CHAPTER 4: SOME EMPIRICAL RESULTS FOR THE DUTCH STOCK MARKET

4.1 INTRODUCTION

This chapter reports empirical investigations into multi-factor models for the Dutch stock market. Before proceeding, we stress that the goal of this chapter is not presenting 'the' model that describes how returns on the Dutch stock market are generated. In our opinion, such a model does not exist (or has at least not been discovered yet). What can be attained is a model that, given the sample of returns in time and cross-section, more or less adequately describes the relationships between stock returns and changes in the economic environment. In my intention, then, this chapter will not be so much a revelation in the sense that it divulges some secret (because 'true') underlying factor model. Instead, this chapter is intended to provide an illustration of the process of constructing and estimating a multi-factor model and of linking the results back to theory by interpreting them in the framework of accepted models. This illustration centers around the following issues, to be discussed below:

- the factor **model** itself:
  - · the interpretation of the nature of a factor model
- the incorporated **factors**:
  - · the nature of the factors
  - · the choice (identity) of the factors
  - · the measurement of the factors
- measuring the **relationships** within the model:
  - · the statistical significance of the relationships
  - · the stability and stationarity of the relationships.

A discussion of applications of the model is postponed until chapter 5.

Factor models

As stressed in chapter three, we consider a (multi-factor) model in its role of a risk model. A risk model relates changes in security (stock) prices to **contemporaneous changes** in (macro-) economic variables. Returns are thus linked to changes in state variables. There exists an increasing body of studies that relate security returns to **levels** of economic variables, in the sense that the (short term) interest rate, the term structure of interest rates, or expected inflation is considered instead of (contemporaneous) changes in these variables. As remarked in section 2.5.2, these studies investigate the predictability of security prices by analyzing the **level** of expected returns (or risk

premiums) over time and the persistence of return components. By relating returns to contemporaneous changes in economic variables, in contrast, implicitly **changes** in expected returns (or risk premiums) are analyzed; these changes in expected returns then propagate into changes in market prices and thus into returns.

Incorporated factors

Changing security prices brings us to the nature of the incorporated factors. In a fairly efficient market, the market expectations regarding changes in the relevant economic environment are already incorporated in the current prices. A change in the (conditional) expectations then implies a change in the prices, and hence a return. Complicating circumstances are here, first, that we do not know the expectations at any point in time and, second, that there can exist a non-flat term structure of expectations that can change in complicated (i.e. non-parallel) ways. A way out of this second problem is to assume that expectations are driven by unforeseen events. This implies that the occurrence of an unexpected change incites the market participants (the investors) to revise their set of expectations. As a result, the information content of a change in the (next period's) expectation with respect to a state variable can be different from the information content of an unexpected change in that state variable.

Focussing on unexpected changes does not resolve the first problem, however, since for knowing unexpected changes one must know the expected component of the change. Information about expectations is not readily available. One possibility is the use of expectational data as collected and published by some institutions. One source is I/B/E/S, the Institutional Brokers Estimate System (a service of Lynch, Jones & Ryan), that gathers analysts' (market) expectations with respect to fundamental firm variables (like earnings and dividends) and macro-economic variables (like interest rates, inflation and exchange rates). This route is left for future research. The alternative, employed almost without exception, is the use of time series models under the assumption of rational expectations. By time series modelling of the changes in the selected factors, the expected component of the change (the prediction) is separated from the unexpected or surprise component (the residual).[1)] The estimated residuals from this auxiliary (regression) model are then considered as actual surprises and used in the main regression of the factor model estimation. The econometric issues involved in two-step procedures, where predictors and residuals generated from an auxiliary model are used as regressors in main regressions, are analyzed by Pagan [1984]. When the main regressions are estimated by ordinary least

---

1) The so-called 'pre-whitening'. Note that in the context of a factor model as a risk model, we are in this respect analyzing the contemporaneous changes in the factors.

squares, he finds that the use of predictions causes severe problems. However, in the case where generated residuals are used, the ordinary least squares estimators of their coefficients in the main regressions are both consistent and efficient. Furthermore, the standard errors of the coefficients of the generated residuals, resulting from the ordinary least squares procedure, are consistent estimators of the true standard errors. This implies that the standard errors (and hence the t-values) estimated in the main regression, can be employed to make valid inferences.

The main regressions lead us to the next issue: the identity of the relevant factors. What variables should be incorporated in the model? Unfortunately, to my knowledge there exists no generally accepted (i.e. firmly validated) theoretical framework that links stock returns to the economy. Nor does there exist agreement about some unique set of economic variables to which stock returns are supposed to be related in some way. As appeared from section 2.5.2, some general economic theory combined with intuition yields a set of candidate factors. Later studies then gratefully use these variables. Other important considerations are the extent to which variables appear in popular financial media, and the availability of the data.

Some frequently used variables can be organized in a diagram, as shown below:

	variables	
sector:	**financial market**	**non-financial market**
real:	commodity futures prices	inflation: · consumer prices · producer prices economic activity: · IP / GNP · new orders of durable goods · car sales consumer confidence
monetary:	interest rates risk premia	money supply
foreign:	exchange rates	imports / exports trade balance effective exchange rate

An obvious classification of the variables is whether they relate to the real sector of an economy, to the monetary (financial) sector, or

(especially for open economies) to the foreign sector. Another important way of classifying the variables would be to ascertain whether they are generated by market forces on a liquid market, or whether they relate to less liquid real markets. The former category comprises price variables whereas the latter category mostly covers volume data. This criterion raises some problems, however. For example, is money supply a real market variable? Are consumer prices financial market data? A better classification in this respect is financial market variables as opposed to non-financial market variables. Of course, distinction is not crisp and clear. Real interest rates, for example, are of a mixed nature. The importance of financial market data is that the variables themselves are generated in efficient markets. It can hence be argued that their total change is unexpected. This eliminates the need for decomposing into estimated anticipated and unanticipated components. Furthermore, financial market data are readily available on a high frequency basis. It can be expected that they constitute a large part of investors' information sets.

Even if economic theory could reveal us the definitions of the 'true' underlying variables, we would have to operationalize the model by choosing available variables that represent (or better: proxy) the 'true' variables. If an interest rate is important, what particular rate is relevant? A short rate or a long rate (how long or how short)? A domestic rate or a foreign rate? And so on. Hollis & Nell [1975, pp.96ff] consider, in a philosophical context, this problem of operationalizing the hunches we may have. In addition, they touch upon the issue of the quality of the data. The accuracy of economic data in its many forms is analyzed in detail in the classic book by Morgenstern [1963a].[2] Although in thirty years the scale and the speed of collecting and processing economic data may have increased considerably (not the least because of the use of computers), it is the question whether the quality of the obtained data has improved in the same pace. This is predominantly a problem of non-financial market variables. Government data are often smoothed over time and frequently revised after initial publication. In addition, some economic series are averaged (for example, when the monthly datum is the average of daily data).[3]

---

2) The telling motto of the book (Morgenstern [1963a, p.2]) has lend itself to the title of a summary article, see Morgenstern [1963b]. The familiar 'garbage in, garbage out' principle applies.

3) Appendix 4.C deals with the spurious autocorrelation that emerges from averaging. This calls for a technical correction of the series that is different from the more economical correction for obtaining unexpected components.

Measuring relationships

In addition to measurement errors that are attached to data, there are estimation errors that result from processing historic data. This brings us to estimating the relationships between stock returns and the relevant factors. Where needed, auxiliary regressions will yield estimates of unexpected factor changes.[4] As noted above, the ordinary least squares output of the main regression of returns on unexpected factor changes (the generated residuals) then provides valid inferences.

In our empirical work, we will focus on finding statistical significant relationships. This implies that we are looking for sensitivities that significantly differ from zero. For the estimated sensitivities, we suggest applying a significance level of 10%. In contrast to what the bulk of econometric work may suggest, the appropriate level of significance is not some physical constant, determined at 5% or 1%. By applying some lower significance level, we do not run the risk of eliminating factors that may be useful in the conditional predictions.

Some comments on this point are in place. Although sensitivities of stocks or indices may significantly differ **from zero**, note that applying any generally accepted statistical significance level (i.e. up to 10%) will lead to the conclusion that these sensitivities do not differ significantly **from each other**. This raises the question whether we are better off with one estimate, identical for all indices or stocks, or that the differences between the estimated sensitivities possess some economic significance.

In (investment) practice, the usual statistical significance criteria are in this sense sometimes too strict. Consider a portfolio manager who can choose between two portfolios, A and B. Thesé portfolios are equivalent, except that the odds are three to one (i.e. in 75 out of 100 cases) that portfolio A will yield an expected return that will exceed portfolio's B expected return by 1% over the next year. From a purely statistical point of view, the 25% significance of the difference is hardly impressing. From an economic point of view, in contrast, the information on the mean return difference is meaningful and the

---

4) Most economic data series are integrated of order one. This implies that the levels of these variables exhibit large autocorrelation. The presence of autocorrelation in the regressors will induce spurious significant results (cf. Lovell [1983, p.7]). As already suggested by Morgenstern [1963a, pp.55ff], first differencing will make autocorrelated series less meaningless. Wasserfallen [1986] notes that differencing will also remove non-stationarities in economic data series. The issue of spurious regression results from non-differenced data is explored in depth by Granger & Newbold [1974], Plosser & Schwert [1978] and Harvey [1980].

portfolio manager will tend to prefer portfolio A over portfolio B.[5)]

The other extreme to strict statistical significance criteria is to consider the point estimates of the sensitivities as the 'true' values. Unfortunately, inspite of a large body of literature on estimation risk, it is common practice to ignore the errors that accompany estimated portfolio weights, performance measures and the like. We will take a middle position by contenting ourselves with a 10% significance level for testing sensitivities against zero and by considering sensitivities as point estimates in mutual comparisons.

Increasing the number of observations will ceteris paribus yield more efficient estimates. One way of doing this is increasing the frequency of observations (i.e. decreasing the length of the observation interval) given the length of a sample period. This introduces the problem of stability: are monthly estimated sensitivities equal to weekly or quarterly estimated sensitivities? An alternative is holding the length of the observation interval constant but increasing the length of the sample period. Unfortunately, when 'ceteris' are not 'paribus' in this case (which is very likely), non-stationarity will cause the estimated sensitivities to deteriorate.

Outline

The outline of this chapter is as follows. We start in section 4.2 by discussing the stock market data. Section 4.3 analyzes the relationship between stock returns and interest rates. We start with interest rates because of the obvious link with bond markets. Interest rates are considered (and indeed appear) to be important variables and many studies investigate their influence. This section intends to provide an illustration of the process of first constructing and estimating a factor model and then of linking the empirical results back to the theoretical framework of present value models. The issues as outlined above will be discussed. In section 4.4, the speed of the analysis is increased. We introduce additional factors and estimate a factor model in a multivariate context. Section 4.5 summarizes the chapter.

---

5) Reversely, we can imagine the case (for example a large scale event study) in which a mean return difference of .01% per year is detected with a significance of .01%. Here the statistical significance of the difference is very high, and its economical significance is quite low (although the mere finding of a statistical significant return difference may possess economic-theoretic significance).

4.2 THE STOCK MARKET DATA

Section 4.2.1 summarizes the stock market data we use in this chapter; a detailed presentation of these data is contained in Appendix 4.A.
Section 4.2.2 discusses the choice of the appropriate return definition; more details on that issue are presented in Appendix 4.B.

4.2.1 Stocks and indices

This section discusses the stock market data that will be used in the rest of the chapter. The discussion of the data on the factors will be postponed until the appropriate sections.

The stock market data base consists of two samples: monthly data on a set of individual common stocks and monthly data on a set of stock market (sub-) indices. The two samples, that span time periods of different length, give us flexibility in our empirical work.

Over the period 1970:1 through 1994:5, monthly price returns (corrected for stock dividends and stock splits) as well as total returns are available for a selection of 36 common stocks[6]. It concerns large capitalization stocks, more or less randomly drawn from various sectors.

Over the period 1980:1 through 1993:12, we have monthly data on 15 stock market (sub-) indices of the Central Bureau of Statistics (CBS). It concerns reinvestment indices and price indices, from which we computed total returns and price returns, respectively. In addition to 6 general stock market indices, there are 9 sector indices. We combined the sub-indices of Banking and Insurance into one single financial sector index. The remaining 8 sector indices are presented in Table 4.1.

The individual stocks are classified according to CBS-sector. As the CBS recognizes a sector 'oil & mining' but does not compute an index for it, we take one major oil stock (Royal Dutch) as representative for the oil sector.

From these two data sets, we constructed two sets of alternative sector indices. Using the sector classification of the individual stocks, we constructed equally-weighted sector indices for the period 1970 - 1994. The five internationals (Akzo, Hoogovens, Philips, Royal Dutch and Unilever) are combined into an equally-weighted internationals index. All 36 stocks are combined into an equally-weighted overall stock market index. In addition, we derived weighted indices. For each sector, we combined the stocks belonging to that sector into a portfolio whose (monthly total) return exhibits the maximum correlation with the return on the appropriate CBS sector index over the period 1980:2 - 1992:1. The portfolio weights are assumed to be constant and used to construct the

---

6) I thank the ABN-AMRO Bank who generously provided me with these stock return data.

time series of returns for the weighted sector indices over the period 1970:1 through 1994:5. Likewise, we derived a weighted internationals index and a weighted overall market index.

Table 4.1 summarizes the data. A detailed description of the data can be found in Appendix 4.A.

Table 4.1: The 8 sector indices and the 36 individual stocks. Monthly returns over the period 1970:1 - 1994:5 (293 observations). EW# and VW# denote equally weighted and derived ('value weighted') indices for sector #.

Sector:	Indices:		our number of stocks:
Consumer Goods	EW1	VW1	7
Capital Goods	EW2	VW2	4
Basic Goods	EW3	VW3	5
Construction	EW4	VW4	2
Transport & Communication	EW5	VW5	4
Non-Financial Services[a]	EW6	VW6	3
Trade	EW7	VW7	5
Banking & Insurance[b]	EW8	VW8	5
Oil	-	-	1
Internationals	EWint	VWint	5
Overall	EWall	VWall	36

[a] The non-financial services index consists only of publishing companies.
[b] Banking & Insurance is a (weighted) combination of the Banking index and the Insurance index. See Appendix 4.A.

