and correlations as well as due to changes in expected returns. While for both types of investors stocks are the riskiest and T-bills are the least risky investment under real returns, the absolute volatilities differ to a large extent. Under cointegration, the risk is almost always lower and especially reduced for bonds in the short run, for T-bills in the long run and for stocks over all horizons. Thus, the real VEC-based investor keeps his exposure to T-bills consistently high and increases the equity exposure with the investment horizon. Turning to nominal returns, the VEC model assigns all assets lower volatilities compared to the VAR model over all horizons, leading to over 50% lower risks for stocks and bonds in the long run. This strong risk reduction of stocks and bonds and the mean-aversion effect of short-term interest rates make T-bills the riskiest asset class under cointegration in the long run. Thus, the very risk-averse nominal VEC-based investor shifts his allocation from T-bills to bonds faster than the VAR-based investor. Furthermore, according to the VEC model, the diversification potential between stocks and bonds diminishes with an increasing investment horizon as the correlations are 83% and 73% in real and nominal terms at a 100-period horizon. However, the correlations in the VAR model are considerably lower and increase to 50% for nominal returns but decrease to 31% for real returns at a 100-period horizon. For this reason, under cointegration and depending on the level of risk aversion, the nominal GMV portfolio includes only the less risky bond position and the more aggressive portfolio includes only stocks due to their higher expected return.

## 3.4 Conclusion

This paper shows that the incorporation of cointegration into the commonly used VAR framework yields important implications for modeling asset price dynamics over all investment horizons. In the presence of common long-run relations, the VEC model captures these effects. Cointegration leads to a significant change in the horizon-dependent risk structure of the asset returns and ultimately in the optimal asset allocations compared to the stationary VAR model.

We find strong evidence that the traditional VAR distorts the term structure of risk because the levels of the variables share common stochastic trends ignored by the stationary VAR. Analyzing the properties of the time series, we detect four cointegration relations between T-bills, stocks, bonds, dividend-price ratio, term spread and inflation. Since deviations of the long-term comovement of the variables cause predictable backward movements that are captured by the VEC, the cointegration model explains the occurred risk premia of stocks and bonds much better than the stationary VAR.

We find substantial differences between the two models with respect to the term structure of risk. In the VEC the risk structure of real T-bills is much lower than in the VAR model in the long run. While the return variation of excess stock returns is mean-reverting in both models, the effect is much more pronounced for the VEC, especially in the first periods. This difference is predominantly caused by a much stronger mean-reversion effect of the dividend-price ratio under cointegration. Furthermore, the term structure of risk for the bond premium decreases in the stationary model over the horizon, while in the VEC, the volatility is hump-shaped with a much steeper drop in the first periods and a subsequent backward movement to the VAR term structure in the long run. The mean-reversion behavior of the bond premium is the result of negative correlations between excess bond returns and inflation, whereas this effect is weakened by a mean-averting influence of the term spread. However, under cointegration, the term spread affects bond volatility only in the long run.

Furthermore, in a variance decomposition exercise, depending on the time horizon, we examine various risk components of real and nominal returns and their interdependencies. We find inflation to be the driving component of nominal interest rates and detect a strong relationship between nominal T-bills and inflation under cointegration in the long run. Moreover, we observe the excess return variation as the main component of the corresponding real stock and bond return variation in both models. The variation of real T-bills only has a marginal effect on the total variation of real returns. Allowing for cointegration, the volatility of nominal stock and bond returns is significantly decreased by the covariation between both risk premia and inflation at long horizons, whereas the VAR model is not able to capture this effect. Finally, these differences in the risk structure influence the optimal portfolio choice. Under cointegration and extreme risk aversion, the optimal real (nominal) return portfolio is much more tilted towards T-bills (bonds). In the VEC, a less risk-averse investor has a much higher equity exposure as the investment horizon lengthens and even leverages the position in the very long run. This behavior is borne by a decreasing bond position compared to the VAR model.

We have tried to illustrate our findings with the use of variables commonly included in the stationary VAR framework. This enables us to compare and link the results to the related literature. However, our analysis can be extended by incorporating additional or other variables into the cointegration model that can influence the results. Moreover, the traditional VAR analysis often includes parameter uncertainty investigations that also have implications for asset allocation decisions across various investment horizons. Analyzing parameter uncertainty within the cointegration framework is an interesting topic for further research.

# 3.A Appendix

## 3.A.1 Bootstrap Method

We apply the residual-based bootstrap method suggested by Benkwitz, Lütkepohl, and Wolters (2001) and Lütkepohl (2005), which consists of the following steps:

1. Estimate the unknown coefficients of the VAR or VEC. Let $\hat{\mathbf{u}}_t$ and $\hat{\boldsymbol{\nu}}_t$ be the estimate of the VAR residuals $\mathbf{u}_t$ and the VEC residuals $\boldsymbol{\nu}_t$, respectively.

2. Calculate centered residuals $\hat{\mathbf{u}}_1 - \bar{\mathbf{u}}, ..., \hat{\mathbf{u}}_T - \bar{\mathbf{u}}$ or $\hat{\boldsymbol{\nu}}_1 - \bar{\boldsymbol{\nu}}, ..., \hat{\boldsymbol{\nu}}_T - \bar{\boldsymbol{\nu}}$, where $\bar{\mathbf{u}}$ and $\bar{\boldsymbol{\nu}}$ are the $n$ usual means for the $n$ residual series.

3. Draw randomly with replacement from the centered residuals to obtain bootstrap residuals $\boldsymbol{\epsilon}_1^*, ..., \boldsymbol{\epsilon}_T^*$.

4. Recursively calculate the bootstrap time series for the VAR as

$$\Delta\mathbf{z}_t^* = \boldsymbol{\mu} + \mathbf{B}_1\Delta\mathbf{z}_{t-1}^* + \cdots + \mathbf{B}_p\Delta\mathbf{z}_{t-p}^* + \boldsymbol{\epsilon}_t^*,\ t = 1, ..., T, \tag{3.17}$$

   where $(\Delta\mathbf{z}_{-p+1}^*, ..., \Delta\mathbf{z}_0^*) = (\Delta\mathbf{z}_{-p+1}, ..., \Delta\mathbf{z}_0)$ holds for each generated series. For the VEC its level representation is used for data generation and hence the bootstrap time series for the VEC are calculated as in Equation (3.17), replacing $\Delta\mathbf{z}_t^*$ by $\mathbf{z}_t^*$ and using the corresponding coefficient matrices $\mathbf{A}_1, ..., \mathbf{A}_p$.

5. Reestimate the coefficients of the VAR or VEC using the bootstrapped data and calculate the statistic of interest $q^*$.

6. Repeat these steps $N$ times.

The bootstrap confidence intervals (standard percentile intervals) are then given by

$$CI = \left[s_{\gamma/2}^*, s_{(1-\gamma/2)}^*\right],$$

where $s_{\gamma/2}^*$ and $s_{(1-\gamma/2)}^*$ are the $\gamma/2$- and $1-(\gamma/2)$-quantiles of the $N$ bootstrap versions of $q^*$.

### 3.A.2 Model Selection

The number of lags to be included in the VAR and VEC models is determined by taking into account the suggestions of the Akaike information criterion (AIC), the Schwarz criterion (SC) and the Hannan & Quinn criterion (HQ). Table 3.13 reports the test statistics of these criteria depending on the number of lags.

Panel A reports the results for the VAR model. The SC and HQ criteria suggest one lag for the VAR model as the test statistics are minimized, while the AIC suggests four lags. Panel B reports the results for the VAR in levels, the basis of the VEC model. The SC and the HQ suggest two lags for the VAR model in levels which is equivalent to a VEC(1), while the AIC again suggests four lags. For the empirical analysis, we follow the suggestions of the SC and HQ and investigate a VAR and a VEC of order one.

Table 3.13: Lag Length Selection

| Panel A | Lags for VAR in Differences | | | |
|---|---|---|---|---|
| Criterion | $p = 1$ | $p = 2$ | $p = 3$ | $p = 4$ |
| AIC(p) | -66.228 | -66.377 | -66.267 | -66.409* |
| HQ(p) | -65.973* | -65.904 | -65.575 | -65.499 |
| SC(p) | -65.596* | -65.204 | -64.553 | -64.153 |

| Panel B | Lags for VAR in Levels | | | |
|---|---|---|---|---|
| Criterion | $p = 1$ | $p = 2$ | $p = 3$ | $p = 4$ |
| AIC(p) | -62.999 | -66.667 | -66.692* | -66.614 |
| HQ(p) | -62.744 | -66.193* | -66.001 | -65.704 |
| SC(p) | -62.367 | -65.493* | -64.978 | -64.358 |

*Notes:* This table reports the test statistics of the Akaike, Schwarz and Hannan & Quinn information criteria to determine the number of lags to be included in the VAR (Panel A) and VEC (Panel B). * denotes the minimum test statistic depending on the number of lags for each information criterion.

# Chapter 4

# Do Stock Prices and Cash Flows Drift Apart? The Influence of Macroeconomic Proxies

This paper is the result of a joint project with *Tim Koniarski*.


## Abstract

The evidence of stationarity of the dividend-price ratio and earnings-price ratio is empirically mixed. Non-stationarity lead to invalid conclusions about return predictability. A breakdown of these relations can be caused by different macroeconomic influences. We investigate the connections of stock prices and cash flows (dividends and earnings) to macroeconomic proxies within a cointegration framework. We find that prices and cash flows are not one-for-one cointegrated and detect a negative inflation link to prices and positive inflation links to cash flows. The risk-free rate significantly decreases dividends and not prices. Government and corporate bond yields have contrary impacts on equity markets.

## 4.1 Introduction

Several studies in the predictability literature use variables such as the dividend-price ratio and earnings-price ratio to forecast stock returns.[1] According to theory, stock prices are the discounted future cash flows and, therefore, prices should move around their fundamentals (dividends and earnings) in the long run. It is generally assumed that prices and cash flows are cointegrated one-for-one or, alternatively, that the dividend-price ratio and earnings-price ratio are stationary variables, since otherwise the conventional $t$-statistics lead to wrong conclusions about the evidence of return predictability. However, the stationarity of these valuation ratios is empirically doubtful (Ang and Bekaert, 2007; Lettau and Van Nieuwerburgh, 2008). A natural question arises whether this observation is blurred by the high persistence of the valuation ratio or whether it is based on a change in the payout policy (Fama and French, 2001; Grullon and Michaely, 2002, 2004; Boudoukh, Michaely, Richardson, and Roberts, 2007) or whether it is actually caused by a breakdown of the one-for-one relation due to different macroeconomic influences on prices and dividends (Lettau and Ludvigson, 2001; Lee, 2010).

In this paper, we extend the loglinear Campbell and Shiller (1988a) model to investigate the influences of macroeconomic variables (inflation, short-term interest rates, government and corporate bond yields) on stock prices and cash flows (dividends and earnings) and, consequently, the implied impacts on total stock returns. Our cointegration model shows that (i) prices and cash flows do not form (trend-) stationary relations, and especially do not form stationary one-for-one relations; (ii) dividends and earnings move close together and only minor different macroeconomic influences are observable; (iii) inflation strongly decreases stock prices and increases cash flows; (iv) the risk-free rate negatively influences all equity market variables; and (v) government and corporate bond yields have contrary impacts on the equity market. Since we approximate total stock returns by price changes and dividends, the returns are, therefore, also linked to the macroeconomic effects of prices and dividends.

[1] See, for example, (Fama and Schwert, 1977; Keim and Stambaugh, 1986; Fama and French, 1988, 1989; Kothari and Shanken, 1997).

We start from a vector autoregressive model (VAR) of non-stationary time series and allow for cointegration. The choice of variables and the model setup are well justified. Campbell and Shiller (1987) propose a cointegration VAR framework between prices and dividends and find a weak long-run relation between these variables. Cochrane (1994) and Lee (1995) investigate the permanent and transitory components of this bivariate model, without questioning the validity and implication of the $[1, -1]$ assumption of the dividend-price ratio. Campbell and Shiller (1988b) and Lamont (1998) illustrate the importance of earnings measures (dividend-earnings or earnings-price ratio) to account for dividend predictability, since these ratios mirror actual business success which dividends do not directly reflect. Lee (1996) confirms a link between dividends and earnings within a cointegration framework. While these studies focus only on a relation between equity market variables, Lettau and Ludvigson (2001) see a natural long-run connection between the equity market and the macroeconomy that mirrors business conditions and, consequently, model it as a cointegration relation between dividends, aggregate consumption and labor income. Other studies proxy macroeconomic conditions by variables such as inflation, interest rates, term spread and credit spread (for example: Fama and French, 1988, 1989; Boudoukh and Richardson, 1993; Campbell and Thompson, 2008; Cochrane, 2008; Goyal and Welch, 2008), but they do not examine their long-run influence on the equity market. Following these studies, we also incorporate the inflation rate, short-term interest rates and government and corporate bond yields in the model to analyze their impacts on prices, dividends and earnings.

When detecting the non-stationarity of these time series, we apply a vector error correction (VEC) model to capture the interactions of the seven variables. We show that the system has four cointegration relations or, alternatively, three remaining stochastic trends. The versatile model setup enables us to test the validity of the stationarity of the dividend-price ratio in a multivariate framework. Moreover, in the same way we also examine the stationarity of further financial ratios such as dividend-earnings, earnings-price, real short-interest rates, term spread and credit spread, which are additionally used in the predictability literature. Our tests show that dividend-earnings and the term spread most likely are stationary or, alternatively, that the underlying variables have the same stochastic trends, whereas the null hypothesis of stationarity is rejected for the remaining ratios. Additionally, we find inflation to have a strong impact on the equity market. While other papers often consider returns, prices and dividends in real terms to avoid inflation effects and assume that inflation influences equity market variables identically, we show a negative linkage between nominal prices and inflation and nominal cash flows to be positively associated to inflation in the long run. Thus, nominal total stock returns are reduced by inflation shocks in the short term, but recover for long time horizons. This result connects the contrary findings of Fama and Schwert (1977) and Boudoukh and Richardson (1993). While Fama and Schwert find a negative relation in the short run, Boudoukh and Richardson find a positive relation in the long run. Moreover, we find that interest rates play a similar role for all equity market variables. Although prices, dividends and earnings are reduced by rising interest rates, the magnitude is much more pronounced for cash flows than for stock prices. Finally, while for corporate bond yields we find large positive effects on the equity market, the influences of the government bond yields are negative.

The remainder of this paper is organized as follows: In the next section, we describe the methodology of the econometric model, the tests used for identifying pulling and pushing forces in the system and derive the framework for the long-horizon analysis. Section 3 introduces the data set, examines the time series properties for further investigations and presents the results of our empirical analysis. Finally, Section 4 summarizes the main findings.

## 4.2 Methodology

In this section, we introduce the VEC model capturing the dynamics of the variables analyzed and, to gain further insights about the pulling and pushing forces acting among the stochastic trends, we then apply four different types of structural hypotheses tests. Finally, we introduce the impulse response analysis to investigate the long-run dynamics implied by the VEC.

### 4.2.1 The Econometric Model

The unrestricted basic model, a $n$-dimensional vector autoregressive model VAR($p$), is defined as follows:

$$\mathbf{z}_t = \mathbf{A}_1\mathbf{z}_{t-1} + \cdots + \mathbf{A}_p\mathbf{z}_{t-p} + \boldsymbol{\Psi}\mathbf{d}_t + \mathbf{u}_t, \qquad t = 1, ..., T, \tag{4.1}$$

where $\mathbf{z}_t$ contains the $n$ variables of interest, both of which are assumed to be integrated of order one, ($I(1)$), and the shocks, $\mathbf{u}_t$, are assumed to be $IID$ with time-invariant zero means and variance-covariance matrix $\boldsymbol{\Sigma}_u$. The matrices $\mathbf{A}_1, ..., \mathbf{A}_p$ are the $(n \times n)$ slope coefficients, while the vector $\mathbf{d}_t$ contains dummy variables, a constant and a time trend and $\boldsymbol{\Psi}$ is the loading matrix of these deterministic components. Dropping the deterministic components for simplification and without imposing binding restrictions, this VAR($p$) can be transformed to a VEC of order $p-1$ by subtracting both sides of Equation (4.1) with $\mathbf{z}_{t-1}$:

$$\Delta\mathbf{z}_t = \boldsymbol{\Pi}\mathbf{z}_{t-1} + \boldsymbol{\Gamma}_1\Delta\mathbf{z}_{t-1} + \cdots + \boldsymbol{\Gamma}_{k-1}\Delta\mathbf{z}_{t-k+1} + \mathbf{u}_t, \tag{4.2}$$

where $\boldsymbol{\Pi} = -(\mathbf{I} - \mathbf{A}_1 - \cdots - \mathbf{A}_p)$ and $\boldsymbol{\Gamma}_j = -(\mathbf{A}_{j+1} + \cdots + \mathbf{A}_p)$ for $j = 1, ..., p-1$. As can be seen in Equation (4.2), matrix $\boldsymbol{\Pi}$ summarizes the long-run effects and the short-run effects remain in the $\boldsymbol{\Gamma}_1, ..., \boldsymbol{\Gamma}_{p-1}$. While the $\boldsymbol{\Gamma}_j$'s are full rank matrices, $\boldsymbol{\Pi}$ must have reduced rank, otherwise a logical inconsistency would occur.[2] To determine the number $r < n$ of cointegration relations, we test the hypothesis

$$H_1(r) : \boldsymbol{\Pi}_r = \boldsymbol{\alpha}\boldsymbol{\beta}', \tag{4.3}$$

where $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are both $(n \times r)$ matrices. Hypothesis $H_1$ is performed stepwise by investigating whether there is a significant difference between the likelihood of the unrestricted model in Equation (4.2) and the likelihood of a model with $\boldsymbol{\Pi}_r$ restricted to rank $r$. The test statistic is

$$-2\mathcal{Q}(H_1(r)|H_0) = -T \sum_{j=r+1}^{n} \log(1 - \tilde{\lambda}_j), \tag{4.4}$$

[2] Assuming $\mathbf{z}_t \sim I(1)$, $\Delta\mathbf{z}_t \sim I(0)$ and considering $\boldsymbol{\Pi} = \mathbf{I}$, the stationary variable $\Delta\mathbf{z}_t$ on the left-hand side of Equation (4.2) would be equal to the sum of stationary variables $\boldsymbol{\Gamma}_j\Delta\mathbf{z}_{t-j}$ and a non-stationary term $\mathbf{z}_{t-1}$ (Juselius, 2006, Chap. 5).

where $\tilde{\lambda}_j$ are the estimated eigenvalues of the reduced model's $\mathbf{\Pi}$ matrix.[3] The optimal rank $r$ corresponds to the most restrictive model without obtaining a significantly different likelihood. After specifying the optimal $r$, we calculate the decomposition of $\mathbf{\Pi}_r = \boldsymbol{\alpha}\boldsymbol{\beta}'$, which leads to the reduced rank system

$$\Delta \mathbf{z}_t = \boldsymbol{\alpha}\boldsymbol{\beta}'\mathbf{z}_{t-1} + \mathbf{\Gamma}_1 \Delta \mathbf{z}_{t-1} + \cdots + \mathbf{\Gamma}_{p-1}\Delta \mathbf{z}_{t-p+1} + \boldsymbol{\nu}_t. \tag{4.5}$$

As shown in Johansen (1996), $\boldsymbol{\beta}'$ transforms the non-stationary $\mathbf{z}_t$ to stationary relations $\boldsymbol{\beta}'\mathbf{z}_t$, which are also known as cointegration relations. The matrix $\boldsymbol{\alpha}$ contains the loadings on the stationary and depended variables $\Delta \mathbf{z}_t$. Note that in case of $r = 0$ or, alternatively, $n$ independent stochastic trends and no cointegration, the matrix $\mathbf{\Pi}_r$ equals $\mathbf{0}$.

### 4.2.2 Hypotheses Testing

Since we want to detect not only the number of cointegration relations, but also to gain further insights about the pulling and pushing forces acting among the stochastic trends, we apply four different types of structural hypotheses tests to the matrices capturing the long-run effects. Thus, we can analyze the exclusion and exogeneity of variables and investigate whether the financial ratios exhibit (trend-)stationary behavior. Following Johansen and Juselius (1992), our tests are:

$$H_2 : \boldsymbol{\beta} = \mathbf{H}_2\boldsymbol{\varphi}, \qquad \mathbf{H}_2(n \times s), \boldsymbol{\varphi}(s \times r), \qquad r \leq s \leq n, \tag{4.6}$$

$$H_3 : \boldsymbol{\beta} = (\mathbf{H}_3, \boldsymbol{\psi}), \qquad \mathbf{H}_3(n \times r_1), \boldsymbol{\psi}(n \times r_2), \qquad r = r_1 + r_2, \tag{4.7}$$

$$H_4 : \boldsymbol{\beta} = (\mathbf{H}_4\boldsymbol{\varphi}, \boldsymbol{\psi}), \quad \mathbf{H}_4(n \times s), \boldsymbol{\varphi}(s \times r_1), \boldsymbol{\psi}(n \times r_2), \quad r \leq s \leq n, \quad r = r_1 + r_2, \tag{4.8}$$

$$H_5 : \boldsymbol{\alpha} = \mathbf{H}_5\boldsymbol{\xi}, \qquad \mathbf{H}_5(n \times m), \boldsymbol{\xi}(m \times r), \qquad r \leq m \leq n, \tag{4.9}$$

where $\mathbf{H}_2$, $\mathbf{H}_3$, $\mathbf{H}_4$ and $\mathbf{H}_5$ are appropriately chosen transformation matrices. Hypothesis $H_2$ sets the same $(n - s)$ restrictions on all $r$ cointegration relations $\boldsymbol{\beta}$, whereas hypothesis $H_3$ assumes $r_1$ cointegration relations to be known and the coefficients of the remaining $r_2$ relations to be estimated. Hypothesis $H_4$, a combination of $H_2$ and $H_3$, sets only a few restrictions on the first $r_1$ cointegration relations

[3] A full discussion of this trace test and its distribution is given in Johansen and Juselius (1990).

and leaves the remaining coefficients (in the $r_1$ relations and in $\boldsymbol{\psi}$) to be estimated. There are two special cases: for $r_2 = 0$, the hypothesis $H_4$ is equal to $H_2$ and for $r_1 = s$ hypothesis, $H_4$ reduces to $H_3$. Hypothesis $H_5$ tests the exclusion of the influence of certain long-run relations. The corresponding test statistics, which are $\chi^2$-distributed in each case, and further details are given in Johansen and Juselius (1992).

We use $H_2$ to test the exclusion of certain variables from all long-run relations, i.e. to test a zero row restriction on $\boldsymbol{\beta}$. If rejected, we cannot omit the variable from the cointegration relations. Moreover, many empirical finance studies use financial ratios, which are assumed to be stationary, to predict asset returns. For example, the dividend-price ratio is assumed to be an one-for-one relation. To test such a hypothesis, we also use $H_2$ to analyze the validity of this relation in the full system, e.g. dividends ($d_t$) and prices ($p_t$) are long-run homogeneous in all cointegration relations. If rejected, we cannot reformulate the long-run relations directly to the dividend-price ratio without a loss of information. If the $H_2$ constraints are too restrictive, we cannot respecify all of the long-run relations to financial ratios without losing information. In contrast to $H_2$, we relax the restrictions with $H_3$ to only $r_1$ relations. Thus, the test shows that whether e.g. dividends, prices or the dividend-price ratio are (trend-)stationary by themselves in a multivariate framework. In the case where $H_3$ is rejected, e.g. the one-for-one relation of a financial ratio, we can test a more general relation (linear combination) between the variables of interest where the coefficients have to be estimated. The $H_4$ test analyzes if there is any stationary linear combination between the variables for each equation, e.g. whether a stationary ratio $(d_t - \beta p_t)$ for some estimated value of $\beta$ exists or not. Moreover, including some additional variables in the $r_1$ linear combinations, the $H_4$ test investigates the stationarity of these extended linear combinations.

Last, a natural question is if the variables adjust to, are pushed by or are weakly exogenous to the estimated long-run relations. As a result, we use $H_5$ to analyze the structural restrictions of the loading effects $\boldsymbol{\alpha}$ of the cointegration relations. For example, in the presence of a disequilibrium between dividends and prices, the issue can be addressed as to whether there is a significant adjustment back to the equilibrium and if it is due to changes in stock prices or dividends.

### 4.2.3 Long-Run Analyses

To investigate the long-run dynamics implied by the VEC, we examine the horizon-dependent influence of unexpected shocks on the stock return. The corresponding statistics are based on appropriately iterated coefficient matrices of the VEC. Therefore, we start by retransforming the reduced rank VEC$(p-1)$ in Equation (4.5) back to a VAR$(p)$ by setting $\mathbf{A}_{1,r} = \mathbf{I} + \mathbf{\Pi}_r + \mathbf{\Gamma}_1$, $\mathbf{A}_{j,r} = \mathbf{\Gamma}_j - \mathbf{\Gamma}_{j-1}$ for $j = 2, ..., p-1$ and $\mathbf{A}_{p,r} = -\mathbf{\Gamma}_{p-1}$. Afterwards, we rewrite the VAR$(p)$ as a VAR(1) with the $(pn \times pn)$ coefficient matrix $\mathbf{A}_r$.

The influence of an unexpected shock of one variable on the variables is examined by an impulse-response analysis. The effects of the shocks can be seen in the Wold (moving average) representation theorem:

$$\mathbf{z}_t^* = \mathbf{A}_r^0 \boldsymbol{\nu}_t^* + \mathbf{A}_r^1 \boldsymbol{\nu}_{t-1}^* + \mathbf{A}_r^2 \boldsymbol{\nu}_{t-2}^* + \cdots ,$$

where $\mathbf{z}_t^* = (\mathbf{z}_t, ..., \mathbf{z}_{t-p+1})'$ and $\boldsymbol{\nu}_t^*$ are the residuals of the VEC in Equation (4.5) (stacked with a vector of zeros). Since the variables in $\mathbf{z}_t$ are assumed to be non-stationary, the elements in $\mathbf{A}_r^k$ do not need to converge to zero as $k \to \infty$ and some shocks can consequently have permanent effects.[4]

The horizon-dependent risk statistics are based on the covariance matrix of the residuals and the iterated coefficient matrices. Starting with the future value $\mathbf{z}_{t+k}^*$, which can be described by its current value $\mathbf{z}_t^*$ and a sum of intermediate shocks

$$\mathbf{z}_{t+k}^* = \mathbf{A}_r^k \mathbf{z}_t^* + \mathbf{A}_r^{k-1} \boldsymbol{\nu}_{t+1}^* + \mathbf{A}_r^{k-2} \boldsymbol{\nu}_{t+2}^* + \cdots + \mathbf{A}_r \boldsymbol{\nu}_{t+k-1}^* + \boldsymbol{\nu}_{t+k}^*,$$

we obtain the conditional $k$-period variance-covariance matrix of the VEC, scaled by the investment horizon:

$$\frac{1}{k} Var\left(\mathbf{z}_{t+k}^*\right) = \frac{1}{k}\left[\mathbf{A}_r^{k-1} \mathbf{\Sigma}^* \left(\mathbf{A}_r^{k-1}\right)' + \mathbf{A}_r^{k-2} \mathbf{\Sigma}^* \left(\mathbf{A}_r^{k-2}\right)' + \cdots + \mathbf{A}_r \mathbf{\Sigma}^* \mathbf{A}_r' + \mathbf{\Sigma}^*\right], \tag{4.10}$$

where $\mathbf{\Sigma}^*$ is the $(pn \times pn)$ covariance matrix of the residuals $\boldsymbol{\nu}^*$.

[4]Some elements of the iterated coefficient matrix of a non-stationary VAR in levels diverge as the horizon $k \to \infty$. However, in the case of cointegrated variables, the elements of $\mathbf{A}_r^k$ of the VEC can be bounded (Lütkepohl, 2005, pp. 258–262).

### 4.2.4 Returns

Using the loglinear framework of Campbell and Shiller (1988a) allows us to derive an approximation of the stock returns, although we only model the movements of stock prices and dividends:

$$\begin{aligned} r_t &= p_t - p_{t-1} + \log(1 + \exp(d_t - p_t)) \\ &= \rho p_t + (1-\rho) d_t - p_{t-1} + c + e_t^*, \end{aligned} \tag{4.11}$$

where $\rho = \left(1 + \exp(\overline{d_t - p_t})\right)^{-1}$, $(\overline{d_t - p_t})$ denotes the average log dividend-price ratio, $c = -\log(\rho) - (1-\rho)\log(1/\rho - 1)$ and $e_t^*$ is an approximation error. Since $\rho$ is close to one considering quarterly data, the weight of the stock price in $t$ on stock returns is large while the impact of dividends in $t$ is small. This approximation holds exactly when the dividend-price ratio $(d_t - p_t)$ is constant over time and accurately when the variation between dividends and prices is small. Nevertheless, Engsted, Pedersen, and Tanggaard (2010) attest the Campbell-Shiller approximation great properties even in the presence of rational explosive bubbles, where $d_t$ and $p_t$ do not move one-for-one and the stationarity of the dividend-price ratio may be questionable.

Modeling prices and dividends in the VEC separately, we do not assume a $[1, -1]$ relationship and handle the cointegration relation more flexibly. To calculate the effects of total returns implied by the VEC model, we apply a selection vector, $\mathbf{m}$, to the corresponding statistics of interest. Setting prices and dividends as the first elements of $\mathbf{z}_t$, the vector $\mathbf{m}$ is defined as

$$\mathbf{m} = (\rho, (1-\rho), 0, ..., 0, -1, 0, ..., 0), \tag{4.12}$$

where $\rho$ and $(1-\rho)$ extracts the first two elements of Equation (4.11) and the $-1$ subtracts the lagged price impact. The constant $c$ is omitted, since we only want to analyze the return dynamics (not the absolute values of the total returns).

## 4.3 Empirical Analysis

### 4.3.1 Data and Time Series Properties

Our empirical application is based on quarterly U.S. data spanning the period 1927:Q1 to 2011:Q4 ($n = 340$ observations) and includes seven variables measured as log: stock price index ($p_t$), dividends ($d_t$), earnings ($e_t$), inflation rate ($\pi_t$), 90-day nominal T-bill rates ($tb_t^{\$}$) and long-term government ($y_t^g$) and corporate bond ($y_t^c$) yields. These variables are denoted as levels in the sequel.

The stock price index is taken from the Center for Research in Security Press (CRSP), the quarterly dividends are extracted from the CRSP total and price return data and earnings (the 12-month moving sums) are from Robert Shiller's website.[5] The Treasury bill rates are taken from the National Bureau of Economic Research (NBER) Macrohistory Data-base up to 1934 and then from the Federal Reserve Bank of St. Louis (FRED) subsequently. The source of the inflation rate is the Consumer Price Index (All Urban Consumers) from the Bureau of Labor Statistics and the source of the long-term government and AAA-rated corporate bond yields data is Ibbotson's *Stocks, Bonds, Bills and Inflation Yearbook*.[6]

Table 4.1 presents the univariate unit root and stationarity properties of the time series analyzed. We use the augmented Dickey-Fuller test (ADF) with the null of a unit root and the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test with the null of stationarity. Both tests are performed by allowing for a constant but not for a deterministic time trend. The number of lags used is given in parentheses, where the ADF's lag length is determined by the Akaike Information Criterion (AIC). The KPSS's lag length is determined by the integer value of $(4 \cdot (n/100)^{0.25})$, which depends only on the number of observations. The non-stationarity hypothesis is supported for all levels except for the inflation rate, which is rejected on a 5% level,

[5] First, we calculate the dividend-price ratio with total return, $R_t$, and price return, $P_t$, as $D_t/P_t = (R_t/P_t) - 1$. Then, we obtain dividend growth by the identity $D_t/D_{t-1} = (D_t/P_t)(P_{t-1}/D_{t-1})(P_t/P_{t-1})$. Finally, cumulating the dividend growth leads to the level of dividends.

[6] We would like to thank Amit Goyal for providing the data used in Goyal and Welch (2008), for which an updated version is available on his website: http://www.hec.unil.ch/agoyal/.

Table 4.1: Univariate Stationarity

| | Levels | | | First Differences | |
|---|---|---|---|---|---|
| Variable | ADF$_\mu(q)$ | KPSS$_\mu(q)$ | Variable | ADF$_\mu(q)$ | KPSS$_\mu(q)$ |
| $p_t$ | 0.08 (4) | 5.51*** (5) | $\Delta p_t$ | -9.23*** (3) | 0.10 (5) |
| $d_t$ | 0.28 (15) | 5.66*** (5) | $\Delta d_t$ | -5.26*** (14) | 0.08 (5) |
| $e_t$ | -0.03 (12) | 5.58*** (5) | $\Delta e_t$ | -6.75*** (11) | 0.04 (5) |
| $\pi_t$ | -2.93**(15) | 0.72** (5) | $\Delta \pi_t$ | -8.63*** (14) | 0.03 (5) |
| $tb_t^\$$ | -1.65 (8) | 1.97*** (5) | $\Delta tb_t^\$$ | -7.83*** (7) | 0.09 (5) |
| $y_t^g$ | -1.11 (5) | 2.81*** (5) | $\Delta y_t^g$ | -9.10*** (4) | 0.25 (5) |
| $y_t^c$ | -1.20 (5) | 2.82*** (5) | $\Delta y_t^c$ | -8.17*** (4) | 0.21 (5) |

*Notes:* The table reports the results of the univariate unit root test regressions. All tests include a constant but no deterministic time trend. The number of lags used are given in parentheses; the symbols *, ** and *** denote significance at the 10, 5 and 1% level, respectively. The ADF tests the null of non-stationarity and the lag length is determined by the Akaike Information Criterion (AIC). The KPSS tests the null of stationarity and the lag length is determined by the integer value of $(4 \cdot (n/100)^{0.25})$.

but non-stationarity is strongly rejected for all first differences. The stationarity hypothesis of the KPSS test is rejected for all levels at 1% significance (except for inflation, which is rejected at 5% significance), but stationarity is supported for all first differences. Hence, we assume the levels of all variables to have a stochastic trending behavior and to be $I(1)$.