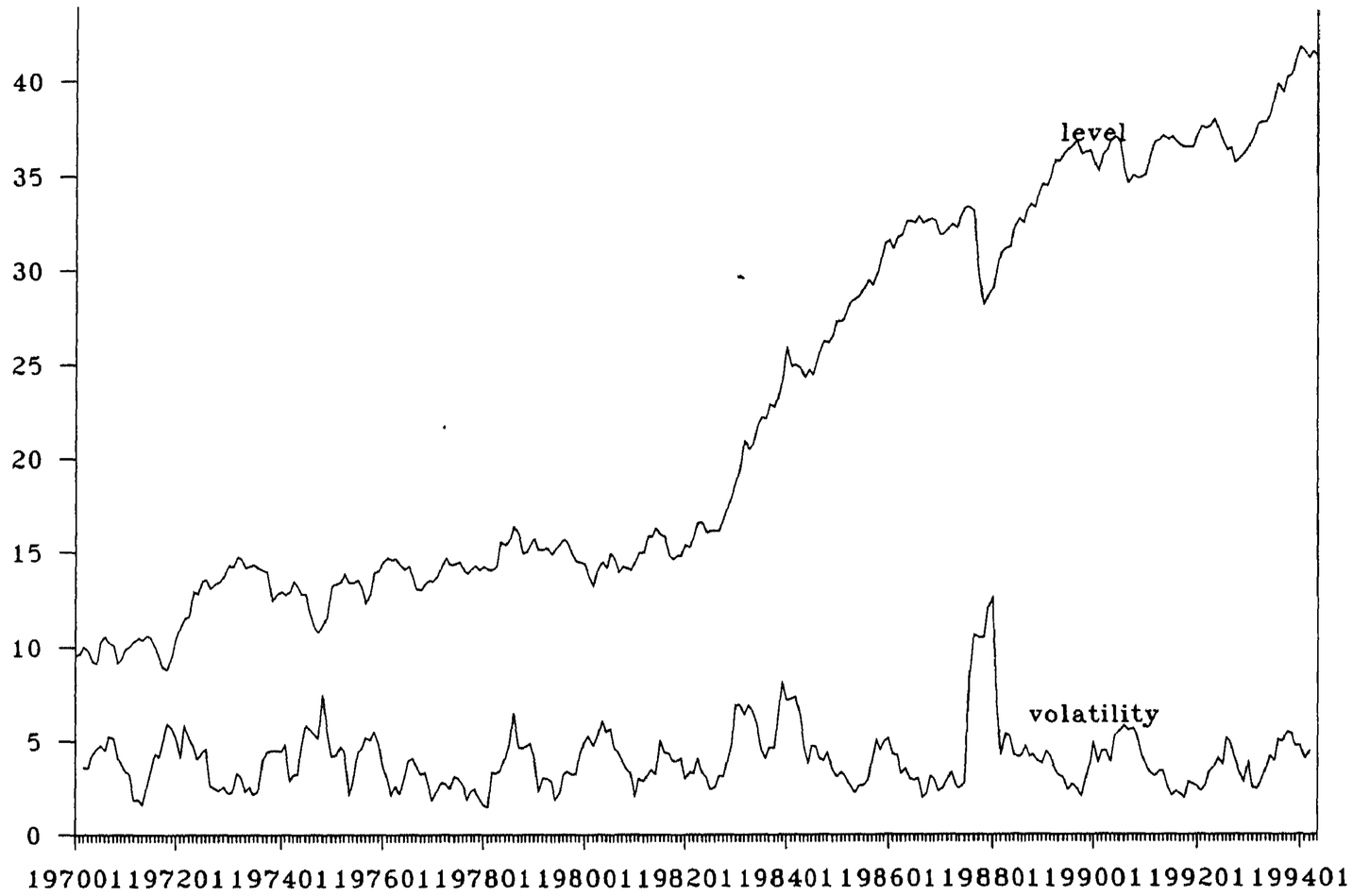
The course of the 36-stock equally weighted total return index is depicted in Figure 4.1. As shown, the logarithm of the level shows a moderate increase over the period 1970 - 1982. Over the remaining sample period, the mean return increases. The volatility is measured by the absolute value of the (log) returns, averaged over 6 months. For symmetric (finite variance) distributions, the expected value of this is a function of the standard deviation.[7)]

In our exploratory analyses, we examine the total returns on the equally weighted (sector and overall) indices. In this way, we feel that we eliminate the risk of missing factors that are only relevant for some subset of stocks and whose influence is washed out on a general market level. When the set of relevant factors is identified, we will also present results for the weighted indices and, later, for the individual stocks.

---

7) For normally distributed log returns $\underline{R} \sim N(\mu,\sigma)$, we have $E|\underline{R}-\mu| = \sigma \cdot (2/\pi)^{½}$ exact.

Figure 4.1: The level (in logs) and the volatility of the equally weighted total return index (EWall). The volatility for month t is measured by the average absolute log return over [t-3,t+2].



4.2.2 Choosing a return definition

Discrete-time portfolio analysis is cast in discretely compounded returns or 'percentage returns'. In empirical work, however, almost without exception continuous compounded returns or 'log returns' are used. The underlying reason is that it is expected that these returns provide a better approximation to the normal (or at least a symmetrical) distribution. The other side of the coin is that the log transformation of one plus the percentage returns (emanating from the continuous compounding) deprives the returns of their cross-sectional additivity. As a result, the portfolio log return is no longer a simple weighted average of the component securities' log returns.

The differences between the two return definitions is explored in Appendix 4.B. We find that a linearly weighted average of security log returns will understate the true portfolio log return and leads to a serious negative bias in mean returns. The results imply that the rash use of log returns in lieu of percentage returns in portfolio optimization can lead to erroneous results. However, when relating

security returns to other variables as is done in factor models, we are interested in the correlation between changes in the logs of the prices or factor values at one side and percentage changes in these prices or factors values on the other side, as well as in the correlation between true portfolio log returns at one side and linearly weighted average security log returns on the other side. As (by definition) the correlation coefficient is corrected for the different means and standard deviations of both types of returns, the apparent biases in means and standard deviations lose their relevance. Appendix 4.A confirms that the correlation between log returns and percentage returns will be very close to one. So from a **correlation** point of view, log returns can be substituted for percentage returns, even in a portfolio context. For this reason, we will use log returns (changes in logs) in the rest of this chapter.[8)]

4.3 THE RELATIONSHIP BETWEEN COMMON STOCK RETURNS AND INTEREST RATES

4.3.1 Introduction and summary

Inspired by the analysis of interest rate sensitivities of bonds, a profound attention is paid in the literature to estimate 'equity duration', as a measure for the (negative of the) sensitivity of common stock returns to interest rate changes. An appropriately defined equity duration is the basis for an adequate analysis and possible control of interest rate risk of stock portfolios. Observing institutional investors (like pension funds) in many countries extending their bond portfolios with increasing investments in stocks, incorporating an equity duration measure into the calculation of portfolio duration would be a further step towards the effective management of their assets.

In this section, we focus on the question how the empirical relationship between common stock returns and (nominal) interest rates can be moulded. In section 4.3.2, we review some empirical work on gauging equity duration.

Section 4.3.3 starts our empirical explorations (extending Hallerbach [1994c]). We use monthly data over the period 1970:1 through 1994:5. We first discuss the interest rate series. Special attention is devoted to the correction of the interest rate series for the spurious serial correlation that arises because part of the series consists of monthly averaged daily rates.

In section 4.3.4, we estimate interest rate sensitivities of sector indices. We find that the relevant interest rate information is

---

8) In forming the indices, as described in section 4.2.1 and Appendix 4.A, we used percentage returns.

contained in the Dutch long rate. The influence of the idiosyncratic US long rate and the short rates appears to be absent. The sensitivity of the overall weighted index is about -5.5, with an average explanatory power of over 10%. The overall period results are supplemented with analyses of stability and stationarity. We investigate the stability and stationarity of the relationships. In the more recent period 1979:10 - 1994:5, we find for the overall index a higher sensitivity of -6.5, accompanied by an explanatory power of 20%.

Section 4.3.5 explores non-linearities. There appears to be a convexity effect in that the sensitivities for interest rate decreases is larger (in absolute value) than for interest rate increases. A non-linear model adequately accounts for this convexity, especially over the sub-period 1979:10 - 1994:5, where the strength of the relationship between interest rates and stock returns is higher.

Section 4.3.6, finally, confronts empirical duration estimates and theoretical estimates. The conventional duration of the overall index is about 23. We relate to the theoretical analysis in section 3.5.3, which uncovered two biases in the conventional theoretical duration estimate. By taking the exogenous growth rate bias into account, the adjusted duration ranges from about 9 to about 12. This is in line with the empirical estimate of just over 9 (based on yearly returns).

4.3.2 Estimating 'equity duration': some empirical studies

In empirical studies, several approaches are followed to estimate the interest rate sensitivity of stocks. Stone [1974], Chance & Lane [1980], Lynge & Zumwalt [1980] and Chance [1982] establish an **indirect** relationship between stock returns and interest rate changes by regressing security returns on both a stock and a bond index. Leibowitz [1986] extends this approach to a multi-step procedure in which the interest rate sensitivity is estimated by combining the univariate (regression) relations between the stocks, a stock market index, a 'representative' bond market index and changes in its yield to maturity. For the period 1980-1985, he estimates an implied duration for the S&P-Index of 2.2. Johnson [1989], however, shows that this combination of univariate regressions raises statistical problems, resulting in a (downward) bias of the empirical duration estimates.

Aside from these indirect approaches, we have studies in which a **direct** relation between stock returns and interest rate changes is estimated. Haugen, Stroyny & Wichern [1978] estimate the interest elasticity of utility stocks as measured by the arc-elasticity over a period of two months (1970:12-1971:1). For the utility industry, they estimated an elasticity of approximately -10. From the estimation results reported by Joehnk & Petty [1980], we can infer that empirical interest rate sensitivities of various stocks (ranging from growth stocks to utilities) vary from approximately -1 to -13. These results

are in line with those of Hallerbach [1994c].

4.3.3 The interest rate series

In the next two sub-sections, we discuss the interest rate variables for the Netherlands and the US and their statistical properties. In section 4.3.3.A, attention is devoted to a technical correction of monthly averaged interest rate series. In section 4.3.3.B, we investigate the nature and relevance of a more economical correction for obtaining series of unexpected interest rate changes.

4.3.3.A The interest rate series for the Netherlands and the US

The Netherlands

The long term interest rate is proxied by the yield to maturity (redemption yield) of long term Dutch government bonds. From 1970:1 through 1979:12, it is the average yield on the three most recently issued long government bonds and from 1980:1 to 1994:5 it is the average yield on the five government bonds with the longest average remaining maturity. The series is provided partly by the DNB, the Dutch Central Bank (before 1981) and partly by the CBS, the Central Bureau of Statistics (from 1981:1 on).

The short term interest rate is proxied by the rate on 3-months lower government paper and provided by the DNB.

The later parts of both interest rate series consist of ultimo month rates. From 1970:1 through 1979:12 for the long rate and from 1970:1 through 1974:12 for the short rate, however, the data consist of monthly averages of daily observations. This averaging introduces a spurious first order moving average component in the first differences of the time series. Appendix 4.C deals with this effect and presents a method to correct for this spurious serial correlation. We used this method to filter the long and short interest rate over the relevant sub-periods. Note that this correction cannot add information to the series of averaged rates, in the sense that ultimo rates would be obtained. Instead, the filter removes a spurious (first order) predictable component in the series that would otherwise be picked up in the following stage of separating expected from unexpected rate changes. The filtering produces a series of 'quasi-ultimo rates' which in principle possess the same time series characteristics as actual ultimo rates.

For consistency with log returns (as indicated in section 4.2.2), we will use continuous compounded interest rates. Ultimo month t, the long and short interest rates for the Netherlands are indicated by RNL_t and RNS_t, respectively. The changes in the rates over period t are denoted

as ΔRNL_t and ΔRNS_t.

In order to account for a possible effect of changes in the slope of the term structure, we used the term spread RNL_t - RNS_t to construct the term structure variable:

(4.1) $\Delta TSN_t = \Delta RNL_t - \Delta RNS_t$

Given the long and the short rate, the term structure variable adds no information. For this reason, the long rate can be combined with either the short rate or the term structure variable. For the sake of completeness, we will provisionally consider all three interest variables.

For the Netherlands, the course of the long and short rate is depicted in Figure 4.2. The long rate starts at about 8%, raises primo 1978 sharply to almost 12% and then halves in the period to primo 1988. After increasing to about 9% in primo 1991, the rate starts its decrease to the level of 6% again. Primo 1994 marks the beginning of an increase.

From about primo 1983, the short rate follows the course of the long rate. Before that period, however, the short rate behaves very volatile. The sharp increase during the oil crisis in 1973-1974 is much more pronounced than for the long rate. The sharp peak in 1976:8 and 1976:9 (i.e. the rates primo september and october 1976) is due to the monetary policy of the DNB, supporting the guilder. Also more pronounced than for the long rate is the sharp increase and decrease over the period ultimo 1979 to ultimo 1982.

The US

The US long term interest rate is proxied by the yield to maturity of US Treasury Bonds with a remaining maturity of ten years and over. The US short term interest rate is proxied by the (annualized) discount rate on new issues of 3-month Treasury Bills, available from 1972:1 on. Both series are obtained from the OECD Main Economic Indicators Series.