Descriptive statistics of the stationary first-differences are reported in Table 4.2. Panel A of the table shows the summary statistics of the sample. Panel B reports simultaneous correlations between the variables: price returns, dividends and earnings growth rates, changes in inflation rate, the short-term interest rate and the long-term government and corporate bond yields. Prices, dividends and earnings grow high on average and their changes exhibit high variability. The dividend growth volatility is about twice the price return volatility, which is a result of our calculation methodology since we assume quarterly dividends to be reinvested at stock market rates. Changes measured quarterly in the inflation rate are quite volatile in our sample. The changes in the interest rates and the long-term yields have low variability and nearly no growth over the sample period. All time series have a relatively small skewness but show an extremely high non-normal kurtosis.

While previous research only focuses on the link between (real) stock prices and (real) cash flows, intuition suggests additional links between the equity market and macroeconomic factors like inflation or short and long-term interest rates. Hence,

Table 4.2: Descriptive Statistics

Panel A

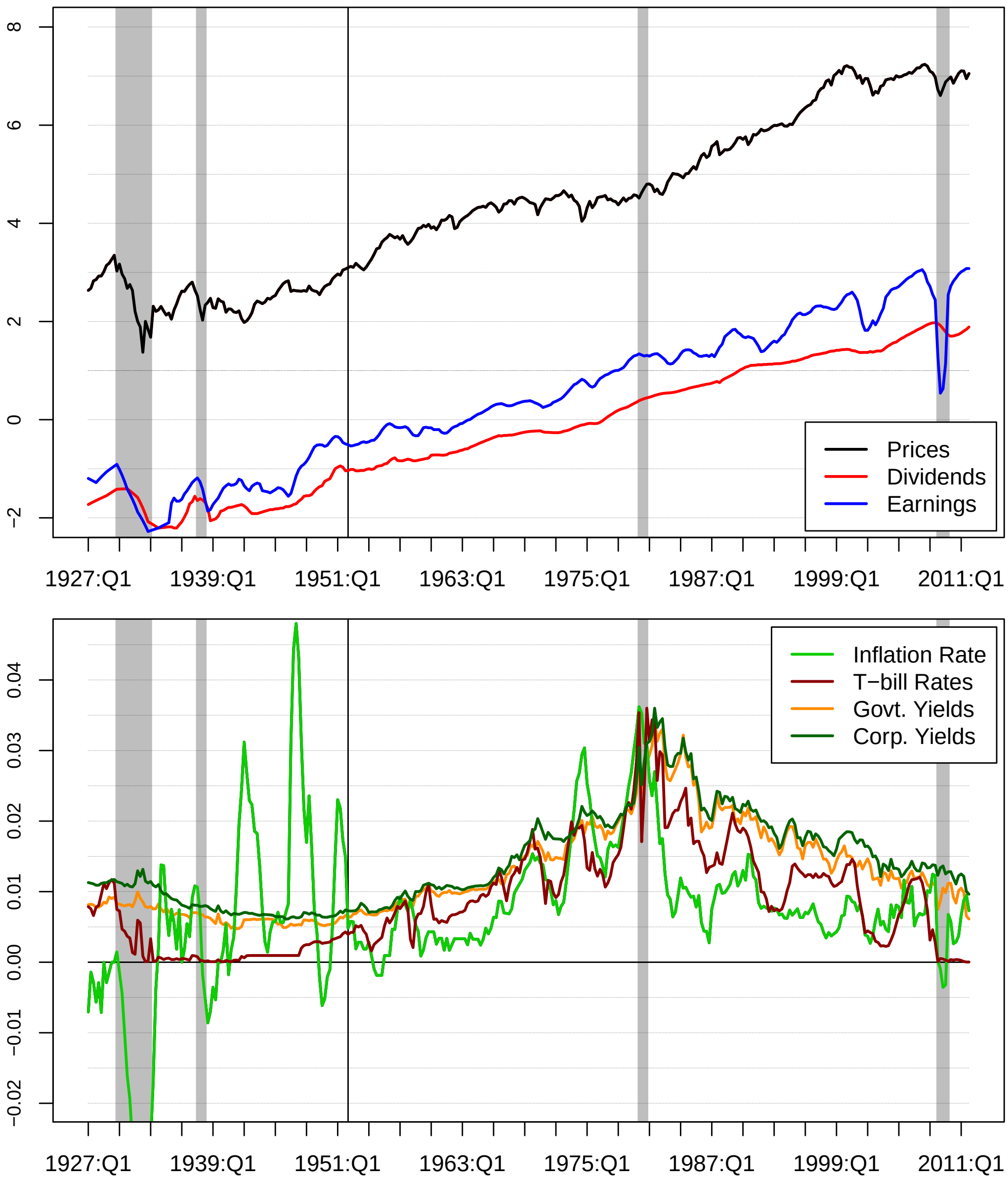
| Variable | Mean | Sd | Min | Max | Skew | Kurt | Autocor |
|---|---|---|---|---|---|---|---|
| $\Delta p_t$ | 1.30% | 10.84% | -51.59% | 63.16% | 0.07 | 10.83 | -3.41% |
| $\Delta d_t$ | 1.09% | 21.38% | -116.21% | 70.90% | -0.48 | 6.97 | -63.63% |
| $\Delta e_t$ | 1.26% | 12.92% | -112.75% | 140.23% | 1.13 | 63.05 | 52.11% |
| $\Delta \pi_t$ | 0.01% | 1.29% | -4.32% | 6.71% | 0.47 | 6.81 | -34.19% |
| $\Delta tb_t^{\$}$ | 0.00% | 0.20% | -1.83% | 1.16% | -2.16 | 29.04 | -10.47% |
| $\Delta y_t^g$ | 0.00% | 0.11% | -0.52% | 0.51% | -0.57 | 9.05 | -10.77% |
| $\Delta y_t^c$ | 0.00% | 0.09% | -0.53% | 0.50% | -0.22 | 10.94 | -5.91% |

Panel B

| Correlation | $\Delta p_t$ | $\Delta d_t$ | $\Delta e_t$ | $\Delta \pi_t$ | $\Delta tb_t^{\$}$ | $\Delta y_t^g$ | $\Delta y_t^c$ |
|---|---|---|---|---|---|---|---|
| $\Delta p_t$ | 1 | 1.31% | 13.84% | 4.32% | -2.64% | -6.77% | -20.59% |
| $\Delta d_t$ | | 1 | 11.06% | -5.25% | 6.81% | 1.54% | 3.84% |
| $\Delta e_t$ | | | 1 | 1.52% | 13.03% | 12.80% | 5.34% |
| $\Delta \pi_t$ | | | | 1 | 10.14% | 20.95% | 18.17% |
| $\Delta tb_t^{\$}$ | | | | | 1 | 55.11% | 62.82% |
| $\Delta y_t^g$ | | | | | | 1 | 86.55% |
| $\Delta y_t^c$ | | | | | | | 1 |

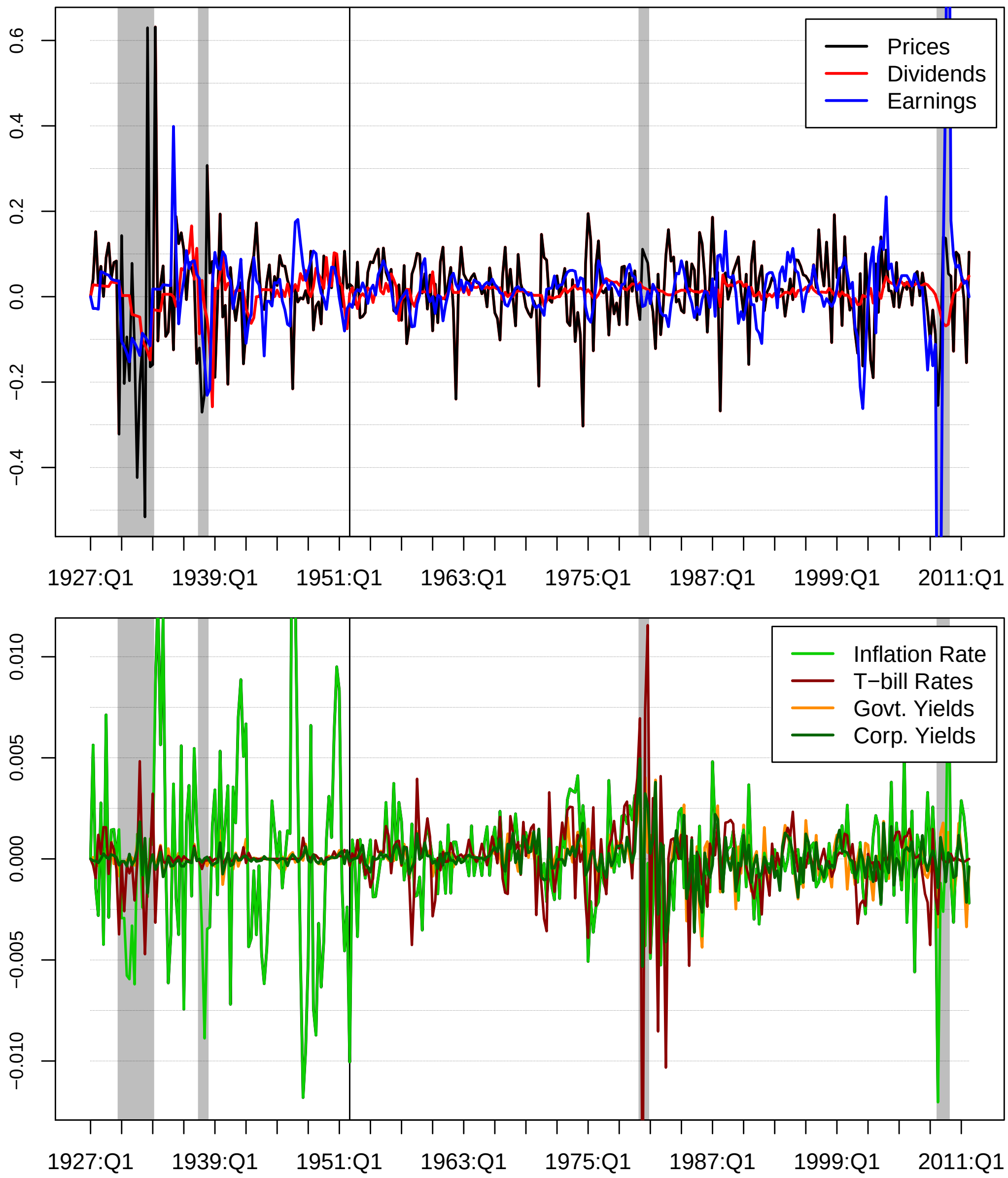
*Notes:* The table reports the descriptive statistics of the variables: price returns, dividends and earnings growth rates, the changes in inflation rate, the short-term interest rate, the long-term yield and the corporate bond yield. Panel A of the table reports summary statistics of the sample from 1927:Q1 to 2011:Q4 (340 data points). "Sd" denotes standard deviation; "Min" denotes minimum; "Max" denotes maximum; "Skew" denotes skewness; "Kurt" denotes kurtosis of the time series; and "Autocor" the first-order autocorrelation. Panel B reports simultaneous correlations between the variables used.

Figure 4.1: Level Variables




*Notes:* This figure plots the logarithms of the level variables. The upper graph contains the time series of $p_t$, $d_t$ and $e_t$, and the lower graph $\pi_t$, $tb_t^{\$}$, $y_t^g$ and $y_t^c$. The gray vertical bars denote the extreme events where dummy variables are set. The black vertical line denotes the quarter 1952:Q1.

Figure 4.2: Differenced Variables




*Notes:* This figure plots the logarithms of the differenced level variables. The upper graph contains the time series of $\Delta p_t$, $\Delta d_t$ and $\Delta e_t$, and the lower graph $\Delta \pi_t$, $\Delta tb^{\$}_t$, $\Delta y^g_t$ and $\Delta y^c_t$. The gray vertical bars denote the extreme events where dummy variables are set. The black vertical line denotes the quarter 1952:Q1.

our set of information for the upcoming analysis is defined as:

$$\mathbf{z}_t = \left(p_t, d_t, e_t, \pi_t, tb_t^{\$}, y_t^g, y_t^c\right)^{'} . \quad (4.13)$$

Graphical inspection of the variables $\mathbf{z}_t$ and $\Delta\mathbf{z}_t$ indicates three extreme events in the sample analyzed (see Figures 4.1 and 4.2).[7] First, the Great Depression had dramatic negative effects on the equity market and the inflation rate. Second, we observe extraordinary transitory shocks on inflation, interest rates and yields at the beginning of the Volcker era in around 1980. Third, due to the recent financial crisis the stock market overreacted with a steep drop at the end of 2008 and recovered subsequently. To account for these outliers and to eliminate the greatest sources of non-normal kurtosis, we set a mean-shift dummy, $d_{s,t}$, for the periods $t$ = 1929:Q1,...,1933:Q1 and $t$ = 1937:Q3,...,1938:Q2 and for transitory shock dummies, $d_{tr1,t}$ and $d_{tr2,t}$, for the periods $t$ = 1980:Q1,...,1980:Q4 and $t$ = 2008:Q4,...,2009:Q4, respectively.[8] Thus, the deterministic part of the model is defined as $\mathbf{d}_t = (d_{s,t}, d_{tr1,t}, d_{tr2,t}, t, 1)^{'}$. In addition to the extreme events, Figure 4.2 shows visible heteroskedastic behavior in the data. While the volatility of the equity series is quite homogeneous, except during the Great Depression and the recent financial crisis, the fixed-income series is highly volatile at the beginning of Volcker era. The inflation variability is about four times higher before the Treasury-Federal Reserve (FED) Accord of late 1951 compared to the subsequent period, and interest rates are nearly constant during World War II.

### 4.3.2 Cointegration Rank Analysis

To determine the number of cointegration relations, we apply the Johansen rank test. The trace test has been shown to be more robust than the maximum eigenvalue test in terms of non-normality (Cheung and Lai, 1993) and is not sensitive to heteroskedasticity effects (Lee and Tse, 1996; Rahbek, Hansen, and Dennis, 2002).

[7] For a better visual presentation, we use the 12-month moving average of dividends and inflation, since the two original time series are highly volatile at quarterly frequencies.

[8] With the exclusion of these outliers we capture the common market movement with our model, since the estimation results are not biased by these rare events. Of course, this model forecasts regular market movements and is not able to predict financial crises or other extreme events.

As a result, we use the trace test to account for the skewness, kurtosis and heteroskedasticity in the data. We find four cointegration relations or, alternatively, three remaining stochastic trends at the 5% level in our model, where the number of lags is two, as suggested by the Schwarz (SC) criterion (see Appendix: Table 4.8, Panel A).[9]

To investigate the stochastic trends in our model in more detail, we test the cointegration rank of models with stepwise increasing information sets. The results of these nested models $\mathcal{M}_1$ to $\mathcal{M}_6$ are reported in Table 4.3. As for $\mathcal{M}_6$, all submodels are estimated as first-order VECs.[10] Boldfaced values denote the cointegration rank supported at the 5% level. The $p$-values of the trace test and the modulus of the largest unrestricted characteristic roots, $\rho_{max}$, are presented for each model and each possible cointegration rank. The latter statistic is taken into consideration when checking the robustness of the trace test. If an additional $(r+1)$th cointegration relation is mistakenly included in the model, the largest characteristic root will take a value close to one, which indicates the non-stationarity of the $(r+1)$th cointegration vector (Juselius, 2006, Chap. 8).

Following Campbell and Shiller (1987), we start with model $\mathcal{M}_1$ and only include stock prices and dividends. The trace test and our model specifications confirm the weak cointegration relation Campbell and Shiller find in their model and sample. Based on Campbell and Shiller (1988b)'s findings that prices and dividends are connected to a measure of earnings, we extend the first model by earnings. The rank test for the resulting model, $\mathcal{M}_2$, clearly indicates only one cointegration relation. However, the results for models $\mathcal{M}_1$ and $\mathcal{M}_2$ are inconsistent, as theory would suggest two cointegration relations for the second model. Since prices and dividends have the same stochastic trend, earnings should follow this trend because dividends are derived by earnings in the long run. According to the results, however, either earnings would follow another stochastic trend than prices and dividends or

[9]The results of the cointegration rank test can vary with the number of lags included in the VAR. However, up to five lags in the VAR our results remain stable around three to four relations depending on the significance level considered. The stability of the cointegration rank regarding the lag length is reported in the Appendix Table 4.8, Panel B.

[10]We assume the data generating process of the level variables to have two lags and not to change in the submodels.

Table 4.3: Cointegration Rank

| Variables | | Statistic | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|---|---|---|
| $\mathcal{M}_1$ : | $p_t$, $d_t$ | | | | | | | | | |
| | | $p$-value | 0.03 | **0.82** | - | | | | | |
| | | $\rho_{max}$ | 0.65 | **0.86** | 1.00 | | | | | |
| $\mathcal{M}_2$ : | $p_t$, $d_t$, $e_t$ | | | | | | | | | |
| | | $p$-value | 0.00 | **0.10** | 0.67 | - | | | | |
| | | $\rho_{max}$ | 0.66 | **0.76** | 0.92 | 1.00 | | | | |
| $\mathcal{M}_3$ : | $p_t$, $d_t$, $e_t$, | | | | | | | | | |
| | $\pi_t$ | $p$-value | 0.00 | 0.00 | **0.15** | 0.82 | - | | | |
| | | $\rho_{max}$ | 0.66 | 0.67 | **0.77** | 0.93 | 1.00 | | | |
| $\mathcal{M}_4$ : | $p_t$, $d_t$, $e_t$, | | | | | | | | | |
| | $\pi_t$, $tb_t^{\$}$ | $p$-value | 0.00 | 0.00 | **0.20** | 0.45 | 0.94 | - | | |
| | | $\rho_{max}$ | 0.66 | 0.68 | **0.76** | 0.92 | 0.96 | 1.00 | | |
| $\mathcal{M}_5$ : | $p_t$, $d_t$, $e_t$, | | | | | | | | | |
| | $\pi_t$, $tb_t^{\$}$, $y_t^g$ | $p$-value | 0.00 | 0.00 | 0.00 | **0.49** | 0.82 | 0.78 | - | |
| | | $\rho_{max}$ | 0.66 | 0.67 | 0.82 | **0.83** | 0.90 | 0.98 | 0.99 | |
| $\mathcal{M}_6$ : | $p_t$, $d_t$, $e_t$, | | | | | | | | | |
| | $\pi_t$, $tb_t^{\$}$, $y_t^g$, | $p$-value | 0.00 | 0.00 | 0.00 | 0.02 | **0.58** | 0.91 | 0.94 | - |
| | $y_t^c$ | $\rho_{max}$ | 0.66 | 0.67 | 0.82 | 0.81 | **0.86** | 0.90 | 0.99 | 1.00 |

*Notes:* The table reports the results for the cointegration rank determination. The models $\mathcal{M}_1$ to $\mathcal{M}_6$ contain stepwise increasing information sets. The $p$-values of the trace test and the moduli of the largest unrestricted characteristic roots, $\rho_{max}$, are presented for each model and each possible cointegration rank. Boldfaced values denote the cointegration rank supported at the 5% level.

the result of the first model is misleading. Previous studies strengthen the latter possibility. Analyzing a trivariate system of prices, dividends and earnings, Lee (1996) finds one cointegration relation and a strong comovement between dividends and earnings without detecting a significant link to prices. Lamont (1998) confirms these results with his bivariate cointegration tests between the three variables.

In contrast to Campbell and Shiller (1988b), Lee (1996) and Lamont (1998), who only focus on the link between (real) stock prices and (real) cash flows, we also analyze the links of macroeconomic factors like inflation or short and long-term interest rates to the stock market, since these links can influence the variables of the valuation ratios differently. Therefore, we stepwise extend model $\mathcal{M}_2$ by the macroeconomic variables $\pi_t$, $tb_t^{\$}$, $y_t^g$ and $y_t^c$. In a subsequent analysis, we show the importance of all seven variables in the long run and their significant influence on each other. Adding inflation increases the number of cointegration relations as the tests indicate that the model $\mathcal{M}_3$ has a cointegration rank of two. Thus, $\pi_t$ forms a new stationary relation with the variables in the system. Adding $tb_t^{\$}$ does not increase the number of cointegration relations, i.e. a variable with a new stochastic trend is added. However, inclusion of $y_t^g$ and $y_t^c$ raises the cointegration rank by one in each case and suggests that the two variables follow stochastic trends already existing in the system, which leads to our full model, $\mathcal{M}_6$, with four cointegration relations.

### 4.3.3 Restriction Tests

Thus far, the connection between the stochastic trends of the equity market and the macroeconomic variables is no clear-cut. Therefore, we perform various long-run restriction tests on the matrices $\boldsymbol{\beta}$ and $\boldsymbol{\alpha}$. Testing the long-run exclusion of a variable (a row of zeros) in $\boldsymbol{\beta}$, we gain insights about whether the tested variable can be excluded or adds new information to the long-run structure. Likewise, the test of weak exogeneity of a variable (a row of zeros) in $\boldsymbol{\alpha}$ can be informative if the tested variable is affected by the long-run equations and a new added variable changes the previous exogeneity and endogeneity characteristics of the remaining variables. Testing the trend-stationarity of a variable (a unit vector) in $\boldsymbol{\beta}$, we analyze whether the tested variables have deterministic growth rates in the multivariate model.

The results of the $\boldsymbol{\beta}$ restriction tests are presented in Table 4.4. Boldfaced values denote the support of the null hypothesis at the 5% level. Panel A shows the results of the exclusion tests of the variables in each model ($\mathcal{M}_1$ to $\mathcal{M}_6$). In our full model, $\mathcal{M}_6$, neither the variables nor the trend can be excluded from the system. Since stock prices are excludable in the model $\mathcal{M}_2$, there is a connection between stock prices and inflation. Dividends and earnings seem to be important long-run pushing

Table 4.4: $\boldsymbol{\beta}$ Restriction Tests

Panel A: Long-Run Exclusion Test (Zero Row in $\boldsymbol{\beta}$)

| Model | | $p_t$ | $d_t$ | $e_t$ | $\pi_t$ | $tb_t^{\$}$ | $y_t^g$ | $y_t^c$ | *trend* |
|---|---|---|---|---|---|---|---|---|---|
| $\mathcal{M}_1$ : | $\chi^2(1)$ | 12.33 | 20.52 | | | | | | 6.67 |
| | $p$-value | 0.00 | 0.00 | | | | | | 0.01 |
| $\mathcal{M}_2$ : | $\chi^2(1)$ | **2.62** | 26.87 | 29.66 | | | | | **0.90** |
| | $p$-value | **0.11** | 0.00 | 0.00 | | | | | **0.34** |
| $\mathcal{M}_3$ : | $\chi^2(1)$ | 20.21 | 24.89 | 32.07 | 96.97 | | | | **2.43** |
| | $p$-value | 0.00 | 0.00 | 0.00 | 0.00 | | | | **0.30** |
| $\mathcal{M}_4$ : | $\chi^2(2)$ | 12.26 | 24.90 | 27.77 | 101.14 | **5.98** | | | **4.30** |
| | $p$-value | 0.00 | 0.00 | 0.00 | 0.00 | **0.05** | | | **0.12** |
| $\mathcal{M}_5$ : | $\chi^2(3)$ | 17.60 | 27.02 | 30.51 | 106.87 | 44.50 | 44.94 | | 12.42 |
| | $p$-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | | 0.01 |
| $\mathcal{M}_6$ : | $\chi^2(4)$ | 26.40 | 26.97 | 28.19 | 107.56 | 50.46 | 36.74 | 29.22 | 14.30 |
| | $p$-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 |

Panel B: Trend-Stationarity Test (Unit Vector in $\boldsymbol{\beta}$)

| Model | | $p_t$ | $d_t$ | $e_t$ | $\pi_t$ | $tb_t^{\$}$ | $y_t^g$ | $y_t^c$ |
|---|---|---|---|---|---|---|---|---|
| $\mathcal{M}_6$ : | $\chi^2(3)$ | 34.18 | 30.35 | 29.81 | 15.98 | 32.61 | 32.59 | 32.07 |
| | $p$-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

*Notes:* The table reports the results for the restriction tests on the long-run equation matrix $\boldsymbol{\beta}$. Boldfaced values denote the support of the null at the 5% level. Panel A shows the results of the exclusion tests of the variables (zero row in $\boldsymbol{\beta}$) in the models $\mathcal{M}_1$ to $\mathcal{M}_6$. Panel B shows the results of the trend-stationarity tests of each variable (unit vector in $\boldsymbol{\beta}$) in the multivariate model $\mathcal{M}_6$.

components in each model. Moreover, we find that the short-term interest rates can be omitted in the model without long-term yields. Hence, there seems to be no direct link between the stochastic trends of T-bills and the equity market. Panel B shows the results of the trend-stationarity tests of each variable in the multivariate

Table 4.5: $\boldsymbol{\alpha}$ Restriction Tests

| Weak Exogeneity (Zero Row in $\boldsymbol{\alpha}$) | | Variable | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Model | | $p_t$ | $d_t$ | $e_t$ | $\pi_t$ | $tb_t^{\$}$ | $y_t^g$ | $y_t^c$ |
| $\mathcal{M}_1$ : | $\chi^2(1)$ | **2.22** | 16.38 | | | | | |
| | $p$-value | **0.14** | 0.00 | | | | | |
| $\mathcal{M}_2$ : | $\chi^2(1)$ | **0.00** | 24.21 | 9.51 | | | | |
| | $p$-value | **0.95** | 0.00 | 0.00 | | | | |
| $\mathcal{M}_3$ : | $\chi^2(1)$ | 20.85 | 29.55 | 11.83 | 88.02 | | | |
| | $p$-value | 0.00 | 0.00 | 0.00 | 0.00 | | | |
| $\mathcal{M}_4$ : | $\chi^2(2)$ | 19.87 | 29.45 | 13.91 | 85.08 | **0.24** | | |
| | $p$-value | 0.00 | 0.00 | 0.00 | 0.01 | **0.89** | | |
| $\mathcal{M}_5$ : | $\chi^2(3)$ | 19.02 | 36.12 | 22.58 | 88.01 | 9.30 | 15.15 | |
| | $p$-value | 0.00 | 0.00 | 0.00 | 0.03 | 0.00 | 0.00 | |
| $\mathcal{M}_6$ : | $\chi^2(4)$ | 22.89 | 35.73 | 25.31 | 86.11 | 17.45 | 18.84 | 31.05 |
| | p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

*Notes:* The table reports the results of the weak exogeneity tests of the variables (zero row in $\boldsymbol{\alpha}$) in the models $\mathcal{M}_1$ to $\mathcal{M}_6$. Boldfaced values denote the support of the null at the 5% level.

model $\mathcal{M}_6$. The null of trend-stationarity is rejected in each case, strengthening the results of the univariate stationarity tests presented above.[11]

Table 4.5 reports the results of the $\boldsymbol{\alpha}$ restriction tests. Boldfaced values denote the support of the null hypothesis at the 5% level. Panel A shows the results of the weak exogeneity tests of the variables in each model ($\mathcal{M}_1$ to $\mathcal{M}_6$). In our full model, $\mathcal{M}_6$, none of the variables are weakly exogenous. However, stock prices can be treated weakly exogenous in the models $\mathcal{M}_1$ and $\mathcal{M}_2$ and are not affected by the long-run equations. Incorporating the macroeconomic variables, stock prices become endogenous in the models and are pushed by them. Dividends and earnings are strongly influenced by the long-run relations in each model. Furthermore, the short-

[11]To save space, the results are only reported for model $\mathcal{M}_6$, but remain stable for all models. Although the trend-stationarity tests are sensitive to the chosen cointegration rank, the rejection of the null is also obtained for $r = 3$ and $r = 5$ in model $\mathcal{M}_6$.

term interest rates are exogenous in the model, $\mathcal{M}_4$, without the long-term yields and, thus, no significant adjustment of T-bills to the equity market components and inflation takes place.

To sum up, all variables analyzed need to be included in the model, since they have significant long-run influences on and adjustments to each other. Moreover, we detect stock prices pushing dividends without adjusting to the dividend-price relation in model $\mathcal{M}_1$. In the second model, stock prices are also obsolete in the long-run equation and, hence, dividends are only related to earnings here. Since stock prices are no longer excludable and weak exogenous in model $\mathcal{M}_3$, there seems to be a strong link between the equity market variables and inflation.

### 4.3.4 Testing the Financial Ratios

To further analyze common stochastic trends, we test the validity of the stationarity of the dividend-price ratio and additional financial ratios such as dividend-earnings, earnings-price, real short-interest rates, term spread and credit spread, which are often used in the predictability literature. If the financial ratio has a constant mean, then we can infer that the corresponding non-stationary variables follow the same stochastic trend.

Table 4.6 reports the results of the financial ratio stationarity tests in a multivariate framework. We test the following ratios: dividend-price ($d_t - p_t$); dividend-earnings ($d_t - e_t$); earnings-price ($e_t - p_t$); real T-bills ($tb_t^{\$} - \pi_t$); term spread ($y_t^g - tb_t^{\$}$); and credit spread ($y_t^c - y_t^g$). Panel A presents the results for assuming fixed $[1, -1]$ ratios and are performed with hypotheses test $H_3$.[12] Panel B presents the results for assuming arbitrary $[1, -\beta]$ ratios and are performed with hypotheses test $H_4$. Boldfaced values denote the support of the null of stationarity at a 5% significance level. If trend-stationarity of the restricted cointegration relation cannot be rejected, more restrictive stationarity tests without a deterministic trend are performed. The null of trend-stationarity of the $[1, -1]$ ratios has to be rejected for dividend-price as well as all other ratios except for $d_t - e_t$ and $y_t^g - tb_t^{\$}$. However, these two ratios

[12] Additionally, we test the stationarity of the $[1, -1]$ financial ratios with the univariate ADF and KPSS test. The results of these tests are reported in Table 4.9 of the Appendix.

Table 4.6: Financial Ratio Stationarity Tests

Panel A: Financial Ratio Stationarity Tests $[1, -1]$

| | Ratio | *trend* $\times 10^4$ | $\chi^2(\nu)$ | $p$-value |
|---|---|---|---|---|
| $\mathcal{H}_1$ : | $d_t - p_t$ | 38.13 | 31.61 (3) | 0.00 |
| $\mathcal{H}_{2.1}$ : | $d_t - e_t$ | 11.68 | **3.13 (3)** | **0.37** |
| $\mathcal{H}_{2.2}$ : | $d_t - e_t$ | - | 11.42 (4) | 0.02 |
| $\mathcal{H}_3$ : | $e_t - p_t$ | 24.23 | 28.83 (3) | 0.00 |
| $\mathcal{H}_4$ : | $tb_t^{\$} - \pi_t$ | -0.26 | 26.75 (3) | 0.00 |
| $\mathcal{H}_{5.1}$ : | $y_t^g - tb_t^{\$}$ | -0.09 | **5.87 (3)** | **0.12** |
| $\mathcal{H}_{5.2}$ : | $y_t^g - tb_t^{\$}$ | - | 11.50 (4) | 0.02 |
| $\mathcal{H}_6$ : | $y_t^c - y_t^g$ | -42.13 | 34.23 (3) | 0.00 |

Panel B: Financial Ratio Stationarity Tests $[1, -\beta]$

| | Ratio | $\beta$ | *trend* $\times 10^4$ | $\chi^2(\nu)$ | $p$-value |
|---|---|---|---|---|---|
| $\mathcal{H}_7$ : | $d_t - \beta \cdot p_t$ | 0.41 | -63.10 | 22.44 (2) | 0.00 |
| $\mathcal{H}_{8.1}$ : | $d_t - \beta \cdot e_t$ | 0.88 | -6.11 | **2.32 (2)** | **0.31** |
| $\mathcal{H}_{8.2}$ : | $d_t - \beta \cdot e_t$ | 0.92 | - | **2.42 (3)** | **0.49** |
| $\mathcal{H}_9$ : | $e_t - \beta \cdot p_t$ | 0.46 | -66.61 | 23.63 (2) | 0.00 |
| $\mathcal{H}_{10}$ : | $tb_t^{\$} - \beta \cdot \pi_t$ | 3.45 | -0.28 | 13.73 (2) | 0.00 |
| $\mathcal{H}_{11.1}$ : | $y_t^g - \beta \cdot tb_t^{\$}$ | 0.96 | -0.10 | **5.48 (2)** | **0.06** |
| $\mathcal{H}_{11.2}$ : | $y_t^g - \beta \cdot tb_t^{\$}$ | 1.05 | - | 10.91 (3) | 0.01 |
| $\mathcal{H}_{12}$ : | $y_t^c - \beta \cdot y_t^g$ | 0.97 | -0.03 | 8.65 (2) | 0.01 |

*Notes:* The table reports the results of the financial ratio stationarity tests. Panel A presents the results for fixed $[1, -1]$ ratios and are performed with hypotheses test $H_3$. Panel B presents the results for $[1, -\beta]$ ratios and are performed with hypotheses test $H_4$. Boldfaced values denote the support of the null of stationarity at a 5% significance level. If trend-stationarity cannot be rejected, further stationarity tests without a deterministic trend are performed.

have unit roots if the deterministic trend is omitted. The rejection of $\mathcal{H}_{2.2}$ can be justified by a changed dividend payout policy over the sample period (Fama and French, 2001; Grullon and Michaely, 2002, 2004; Boudoukh, Michaely, Richardson, and Roberts, 2007; Park and Kim, 2012) and makes dividends and earnings move slightly apart with a deterministic trend. One might argue that similar reasons hold for the rejection of the stationarity of the dividend-price ratio, but according to Lettau and Van Nieuwerburgh (2008) "[...] structural changes in payout policies [...] can only explain a small part of the change in the dividend-price ratio." Thus, the gap between stock prices and dividends became far to big to be caused only by a changed payout policy. Furthermore, the short interest rates and the government yields drift apart in a deterministic way, indicating either a steadily increase of the requested bond yield relative to the short rates or a steadily increasing spread because of too low T-bill rates.