Like parts of the Dutch interest rate data, the whole series consist of monthly averages of daily observations. We therefore corrected both series as indicated in Appendix 4.C. In addition, we converted the 3-month discount rate to an investment rate.[9)]

---

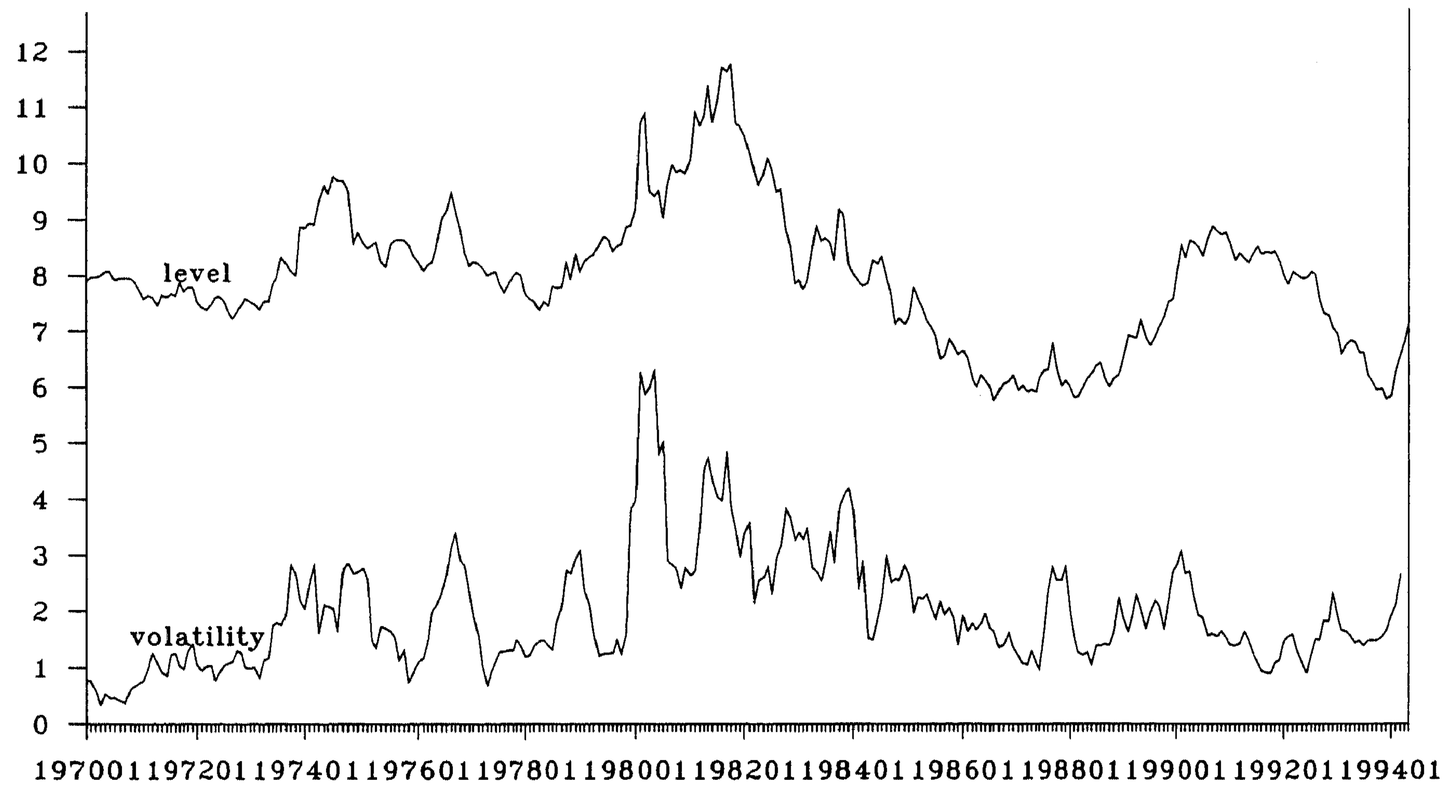
9) For simplicity, a discount rate ignores the compounding of interest rates and uses a 360-day year. A discount rate DR can be converted to a 'coupon equivalent yield' or an 'investment rate' IR by applying the formula:

$$IR = 365 \cdot DR / (360 - DR \cdot \#days)$$

where #days indicates the number of days to maturity (here 90) and where IR and DR are (annualized) perunages (cf. Rose [1986, p.351]).

Figure 4.2: The level and the volatility of the Dutch interest rates. The volatility for month t is measured by the average absolute change in the continuous compounded rate over [t-3,t+2] (×10 for E{|ΔRNL|} and ×2 for E{|ΔRNS|}).

Panel A: The Dutch long rate



Panel B: The Dutch short rate

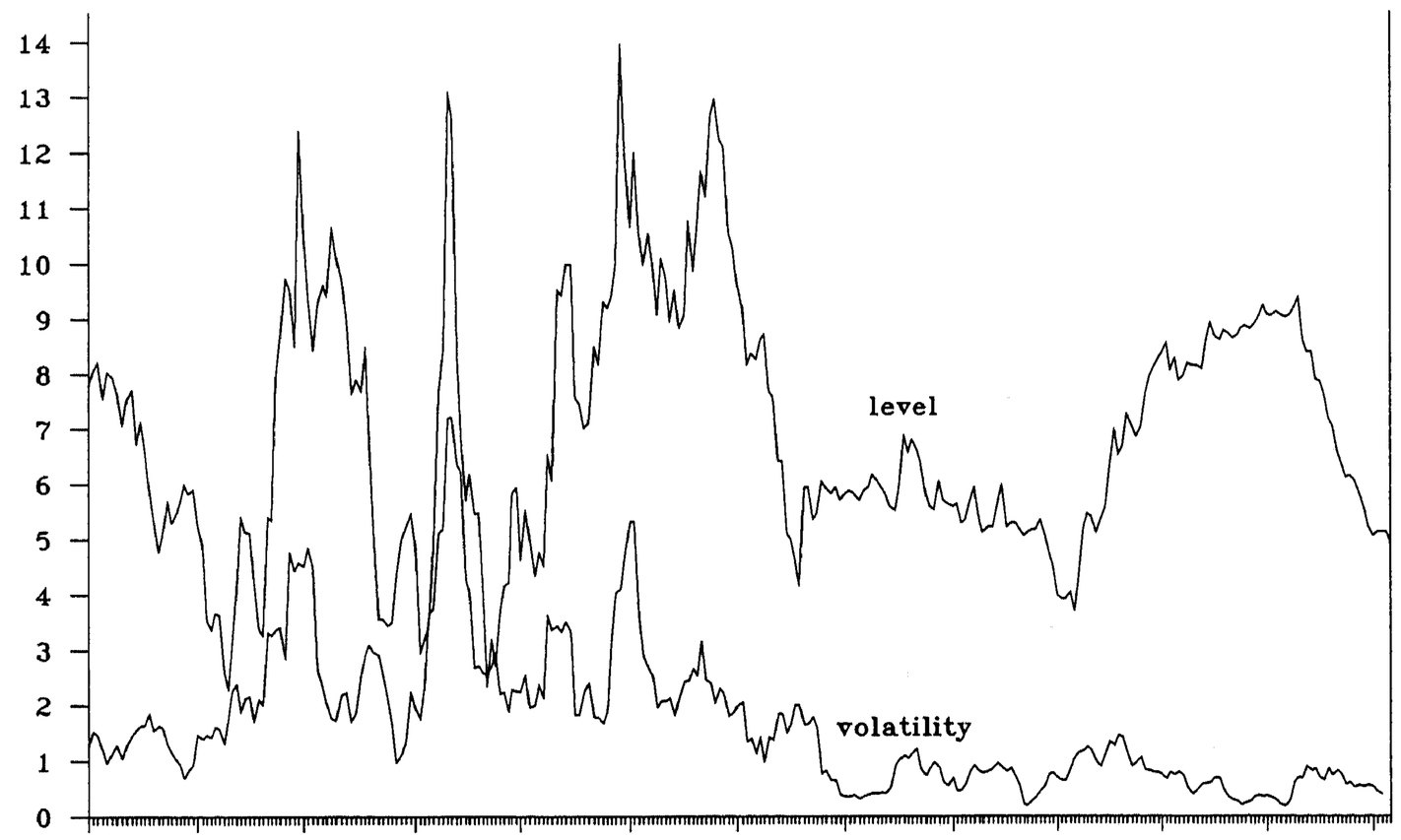
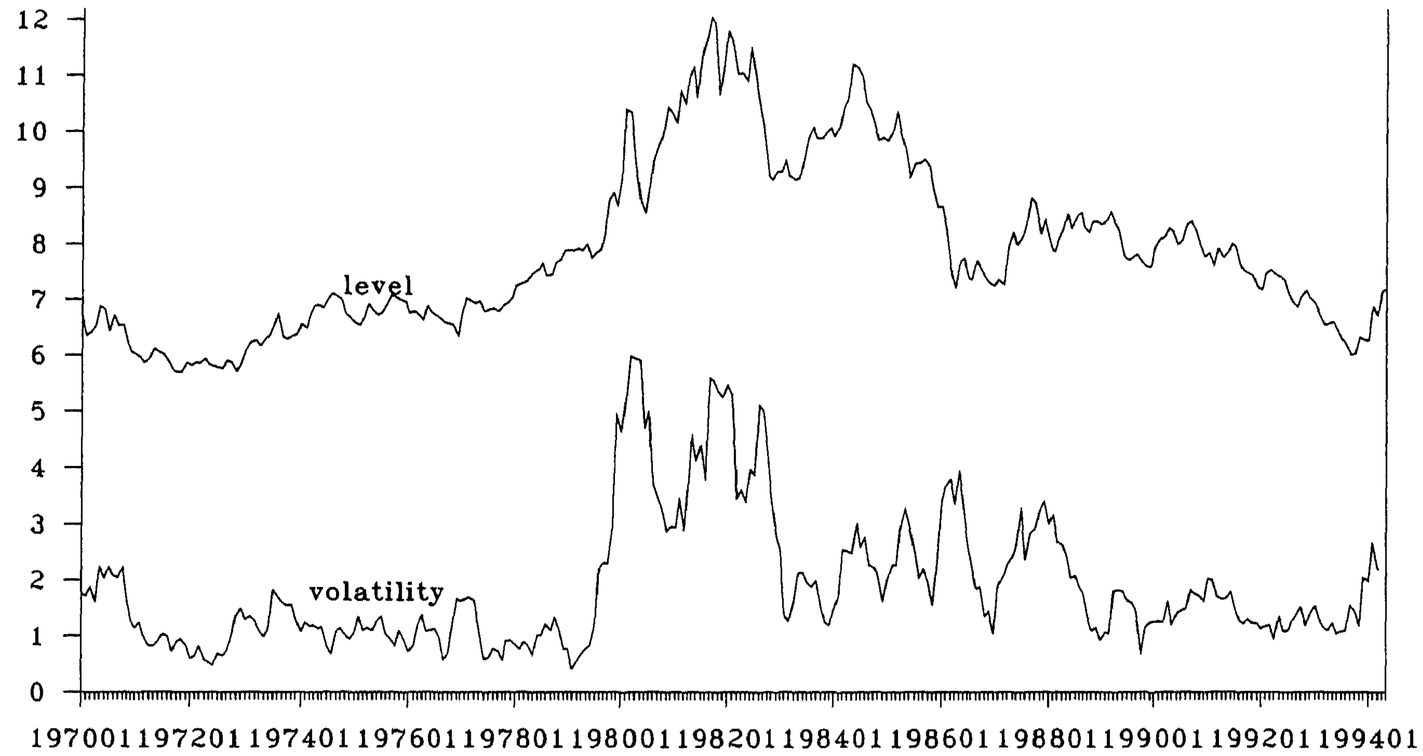
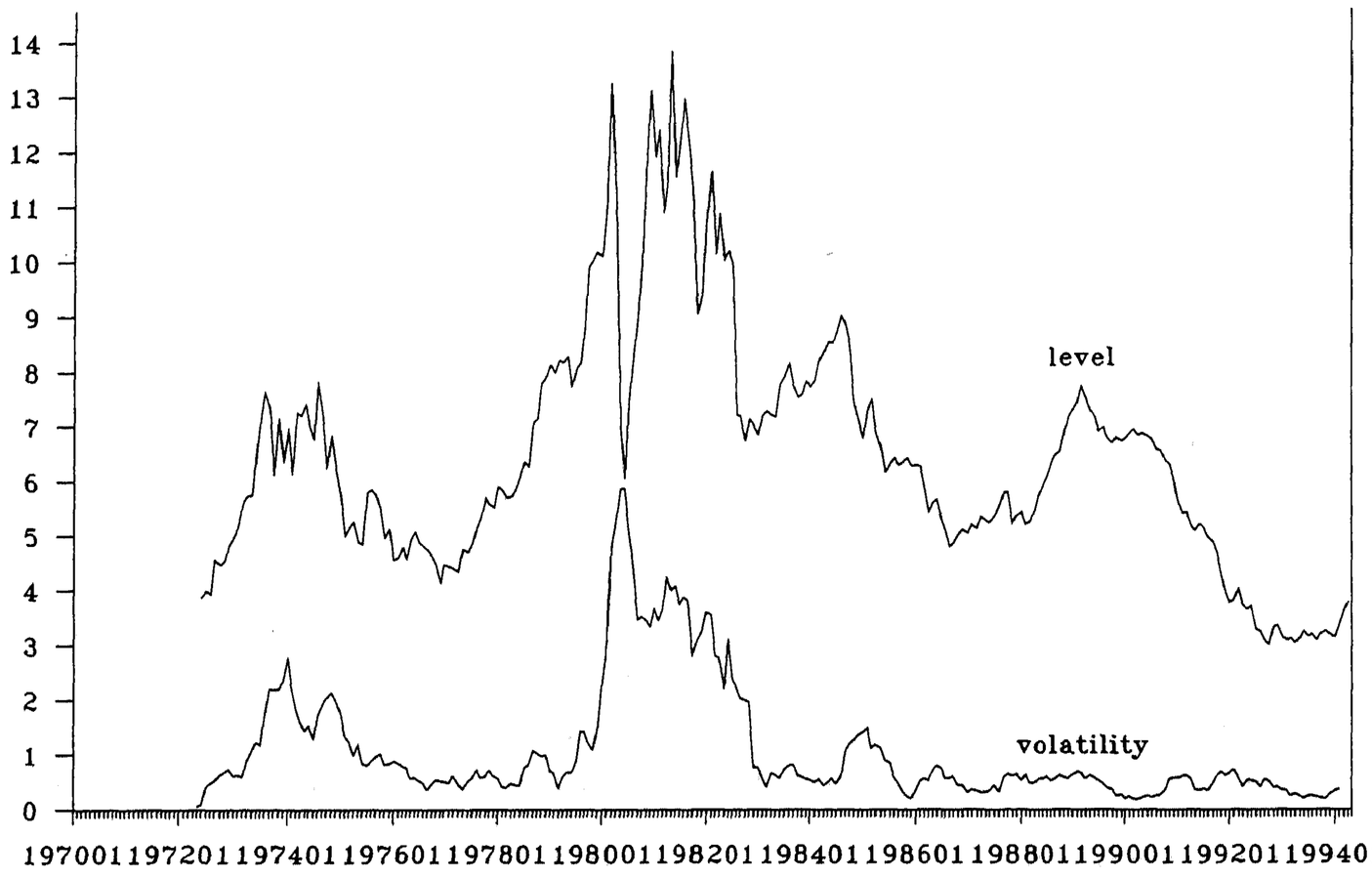


Figure 4.3: The level and the volatility of the US interest rates. The volatility for month t is measured by the average absolute change in the continuous compounded rate over [t-3,t+2] (×10 for E{|ΔRUL|} and ×3 for E{|ΔRUS|}).