Relaxing the $[1, -1]$ conditions, we observe that the adjusted dividend-earnings ratio is stationary and term spread is trend-stationary. As interpreted in Froot and Obstfeld (1991), the coefficient in $(d_t - \beta \cdot e_t)$ is less than one and implies that earnings move more than dividends. The same argumentation holds for $\mathcal{H}_{11.1}$, while in this case the $\beta$ is much closer to one. For all other ratios, even the relaxation of the $[1, -1]$ assumption does not lead to trend-stationary behavior and, thus, strongly suggests the influence of different stochastic trends. Since the $(d_t - e_t)$ and $(y_t^g - tb_t^\$)$ ratios are trend-stationary in a single relation, we further test whether this result holds for all cointegration vectors. According to the global test results, the use of the dividend-earnings ratio causes no loss of information ($\chi^2_4 = 3.83$ and $p$-value $= 0.43$), while the hypothesis is strongly rejected for the term spread ($\chi^2_4 = 28.39$ and $p$-value $= 0.00$).

### 4.3.5 Level Effects

The previous analysis shows that the null of cointegration between prices and the stock's cash flows is rejected by allowing the influence of other macroeconomic factors. However, we find four cointegration relations among the seven variables analyzed. These four relations can be extracted by the decomposition of long-run effect matrix $\mathbf{\Pi}_r$ in its cointegration matrix $\boldsymbol{\beta}'$ and the adjustments $\boldsymbol{\alpha}$. Since the decomposition in $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}'$ is not unique, we focus on the level matrix $\mathbf{\Pi}_r$ to investigate the different long-run impacts on the variables.

Table 4.7 reports the coefficient estimates of the long-run matrix $\mathbf{\Pi}_r$ of model $\mathcal{M}_6$. Bootstrap standard errors, which are calculated from 10,000 paths under the assumption that the initial estimated VEC model truly generates the data process, are reported in parentheses.[13] Boldfaced coefficients imply significance on a 5% level according to bootstrapped intervals. The first row of this table represents the error correction equation for stock price returns and shows that only the own lagged level and the lagged inflation rate have a significant negative influence, which illustrates a macroeconomic long-run link. Dividends and earnings, in contrast, are

[13] A more detailed description of the bootstrapping method is given in Appendix 4.A.4.

Table 4.7: $\mathbf{\Pi}_r$ Matrix of Model $\mathcal{M}_6$ and $r = 4$

| | Variable | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | $p_{t-1}$ | $d_{t-1}$ | $e_{t-1}$ | $\pi_{t-1}$ | $tb^{\$}_{t-1}$ | $y^g_{t-1}$ | $y^c_{t-1}$ | $trend \times 10^3$ |
| $\Delta p_t$ | **-0.035** | -0.045 | 0.050 | **-2.738** | -0.557 | -13.929 | 15.264 | 0.396 |
| | (0.022) | (0.047) | (0.036) | (0.734) | (3.090) | (10.407) | (9.850) | (0.506) |
| $\Delta d_t$ | **0.079** | **-0.284** | **0.192** | **2.523** | **-8.898** | 6.524 | 3.465 | -0.418 |
| | (0.039) | (0.072) | (0.053) | (1.114) | (4.731) | (15.831) | (15.286) | (1.130) |
| $\Delta e_t$ | 0.013 | **0.060** | **-0.044** | 0.764 | **-4.210** | **10.911** | -6.779 | -0.394 |
| | (0.012) | (0.024) | (0.021) | (0.403) | (1.667) | (5.680) | (5.531) | (0.322) |
| $\Delta \pi_t$ | **-0.008** | 0.002 | 0.002 | **-0.648** | 0.482 | -0.843 | 0.450 | 0.080 |
| | (0.002) | (0.005) | (0.004) | (0.073) | (0.310) | (1.032) | (1.002) | (0.067) |
| $\Delta tb^{\$}_t$ | **0.001** | 0.000 | 0.000 | 0.005 | **-0.085** | **0.515** | **-0.425** | -0.010 |
| | (0.000) | (0.001) | (0.001) | (0.011) | (0.049) | (0.159) | (0.156) | (0.009) |
| $\Delta y^g_t$ | 0.000 | 0.000 | 0.000 | 0.001 | **0.098** | -0.109 | 0.003 | 0.005 |
| | (0.000) | (0.000) | (0.000) | (0.007) | (0.030) | (0.103) | (0.098) | (0.005) |
| $\Delta y^c_t$ | 0.000 | 0.000 | 0.000 | 0.003 | **0.089** | 0.067 | **-0.165** | 0.002 |
| | (0.000) | (0.000) | (0.000) | (0.006) | (0.024) | (0.081) | (0.079) | (0.005) |

*Notes:* The table reports the coefficient estimates of the long-run matrix $\mathbf{\Pi}_r$ of model $\mathcal{M}_6$ and $r = 4$. Bootstrap standard errors, which are calculated from 10,000 paths under the assumption that the initial estimated VEC model truly generates the data process, are reported in parentheses. Boldfaced coefficients imply significance on a 5% level according to bootstrapped intervals.

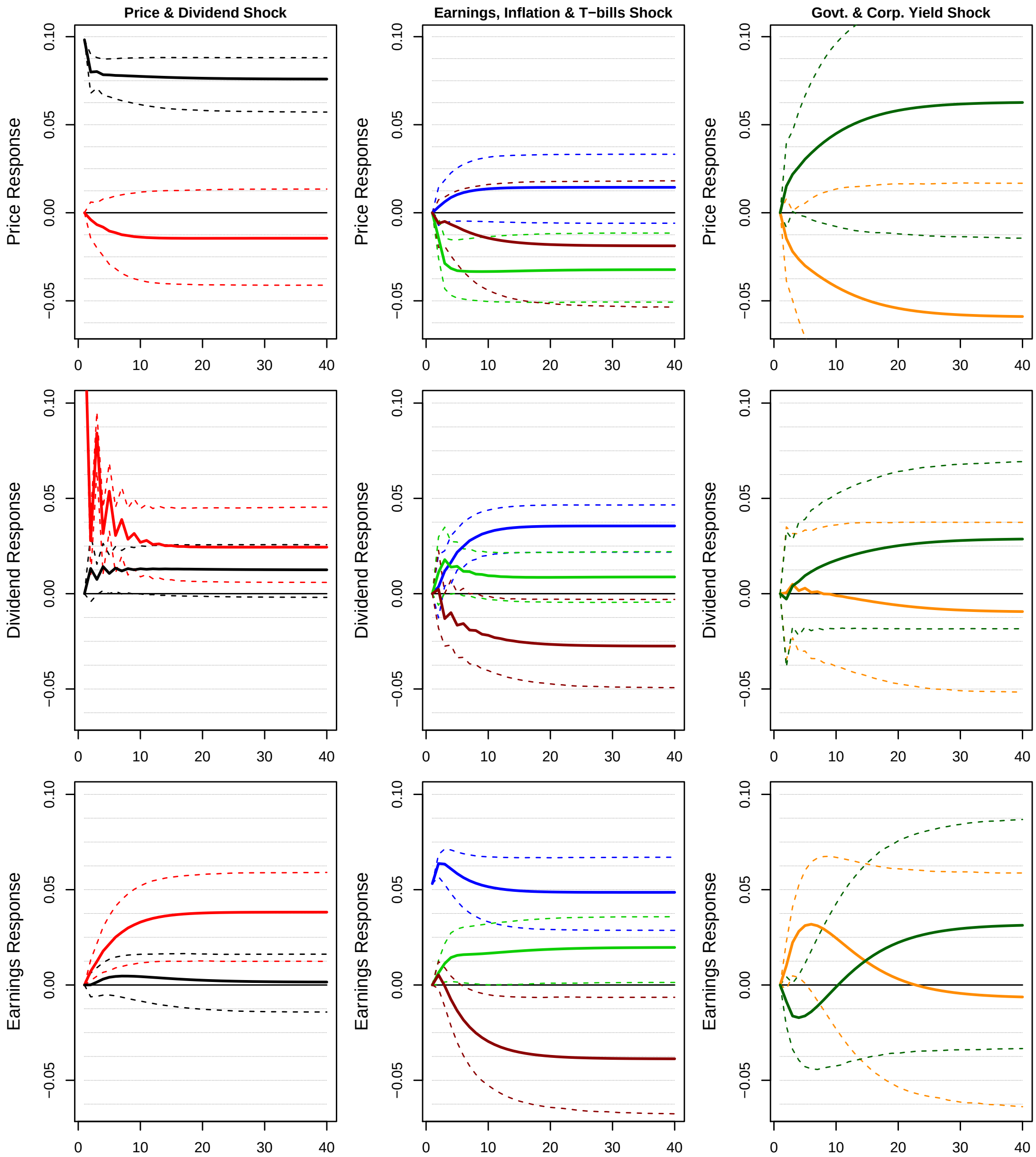
not significant predictors of price changes, even if theory would expect a strong long-run connection. The last three level variables have no significant effects, albeit the coefficients of the yields are large and nearly related $[1, -1]$ almost forming the credit spread. The second row corresponds to the dividend growth, which is significantly explained by lagged prices, dividends, earnings, inflation rate and short-term interest rates. As the third row shows, the influences on earnings growth is less pronounced and only significant for lagged dividends, earnings, T-bills and long-term yields. Comparing the equations of dividends and earnings demonstrates their strong interdependence, although some different effects remain. While the dividends significantly change with prices and inflation, earnings remain nearly unchanged by these two variables. The negative effect of short-term rates is more than twice as high for dividends compared to earnings growth. Government bond yields have only significant level effects on earnings growth. Comparing the influences of the macroeconomic variables on prices and cash flows changes, we observe significant differences: completely contrary inflation effects, T-bills and long-term yields affect only cash flows. As the last four rows show, the equity market has a moderate effect on the macroeconomic variables. Only stock prices predict changes in inflation and T-bills. Furthermore, short-term rates and bond yields are interrelated.

### 4.3.6 Horizon-Dependent Analysis

Because longer horizon dynamics in the VEC are complicated to assess by considering estimated coefficients matrices, we further investigate the impact of unexpected shocks by an impulse response analysis. This is done by extracting the innovations' influence of the equity market and the macroeconomic variables on prices, dividends and earnings. Furthermore, applying the loglinear approximation for total returns allows us to use the responses of prices and dividends to calculate the stock return response.

Figure 4.3 plots the responses of prices, dividends and earnings (line-by-line) to one standard deviation shocks in prices (black), dividends (red), earnings (blue), inflation (green), T-bills (dark red), long-term yields (orange) and corporate yields (dark green) with the corresponding bootstrapped 5% intervals from left to right.

Figure 4.3: Impulse Response Functions



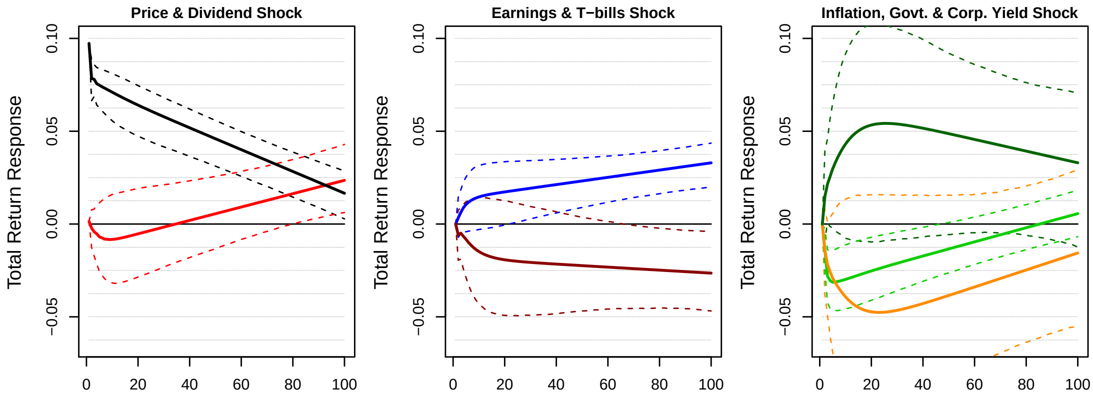

*Notes:* This figure plots the responses of prices, dividends and earnings (line-by-line) to one standard deviation shocks in prices (black), dividends (red), earnings (blue), inflation (green), T-bills (dark red), long-term government yields (orange) and corporate yields (dark green) with the corresponding bootstrapped 5% intervals from left to right. The intervals are calculated from 10,000 paths under the assumption that the initial estimated VEC model truly generates the data process. The depicted horizon comprises 40 quarters.

The intervals are calculated from 10,000 paths under the assumption that the initial estimated VEC model truly generates the data process. The depicted horizon comprises 40 quarters. The figure shows that nearly all shocks on the equity market variables have permanent effects, although not necessarily statistically permanent. Considering stock price responses, we see that a dividend shock cause a negative price reaction and an earnings shock a positive (insignificant) price reaction. An unexpected price impulse never disappears and nearly remains on the initial level. Turning to macroeconomic shocks, all variables (except corporate bond yields) lead to negative effects, but only an inflation innovation reduces prices fast and significantly. Again, the strong link between stock prices and the inflation rate is visible. The dividend response to a price impulse is positive, but only significant in the short term. Hence, dividends adjust due to price shocks. An unexpected change in dividends decays fast (10 quarters) to a sixth of the base level. Opposed shocks of dividends and earnings on each other result in a significant rise of the cash flow variables. While the influence of earnings on dividends is well established, the opposite connection can be interpreted as the managers' ability to adjust today's dividends according to their expected future business success. The responses of the two cash flow variables to macroeconomic impulses are comparable to each other in the long run. Both T-bills and inflation innovations have significant negative and positive influences, respectively. While cash flows respond positively to shocks of corporate bond yields, contrary responses are present for government bond yields in the long term.

Comparing these results to those of Cochrane (1994) and Lamont (1998), we find contrary effects, as they show that prices and dividends are permanently affected by a dividend innovation, and price innovations are transitory for prices and neglectable for dividends. These differences can be caused for three reasons. First, while they allow for only stock prices and cash flows in their models, we extend the system by macroeconomic information. Second, they make the strong assumption that prices and cash flows all share one common trend and, third, that all these variables move one-for-one.

Although we only model stock prices and dividends, we are able to investigate the effects of the innovations of the variables analyzed on total stock returns by

Figure 4.4: Impulse Response Functions of Returns




*Notes:* This figure plots the cumulative responses of the total stock returns to one standard deviation shocks in prices (black), dividends (red), earnings (blue), inflation (green), T-bills (dark red), long-term government yields (orange) and corporate yields (dark green) with the corresponding bootstrapped 5% intervals from left to right. The intervals are calculated from 10,000 paths under the assumption that the initial estimated VEC model truly generates the data process. The depicted horizon comprises 100 quarters.

applying the loglinear return approximation in Equation (4.11). Figure 4.4 plots the cumulative responses of the total stock returns to one standard deviation shocks in prices (black), dividends (red), earnings (blue), inflation (green), T-bills (dark red), long-term yields (orange) and corporate yields (dark green) with the corresponding bootstrapped 5% intervals from left to right. The intervals are calculated from 10,000 paths under the assumption that the initial estimated VEC model truly generates the data process. The depicted horizon comprises 100 quarters. In response to a price shock, cumulated returns are expected to decrease subsequently. On the other hand, an innovation in dividends increases returns with a significant positive response in the long run. These two findings are a direct result of the impulse responses between prices and dividends and the loglinear approximation. Due to a price shock, permanent responses of prices and dividends decrease returns because the negative response factor caused by $\rho p_{t+k} - p_{t+k-1}$ dominates the positive factor caused by $(1-\rho)d_{t+k}$. Thus, cumulated returns decline over the investment horizon. In contrast, the typical approach of restricting prices and dividends to move one-for-one results in a vanishing (transitory) cumulative return response as the factors compensate each other and makes discount rate (price) shocks transitory in the long run. Applying the same argumentation for a dividend shock, cumulated returns increase permanently since the factors caused by $\rho p_{t+k} - p_{t+k-1}$ and $(1-\rho)d_{t+k}$ are positive in the long run. In this case, restricting prices and dividends to move one-for-one results in a transitory return response and yields dividend news to be permanent with a positive shift in cumulated returns. Turning to earnings shocks, we see that the positive response of prices and dividends leads to a positive and significant rise of long-horizon returns. On the other side, a T-bill shock causes a negative response of the equity market variables and leads to a negative and significant decrease of long-horizon returns. While an inflation innovation significantly depletes stock prices, cumulative returns (including dividends) recover subsequently after a steep drop in the first periods (which is in line with the findings of Fama and Schwert, 1977 and Boudoukh and Richardson, 1993). Impulses of the two bond yields lead to large and contrary effects of the cumulated stock returns, which diminish in the long run.

## 4.4 Conclusion

Valuation ratios such as the dividend-price ratio and earnings-price ratio have been often used in the predictability literature to forecast stock returns. For this question it is assumed that prices and cash flows are cointegrated one-for-one or, alternatively, that the dividend-price ratio and earnings-price ratio are stationary variables. Otherwise the conventional $t$-test infers invalid conclusions about the return predictability. However, the empirical evidence on the dividend-price ratio's stationarity is, at best, mixed. This raises the question as to whether this problem is blurred by the high persistence of the valuation ratio, is based on a change in the payout policy or is actually caused by a breakdown of the one-for-one relation due to various macroeconomic influences on prices and dividends.

By extending the bivariate model of prices and dividends with earnings, inflation rate, short-term interest rates and government and corporate bond yields, we investigate the influence of macroeconomic proxies on stock prices and cash flows within a cointegration framework and consequently deduce the impact on total stock returns with the loglinear approximation. We find four cointegration relations among the seven non-stationary time series. Testing the dividend-price and further financial ratios (dividend-earnings, earnings-price, real short-interest rates, term spread and credit spread) for stationarity in a multivariate framework, we reject the null for the dividend-price ratio and only find the variables of dividend-earnings and the term spread to most likely have common stochastic trends. We then empirically analyze the macroeconomic impacts on the equity market. We show that inflation has a very strong impact on the equity market. While previous research typically considers the real terms of returns, prices and dividends to eliminate inflation effects and assume that inflation has the same impact on all equity market variables, we find a negative linkage of nominal prices and inflation and nominal cash flows to be positively associated to inflation in the long run. These effects erode nominal returns in the short term and yield returns to recover in the long run. The risk-free rate has the same negative connection to all equity market variables, but the magnitude is much more pronounced for cash flows than for stock prices. While for corporate bond yields we find large positive effects on the equity market, the influences of the government bond yields are negative.

We hope that our results will stimulate the asset pricing and predictability literature. Finding different macroeconomic effects on prices, dividends and earnings, we would suggest considering modified (stationary) valuation ratios to better predict future returns. We leave this topic for further research.

# 4.A Appendix

## 4.A.1 Model Selection

The number of lags to be included in the VEC model $\mathcal{M}_6$ is determined by considering the Akaike information criterion (AIC), the Schwarz criterion (SC) and the Hannan & Quinn criterion (HQ). Additionally, the results of the cointegration rank test can vary with the number of lags included in the VAR. Table 4.8, Panel A reports the test statistics of these criteria depending on the number of lags. Panel B shows the stability of the cointegration rank of the Johansen (1988) trace test

Table 4.8: Lag Length Selection and Cointegration Rank Stability

| Panel A | Lags $p$ in VAR Model | | | | | |
|---|---|---|---|---|---|---|
| Criterion | $p=1$ | $p=2$ | $p=3$ | $p=4$ | $p=5$ | $p=6$ |
| AIC($p$) | -45.64 | -46.27 | -46.28 | **-46.79** | -46.78 | -46.76 |
| HQ($p$) | -45.29 | -45.69 | -45.47 | **-45.77** | -45.53 | -45.29 |
| SC($p$) | -44.76 | **-44.82** | -44.26 | -44.22 | -43.64 | -43.06 |

| Panel B | Critical Values | | | Lags $p$ in VAR Model | | | |
|---|---|---|---|---|---|---|---|
| Rank | 10% | 5% | 1% | $p=2$ | $p=3$ | $p=4$ | $p=5$ |
| $r \leq 6$ | 10.49 | 12.25 | 16.26 | 3.36 | 3.93 | 3.78 | 3.18 |
| $r \leq 5$ | 22.76 | 25.32 | 30.45 | 12.57 | 16.29 | 14.29 | 14.69 |
| $r \leq 4$ | 39.06 | 42.44 | 48.45 | **40.45** | **40.35** | 30.02 | 31.81 |
| $r \leq 3$ | 59.14 | 62.99 | 70.05 | 74.21 | 68.13 | **52.73** | **55.48** |
| $r \leq 2$ | 83.2 | 87.31 | 96.58 | 133.15 | 121.19 | 91.22 | 99.54 |
| $r \leq 1$ | 110.42 | 114.9 | 124.75 | 227.96 | 177.02 | 143.07 | 154.81 |
| $r = 0$ | 141.01 | 146.76 | 158.49 | 334.41 | 257.16 | 228.18 | 223.00 |

*Notes:* The table reports the lag length selection and cointegration rank stability. Panel A shows the test statistics of the Akaike, Schwarz and Hannan & Quinn information criteria to determine the number of lags to be included in the VAR. Boldfaced values denote the minimum test statistic depending on the number of lags for each information criterion. Panel B shows the Johansen (1988) trace test results for various lag lengths. Boldfaced values denote the supported rank at the 5% significance level.

results for various lag lengths. Boldfaced values denote the supported rank at the 5% significance level.

The SC suggests two lags for the VAR model in levels which is equivalent to a VEC(1), while the AIC and the HQ suggest four lags. For the empirical analysis, we follow the suggestions of the SC and investigate a first order VEC. Turning to the cointegration rank stability in Panel B, which has up to five lags in the VAR, our results remain stable at around three to four relations depending on the significance level considered.

### 4.A.2 Univariate Stationarity of the Financial Ratios

The stationarity of the financial ratios such as dividend-price, dividend-earnings, earnings-price, real short-interest rates, term spread and credit spread is often doubtful. To test these hypotheses, we use the ADF test with the null of a unit root and the KPSS test with the null of stationarity. Both tests are performed by allowing for a constant but not for a deterministic time trend. The number of lags used is given in parentheses, where the ADF's lag length is determined by the AIC. The KPSS's

Table 4.9: Univariate Stationarity of Financial Ratios

| | Levels | | | | | First Differences | | | |
|---|---|---|---|---|---|---|---|---|---|
| Variable | $ADF_\mu(q)$ | | $KPSS_\mu(q)$ | | Variable | $ADF_\mu(q)$ | | $KPSS_\mu(q)$ | |
| $(d_t - p_t)$ | -1.99 | (4) | 3.40*** | (5) | $\Delta(d_t - p_t)$ | -8.69*** | (6) | 0.03 | (5) |
| $(e_t - p_t)$ | -3.26** | (5) | 1.34*** | (5) | $\Delta(e_t - p_t)$ | -8.71*** | (6) | 0.02 | (5) |
| $(d_t - e_t)$ | -3.00** | (10) | 1.96*** | (5) | $\Delta(d_t - e_t)$ | -8.11*** | (9) | 0.02 | (5) |
| $(y_t^g - tb_t^\$)$ | -5.10*** | (5) | 0.62** | (5) | $\Delta(y_t^g - tb_t^\$)$ | -7.18*** | (16) | 0.02 | (5) |
| $(y_t^c - y_t^g)$ | -3.54*** | (6) | 0.63** | (5) | $\Delta(y_t^c - y_t^g)$ | -8.37*** | (7) | 0.09 | (5) |
| $(tb_t^\$ - \pi_t)$ | -3.46*** | (11) | 0.26 | (5) | $\Delta(tb_t^\$ - \pi_t)$ | -8.23*** | (14) | 0.02 | (5) |

*Notes:* The table reports the results of the univariate unit root test regressions of the sample from 1927:Q1 to 2011:Q4. All tests include a constant but no deterministic time trends. The number of lags used is given in parentheses; the symbols *, ** and *** denote significance at the 10, 5 and 1% level, respectively. The ADF tests the null of non-stationarity and the lag length is determined by the *Akaike Information Criterion* (AIC). The KPSS tests the null of stationarity and the lag length is determined by the integer value of $(4 \cdot (n/100)^{0.25})$.

lag length is determined by the integer value of $(4 \cdot (n/100)^{0.25})$, which depends only on the number of observations. Table 4.9 reports the corresponding results.

The non-stationarity hypothesis is rejected for all ratios except for the dividend-price ratio, but non-stationarity is strongly rejected for all the first differences. The stationarity hypothesis of the KPSS test, in contrast, is rejected for all ratios except the real short-term interest rate, but stationarity is supported for all first differences.

### 4.A.3 Stability of the Long-Run Matrices across the Models

To see the changes in long-run effects, we compare the long-run matrices, $\mathbf{\Pi}_r$, of various models. The results are presented in Table 4.10, which reports the coefficient estimates of the long-run matrices $\mathbf{\Pi}_r$ of models $\mathcal{M}_1$ to $\mathcal{M}_6$ and a model of the macroeconomic variables $\pi_t$, $tb_t^{\$}$, $y_t^g$ and $y_t^c$ denoted as $\mathcal{M}_m$. Panels A to G report the row of the corresponding variable in each model. Each model is based on a second-order level VAR. The cointegration rank is set as presented in Table 4.3 and shown in the second column. Boldfaced coefficients imply significance on a 5% level according to bootstrapped intervals and are calculated from 10,000 paths under the assumption that the initial estimated VEC model truly generates the data process. Comparing the results of the submodels to the full model, we obtain stable coefficient estimates with respect to the sign and magnitude in the long-run matrix.

Table 4.10: Stability Analysis of the Long-Run Matrices

| Π Matrices of the Models | | Variable | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Panel A: $\Delta p_t$ | | $p_{t-1}$ | $d_{t-1}$ | $e_{t-1}$ | $\pi_{t-1}$ | $tb^{\$}_{t-1}$ | $y^{g}_{t-1}$ | $y^{c}_{t-1}$ | $trend \times 10^3$ |
| $\mathcal{M}_6$ : | $r=4$ | **-0.035** | -0.045 | 0.050 | **-2.738** | -0.557 | -13.929 | 15.264 | 0.396 |
| $\mathcal{M}_5$ : | $r=3$ | -0.019 | -0.037 | 0.038 | **-2.723** | -0.610 | 1.364 | | 0.224 |
| $\mathcal{M}_4$ : | $r=2$ | **-0.022** | -0.032 | 0.032 | **-2.810** | 1.064 | | | 0.293 |
| $\mathcal{M}_3$ : | $r=2$ | **-0.031** | -0.023 | 0.041 | **-2.754** | | | | 0.212 |
| $\mathcal{M}_2$ : | $r=1$ | 0.000 | -0.002 | 0.001 | | | | | 0.003 |
| $\mathcal{M}_1$ : | $r=1$ | -0.021 | 0.047 | | | | | | -0.282 |
| Panel B: $\Delta d_t$ | | $p_{t-1}$ | $d_{t-1}$ | $e_{t-1}$ | $\pi_{t-1}$ | $tb^{\$}_{t-1}$ | $y^{g}_{t-1}$ | $y^{c}_{t-1}$ | $trend \times 10^3$ |
| $\mathcal{M}_6$ : | $r=4$ | **0.079** | **-0.284** | **0.192** | **2.523** | **-8.898** | 6.524 | 3.465 | -0.418 |
| $\mathcal{M}_5$ : | $r=3$ | **0.081** | **-0.278** | **0.191** | **2.487** | -8.757 | 9.551 | | -0.514 |
| $\mathcal{M}_4$ : | $r=2$ | **0.059** | **-0.255** | **0.161** | 2.127 | -0.057 | | | 0.098 |
| $\mathcal{M}_3$ : | $r=2$ | **0.060** | **-0.261** | **0.160** | **2.080** | | | | 0.191 |
| $\mathcal{M}_2$ : | $r=1$ | 0.040 | **-0.280** | **0.187** | | | | | 0.401 |
| $\mathcal{M}_1$ : | $r=1$ | **0.090** | **-0.199** | | | | | | **1.198** |
| Panel C: $\Delta e_t$ | | $p_{t-1}$ | $d_{t-1}$ | $e_{t-1}$ | $\pi_{t-1}$ | $tb^{\$}_{t-1}$ | $y^{g}_{t-1}$ | $y^{c}_{t-1}$ | $trend \times 10^3$ |
| $\mathcal{M}_6$ : | $r=4$ | 0.013 | **0.060** | **-0.044** | 0.764 | **-4.210** | **10.911** | -6.779 | -0.394 |
| $\mathcal{M}_5$ : | $r=3$ | 0.004 | **0.062** | **-0.037** | **0.761** | **-4.303** | **4.117** | | -0.389 |
| $\mathcal{M}_4$ : | $r=2$ | -0.005 | **0.074** | **-0.052** | 0.667 | -0.431 | | | -0.145 |
| $\mathcal{M}_3$ : | $r=2$ | -0.002 | **0.068** | **-0.052** | 0.549 | | | | -0.122 |
| $\mathcal{M}_2$ : | $r=1$ | -0.009 | **0.064** | **-0.043** | | | | | -0.092 |
| Panel D: $\Delta \pi_t$ | | $p_{t-1}$ | $d_{t-1}$ | $e_{t-1}$ | $\pi_{t-1}$ | $tb^{\$}_{t-1}$ | $y^{g}_{t-1}$ | $y^{c}_{t-1}$ | $trend \times 10^3$ |
| $\mathcal{M}_6$ : | $r=4$ | **-0.008** | 0.002 | 0.002 | **-0.648** | 0.482 | -0.843 | 0.450 | 0.080 |
| $\mathcal{M}_5$ : | $r=3$ | **-0.007** | 0.001 | 0.001 | **-0.652** | 0.521 | -0.405 | | 0.087 |
| $\mathcal{M}_4$ : | $r=2$ | **-0.006** | 0.001 | 0.002 | **-0.634** | 0.219 | | | 0.057 |
| $\mathcal{M}_3$ : | $r=2$ | **-0.008** | 0.003 | 0.004 | **-0.597** | | | | 0.036 |
| $\mathcal{M}_m$ : | $r=3$ | | | | **-0.624** | 0.331 | 0.124 | -0.204 | -0.004 |
| Panel E: $\Delta tb^{\$}_t$ | | $p_{t-1}$ | $d_{t-1}$ | $e_{t-1}$ | $\pi_{t-1}$ | $tb^{\$}_{t-1}$ | $y^{g}_{t-1}$ | $y^{c}_{t-1}$ | $trend \times 10^3$ |
| $\mathcal{M}_6$ : | $r=4$ | **0.001** | 0.000 | 0.000 | 0.005 | **-0.085** | **0.515** | **-0.425** | -0.009 |
| $\mathcal{M}_5$ : | $r=3$ | 0.000 | 0.000 | 0.000 | 0.005 | **-0.115** | **0.121** | | -0.007 |
| $\mathcal{M}_4$ : | $r=2$ | 0.000 | 0.000 | 0.000 | 0.005 | -0.002 | | | 0.000 |
| $\mathcal{M}_m$ : | $r=3$ | | | | 0.003 | -0.057 | **0.409** | **-0.363** | 0.001 |
| Panel F: $\Delta y^{g}_t$ | | $p_{t-1}$ | $d_{t-1}$ | $e_{t-1}$ | $\pi_{t-1}$ | $tb^{\$}_{t-1}$ | $y^{g}_{t-1}$ | $y^{c}_{t-1}$ | $trend \times 10^3$ |
| $\mathcal{M}_6$ : | $r=4$ | 0.000 | 0.000 | 0.000 | 0.001 | **0.098** | -0.109 | 0.003 | 0.005 |
| $\mathcal{M}_5$ : | $r=3$ | 0.000 | 0.000 | 0.000 | 0.001 | **0.089** | **-0.095** | | 0.005 |
| $\mathcal{M}_m$ : | $r=3$ | | | | 0.001 | **0.080** | -0.103 | 0.020 | 0.001 |
| Panel G: $\Delta y^{c}_t$ | | $p_{t-1}$ | $d_{t-1}$ | $e_{t-1}$ | $\pi_{t-1}$ | $tb^{\$}_{t-1}$ | $y^{g}_{t-1}$ | $y^{c}_{t-1}$ | $trend \times 10^3$ |
| $\mathcal{M}_6$ : | $r=4$ | 0.000 | 0.000 | 0.000 | 0.003 | **0.089** | 0.067 | **-0.165** | 0.002 |
| $\mathcal{M}_m$ : | $r=3$ | | | | 0.001 | **0.081** | 0.044 | **-0.133** | 0.001 |

*Notes:* The table reports the coefficient estimates of the long-run matrices, $\mathbf{\Pi}_r$, of models $\mathcal{M}_1$ to $\mathcal{M}_6$ and a model of the macroeconomic variables $\pi_t$, $tb^{\$}_t$, $y^{g}_t$ and $y^{c}_t$ denoted as $\mathcal{M}_m$. Each model is based on a second-order level VAR. The cointegration rank is set as presented in Table 4.3 and shown in the second column of the table. Boldfaced coefficients imply significance on a 5% level according to bootstrapped intervals and are calculated from 10,000 paths under the assumption that the initial estimated VEC model truly generates the data process.