Panel A: The US long rate



Panel B: The US short rate



The continuous compounded (corrected) US long and short rates ultimo month t are indicated by RUL_t and RUS_t, respectively. The US term spread TSU_t is RUL_t - RUS_t. In the following, we will consider the changes in these variables over period t: ΔRUL_t, ΔRUS_t and ΔTSU_t.

The course of the long and short rate for the US is depicted in Figure 4.3. The level of the US long rate resembles to some degree the course of its Dutch counterpart. Ultimo 1979, the level of the long rate sharply increases. Also the volatility peaks during the period ultimo 1979 to ultimo 1982. The incline of the level and the outburst in volatility during this period is even more clear for the short rate. Whereas the level of the long rate later declines, the volatility remains at a level higher than in the 1970's.

The graphs of the level and the volatility of the US rates (but also of the Dutch rates) clearly shows the abrupt change in the US Federal Reserve's monetary policy operating procedures. Prior to 1979:10, the monetary policy was oriented towards interest rate targeting. In 1979:10, operating procedures shifted towards unborrowed reserve targeting (directed at the supply of bank reserves). In addition, from 1979:10 through 1982:9, the Fed did not follow a federal funds rate stabilization procedure.[10)]

4.3.3.B Statistical properties of the interest rate series

The correction for spurious autocorrelation as discussed in section 4.3.3.A and Appendix 4.C is a purely technical issue. In order to estimate interest rate sensitivities of stock returns, also a correction of a more economical nature is appropriate. After all, in a fairly efficient market, the expectations with respect to interest rate changes are already incorporated in the market prices. Therefore, we are interested in decomposing interest rate changes into an expected component and a surprise component. Note that we are in this respect analyzing **changes** in the interest rates; modelling the properties of the interest rate **levels** is in this case not relevant.[11)]

Table 4.3 presents some descriptive statistics for the interest rate variables. The mean change is approximately zero and, as expected, the standard deviation of (changes in) the short rates are much higher than for the long rates. The Dutch interest rate changes show no auto-correlation. The US long rate shows significant first and second order autocorrelation and for the US short rate there appears to be some second order autocorrelation. Without exception, the **squares** of the rate changes exhibit considerable autocorrelation, indicating the presence of

---

10) See for example Simon [1990].

11) For a detailed analysis of the Dutch term structure of interest rates, we refer to Schotman [1989, Ch.1].

Table 4.3: Descriptive statistics of changes in the annualized interest rates and spreads (in %). Sample period 1970:1 - 1994:5. 293 observations (262 observations for ΔRUS and ΔTSU)

	mean	StdDev	[Min, Max]	autocorrelation order[a] 1	2	3	archQ*(6)[b]
ΔRNL	.00	.29	-1.40, 1.53	.062	-.068	.085	33.93
ΔRNS	-.01	.88	-4.28, 4.66	.029	.045	.037	60.87
ΔTSN	.01	.79	-4.33, 3.92	.014	.042	-.017	64.45
ΔRUL	.00	.27	-1.26, 1.26	.136	-.169	-.063	71.51
ΔRUS	.00	.62	-4.13, 2.40	.055	-.136	-.070	80.51
ΔTSU	.01	.52	-2.44, 3.46	-.047	-.141	.022	62.10

[a] Standard deviation of autocorrelations: .058 (.061 for ΔRUS and ΔTSU).
[b] LM-test for ARCH(6) type heteroskedasticity (modified Box-Pierce Q-statistic, $\chi^2(6)$), based on autocorrelations of the squares of the variable (see Harvey [1990, pp.212,223]). All significant at .1%.

autoregressive heteroskedasticity. The characteristics of the term structure variables are dominated by the characteristics of the short rates.

For interest rates, it is natural to consider a mean-reverting process:

$$(4.2) \qquad \underline{\Delta R\cdot}_t = a + b\, \underline{R\cdot}_{t-1} + \underline{e}_t$$

$$\text{with} \qquad E(\underline{e}_t) = 0,$$

where R· denotes any interest rate and where b is the mean-reversion parameter.[12] The residuals e_t are then estimates of the unexpected components of the interest rate changes. For the US long rate, instead, the (partial) autocorrelation functions suggest an AR(2)-process. The estimation results for the Dutch and US interest rate variables are presented in Panels A of Tables 4.4 and 4.5, respectively. Both the Dutch and US short rates and term spreads show a strong mean-reversion

[12] In a more familiar form, we have $\underline{\Delta R\cdot}_t = a' + b\,[\,\underline{R\cdot}_{t-1} - R\cdot^*\,]$ for a mean reverting process, where R·* is the long term average of $\underline{R\cdot}_t$. This can be rewritten as $\underline{\Delta R\cdot}_t = [\,a' - b\,R^*\,] + b\,\underline{R\cdot}_{t-1}$, which is (4.2). Estimating the mean-reversion in the form of (4.2) has the advantage that changes in the intercept a′ and in the long term average R·* are separated from changes in the mean-reversion parameter b. In this way, by introducing dummies for the slope and intercept, the stationarity of the mean-reversion process over different sub-periods can easily be analyzed.

effect; the Dutch long rate exhibits a weaker mean-reversion.[13] Changes of the US long rate are fitted to an AR(2)-process.

As noted in section 4.3.3.A, the changes in the US Fed's operating procedures (most notably in 1979:10 but also in 1982:10) had their repercussions on the level and volatility of interest rates. For this reason, we analyzed the stationarity of the estimated relationships over the sub-periods, suggested by the changes in US monetary policy.[14] For the interest rates, it then appeared that the estimated relationships heavily depend on the sub-period 1979:10-1982:9.[15] Given the relatively high volatility of the rates during that period and the significant autoregressive heteroskedasticity of the residuals (indicated by the archQ*(6) statistic), we decided to correct for the autoregressive conditional heteroskedasticity.

The estimation procedure is in the same spirit as the autoregressive standard deviation model, applied by Schwert [1989, pp.1117-1118; 1990, pp.82-83] and discussed in its general form by Davidian & Carroll [1987].[16] For each initial time series model (the main regressions), we estimate an autoregressive process for the absolute values of the (estimated) residuals:[17]

$$(4.3) \qquad |e_t| = = \theta_0 + \sum_{j=1}^{p} \theta_j \, |e_{t-j}| + u_t$$

The fitted values $|e_t| - u_t$ of this auxiliary regression are estimates for the conditional standard deviations of the residuals $\underline{e}_t$, given the

---

13) Over the period 1970:1 to 1979:12, the Dutch (corrected) long rate exhibits an even less pronounced mean reversion effect. Without the correction of the long term rate over this period (as discussed in section 4.3.3.A and Appendix 4.C), however, the mean reversion vanishes. In general, we would not expect a very strong mean-reversion effect as this would imply that bond returns were predictable to some extent.

14) We introduced some dummy variables for the sub-periods 1970:1-1979:9, 1979:10-1982:9, and 1982:10-1994:5 in the time series models. For the use of dummy variables to analyze stationarity (as to perform Chow tests), see for example Kennedy [1992, p.224].

15) Schotman [1989, pp.115ff] finds that his regression results heavily depend on the special character of the period 1979:10-1981:12. For the reason outlined above, we choose the sub-period 1979:10-1982:9.

16) This method is similar to the ARCH-model of Engle [1982]. However, Davidian & Carroll [1987, p.1088] suggest that a specification in standard deviations (absolute residuals) is more robust than a specification in variances (squared residuals). Furthermore, considering the robustness to possible departures from distributional assumptions and their relative computational simplicity, Davidian & Carroll (p.1083) tend to prefer (iterated) weighted regression methods over maximum likelihood estimation.

17) The appropriate number of lags p is determined from the autocorrelation functions of the squared residuals.

Table 4.4: Estimates of the mean reversion process for the Dutch interest rate variables. 293 observations.

Panel A: Main regressions for mean reversion:[a] $\Delta X_t = a + b\ X_{t-1}$

	initial				corrected		
	a	b	R^2/DW	archQ*(6)[b]	a	b	R^2/DW
RNL:	**.210**	**-.027**	**.013**	**34.01**	**.127**	**-.016**	**.005**
	1.91	-1.95	1.84		1.15	-1.13	1.81
	.057	.052		.000	.252	.260	
RNS:	**.508**	**-.075**	**.037**	**43.58**	**.196**	**-.027**	**.008**
	3.10	-3.33	1.87		1.53	-1.49	1.84
	.002	.001		.000	.128	.138	
TSN:	**.115**	**-.104**	**.052**	**43.70**	**.037**	**-.067**	**.031**
	2.19	-3.99	1.87		1.06	-3.12	1.84
	.029	.001		.000	.290	.002	

Panel B: Auxiliary regressions for autoregressive standard deviation (3rd iteration):[a] $|e_t| = \theta_0 + \sum \theta_j\ |e_{t-j}|$

	θ	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6	R^2
RNL:	**.120**	**.024**	**.123**	**-.022**	**.013**	**.132**	**.160**	**.067**
	4.26	.40	2.05	-.37	.212	2.20	2.65	3.20
	.000	.691	.041	.710	.830	.029	.008	.005
RNS:	**.216**	**.105**	**.303**	**-.016**	**.211**			**.210**
	3.69	1.78	5.12	-.27	3.58			18.30
	.003	.080	.000	.786	.000			.000
TSN:	**.168**	**.114**	**.318**	**-.075**	**.104**	**.067**	**.128**	**.223**
	3.06	1.88	5.21	-1.18	1.63	1.10	2.12	12.76
	.002	.062	.000	.240	.104	.274	.035	.000

[a] For coefficients: t- and p-values on second and third lines. For R^2: F- and p-value on second and third line.

[b] LM-test for ARCH(6) type heteroskedasticity (modified Box-Pierce Q-statistic, $\chi^2(6)$), based on the autocorrelations of the squared residuals (see Harvey [1990, pp.212,223]).

information available before month t. Next, the initial time series model is re-estimated using weighted least squares, where the residual conditional standard deviations serve as weights.[18] Davidian & Carroll [1987, p.1085] suggest to repeat this process at least twice to obtain more efficient estimates, so we iterated three times between the original time series models (eq.(4.2) or the AR(2)-process) and the autoregressive standard deviation model eq.(4.3). The results of the auxiliary regressions (last iteration) are in Panels B of the Tables 4.4

18) When daily data were available, within-month standard deviations could be estimated and used in the weighted least squares estimation; cf. French, Schwert & Stambaugh [1987].

Table 4.5: Estimates of the models for the US interest rate variables. 293 observations for dRUL, 262 for dRUS and dTSU.

Panel A.1: Main regression for AR(2):[a] $\Delta X_t = a + b1\ \Delta X_{t-1} + b2\ \Delta X_{t-2}$

	initial					corrected			
	a	b1	b2	R^2/F/p	archQ*(6)[b]	a	b1	b2	R^2/F/p
ΔRUL:	.003	.162	-.193	.055	61.21	.010	.129	-.114	.019
	.17	2.81	-3.33	8.39		.82	1.89	-1.61	2.71
	.863	.005	.001	.000	.000	.413	.060	.109	.068

Panel A.2: Main regressions for mean reversion:[a] $\Delta X_t = a + b\ X_{t-1}$

	initial				corrected		
	a	b	R^2/DW	archQ*(6)[b]	a	b	R^2/DW
RUS:	**.258**	**-.040**	**.020**	**99.74**	**-.000**	**-.001**	**.000**
	2.16	-2.29	1.85		-.00	-.08	1.67
	.031	.023		.000	.999	.940	
TSU:	**.115**	**-.068**	**.033**	**63.19**	**.061**	**-.026**	**.008**
	2.37	-2.96	2.02		1.43	-1.43	1.92
	.019	.003		.000	.155	.155	

Panel B: Auxiliary regressions for autoregressive standard deviation (3rd iteration):[a] $|e_t| = \theta_0 + \sum \theta_j\ |e_{t-j}|$

	θ	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6	R^2
RUL:	**.071**	**.135**	**.164**	**.120**	**.207**			**.180**
	3.91	2.27	2.76	2.00	3.46			15.00
	.000	.024	.006	.046	.001			.000
RUS:	**.060**	**.239**	**.305**	**-.032**	**-.054**	**.141**	**.218**	**.402**
	1.66	3.77	4.74	-.48	-.81	2.21	3.48	26.51
	.099	.000	.000	.633	.418	.028	.001	.000
TSU:	**.068**	**.150**	**.292**	**.013**	**-.043**	**.127**	**.228**	**.310**
	2.04	2.37	4.63	.20	-.66	2.02	3.65	17.74
	.043	.019	.000	.844	.508	.045	.000	.000

[a,b] See Table 4.4.

and 4.5 and show high significance. Summing the slope coefficients indicates a volatility persistence of over 40% to 80%.

The results of the iterated weighted least squares estimations of the main regressions (last iteration) are in Panels A of the Tables 4.4 and 4.5 under the heading 'corrected'. We observe a decrease in the slope coefficients and (except for the Dutch term spread) a drastic decline of their significance. On the basis of these results, we conclude that, except for the Dutch term spread, all of the changes in

the interest rate variables can be considered as unexpected.[19)]

4.3.4 The interest rate sensitivities

This section reports results on estimating interest rate sensitivities for stocks. Except for the Dutch term spread, we treat the total changes in the interest rate variables as innovations. In order to eliminate the effect of the 1987 stock market crash, we deleted the months 1987:10 and 1987:11 from the sample when estimating interest sensitivities. In our exploratory analyses, we examine the total returns on the equally weighted sector and overall indices. This reduces the risk of missing factors whose influence is more or less sector specific. In a later stage, we will also present results for the weighted sector indices and the individual stocks.

From the last section, we are left with four interest rate variables. Section 4.3.4.A deals with the question whether all of these variables are important in their effect on stock returns, or whether there is one particular variable whose influence surpasses that of the other variables. The stability and stationarity of the estimated relationships are considered in sections 4.3.4.B and 4.3.4.C.

4.3.4.A The relative importance of the interest rate variables

As a first step in the process to delineate the set of relevant variables is to consider interest rate sensitivities in an univariate context. We ran univariate regressions of the equally weighted (sector and overall) total return indices against the interest rate variables. The results are reported in Table 4.6. Neither of the term structure variables (ΔTSU and the mean-reversion corrected ΔTSN) appeared to influence the stock returns. Therefore we do not report the results for these variables.

Without exception (and as expected), all sensitivities are negative. We see that changes in both the Dutch and the US long term interest rates do have a significant impact on stock returns. The sectors Publishing (EW6) and Banking & Insurance (EW8) experience the greatest sensitivity to changes in the Dutch long rate. Judged by R^2, the influence of interest rates is most important for the financial sector and the consumer goods industry (EW1). The sensitivities for changes in the US long rate are smaller, as is its relevance in explaining return variability. The latter applies even more to the impact of both the Dutch and the US short rates. In contrast to what one

---

19) We repeated the estimations of eq.(4.2) under the assumption that either $E(\underline{e}_t^2) = \sigma^2 \underline{R\cdot}_{t-1}$ (cf. Cox, Ingersoll & Ross [1985b]) or $E(\underline{e}_t^2) = \sigma^2 \underline{R\cdot}^2_{t-1}$ (cf. Chan, Karolyi, Longstaff & Sanders [1992, p.1213]). This yielded comparable results.

Table 4.6: Univariate regression coefficients and statistics. 291 observations (260 for ΔRUS).

	ΔRNL		ΔRNS		ΔRUL		ΔRUS	
	b/t/p	R^2/DW	b/t/p	R^2/DW	b/t/p	R^2/DW	b/t/p	R^2/DW
EW1	**-5.86**	**.109**	**-.94**	**.027**	**-4.88**	**.066**	**-1.01**	**.015**
	-5.95	1.85	-2.82	1.83	-4.53	1.81	-2.00	1.82
	.000		.005		.000		.046	
EW2	**-4.38**	**.035**	**-.58**	**.006**	**-3.12**	**.016**	**-1.19**	**.013**
	-3.25	1.57	-1.31	1.58	-2.15	1.57	-1.82	1.57
	.001		.192		.033		.070	
EW3	**-4.07**	**.028**	**-.39**	**.002**	**-2.45**	**.009**	**-.60**	**.003**
	-2.89	1.62	-.84	1.62	-1.62	1.61	-.85	1.60
	.004		.400		.107		.397	
EW4	**-6.26**	**.068**	**-.42**	**.003**	**-3.50**	**.019**	**-.15**	**.000**
	-4.61	1.89	-.92	1.83	-2.35	1.84	-.22	1.79
	.000		.358		.020		.829	
EW5	**-3.14**	**.020**	**-.83**	**.013**	**-2.74**	**.013**	**-.74**	**.005**
	-2.41	1.82	-1.95	1.82	-1.96	1.81	-1.15	1.80
	.017		.052		.051		.250	
EW6	**-6.88**	**.088**	**-1.11**	**.022**	**-4.75**	**.037**	**-1.31**	**.017**
	-5.29	1.67	-2.53	1.69	-3.33	1.63	-2.14	1.74
	.000		.012		.001		.034	
EW7	**-5.66**	**.070**	**-.73**	**.011**	**-4.42**	**.037**	**-.84**	**.007**
	-4.66	1.81	-1.80	1.79	-3.35	1.78	-1.36	1.80
	.000		.074		.001		.175	
EW8	**-6.67**	**.157**	**-.92**	**.028**	**-4.50**	**.063**	**-1.22**	**.025**
	-7.34	1.98	-2.90	1.93	-4.40	1.91	-2.58	1.92
	.000		.004		.000		.010	
EWint	**-3.83**	**.037**	**-.19**	**.001**	**-3.38**	**.025**	**-1.22**	**.018**
	-3.34	1.68	-.49	1.69	-2.74	1.67	-2.18	1.66
	.001		.626		.007		.030	
EWall	**-5.23**	**.092**	**-.74**	**.017**	**-3.81**	**.043**	**-.92**	**.014**
	-5.41	1.70	-2.26	1.69	-3.60	1.66	-1.88	1.68
	.000		.025		.000		.061	

may expect, the sensitivity of the internationals for the US long rate is among the lowest.

Long versus short rates

In order to reduce the number of variables, we first consider the relevance of long rates versus short rates. The irrelevance of the term structure variables (in which short rates dominate) and the results in Table 4.6 seem to point at a minor importance of short rates. Table 4.7 presents correlation coefficients between changes in the various interest rates. Both the Dutch and the US long and short rates share a significant proportion of their variance. To investigate whether the

Table 4.7: Correlations between the interest rate changes. ΔRX|Y is the component of changes in rate X uncorrelated with rate Y. 291 observations (260 where ΔRUL|US, ΔRUS or ΔRUS|UL is involved). p-values (2-sided test) below the coefficients.

	ΔRNL	ΔRNL|NS	ΔRNS	ΔRNS|NL	ΔRUL	ΔRUL|US	ΔRUS
ΔRNL|NS	**.886**						
	.000						
ΔRNS	**.463**	**.000**					
	.000	1					
ΔRNS|NL	**.000**	**-.463**	**.886**				
	1	.000	.000				
ΔRUL	**.500**	**.481**	**.160**	**-.081**			
	.000	.000	.006	.170			
ΔRUL|US	**.427**	**.411**	**.141**	**-.067**	**.829**		
	.000	.000	.023	.284	.000		
ΔRUS	**.280**	**.274**	**.085**	**-.053**	**.559**	**.000**	
	.000	.000	.174	.399	.000	1	
ΔRUS|UL	**-.006**	**-.003**	**-.009**	**-.006**	**.000**	**-.559**	**.829**
	.918	.964	.892	.920	1	.000	.000

Dutch short rate has explanatory power on its own, we ran the following auxiliary regressions:

$$\Delta RNL_t = .002 + .15\ \Delta RNS_t + \Delta RNL_t|NS_t \qquad (DW = 1.88)$$

$$\Delta RNS_t = -.011 + 1.42\ \Delta RNL_t + \Delta RNS_t|NL_t \qquad (DW = 1.97) \qquad (4.4)$$

where the residual ΔRNL|NS is the long rate, corrected for the short rate and ΔRNS|NL is the short rate corrected for the long rate (R^2=.215, slope t=8.89). We repeated the procedure for the US rates:

$$\Delta RUL_t = .007 + .25\ \Delta RUS_t + \Delta RUL_t|US_t \qquad (DW = 1.91)$$

$$\Delta RUS_t = -.008 + 1.25\ \Delta RUL_t + \Delta RUS_t|UL_t \qquad (DW = 2.13) \qquad (4.5)$$

Likewise, the residual ΔRUL|US (ΔRUS|UL) is the long (short) rate, corrected for the short (long) rate (R^2=.312, slope t=10.83).

For the Netherlands as well as for the US, we now have two pairs of mutually uncorrelated variables. Next, we regress the sector returns on the changes in the long rate ΔR·L and the corrected short rate ΔR·S|·L. In addition, we regress the returns on changes in the short rate ΔR·S and the corrected long rate ΔR·L|·S. Panels A and B of Table 4.8 contain the regression results for the Netherlands and the US, respectively. The overall picture that emerges is that when a long rate is corrected for the corresponding short rate, the long rates remain significant. However, when a short rate is corrected for the corresponding long rate, its significance disappears. This implies that

Table 4.8: Sensitivities for decomposed long and short rates (residuals from auxiliary regressions eqs.(4.4-5)).

Panel A: The Netherlands (coefficient/t/p and R^2/F/p):

	ΔRNS|NL	ΔRNL	ΔRNS	ΔRNL|NS	R^2	DW
EW1	**-.08**	**-5.86**	**-.94**	**-5.75**	**.109**	**1.86**
	-.21	-5.94	-2.94	-5.16	17.64	
	.831	.000	.004	.000	.000	
EW2	**.10**	**-4.38**	**-.58**	**-4.53**	**.035**	**1.57**
	.20	-3.24	-1.32	-2.96	5.27	
	.842	.001	.187	.003	.006	
EW3	**.28**	**-4.07**	**-.39**	**-4.47**	**.029**	**1.62**
	.55	-2.89	-.85	-2.81	4.32	
	.584	.004	.395	.005	.014	
EW4	**.67**	**-6.26**	**-.42**	**-7.21**	**.074**	**1.87**
	1.34	-4.61	-.95	-4.71	11.53	
	.183	.000	.341	.000	.000	
EW5	**-.46**	**-3.14**	**-.83**	**-2.49**	**.023**	**1.82**
	-.95	-2.41	-1.96	-1.69	3.35	
	.341	.017	.051	.092	.037	
EW6	**-.09**	**-6.89**	**-1.11**	**-6.75**	**.088**	**1.68**
	-.19	-5.28	-2.62	-4.59	13.96	
	.846	.000	.009	.000	.000	
EW7	**.15**	**-5.66**	**-.73**	**-5.88**	**.070**	**1.80**
	.35	-4.65	-1.85	-4.28	10.87	
	.730	.000	.066	.000	.000	
EW8	**.11**	**-6.67**	**-.92**	**-6.82**	**.158**	**1.98**
	.32	-7.33	-3.11	-6.65	26.92	
	.748	.000	.002	.000	.000	
EWint	**.50**	**-3.83**	**-.19**	**-4.55**	**.042**	**1.66**
	1.19	-3.34	-.50	-3.51	6.30	
	.236	.001	.620	.001	.002	
EWall	**.06**	**-5.23**	**-.74**	**-5.32**	**.092**	**1.70**
	.18	-5.40	-2.35	-4.87	14.58	
	.860	.000	.020	.000	.000	

(continued on next page)

changes in the long rates adequately capture the component of short rate changes that is relevant for stock returns. We conclude that an idiosyncratic influence of both short rates on stock returns is absent in this sample.

Dutch versus US rates

Restricting ourselves to long rates, Table 4.7 shows that these are also strongly correlated. To investigate whether either the Dutch or the US long rate has explanatory power on its own, we repeat the procedure. The

(Table 4.8 continued)

Panel B: The US (coefficient/t/p and R^2/F/p):

	ΔRUS|UL	ΔRUL	ΔRUS	ΔRUL|US	R^2	DW
EW1	**.41**	**-5.17**	**-1.01**	**-5.68**	**.082**	**1.85**
	.69	-4.73	-2.07	-4.31	11.44	
	.488	.000	.0394	.000	.000	
EW2	**-.50**	**-3.39**	**-1.19**	**-2.77**	**.022**	**1.58**
	-.64	-2.32	-1.83	-1.57	2.90	
	.526	.021	.069	.117	.057	
EW3	**.13**	**-2.75**	**-.60**	**-2.91**	**.012**	**1.60**
	.16	-1.75	-.85	-1.54	1.55	
	.876	.081	.396	.124	.214	
EW4	**1.03**	**-3.43**	**-.15**	**-4.71**	**.025**	**1.83**
	1.26	-2.26	-.22	-2.58	3.35	
	.209	.025	.827	.010	.037	
EW5	**-.14**	**-2.59**	**-.74**	**-2.42**	**.013**	**1.79**
	-.18	-1.80	-1.16	-1.40	1.64	
	.858	.073	.249	.164	.196	
EW6	**-.20**	**-4.71**	**-1.31**	**-4.46**	**.045**	**1.72**
	-.27	-3.47	-2.16	-2.72	6.04	
	.786	.001	.032	.007	.003	
EW7	**.40**	**-4.49**	**-.84**	**-5.00**	**.041**	**1.82**
	.55	-3.29	-1.38	-3.03	5.56	
	.583	.001	.168	.003	.004	
EW8	**-.10**	**-4.61**	**-1.22**	**-4.48**	**.072**	**1.94**
	-.18	-4.46	-2.64	-3.59	9.94	
	.856	.000	.009	.000	.000	
EWint	**-.39**	**-3.82**	**-1.22**	**-3.34**	**.037**	**1.65**
	-.58	-3.07	-2.20	-2.22	4.87	
	.562	.002	.029	.027	.008	
EWall	**.10**	**-3.95**	**-.92**	**-4.07**	**.050**	**1.69**
	.17	-3.68	-1.91	-3.15	6.78	
	.865	.000	.057	.002	.001	

auxiliary regressions are:

$$\Delta RNL_t = -.002 + .53\ \Delta RUL_t + \Delta RNL_t|UL_t \qquad (DW = 2.01)$$

$$\Delta RUL_t = .004 + .47\ \Delta RNL_t + \Delta RUL_t|NL_t \qquad (DW = 1.85) \qquad (4.6)$$

where the residual ΔRNL|UL is the Dutch long rate, corrected for the US long rate and ΔRUL|NL is the US long rate corrected for the Dutch long rate (R^2=.250, slope t=9.82). The results of the regression of the returns on the two sets of mutually uncorrelated variables are in Table 4.9. Except for one case (Transport & Communication), the influence of the Dutch long rate remains significant after correcting for the US rate. When in contrast the US rate is corrected for the Dutch rate, its significance vanishes in almost all cases. The Consumer Goods industry

Table 4.9: Sensitivities for decomposed Dutch and US long rates (residuals from auxiliary regressions eq.(4.6)). 291 observations.