### 4.A.4 Bootstrap Method

We apply the residual-based bootstrap method suggested by Benkwitz, Lütkepohl, and Wolters (2001) and Lütkepohl (2005), which consists of the following steps:

1. Estimate the unknown coefficients of the VEC. Let $\hat{\boldsymbol{\nu}}_t$ be the estimate of the VEC residuals $\boldsymbol{\nu}_t$.

2. Calculate centered residuals $\hat{\boldsymbol{\nu}}_1 - \bar{\boldsymbol{\nu}}, ..., \hat{\boldsymbol{\nu}}_T - \bar{\boldsymbol{\nu}}$, where $\bar{\boldsymbol{\nu}}$ are the $n$ usual means for the $n$ residual series.

3. Draw randomly with replacement from the centered residuals to obtain bootstrap residuals $\boldsymbol{\epsilon}_1^*, ..., \boldsymbol{\epsilon}_T^*$.

4. Recursively calculate the bootstrap time series for the VAR as

$$\mathbf{z}_t^* = \boldsymbol{\mu} + \mathbf{A}_1 \mathbf{z}_{t-1}^* + \cdots + \mathbf{A}_p \mathbf{z}_{t-p}^* + \boldsymbol{\epsilon}_t^*, \ t = 1, ..., T,$$

   where $(\mathbf{z}_{-p+1}^*, ..., \mathbf{z}_0^*) = (\mathbf{z}_{-p+1}, ..., \mathbf{z}_0)$ holds for each generated series.

5. Reestimate the coefficients of the VEC using the bootstrapped data and calculate the statistic of interest $q^*$.

6. Repeat these steps $N$ times.

The bootstrap confidence intervals (standard percentile intervals) are then given by

$$CI = \left[ s_{\gamma/2}^*, s_{(1-\gamma/2)}^* \right],$$

where $s_{\gamma/2}^*$ and $s_{(1-\gamma/2)}^*$ are the $\gamma/2$- and $1 - (\gamma/2)$-quantiles of the $N$ bootstrap versions of $q^*$.

# References

Akerlof, G. A., and R. J. Shiller, 2009, *Animal Spirits*. Princeton University Press, Princeton and Oxford.

Amenc, N., L. Martellini, V. Milhau, and V. Ziemann, 2009, "Asset-Liability Management in Private Wealth Management," *Journal of Portfolio Management*, 36(1), 100–120.

Amenc, N., L. Martellini, and V. Ziemann, 2009, "Inflation-Hedging Properties of Real Assets and Implications for Asset-Liability Management Decisions," *Journal of Portfolio Management*, 35(4), 94–110.

Ang, A., and G. Bekaert, 2007, "Stock Return Predictability: Is it There?," *Review of Financial Studies*, 20(3), 651–707.

Bansal, R., R. F. Dittmar, and D. Kiku, 2009, "Cointegration and Consumption Risks in Asset Returns," *Review of Financial Studies*, 22, 1343–1375.

Bansal, R., R. A. Gallant, and G. Tauchen, 2007, "Rational Pessimism, Rational Exuberance, and Asset Pricing Models," *Review of Economics Studies*, 74, 1005–1033.

Bansal, R., and D. Kiku, 2011, "Cointegration and Long-Run Asset Allocation," *Journal of Business and Economic Statistics*, 29, 161–173.

Barberies, N., 2000, "Investing for the Long Run When Returns Are Predictable," *Journal of Finance*, 55, 225–264.

Barkham, R., and D. Geltner, 1994, "Unsmoothing British Valuation-Based Returns without Assuming an Efficient Market," *Journal of Property Research*, 11, 81–95.

——— , 1995, "Price Discovery in American and British Property Markets," *Real Estate Economics*, 23, 21–44.

Benkwitz, A., H. Lütkepohl, and J. Wolters, 2001, "Comparison of Bootstrap Confidence Intervals for Impulse Responses of German Monetary Systems," *Macroeconomic Dynamics*, 5, 81–100.

Bodie, Z., 1976, "Common Stocks as a Hedge Against Inflation," *Journal of Finance*, 31, 459–470.

Boudoukh, J., R. Michaely, M. Richardson, and M. R. Roberts, 2007, "On the Importance of Measuring Payout Yield: Implications for Empirical Asset Pricing," *Journal of Finance*, 62, 877–915.

Boudoukh, J., and M. Richardson, 1993, "Stock Returns and Inflation: A Long-Horizon Perspective," *American Economic Review*, 83, 1346–1355.

Brueggeman, W. B., A. H. Chen, and T. G. Thibodeau, 1984, "Real Estate Investment Funds: Performance and Portfolio Considerations," *AREUEA Journal*, 12, 333–354.

Campbell, J. Y., 1987, "Stock Returns and the Term Structure," *Journal of Financial Economics*, 18, 373–399.

——— , 1991, "A Variance Decomposition of Stock Returns," *Economic Journal*, 101, 157–179.

Campbell, J. Y., and J. Ammer, 1993, "What Moves the Stock and Bond Markets? A Variance Decomposition for Long-Term Asset Returns," *Journal of Finance*, 48(1), 3–37.

Campbell, J. Y., L. Y. Chan, and L. M. Viceira, 2003, "A Multivariate Model of Strategic Asset Allocation," *Journal of Financial Economics*, 67, 41–80.

Campbell, J. Y., and R. J. Shiller, 1987, "Cointegration and Tests of Present Value Models," *Journal of Political Economy*, 95(5), 1062–1088.

——— , 1988a, "The Dividend-Price Ratio and Expectations of Future Dividends and Discount Rates," *Review of Financial Studies*, 1, 195–228.

——— , 1988b, "Stock Prices, Earnings, and Expected Dividends," *Journal of Finance*, 43, 661–76.

——— , 1991, "Yield Spreads and Interest Rates Movement: A Bird's Eye View," *Review of Economic Studies*, 58, 495–514.

Campbell, J. Y., and S. B. Thompson, 2008, "Predicting Excess Stock Returns Out of Sample: Can Anything Beat the Historical Average?," *Review of Financial Studies*, 21(4), 1509–1531.

Campbell, J. Y., and L. M. Viceira, 2002, *Strategic Asset Allocation: Portfolio Choice for Long-Term Investors*. Oxford University Press, Oxford and New York.

——— , 2004, "Long-Horizon Mean-Variance Analysis: A User Guide," Harvard University.

——— , 2005, "The Term Structure of the Risk-Return Trade-Off," *Financial Analyst Journal*, 61(1), 34–44.

Campbell, J. Y., and T. Vuolteenaho, 2004a, "Bad Beta, Good Beta," *American Economic Review*, 94, 1249–1275.

——— , 2004b, "Inflation Illusion and Stock Prices," *American Economic Review (Papers and Proceedings)*, 94, 19–23.

Case, B., W. Goetzmann, and K. G. Rouwenhorst, 1999, "Global Real Estate Markets: Cycles and Fundamentals," Yale International Center for Finance.

Cheung, Y. W., and K. S. Lai, 1993, "Finite-Sample Sizes of Johansen's Likelihood Ratio Tests for Conintegration," *Oxford Bulletin of Economics and Statistics*, 55(3), 313–328.

Cochrane, J. H., 1994, "Permanent and Transitory Components of GNP and Stock Prices," *Quarterly Journal of Economics*, 109(1), 241–265.

——— , 2008, "The Dog That Did Not Bark: A Defense of Return Predictability," *Review of Financial Studies*, 21, 1533–1575.

Collet, D., C. Lizieri, and C. Ward, 2003, "Timing and the Holding Periods of Institutional Real Estate," *Real Estate Economics*, 31, 205–222.

Edgerton, D., and G. Shukur, 1999, "Testing autocorrelation in a system perspective," *Econometric Reviews*, 18(4), 343–386.

Engle, R. F., and C. W. J. Granger, 1987, "Cointegration and Error-Correction: Representation, Estimation and Testing," *Econometrica*, 55, 251–276.

Engsted, T., T. Q. Pedersen, and C. Tanggaard, 2010, "The Log-Linear Return Approximation, Bubbles, and Predictability," Working Paper, Aarhus University.

Fama, E. F., and R. R. Bliss, 1987, "The Information in Long-Maturity Forward Rates," *American Economic Review*, 77, 680–692.

Fama, E. F., and K. R. French, 1988, "Dividend Yields and Expected Stock Returns," *Journal of Financial Economics*, 22, 3–25.

——— , 1989, "Business Conditions and Expected Returns on Stocks and Bonds," *Journal of Financial Economics*, 25(1), 23–49.

——— , 2001, "Disappearing Dividends: Changing Firm Characteristics or Lower Propensity to Pay?," *Journal of Financial Economics*, 60(1), 3–43.

Fama, E. F., and G. W. Schwert, 1977, "Asset Returns and Inflation," *Journal of Financial Economics*, 5, 115–146.

Fisher, J. D., and M. S. Young, 2000, "Holding Periods for Institutional Real Estate in the NCREIF Database," *Real Estate Finance*, 17(3), 27–34.

Froot, K. A., and M. Obstfeld, 1991, "Intrinsic Bubbles: The Case of Stock Prices," *American Economic Review*, 81(5), 1189–1214.

Fu, Y., and L. K. Ng, 2001, "Market Efficiency and Return Statistics: Evidence from Real Estate and Stock Markets Using a Present-Value Approach," *Real Estate Economics*, 29(2), 227–250.

Fugazza, C., M. Guidolin, and G. Nicodano, 2007, "Investing for the Long-run in European Real Estate," *Journal of Real Estate Finance and Economics*, 34(1), 35–80.

——— , 2009, "Time and Risk Diversification in Real Estate Investments: Assessing the Ex Post Economic Value," *Real Estate Economics*, 37(3), 341–381.

Geltner, D., 1993, "Estimating Market Values from Appraised Values without Assuming an Efficient Market," *Journal of Real Estate Research*, 8, 325–345.

Glosten, L. R., R. Jagannathan, and D. Runkle, 1993, "On the Relation Between the Expected Value and the Volatility of the Nominal Excess Return on Stocks," *Journal of Finance*, 48, 1779–1801.

Goetzmann, W. N., and P. Jorion, 1993, "Testing the Predictive Power of Dividend Yields," *Journal of Finance*, 48, 663–679.

Goyal, A., and I. Welch, 2003, "Predicting the Equity Premium with Dividend Ratios," *Management Science*, 49, 639–654.

——— , 2008, "A Comprehensive Look at The Empirical Performance of Equity Premium Prediction," *Review of Financial Studies*, 21, 1455–1508.

Granger, C. W. J., 1981, "Some Properties of Time Series Data and Their Use in Econometric Model Specification," *Journal of Econometrics*, 16, 121–130.

Grullon, G., and R. Michaely, 2002, "Dividends, Share Repurchases and the Substitution Hypothesis," *Journal of Finance*, 57, 1649–1684.

——— , 2004, "The Information Content of Share Repurchase Programs," *Journal of Finance*, 59(2), 651–680.

Gultekin, N. B., 1983, "Stock Market Returns and Inflation: Evidence from Other Countries," *Journal of Finance*, 38, 49–65.

Gyourko, J., and D. B. Keim, 1992, "What Does the Stock Market Tell Us About Real Estate Returns?," *AREUEA Journal*, 20, 457–485.

Gyourko, J., and P. Linneman, 1988, "Owner-Occupied Homes, Income-Producing Properties, and REITs as Inflation Hedges: Empirical Findings," *Journal of Real Estate Finance and Economics*, 1, 347–372.

Hansen, L. P., J. C. Heaton, and N. Li, 2008, "Consumption Strikes Back? Measuring Long-Run Risk," *Journal of Political Economy*, 116(2), 260–302.

Hartzell, D., J. S. Hekman, and M. E. Miles, 1987, "Real Estate Returns and Inflation," *AREUEA Journal*, 15, 617–637.

Hodrick, R. J., 1992, "Dividend Yields and Expected Stock Returns: Alternative Procedures for Inference and Measurement," *Review of Financial Studies*, 5, 357–386.

Hoesli, M., C. Lizieri, and B. MacGregor, 2008, "The Inflation Hedging Characteristics of US and UK Investments: A Multi-Factor Error Correction Approach," *Journal of Real Estate Finance and Economics*, 36, 183–206.

Hoevenaars, R. P. M. M., R. D. J. Molenaar, P. C. Schotman, and T. B. M. Steenkamp, 2008, "Strategic Asset Allocation with Liabilities: Beyond Stocks and Bonds," *Journal of Economic Dynamic and Control*, 32, 2939–2970.

Jaffe, J. F., and G. Mandelker, 1976, "The "Fisher Effect" for Risky Assets: An Empirical Investigation," *Journal of Finance*, 31, 447–458.

Johansen, S., 1988, "Statistical Applications of Cointegrated Vectors," *Journal of Economic Dynamics and Control*, 12, 231–254.

——— , 1991, "Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models," *Econometrica*, 59, 1551–1580.

——— , 1996, *Likelihood-Based Inference in Cointegrated Vector Autoregressive Models*. Oxford University Press, Oxford, 2. edn.

Johansen, S., and K. Juselius, 1990, "Maximum Likelihood Estimation and Inference on Cointegration – with Applications to the Demand for Money," *Oxford Bulletin of Economics and Statistics*, 52, 169–210.

———, 1992, "Testing Structural Hypotheses in a Multivariate Cointegration Analysis of the PPP and the UIP for UK," *Journal of Econometrics*, 53, 211–244.

Jurek, J. W., and L. M. Viceira, 2011, "Optimal Value and Growth Tilts in Long-Horizon Portfolios," *Review of Finance*, 15(1), 29–74.

Juselius, K., 2006, *The Cointegrated VAR Model*. Oxford University Press, Oxford.

Kandel, E., and R. Stambaugh, 1996, "On the Predictability of Stock Returns: An Asset Allocation Perspective," *Journal of Finance*, 51, 385–424.

Keim, D., and R. Stambaugh, 1986, "Predictability Returns in the Stock Returns and Bond Markets," *Journal of Financial Economics*, 17, 357–390.

Key, T., F. Zarkesh, and N. Haq, 1999, "The UK Property Cycle: A History from 1921 to 1997," *RICS Research: London*.

Kothari, S., and J. Shanken, 1997, "Book-to-Market, Dividend Yield, and Expected Market Returns: A Time-Series Analysis," *Journal of Financial Economics*, 44, 169–203.

Lamont, O., 1998, "Earnings and Expected Returns," *Journal of Finance*, 53(5), 1563–1587.

Lee, B.-S., 1995, "The Response of Stock Prices to Permanent and Temporary Shocks to Dividends," *Journal of Financial and Quantitative Analysis*, 30(1), 1–22.

——— , 1996, "Comovements of Earnings, Dividends, and Stock Prices," *Journal of Empirical Finance*, 3, 327–346.

——— , 2010, "Stock Returns and Inflation Revisited: An Evaluation of the Inflation Illusion Hypothesis," *Journal of Banking and Finance*, 34, 1257–1273.

Lee, T.-H., and Y. Tse, 1996, "Cointegration Tests with Conditional Heteroskedasticity," *Journal of Econometrics*, 73, 401–410.

Lettau, M., and S. C. Ludvigson, 2001, "Consumption, Aggregate Wealth, and Expected Stock Returns," *Journal of Finance*, 56(3), 815–849.

——— , 2005, "Expected Returns and Expected Dividend Growth," *Journal of Financial Economics*, 76, 583–626.

Lettau, M., and S. Van Nieuwerburgh, 2008, "Reconciling the Return Predictability Evidence," *Review of Financial Studies*, 21(4), 1607–1652.

Limmack, R. J., and C. W. R. Ward, 1988, "Property Returns and Inflation," *Land Development Studies*, 5, 47–55.

Lütkepohl, H., 2005, *New Introduction to Multiple Time Series Analysis*. Springer, Berlin.

Luintel, K. B., and K. Paudyal, 2006, "Are Common Stocks a Hedge against Inflation?," *Journal of Financial Research*, 29(1), 1–19.

MacKinnon, G. H., and A. Al Zaman, 2009, "Real Estate for the Long Term: The Effect of Return Predictability on Long-Horizon Allocations," *Real Estate Economics*, 37(1), 117–153.

Modigliani, F., and R. A. Cohn, 1979, "Inflation, Rational Valuation and the Market," *Financial Analysts Journal*, 35(2), 24–44.

Nasseh, A., and J. Strauss, 2000, "Stock Prices and Domestic and International Macroeconomic Activity: A Cointegration Approach," *Quarterly Review of Economics and Finance*, 40, 229–245.

Park, C., and C.-J. Kim, 2012, "Disappearing Dividends: Implications for the Dividend-Price Ratio and Return Predictability," Working Paper, Korea University.

Plazzi, A., W. Torous, and R. Valkanov, 2010, "Expected Returns and the Expected Growth in Rents of Commercial Real Estate," *Review of Financial Studies*, 23(9), 3469–3519.

Quan, D. C., and S. Titman, 1999, "Do Real Estate Prices and Stock Prices Move Together? An International Analysis," *Real Estate Economics*, 27, 183–207.

Rahbek, A., E. Hansen, and J. G. Dennis, 2002, "ARCH Innovations and Their Impact on Cointegration Rank Testing," Working Paper, University of Copenhagen.

Rehring, C., 2012, "Real Estate in a Mixed-Asset Portfolio: The Role of the Investment Horizon," *Real Estate Economics*, 40(1), 65–95.

Rubens, J. H., M. T. Bond, and J. R. Webb, 1989, "The Inflation-Hedging Effectiveness of Real Estate," *Journal of Real Estate Research*, 4, 45–55.

Schotman, P. C., and M. Schweitzer, 2000, "Horizon Sensitivity of the Inflation Hedge of Stocks," *Journal of Empirical Finance*, 7, 301–315.

Schätz, A., and S. Sebastian, 2009, "The Links Between Property and the Economy: Evidence From the British and German Markets," *Journal of Property Research*, 26, 171–191.

Scott, P., 1996, *The Property Masters: A History of the British Commercial Property Sector*. Taylor & Francis SPON, London.

Scott, P., and G. Judge, 2000, "Cycles and Steps in British Commercial Property Values," *Applied Economics*, 32, 1287–1297.

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Kolb, Christian: Corporate Governance bei deutschen Immobilienkapitalgesellschaften / Schulte, Karl-Werner (Hrsg.); Bone-Winkel, Stephan (Hrsg.). Köln: Müller, 2007 (Schriften zur Immobilienökonomie 41)

Holzmann, Christoph: Entwicklung eines Real Estate Confidence Indicator zur kurzfristigen Konjunkturprognose auf Immobilienmärkten / Schulte, Karl-Werner (Hrsg.); Bone-Winkel, Stephan (Hrsg.). Köln: Müller, 2007 (Schriften zur Immobilienökonomie 40)

Zimmermann, Matthias: Projektentwicklung im Immobilienbestand institutioneller Investoren: Konzeption, Make-or-Buy-Entscheidung und empirische Analyse zur Revitalisierung von Büroimmobilien / Schulte, Karl-Werner (Hrsg.); Bone-Winkel, Stephan (Hrsg.). Köln: Müller, 2006 (Schriften zur Immobilienökonomie 39)

Sturm, Verena: Erfolgsfaktoren der Revitalisierung von Shopping-Centern: ein Turnaround-Management-Ansatz / Schulte, Karl-Werner (Hrsg.); Bone-Winkel, Stephan (Hrsg.). Köln: Müller, 2006 (Schriften zur Immobilienökonomie 38)

Beidatsch, Kaja: Geographic Selection - Auswahl von Zielmärkten im Portfoliomanagement: Eine empirische Analyse am Beispiel ausgewählter deutscher Büromärkte / Schulte, Karl-Werner (Hrsg.); Bone-Winkel, Stephan (Hrsg.). Köln: Müller, 2006 (Schriften zur Immobilienökonomie 37)

Pelzeter, Andrea: Lebenszykluskosten von Immobilien: Einfluss von Lage, Gestaltung und Umwelt / Schulte, Karl-Werner (Hrsg.); Bone-Winkel, Stephan (Hrsg.). Köln: Müller, 2006 (Schriften zur Immobilienökonomie 36)

Gier, Sonja: Bereitstellung und Desinvestition von Unternehmensimmobilien / Schulte, Karl-Werner (Hrsg.); Bone-Winkel, Stephan (Hrsg.). Köln: Müller, 2006 (Schriften zur Immobilienökonomie 35)

Breidenbach, Marc: Real Estate Securitisation – Asset-backed security financing for the property industry, an international comparison applied to the case of Germany / Schulte, Karl-Werner (Hrsg.); Bone-Winkel, Stephan (Hrsg.). Köln: Müller, 2005 (Schriften zur Immobilienökonomie 34)

Focke, Christian: Gewerbeimmobilien-Investments in Polen – Eine Analyse der Marktentwicklung, Eignung und Akzeptanz aus der Perspektive deutscher institutioneller Investoren / Schulte, Karl-Werner (Hrsg.); Bone-Winkel, Stephan (Hrsg.). Köln: Müller, 2005 (Schriften zur Immobilienökonomie 33)

Matzen, Frank J.: Unternehmensbewertung von Wohnungsbauunternehmen unter besonderer Berücksichtigung der Besteuerung und Finanzierung / Schulte, Karl-Werner (Hrsg.); Bone-Winkel, Stephan (Hrsg.). Köln: Müller, 2005 (Schriften zur Immobilienökonomie 32)

Wernecke, Martin: Büroimmobilienzyklen - Eine Analyse der Ursachen, der Ausprägungen in Deutschland und der Bedeutung für Investitionsentscheidungen / Schulte, Karl-Werner (Hrsg.); Bone-Winkel, Stephan (Hrsg.). Köln: Müller, 2004 (Schriften zur Immobilienökonomie 31)

Pitschke, Christoph: Die Finanzierung gewerblicher Immobilien-Projektentwicklungen unter besonderer Berücksichtigung der Neuen Baseler Eigenkapitalvereinbarung / Schulte, Karl-Werner (Hrsg.); Bone-Winkel, Stephan (Hrsg.). Köln: Müller, 2004 (Schriften zur Immobilienökonomie 30). - Umschlagtitel: Die Finanzierung gewerblicher Immobilien-Projektentwicklungen unter Basel II

Rottke, Nico: Investitionen mit Real Estate Private Equity – Herleitung eines anreizkompatiblen Beteiligungsmodells unter Berücksichtigung der Transaktionskosten- und Agency-Theorie / Schulte, Karl-Werner (Hrsg.); Bone-Winkel, Stephan (Hrsg.). Köln: Müller, 2004 (Schriften zur Immobilienökonomie 29)

Blumenthal, Ira: Anforderungen an ein Marketingkonzept für Facilities-Management-Dienstleistungsunternehmen – Ein Vergleich zwischen Theorie und Empirie / Schulte, Karl-Werner (Hrsg.). Köln: Müller, 2004 (Schriften zur Immobilienökonomie 28)

Ecke, Christian: Strategisches Immobilienmanagement der öffentlichen Hand – empirische Untersuchungen und Handlungsempfehlungen / Schulte, Karl-Werner (Hrsg.). Köln: Müller, 2004 (Schriften zur Immobilienökonomie 27)

Fischer, Carsten: Projektentwicklung: Leistungsbild und Honorarstruktur / Schulte, Karl-Werner (Hrsg.). Köln: Müller, 2004 (Schriften zur Immobilienökonomie 26)

Busz, Pamela: Seniorenimmobilien als Investitionsobjekte - Entwicklung und empirische Analyse eines Beurteilungsmodells / Schulte, Karl-Werner (Hrsg.). Köln: Müller, 2003 (Schriften zur Immobilienökonomie 25)

Gerhard, Jan: Immobilienportfoliomanagement mit Immobilienindex-Derivaten: Eine kritische Analyse und Bewertung der Einsatzmöglichkeiten immobilienindexbasierter Finanzinstrumente auf dem deutschen Markt / Schulte, Karl-Werner (Hrsg.). Köln: Müller, 2003 (Schriften zur Immobilienökonomie 24)

Iblher, Felix: Internetbasierte Immobilienfinanzierung: Auswirkungen des Electronic Business auf die Finanzierung privater Wohnimmobilien / Schulte, Karl-Werner (Hrsg.). Köln: Müller, 2003 (Schriften zur Immobilienökonomie 23)

Vogel, Ludwig: Projektentwicklung von Factory Outlet Centern - eine akzeptanztheoretische Untersuchung / Schulte, Karl-Werner (Hrsg.). Köln: Müller, 2003 (Schriften zur Immobilienökonomie 22)

Hagemeier, Irene M.: Der Einsatz staatlicher Instrumente in der Wohnungs- und Bodenpolitik des 20. Jahrhunderts: Deutschland, Spanien, Schweden und die USA im Vergleich / Schulte, Karl-Werner (Hrsg.). Köln: Müller, 2003 (Schriften zur Immobilienökonomie 21)

Werner, Jeannette: Die Besteuerung von Gewerbeimmobilien in Europa: effektive Steuerbelastung und Steuerbeständigkeit in einem Fünf-Länder-Vergleich / Schulte, Karl-Werner (Hrsg.). Köln: Müller, 2002 (Schriften zur Immobilienökonomie 20)

Schulz-Eickhorst, Antje: Die Bauherren-Architekten-Beziehung: eine institutionenökonomische Problemanalyse mit Lösungsansätzen / Schulte, Karl-Werner (Hrsg.). Köln: Müller, 2002 (Schriften zur Immobilienökonomie 19)

Cieleback, Marcus: Optionsaspekte der Zinssicherung durch Bauspardarlehen und ihre Implikationen für die Wohneigentumsfinanzierung / Schulte, Karl-Werner (Hrsg.). Köln: Müller, 2001 (Schriften zur Immobilienökonomie 18). - Umschlagtitel: Bausparen und Optionstheorie

Crommen, Marcel: Finanzierung von Unternehmensimmobilien: Eine Shareholder Value-orientierte Analyse / Schulte, Karl-Werner (Hrsg.). Köln: Müller, 2001 (Schriften zur Immobilienökonomie 17)

Sotelo, Ramon: Ökonomische Grundlagen der Wohnungspolitik / Schulte, Karl-Werner (Hrsg.). Köln: Müller, 2001 (Schriften zur Immobilienökonomie 16)

Walbröhl, Victoria: Die Immobilienanlageentscheidung im Rahmen des Kapitalanlagemanagements institutioneller Anleger – eine Untersuchung am Beispiel deutscher Lebensversicherungsunternehmen und Pensionskassen / Schulte, Karl-Werner (Hrsg.). Köln: Müller, 2001 (Schriften zur Immobilienökonomie 15)

Pierschke, Barbara: Die organisatorische Gestaltung des betrieblichen Immobilienmanagements / Schulte, Karl-Werner (Hrsg.). Köln: Müller, 2001 (Schriften zur Immobilienökonomie 14)

Hens, Markus: Marktwertorientiertes Management von Unternehmensimmobilien / Schulte, Karl-Werner (Hrsg.). Köln: Müller, 1999 (Schriften zur Immobilienökonomie 13)

Straßheimer, Petra: Internationales Corporate Real Estate Management: Implikationen der Internationalisierung von Unternehmen auf das betriebliche Immobilienmanagement / Schulte, Karl-Werner (Hrsg.). Köln: Müller, 1999 (Schriften zur Immobilienökonomie 12)

Väth, Arno: Die Grundstücks-Investmentaktiengesellschaft als Pendant zum REIT: Entwicklung einer Konzeption auf Basis der KAGG-Novelle ’98 / Schulte, Karl-Werner (Hrsg.). Köln: Müller, 1999 (Schriften zur Immobilienökonomie 11)

Vaaßen, Nicole: Gewerbliches Immobilienleasing: eine quantitative und qualitative Analyse aus Sicht des Leasingnehmers / Schulte, Karl-Werner (Hrsg.). Köln: Müller, 1999 (Schriften zur Immobilienökonomie 10)

Buse, Christoph: Strategisches Management von industrieverbundenen Wohnungsunternehmen / Schulte, Karl-Werner (Hrsg.). Köln: Müller, 1999 (Schriften zur Immobilienökonomie 9)

Isenhöfer, Björn: Strategisches Management von Projektentwicklungsunternehmen / Schulte, Karl-Werner (Hrsg.). Köln: Müller, 1999 (Schriften zur Immobilienökonomie 8)

Brade, Kerstin H.: Strategischer Marketingplanungsprozeß für Büroimmobilien: Anwendung der Kausalanalyse zur Erforschung des Mieterverhaltens / Schulte, Karl-Werner (Hrsg.). Köln: Müller, 1998 (Schriften zur Immobilienökonomie 7)

Leopoldsberger, Gerrit: Kontinuierliche Wertermittlung von Immobilien / Schulte, Karl-Werner (Hrsg.). Köln: Müller, 1998 (Schriften zur Immobilienökonomie 6)

Ropeter, Sven-Eric: Investitionsanalyse für Gewerbeimmobilien / Schulte, Karl-Werner (Hrsg.). Köln: Müller, 1998 (Schriften zur Immobilienökonomie 5)

Kirsch, Daniela: Public Private Partnership: Eine empirische Untersuchung der kooperativen Handlungsstrategien in Projekten der Flächenerschließung und Immobilienentwicklung / Schulte, Karl-Werner (Hrsg.). Köln: Müller, 1997 (Schriften zur Immobilienökonomie 4)

Schäfers, Wolfgang: Strategisches Management von Unternehmensimmobilien: Bausteine einer theoretischen Konzeption und Ergebnisse einer empirischen Untersuchung / Schulte, Karl-Werner (Hrsg.). Köln: Müller, 1997 (Schriften zur Immobilienökonomie 3)

Thomas, Matthias: Die Entwicklung eines Performanceindexes für den deutschen Immobilienmarkt / Schulte, Karl-Werner (Hrsg.). Köln: Müller, 1997 (Schriften zur Immobilienökonomie 2)

Bone-Winkel, Stephan: Das strategische Management von offenen Immobilienfonds unter besonderer Berücksichtigung der Projektentwicklung von Gewerbeimmobilien / Schulte, Karl-Werner (Hrsg.). Köln: Müller, 1994 (Schriften zur Immobilienökonomie 1)

## Schriften zum Öffentlichen Immobilienrecht und Infrastrukturrecht

Kühling, Jürgen (Hrsg.): Grünes Baurecht und Energiewende (Tagungsband des 6. Regensburger Immobilienrechtstags am 12. Juli 2013), Köln, München: Heymann, 2014 (Schriften zum Öffentlichen Immobilienrecht und Infrastrukturrecht 10)

Kühling, Jürgen (Hrsg.): Die Einzelhandelsimmobilie - Wirtschaftliche Rationalität und rechtliche Steuerung (Tagungsband des 5. Regensburger Immobilienrechtstags am 13. Juli 2012), Köln, München: Heymann, 2012 (Schriften zum Öffentlichen Immobilienrecht und Infrastrukturrecht 9)

Müller, Kathrin: Das bauordnungsrechtliche Verunstaltungsverbot (Verfahrensoptimierung zur Bewältigung bauästhetischer Konflikte im öffentlichen Raum), Köln, München: Heymann, 2012 (Schriften zum Öffentlichen Immobilienrecht und Infrastrukturrecht 8)

Kühling, Jürgen (Hrsg.): Die Einzelhandelsimmobilie - Bau(recht)liche Todsünden und vernünftige Problemlösungen (Tagungsband des 4. Regensburger Immobilienrechtstags am 15. Juli 2011), Köln, München: Heymann, 2012 (Schriften zum Öffentlichen Immobilienrecht und Infrastrukturrecht 7)

Kühling, Jürgen (Hrsg.): Kooperation im Öffentlichen Immobilien- und Infrastrukturrecht (Tagungsband des 3. Regensburger Immobilienrechtstags am 16. Juli 2010), Köln, München: Heymann, 2011 (Schriften zum Öffentlichen Immobilienrecht und Infrastrukturrecht 6)

Kühling, Jürgen (Hrsg.): Mehrebenenkonflikte im Öffentlichen Immobilien-und Infrastrukturrecht (Tagungsband des 2. Regensburger Immobilienrechtstags am 2. Juli 2009), Köln, München: Heymann, 2010 (Schriften zum Öffentlichen Immobilienrecht und Infrastrukturrecht 5)

Pfeifle, Florian: UNESCO-Weltkulturerbe - Vom globalen Völkerrecht zur lokalen Infrastrukturplanung, Köln, München: Heymann, 2010 (Schriften zum Öffentlichen Immobilienrecht und Infrastrukturrecht 4)

Tigges, Damian: Die Regulierung des Zugangs zum Markt für Hafendienste - Ein Vergleich der horizontalen und vertikalen Regulierungsansätze, Köln, München: Heymann, 2009 (Schriften zum Öffentlichen Immobilienrecht und Infrastrukturrecht 3)

Müller, Friederike: Kommunalrechtliche Grenzen beim Sale-and-lease-back - Ein Beitrag zum Privatisierungsfolgerecht am Beispiel der Privatisierung und öffentlich genutzter Immobilien, Köln, München: Heymann, 2009 (Schriften zum Öffentlichen Immobilienrecht und Infrastrukturrecht 2)

Kühling, Jürgen (Hrsg.): Öffentliches Recht und Investitionssicherheit in der Immobilienwirtschaft (Tagungsband des 1. Regensburger Immobilienrechtstags am 20. Juni 2008), Köln, München: Heymann, 2009 (Schriften zum Öffentlichen Immobilienrecht und Infrastrukturrecht 1)