Main regressions (coefficient/t/p and R^2/F/p):

	dRUL|NL	dRNL	dRUL	dRNL|UL	R^2	DW
EW1	**-2.34**	**-5.86**	**-4.88**	**-4.76**	**.120**	**1.84**
	-1.94	-5.97	-4.66	-4.21	19.71	
	.054	.000	.000	.000	.000	
EW2	**-1.05**	**-4.38**	**-3.12**	**-3.89**	**.037**	**1.57**
	-.63	-3.24	-2.17	-2.49	5.45	
	.530	.001	.031	.013	.005	
EW3	**-.38**	**-4.07**	**-2.45**	**-3.89**	**.028**	**1.62**
	-.22	-2.89	-1.63	-2.39	4.19	
	.829	.004	.104	.017	.028	
EW4	**-.21**	**-6.26**	**-3.50**	**-6.17**	**.068**	**1.89**
	-.12	-4.60	-2.41	-3.92	10.58	
	.902	.000	.017	.000	.000	
EW5	**-1.42**	**-3.14**	**-2.74**	**-2.48**	**.022**	**1.81**
	-.88	-2.41	-1.97	-1.64	3.28	
	.380	.017	.050	.102	.039	
EW6	**-1.44**	**-6.88**	**-4.75**	**-6.21**	**.091**	**1.66**
	-.90	-5.29	-3.42	-4.13	14.38	
	.371	.000	.001	.000	.000	
EW7	**-1.87**	**-5.66**	**-4.42**	**-4.79**	**.075**	**1.80**
	-1.25	-4.66	-3.41	-3.41	11.65	
	.213	.000	.001	.001	.000	
EW8	**-1.25**	**-6.67**	**-4.50**	**-6.08**	**.161**	**1.96**
	-1.12	-7.35	-4.64	-5.80	27.61	
	.263	.000	.000	.000	.000	
EWint	**-1.77**	**-3.83**	**-3.38**	**-3.00**	**.042**	**1.68**
	-1.26	-3.35	-2.76	-2.27	6.38	
	.210	.001	.006	.024	.002	
EWall	**-1.36**	**-5.23**	**-3.81**	**-4.59**	**.096**	**1.69**
	-1.14	-5.41	-3.69	-4.11	15.29	
	.254	.000	.000	.000	.000	

(EW1), a sector for which interest rates are relatively important, is an exception. When checking the individual stocks, we found that this is due to Unilever. This stock shows a highly significant sensitivity for the (uncorrected) US rate. As it has a dominant position in the first weighted sector index, this index also shows a significant (at 5%) US rate sensitivity. Because none of the other stocks (or combinations of them) show significant sensitivities for the corrected US rate, the US long rate cannot be considered as a general factor in this sample. In general, the movements in the Dutch long rate seem to adequately capture the component of US long rate movements that is relevant for stock returns. We conclude that for this sample, an idiosyncratic influence of

the US long rate on Dutch stock returns can be ruled out.[20)]

The selection of the Dutch long rate as the relevant interest rate variable is based on overall-period analyses. We repeated all the above estimations over the sub-periods 1970:1 - 1979:12 and 1980:1 - 1994:5. It appeared that the significance of the overall period relationships heavily depends on the last sub-period. Compared to the first sub-period, the correlation between the Dutch and US long rates is much higher in the latter period. The estimation results fully confirm the above conclusion that an idiosyncratic influence of the US long rate on Dutch stock returns is absent in this sample. Later we will return to the issue of stationarity.

The interest rate sensitivities of the indices

As the Dutch long term interest rate can be considered as the relevant interest rate variable, we can refer to Table 4.6 for the sensitivities of the equally weighted indices. Table 4.10 presents the sensitivities of the weighted indices. As the total returns and the price returns of the indices VW2, VW3, VW6, VWint and VWall exhibit a weak but significant (at the 5% level) positive first order serial correlation, we estimated the regressions according to the Prais-Winsten method.[21)]

The sensitivities of the weighted indices show roughly the same pattern as those of the unweighted indices. The financial and the publishing sector rank highest and the internationals and building & construction rank lowest. The ability of the interest rate to explain stock returns (although *ex post*) is especially high for the consumer goods and financial sectors; it is low for the capital goods and transport & communication sectors.

In all but one case, the interest rate sensitivities of price returns tend to be higher than those of the total returns, but in general the difference is not large. Also the explanatory power tends to be somewhat higher for price returns. Including the exceptionally large negative returns of 1987:10 and, to some lesser degree, 1987:11 in the sample, we observe major changes. The sensitivity of the overall index declines with almost 20% and the explanatory power almost halves. So even for a large sample as this, the influence of a few observations can be considerable.

---

20) The returns of the equally weighted indices EW2, EW3, EW6, EWint and EWall exhibit a weak but significant (at the 5% level) positive first order autocorrelation. This translates into significant first order residual autocorrelation, as indicated by the DW statistics in Tables 4.8 & 4.9. Correcting for this, however, does not alter the conclusions.

21) This is the Cochrane-Orcutt method where the first observation is transformed in a special way; cf. Maddala [1977, p.278]

Table 4.10: The sensitivities of the weighted (sector) indices for changes in the Dutch long term interest rate.
1970:1-1994:5; 1987:10 & 1987:11 excluded. 291 observations.

	total returns			price returns		
	b	(t ; p)	R^2	b	(t ; p)	R^2
VW1	-5.76	(-5.83 ; .000)	.105	-5.81	(-5.80 ; .000)	.104
VW2[a]	-3.88	(-2.71 ; .007)	.025	-4.38	(-3.07 ; .002)	.032
VW3[a]	-4.29	(-2.94 ; .004)	.029	-4.54	(-3.13 ; .002)	.033
VW4	-6.16	(-4.83 ; .000)	.075	-6.60	(-5.11 ; .000)	.083
VW5	-3.25	(-2.36 ; .019)	.019	-3.60	(-2.58 ; .010)	.023
VW6[a]	-6.81	(-5.18 ; .000)	.085	-7.03	(-5.33 ; .000)	.090
VW7	-6.37	(-5.31 ; .000)	.089	-6.27	(-5.20 ; .000)	.085
VW8	-7.03	(-7.62 ; .000)	.167	-7.28	(-7.77 ; .000)	.173
VWint	-2.94	(-2.99 ; .003)	.030	-3.29	(-3.27 ; .001)	.036
VWall[a]	-5.60	(-6.17 ; .000)	.117	-5.82	(-6.31 ; .000)	.121
VWall[a,b]	-4.59	(-4.63 ; .000)	.069			

[a] Corrected for residual serial correlation by the Prais-Winsten method.
[b] Estimated including crash months 1987:10 & 1987:11.

4.3.4.B The stability of interest rate sensitivities

Until now, we used monthly returns. We therefore assumed a time horizon of one month. When extending the time horizon, say to three months, the issue of stability looms ahead. In order to analyse the stability of the sensitivities, we aggregated the monthly (total) returns into quarterly returns. We used three sets of quarterly returns, each starting in a different month. The series Q(1,4,7,10) starts in January 1970, Q(2,5,8,11) starts in February and Q(3,6,9,12) in March. The results for the weighted indices are in Table 4.11.

Comparing the results for Q(1,4,7,10) with Table 4.10, we see that (the absolute values of) the quarterly sensitivities tend to be somewhat larger than the one-month sensitivities. With one exception, this applies even more to the sensitivities estimated from Q(2,5,8,11). The sensitivities of the quarterly returns Q(3,6,9,12) however, are in general smaller. For the sectors basic goods (3) and transport & communication (5), and especially for capital goods (2) and the internationals, the sensitivities even seem to have disappeared. We do not have an explanation for this. In any case, this effect is not due to different standard deviations of the variables in the three series of quarterly returns. The same pattern emerges even when the variables are scaled by their standard deviations (this can simply be read from the R^2's). The series Q(2,5,8,11) not only exhibit the largest sensitivities, but also the largest correlations with interest rate

changes. The results for VWall over the sub-period 1979:10 - 1994:5 confirm this.[22)]

We conclude that it is dangerous and misleading to refer to 'the' interest rate sensitivity of quarterly returns, even when the total sample period is fixed. Although we do not report the results here, similar effects are present in half-year total return series.

For the weighted overall index, we also estimated interest rate sensitivities using sets of yearly returns, each set with a different starting month. The sensitivities vary over the months, with an average of -9.26 (average R^2=.209). The lowest values occur in the months in which (interim and closing) dividends are paid (November and May).

Table 4.11: The interest rate sensitivities of quarterly total returns. The returns are aggregated over quarters starting in 1970:1, 1970:2 and 1970:3, yielding 97, 96 and 97 observations, respectively. 1987:10 & 1987:11 are omitted.

	Q(1,4,7,10)		Q(2,5,8,11)		Q(3,6,9,12)	
	b	R^2	b	R^2	b	R^2
VW1	-6.82***	.122	-8.55***	.183	-4.18**	.060
VW2	-4.21	.018	-6.61**	.043	-.07	.000
VW3	-3.87	.017	-10.09***	.083	-1.91	.005
VW4	-6.67***	.077	-9.83***	.150	-7.66***	.117
VW5	-5.04*	.037	-4.23	.026	-1.33	.003
VW6	-8.71***	.105	-10.08***	.138	-7.42***	.088
VW7	-6.18**	.065	-8.53***	.124	-4.99**	.058
VW8	-7.99***	.193	-8.73***	.210	-5.41***	.117
VWint	-4.62***	.070	-5.96***	.101	-.52	.001
VWall	-6.54***	.111	-8.43***	.180	-3.97**	.058
VWall[a]	-4.89**	.073	-7.19***	.197	-4.25**	.101

Asterisks denote significance: * (10%), ** (5%) and *** (1%).
[a] Estimated over the period 1979:10 - 1994:5 (58 observations).

4.3.4.C The stationarity of interest rate sensitivities

We have the econometric aspect that there can exist no covariability without variability. When the volatility of the interest rate is low, especially compared to the noisy stock returns, we are not able to

22) Although the differences are apparent, it is much harder to attach statistical significance to them. Applying a formal (two-sided) t-test, only the coefficient -10.09 of VW3 in the series Q(2,5,8,11) is significantly different (at the 10% level, with t=1.68) from its value -4.29 in the monthly return series.

identify any possible relationship. The economic aspect is that when the volatility of the interest rate is relatively low, its role in the investors' relevant information set will be modest.

Considering the course of interest rate volatility as depicted in Figure 4.2.A, we would expect large differences in (the explanatory power) of the relationship between interest rate changes and stock returns. Table 4.12 reports the interest rate sensitivities of the overall weighted total return index in partly overlapping 48-month periods. In the period 1979 - 1983, when the level as well as the volatility of the long rate was high, we can indeed observe a relatively high degree of correlation between the index return and changes in the long rate. The increase in explanatory power from 1987 on is again accompanied by higher levels of the rate; however, it cannot be traced to a larger interest rate volatility now. Also in this period, we notice the increased magnitude of the sensitivities. On the whole, there seems to be no clear discernable general relationship between interest rate

Table 4.12: The interest rate sensitivity b of the overall weighted total return index in partly overlapping 48-month periods. OLS-estimation; in cases where rho (first order residual serial correlation) is reported, the Prais-Winsten procedure is used.

period	b	(t ; p)	R^2	DW	rho
1970:1 -1973:12	-4.42	(-1.12 ; .269)	.027	1.60	
1971:1 -1974:12	-1.54	(-.51 ; .610)	.006	1.33	
1972:1 -1975:12	-1.56	(-.47 ; .640)	.005	1.43	
1973:1 -1976:12	-1.82	(-.64 ; .524)	.009	1.43	
1974:1 -1977:12	-2.37	(-.77 ; .443)	.013	1.41	
1975:1 -1978:12	-4.28	(-1.41 ; .164)	.042	1.50	
1976:1 -1979:12	-5.30	(-2.40 ; .020)	.111	1.75	
1977:1 -1980:12	-6.30	(-5.16 ; .000)	.366	2.05	
1978:1 -1981:12	-4.63	(-3.81 ; .000)	.240	2.06	
1979:1 -1982:12	-5.43	(-5.32 ; .000)	.381	2.05	
1980:1 -1983:12	-5.14	(-4.56 ; .000)	.311	1.91	
1981:1 -1984:12	-4.86	(-2.89 ; .006)	.153	2.24	
1982:1 -1985:12	-6.08	(-3.11 ; .003)	.174	2.08	
1983:1 -1986:12	-6.29	(-2.60 ; .012)	.128	2.20	
1984:1 -1987:12[a]	-5.91	(-1.87 ; .068)	.074	2.09	
1985:1 -1988:12[a]	-2.78	(-.87 ; .388)	.017	2.01	
1986:1 -1989:12[a]	-4.38	(-1.37 ; .179)	.041	2.12	
1987:1 -1990:12[a]	-10.61	(-3.62 ; .001)	.234	1.83	.262
1988:1 -1991:12	-12.59	(-4.64 ; .000)	.324	1.93	.293
1989:1 -1992:12	-11.39	(-4.84 ; .000)	.342	2.01	.352
1990:1 -1993:12	-14.04	(-5.33 ; .000)	.381	1.57	
1991:1 -1994:5	-9.66	(-3.48 ; .001)	.237	1.91	
1979:10-1994:5[a]	-6.41	(-6.59 ; .000)	.201	1.89	

[a] Crash months 1987:10 & 1987:11 omitted.

volatility on the one hand and interest rate sensitivities and explanatory power of the 48-month periods on the other.

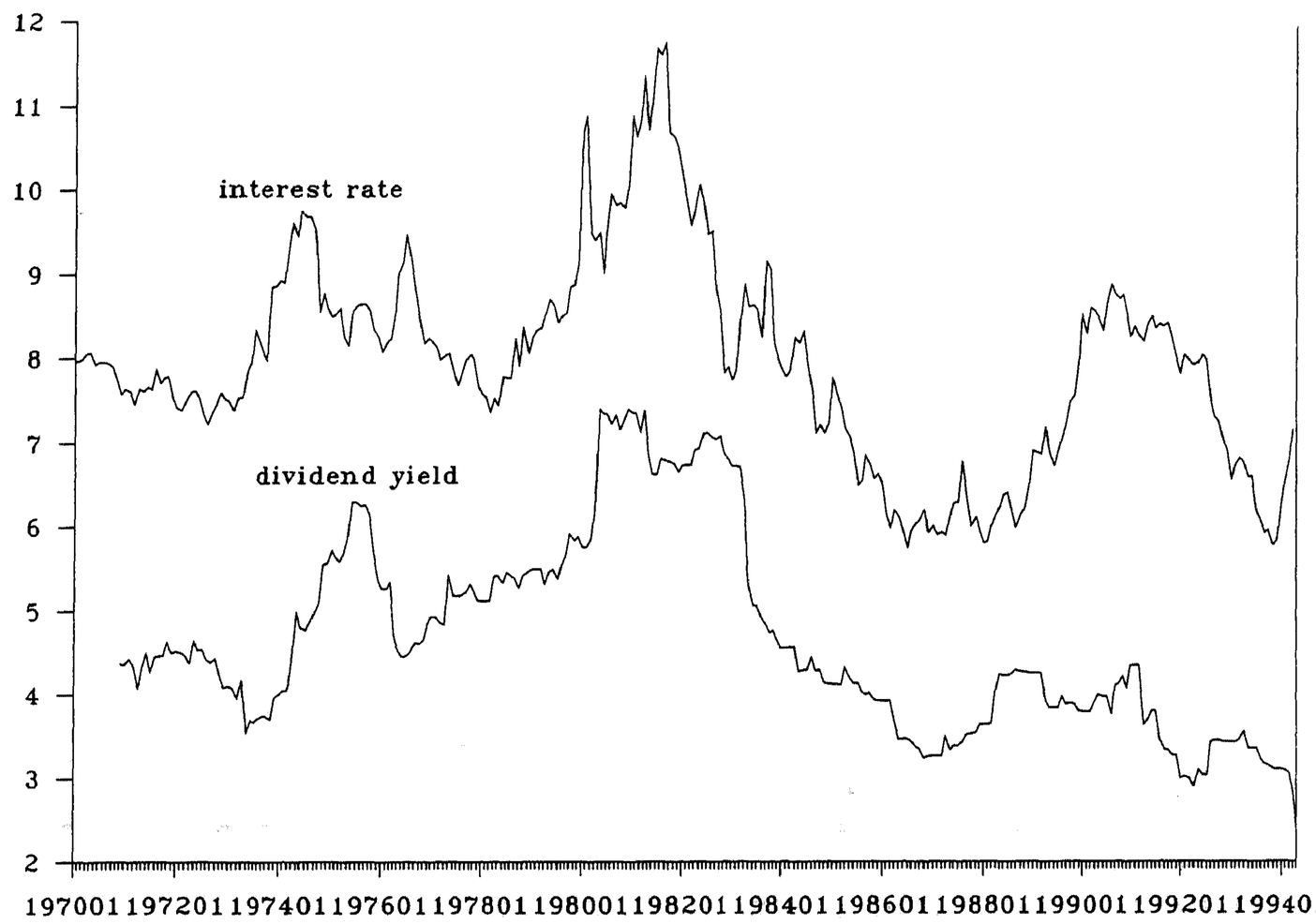
Compared to Table 4.10, the interest sensitivity increases from -5.60 to -6.41 when the period 1970:1 to 1979:9 is deleted from the sample. Not surprisingly, the increase in explanatory power is quite large. For the more recent sub-period 1979:10-1994:5, the long rate appears to be a pervasive variable on the stock market.

4.3.5 Non-linearities: equity convexity

As appeared from section 4.3.4.C, the empirical durations of the indices are by no means constant. Insofar the interest rate sensitivities are related to the interest rate level, convexity effects may occur.

In an informal way, the relationship between dividend yields and the interest rate level can be shown by plotting these variables over time. As the dividend yields are not evenly distributed over the

Figure 4.4: The level of the Dutch long term interest rate RNL_t and the aggregated (yearly) dividend yield ${}_{t-11}\delta_t$ of VWall (in %).



year[23], we compute the dividend yield on a yearly basis. For any month t, we aggregate the (log) dividend yields of the weighted overall index over the 11 preceding months and the current month, [t-11,t], into the yearly dividend yields ${}_{t-11}\delta_t$. Figure 4.4 shows that the dividend yield moves more or less in line with the interest rate. This is not surprising since investments tend to shift from low-yielding asset categories towards high-yielding asset categories. As a result, prices will adjust and, hence, the corresponding yields. The difference between the interest rate and the dividend yield[24] will be influenced by the expected capital gain on stocks (which incorporates its riskiness). A large expected price return allows the dividend yield to decline and vice versa.

To investigate the relationship between dividend yields and interest rate level more formally, we construct non-overlapping dividend yields. As the dividend yields concentrate in May, we aggregate the

Table 4.13: The relationship between the dividend yield, aggregated over each year from June through May, and the long interest rate. Estimates according to the Prais-Winsten procedure; rho is the residual first order serial correlation coefficient. 24 observations (t- and p-values between parentheses).

	annualized	mean (%)	standard deviation (%)
interest rate	RNL_t	8.02	1.23
	${}_{t-11}RNL_t$	7.97	1.18
dividend yield	${}_{t-11}\delta_t$	4.62	1.28

Panel A: The sensitivity of the yearly aggregated dividend yield for the long interest rate ultimo May

intercept	slope	R^2	DW	rho
.504 (.33 ; .740)	.506 (2.75 ; .012)	.264	2.06	.435

Panel B: The sensitivity of the yearly aggregated dividend yield for the long interest rate, averaged from June through May

intercept	slope	R^2	DW	rho
-1.54 (-1.11 ; .281)	.766 (4.44 ; .000)	.484	1.91	.585

23) In fact, the dividend yields concentrate in May (when the bulk of closing dividends is paid) and, to a lesser extent, in November (when most of the interim dividends are paid).

24) The difference between the interest rate and the dividend is indicated as the 'yield gap', whereas their ratio is sometimes called the 'yield ratio'.

yields over the calender periods from June through May. Starting ultimo 1971:5, Table 4.13 reports the sensitivity of the preceding year's dividend yield for the long interest rate ultimo May. The sensitivity is positive and significant. As can be seen, the sensitivity of the preceding year's cumulated dividend yield for the preceding year's **average** long interest rate, $_{t-11}RNL_t$, is even more pronounced.[25,26)]

As the conventional theoretical duration equals one plus the reciprocal of the dividend yield, this implies that the duration decreases when the interest rate increases and vice versa. This implies that the relationship between index (total) returns and changes in the interest rate is convex (as is the case for bond returns and changes in the yield to maturity). This convexity effect arises because of the discounting of the future (certainty equivalent) dividend stream at the interest rate. The question arises whether we can measure the convexity effect in the empirical interest rate sensitivity.

One way to capture a convexity effect is to allow for second order effects in the regression equation (a second order Taylor series expansion). Table 4.14 Panel A presents the estimation results; the contribution of squared interest rate changes is not significant, neither for the overall period nor for the sub-period from 1979:10 on. Repeating the calculations for the sector indices confirmed that the second order effect shows in general a positive sign, but is not significant.

Another route is to distinguish between the effect of interest rate increases and interest rate decreases. We define:

$$\Delta RNL^{+}_{t} \equiv \max[0, \Delta RNL_t] \qquad (4.7)$$
$$\Delta RNL^{-}_{t} \equiv \min[0, \Delta RNL_t]$$

Table 4.14 Panel A indeed shows a remarkable difference for the sensitivities to these variables. As the sensitivity for ΔRNL^{-} is much larger (more negative) than that for ΔRNL^{+}, this could be interpreted as a sign for a convex relationship between total returns and interest rate changes. The same effect can be observed in the sub-period from 1979:10

---

25) This slope is in line with the (significant) slope that results from regressing **monthly** dividend yields on ultimo rates (.0662, or .0662·12=.795 on a yearly basis). Because of the discontinuities in the dividend yields over the year, this is a somewhat 'messy' regression.

26) Renshaw [1989] and Spiro [1990] relate the dividend yield to the (real) short term interest rate (Treasury Bill rate). For the Netherlands, Veraart [1991] investigates the relationship between dividend yield, the long term interest rate and variables, related to solvability.

Table 4.14: The convexity effect in the empirical interest rate sensitivity of overall weighted total return index. OLS estimates according to the Prais-Winsten procedure. 1987:10 & 1987:11 omitted. 291 (174) observations in overall period (sub-period).

Panel A: Second order effects and asymmetry:
(t- and p-values below coefficients)

1970:1 - 1994:5					1979:10 - 1994:5				
ΔRNL	ΔRNL^2	ΔRNL^+	ΔRNL^-	R^2	ΔRNL	ΔRNL^2	ΔRNL^+	ΔRNL^-	R^2
-5.60				.117	-6.41				.201
-6.17					-6.59				
.000					.000				
-5.61	1.03			.119	-6.42	.47			.202
-6.18	.89				-6.58	.40			
.000	.373				.000	.691			
		-3.94	-7.34	.122			-5.63	-7.22	.203
		-2.57	-4.65				-3.36	-4.22	
		.011	.000				.001	.000	

Panel B: Non-linear regression estimates according to eq. (4.7):
(t-values, based on asymptotic standard errors, below coefficients)

1970:1 - 1994:5				1979:10 - 1994:5			
ΔRNL	ΔRNL^+	ΔRNL^-	R^{2*}	ΔRNL	ΔRNL^+	ΔRNL^-	R^{2*}
-5.72			.122	-6.30			.202
-6.39				-6.65			
	-4.36	-6.73	.125		-6.04	-6.49	.202
	-2.74	-4.77			-3.36	-4.30	

* Defined as 1 - (residual sum of squares)/(corrected sum of squares).

on, although the difference between the sensitivities is then lower.[27] Although the sensitivities for the decomposed rate changes do not differ significantly from either the total rate sensitivity or each other at a level of 10%, the evidence is very weak in terms of statistical significance. However, repeating the calculations for the sector indices

27) The monthly standard deviations of ΔRNL^+ and ΔRNL^- equal .180% and .174% in the overall period and .201% and .196% in the sub-period. This implies that the results are not due to different standard deviations of the regressors. Also note that the sensitivity for the overall changes ΔRNL is (indeed) approximately equal to the average of the sensitivities for ΔRNL^+ and ΔRNL^-.

showed that the sensitivities for ΔRNL^+ are (in absolute value) smaller than for ΔRNL^- and sometimes not even significant. This does point at the existence of a convexity effect.

Yet another way to capture a general convexity effect is by estimating the following non-linear equation:

$$(4.8) \qquad (\text{total return})_t = \frac{a_0}{1 - b \cdot \Delta RNL_t} - 1$$

As stated in Appendix 3.C, this relationship is exact for the Gordon growth model. To see whether in this framework the sensitivities for interest rate increases and decreases still show an asymmetry, we also estimated the equation:

$$(4.9) \qquad 1 + (\text{total return})_t = \frac{a_0}{1 - b^+ \cdot \Delta RNL^+_t - b^- \cdot \Delta RNL^-_t}$$

As Panel B of Table 4.14 shows, the modelling of the discounting convexity effect according to eq. (4.8) only yields a marginal improvement of the fit. Estimates of eq. (4.9) for the overall period show that the gap between the sensitivities for ΔRNL^- and ΔRNL^+ has decreased. In the sub-period from 1979:10 on, however, we clearly see that the non-linear formulation completely captures the asymmetric responses that appear to exist in the linear model.[28)]

On the whole, we conclude that there seems to exist a convexity effect in the responses of stock returns to interest rate changes. This effect materializes in an asymmetry between sensitivities for interest rate increases and decreases. The specification of a non-linear relationship between total returns and interest rate changes can account for the asymmetry between sensitivities for interest rate increases and decreases. This applies particularly to the period 1979:10 through 1994:5, which is most important for the relationship between stock returns and interest rate changes.

4.3.6 Confronting theoretical and empirical durations

4.3.6.A The theoretical equity duration

According to the Gordon growth model, the theoretical value of the conventional equity duration equals one plus the reciprocal of the

---

28) Note from Table 4.3 that singularities cannot occur.

dividend yield. We computed the monthly dividend yield of the weighted overall index as the difference between the total returns and the price returns (discretely compounded). Next we calculated the dividend yield on a yearly basis. Again, as the dividend yields concentrate in May, we aggregate each year the monthly (log) yields from June through May.

The average yearly dividend yield is 4.62%. The equity duration on the basis of this average yield is 22.65. Averaging the 'yearly' duration (i.e. one plus the reciprocal of the yearly dividend yield) results in a value of 24.31.[29)]

4.3.6.B Confronting theoretical and empirical durations

As we expected, the theoretical durations are well above the estimated duration of about 4½. In section 3.5.3, we discussed two shortcomings of the conventional equity duration formula. First, the impact of abnormal growth patterns is neglected and second, a relationship between the growth rate of the expected dividends and the interest rate is ignored. By focussing on the weighted overall index, we hope that the effects of abnormal growth opportunity are averaged out. We therefore confine ourselves to the last shortcoming.

When we tried to estimate the relationship between the growth rate of the expected dividends and the long term interest rate, we ran into a severe data problem. After all, this growth rate is unknown to us. As a remedy to this problem, we estimated the growth rate that is implied by the Gordon growth model in certainty equivalent form (cf. chapter three, eq.(3.64)):

$$(4.10) \qquad P_t = \frac{D_t (1+g'_t)}{r_t - g'_t}$$

where P_t is the ex-dividend value of the price index (immediately after the dividends D_t are paid), g'_t is the growth rate of the risk adjusted (certainty equivalent) future dividend stream and r_t is the long term risk free interest rate, all at time t. Assuming that (4.10) holds, we solve for g'_t and get:

$$(4.11) \qquad g'_t = \frac{r_t P_t - D_t}{P_t + D_t} = \frac{r_t - \delta_t}{1 + \delta_t}$$

where δ_t is again the current dividend yield of the index.

As the dividend yields are not spread equally over the months, we will consider yearly periods. The dividend yields clearly cumulate in May. As eq. (4.10) applies immediately after the stock has gone ex-

---

29) Because of Jensen's Inequality, the latter estimate will always be larger.

dividend, we use calender periods from June through May. For any yearly period, we computed the implied growth rate by using the ultimo May interest rate, r_t, and the dividend yields, aggregated over the preceding months June through May, ${}_{t-11}\delta_t$. In our sample, we finally have 24 implied growth rates for the June - May periods.[30)]

Although the actual closing dividends are mainly paid in May, they are announced some time before. This implies that ultimo April the informational content of the dividends will already be incorporated in the stock prices. The change of the stock prices in May, ceteris paribus, then only reflects the actual cash payment of the dividends. For this reason, we also considered the dividend yields aggregated over the 24 periods from May through April.

Relating the implied growth rate to the interest rate r_t seems at first sight as explaining the obvious but, as the dividend yield is related to the interest rate, it is not a tautology. From eq. (4.11), we have:

$$(4.12) \qquad \frac{\partial g'_t}{\partial r_t} = \frac{1}{1 + \delta_t} \left[1 - \frac{d\delta_t}{dr_t} (1 + g'_t) \right]$$

When the interest rates r_t are normally distributed, the mean value $E[\partial g'_t/\partial r_t]$ equals the regression coefficient of g'_t on r_t.[31)] For a first approximation to $E[\partial g'_t/\partial r_t]$, we ignore possible covariance effects and use the average yearly dividend yield, the yearly average implied growth rate and the interest rate sensitivity of the yearly dividend yield in eq.(4.12). As Panel A of Table 4.15 shows, the growth rate's interest rate sensitivity would be .455 for the June - May periods and .608 for the May - April periods. This indicates that, on average, a percentage point change of the interest rate goes together with a change of 45 to 60 basis points in the same direction of the growth rate.[32)] Panel B of Table 4.15 reports the results of a regression of g'_t on r_t. The theoretical estimates indeed correspond closely to the regression estimates.[33)]

---

30) Considering interim dividend payments, we repeated all calculations for the periods December through November. This yielded virtually identical results.

31) Cf. section 3.2.4.

32) From (4.10), the next year's certainty equivalent dividend yield is $\delta'_{t+1} \equiv D_t(1+g'_t)/P_t = r_t - g'_t$. This implies that $\partial g'_t/\partial r_t = 1 - \partial\delta'_{t+1}/\partial r_t$. Proxying $\partial\delta'_{t+1}/\partial r_t$ by the next period's actual dividend yield sensitivity $\partial\delta_{t+1}/\partial r_t$ yields estimates of $\partial g'_t/\partial r_t$ of .543 for the May-April periods and .484 for the June-May periods. Comparing the estimates over different yearly periods revealed that these estimates in general cluster more closely around 0.5.

33) Note that this does not imply the validity of the 'constant growth' model. It only confirms that the interest rate sensitivity of a specific combination of r_t and ${}_{t-11}\delta_t$ can be derived from combining the individual sensitivities.

Table 4.15: Estimating the adjusted interest rate sensitivity of the weighted overall index. Monthly data are aggregated over yearly periods running from May through April (23 observations) and from June through May (24 observations).

Panel A: Theoretical estimates for the implied growth rate's interest rate sensitivity and the adjusted index duration. Data partly from Table 4.13.

	May - April	June - May
$E[(1+_{t-11}\delta_t)^{-1}] \approx 1-E(_{t-11}\delta_t)$	.9538	.9538
$E(g'_t)$	.0314	.0326
$E(d\delta_t/dr_t)$ (regression estimate)	.352	.506
$E[\partial g'_t/\partial r_t]$ (from eq.(4.1))	.608	.455
adjusted index duration	8.81	12.16

Panel B: The empirical relationship between the implied growth rate g' (eq.(4.11) and the ultimo long term interest rate (annualized, in %). Estimates according to the Prais-Winsten procedure; rho is the residual first order serial correlation coefficient. t- and p-values between parentheses.

	intercept	slope	R^2	DW	rho
May - April:	-1.538	.611	.403	2.07	.711
	(-1.16 ; .261)	(3.77 ; .001)			
June - May:	-.395	.463	.236	2.05	.446
	(-.27 ; .792)	(2.55 ; .019)			

The effect of this positive relationship between the implied growth rate and the interest rate is that the conventional equity duration formula substantially overestimates the actual duration. The revised duration of the index, using eq. (3.80) of section 3.5.3, can now be estimated as about 12 for the June - May periods and almost 9 for the May - April periods. This means a significant reduction in the conventional estimate of over 22, but the difference with the monthly duration of 5.6 (see Table 4.10) is still substantial. However, from section 4.3.4.B we know that the sensitivities change with the horizon. So we should compare the estimates with the sensitivity based on yearly returns. As noted before, these **yearly** durations vary over the months, with an average value of 9.26. (This figure actually resembles the empirical monthly duration of the index over the period 1987:1-1994:5.) The differences between the empirical estimate of the duration and the adjusted theoretical estimate are now quite small. Especially the estimates based on the May - April periods match very closely.

We conclude that an equity duration measure that takes into account the relationship between the implied growth rate and the interest rate, can (at least partly) bridge the gap between the

conventional and the empirical duration estimates.[34] Because of the limited availability of data, we are constrained in our empirical analysis. However, the use of fundamental data, preferably combined with high frequency expectational data (for example analysts' expectations from I/B/E/S), would enhance the combination of theoretical models with empirical analyses.

4.4 TOWARDS A MULTI-FACTOR MODEL

In order to give a broader impression of the relationship between stock returns and economic variables, we extend the model to a multi-factor model by considering additional variables. Due to restrictions, posed by the availability of data, we now start the sample period in 1975.

We stress that this empirical analysis is primarily intended as an illustration for the influence of selected variables on Dutch stock returns. For a different study in this field, we refer to Hallerbach [1993b]. One can dispute our choice of variables and the methodology, but the specification of broad multi-factor models for the Dutch stock market in general is left for future research.

Considering the open economy of the Netherlands, the first additional variables we consider are exchange rates. We first have the US dollar / Dutch guilder exchange rate, US$. The continuous compounded changes in this variable can be considered as unanticipated. To incorporate the possible effects of other currencies, we also considered an effective exchange rate. This Dutch guilder effective exchange rate[35] is not only

---

34) In their theoretical analysis, Leibowitz & Kogelman [1993] resolve this 'equity duration paradox' by separating 'tangible value' (emanating from current businesses) from 'franchise value' (from future businesses). Tangible value is generated by a stream of more or less fixed (and hence predictable) cash flows and has consequently a high duration. Franchise value, in contrast, is generated by cash flows that possess high inflation flow through and has consequently a very low duration. Combining the two durations would yield an interest rate sensitivity more in line with empirical estimates. In our empirical work, we estimate the interest rate sensitivities of the growth rates of total dividends, i.e. the **combination** of tangible value and franchise value generating cash flows. Thus the different durations of the components of total value are weighted in the right proportion. See chapter three, section 3.5.3.B.

35) Source: National Government Series/Datastream. The effective exchange rate is a (geometric) weighted average of exchange rates with trading partner countries (expressed in a numeraire currency), where trade flows act as (positive) weights. Germany, France and the US have weights of about 30%, 12% and 12%, respectively. This can easily be checked by regressing the changes in the log effective (footnote continued on next page)

corrected for autocorrelation, but also orthogonalized with respect to the US dollar/guilder exchange rate (the correlation coefficient was 50%). In this sense, the changes in the effective exchange rate EXrate reflect unanticipated non-dollar currency effects. In addition, we considered oil prices (Oil) and Moody's index of commodity pices.[36] Both series are converted to unanticipated changes using ARIMA modelling.

We considered various additional variables, like (consumer) inflation and the real sector variables industrial production (manufacturing) and imports/exports volumina. In raw form, changes in these variables showed some significant correlations with the index returns. However, in 'surprise form' (i.e. after correcting the variables for serial dependencies), the influence of these variables either disappeared or was subsumed by the other variables mentioned above.

Table 4.16 contains the regression results. Royal Dutch is now added to the indices to represent the energy sector.

The proportions explained variance range from 13% to about 30%. This is quite in line with the results of the studies discussed in chapter two, section 2.5.2, and also compares with the figures of Roll [1988] and Fama [1990].[37] The signs of the sensitivities are conform our intuition. The influence of the interest rate variable and both the exchange rate variables is quite significant. Oil prices seem only relevant for two sectors (capital goods and basic goods). The significance of Moody's commodity prices is more general. Here the sensitivities of the basic goods sector is high, while the non-financial services sector shows no relationship.

Next, we consider the most recent 10-year subperiod. This allows us to incorporate a risk premium variable.

As proxy for a risk premium, we chose the return on the Merrill Lynch US long term high yield bond index of industrials (10 years and over).[38] As a measure for the risk premium, one can consider either the

---

exchange rate on the changes in the logs of the respective individual exchange rates. The regression coefficients then represent the average weights of these countries.

36) The oil price is proxied by the producer prices output of industry (crude petroleum). Both the oil price series and the Moody series are from Datastream.

37) Actually, Roll [1988] on the one hand investigates the explanatory power for individual stocks, but on the other hand considers a more detailed factor set: (factor analytically extracted) systematic factors, industry influences (size-matched industry portfolios) and specific firm news events. Fama [1990] focusses on the aggregate stock market but incorporates a.o. a variable like growth rates of production. Campbell & Ammer [1993] extend their results.

38) Source: Bloomberg/Merrill Lynch Global Bond Indices, High Yield Bond Indices). I thank IRIS BV for providing me with the Bloomberg data.

Table 4.16: The sensitivities of the total return indices for selected factors. Sample period 1975:2 - 1994:2 (1987:10 & 1987:11 excluded; 239 observations).
t- and p-values appear below the coefficients.

	const	RNL	US$	EXrate[a)]	Oil[b)]	Moody's	R^2 / DW
VW1	**1.55**	**-6.44**	**.38**	**1.18**	**-.02**	**.14**	**.257**
	5.68	-7.15	4.65	2.74	-.06	1.55	2.21
	.000	.000	.000	.007	.954	.124	
VW2	**1.00**	**-5.83**	**.52**	**2.16**	**-.37**	**.27**	**.149**
	2.19	-3.87	3.85	2.99	-.71	1.77	1.87
	.030	.000	.000	.003	.477	.078	
VW3	**1.40**	**-6.49**	**.61**	**2.89**	**-1.28**	**.34**	**.218**
	3.07	-4.33	4.55	4.04	-2.46	2.28	1.79
	.002	.000	.000	.000	.015	.024	
VW4	**1.46**	**-6.23**	**.43**	**.65**	**-.98**	**.14**	**.159**
	3.70	-4.76	3.66	1.04	-2.14	1.07	2.04
	.000	.000	.000	.299	.034	.284	
VW5	**1.30**	**-4.31**	**.55**	**1.63**	**-.41**	**.26**	**.131**
	2.99	-2.99	4.28	2.36	-.82	1.80	1.99
	.003	.003	.000	.019	.414	.074	
VW6	**1.95**	**-8.58**	**.30**	**.94**	**.04**	**.04**	**.205**
	5.25	-6.98	2.74	1.59	.08	.33	1.87
	.000	.000	.007	.113	.934	.744	
VW7	**1.67**	**-6.95**	**.40**	**1.33**	**-.49**	**.20**	**.190**
	4.53	-5.70	3.69	2.27	-1.15	1.66	1.94
	.000	.000	.000	.024	.252	.099	
VW8	**1.36**	**-7.85**	**.19**	**.75**	**.04**	**.14**	**.254**
	4.67	-8.14	2.15	1.62	.12	1.40	2.14
	.000	.000	.033	.107	.901	.163	
RD	**1.65**	**-2.91**	**.48**	**1.41**	**.45**	**.31**	**.163**
	4.90	-2.62	4.84	2.64	1.16	2.80	2.25
	.000	.010	.000	.009	.249	.006	
VWint	**1.61**	**-3.89**	**.49**	**1.48**	**.22**	**.28**	**.231**
	5.76	-4.20	5.88	3.33	.69	3.04	2.36
	.000	.000	.000	.001	.490	.003	
VWall	**1.49**	**-6.80**	**.38**	**1.36**	**-.23**	**.18**	**.308**
	5.83	-8.03	4.97	3.36	-.78	2.09	2.10
	.000	.000	.000	.001	.435	.038	

[a)] Corrected for changes in the US dollar.
[b)] The oil price sensitivities are multiplied by 10.

yield differential between (long term) low grade corporate bonds (LGCB) and long term government bonds, or the difference in their return. Since we have the combination of low grade bond returns and a long term 'risk free' interest rate, we decided to remove the risk free component of the bond returns by regressing them on the US long term interest rate (the correlation coefficient is 20%). The residual, denoted by RiskPr, is our

proxy for the risk premium.[39)]

Table 4.17: The sensitivities of the total return indices for selected factors. Sample period 1984:11 - 1994:2 (1987:10 & 1987:11 excluded; 109 observations).
t- and p-values appear below the coefficients.

	const	RNL	US$	EXrate	RiskPr[a)]	Oil[b)]	R^2 / DW
VW1	**1.94**	**-8.83**	**.25**	**1.00**	**.44**	**.26**	**.252**
	4.86	-4.39	2.00	1.64	1.35	.68	1.86
	.000	.000	.048	.104	.181	.498	
VW2	**1.22**	**-5.58**	**.07**	**2.68**	**1.65**	**.31**	**.185**
	1.72	-1.57	.33	2.49	2.86	.46	1.79
	.089	.121	.745	.015	.005	.648	
VW3	**2.28**	**-6.21**	**.16**	**2.95**	**1.27**	**-1.19**	**.282**
	3.94	-2.14	.89	3.36	2.70	-2.14	1.78
	.000	.035	.378	.001	.008	.035	
VW4	**2.09**	**-5.06**	**.40**	**1.17**	**.92**	**-1.28**	**.195**
	3.48	-1.68	2.11	1.28	1.87	-2.22	1.97
	.001	.096	.038	.203	.064	.029	
VW5	**1.90**	**-3.72**	**.33**	**1.58**	**1.40**	**-.31**	**.214**
	3.31	-1.29	1.80	1.80	2.99	-.56	1.65
	.001	.201	.074	.074	.004	.575	
VW6	**2.34**	**-8.51**	**.18**	**.62**	**.88**	**.42**	**.177**
	4.49	-3.26	1.10	.78	2.08	.84	2.07
	.000	.002	.272	.438	.040	.405	
VW7	**2.42**	**-6.67**	**.17**	**1.54**	**1.08**	**-.24**	**.236**
	5.14	-2.81	1.14	2.14	2.81	-.53	1.72
	.000	.006	.256	.034	.006	.600	
VW8	**1.66**	**-11.12**	**.24**	**.38**	**.56**	**.44**	**.302**
	4.12	-5.50	1.91	.61	1.72	1.13	2.02
	.000	.000	.059	.541	.089	.260	
RD	**1.80**	**-3.68**	**.37**	**.88**	**.97**	**.85**	**.335**
	5.03	-2.04	3.22	1.62	3.30	2.47	2.18
	.000	.044	.002	.109	.001	.015	
VWint	**1.83**	**-5.03**	**.33**	**1.11**	**.93**	**.61**	**.390**
	5.80	-3.17	3.33	2.31	3.60	2.00	2.05
	.000	.002	.001	.023	.000	.048	
VWall	**1.92**	**-8.32**	**.22**	**1.27**	**.83**	**.10**	**.351**
	5.53	-4.76	2.00	2.41	2.93	.30	1.81
	.000	.000	.049	.018	.004	.762	
CBSGXR	**1.71**	**-7.87**	**.22**	**1.13**	**.77**	**.16**	**.343**
	5.15	-4.70	2.11	2.23	2.83	.49	1.79
	.000	.000	.038	.028	.006	.627	

[a)] LGCB return corrected for changes in the long term US interest rate.
[b)] The oil price sensitivities are multiplied by 10.

[39)] We also considered the consumer confidence index (source: Datastream), which is available from 1988:4 on. Even when corrected for the effect of the Dutch consumer confidence index, the LGCB return exerted a significant influence on the index returns. As the latter variable is also available for a longer period, we decided to use the LGCB return series.

The estimation results are contained in Table 4.17. Again, the sensitivities are quite divers for the various indices. The financial sector is very sensitive to interest rate changes, in contrast to the transport sector. Especially the internationals, the transport sector and the building & construction sector are relatively sensitive for dollar risk, whereas the basis and capital goods industries show relatively large sensitivities to non-dollar currency surprises. Together with the transport sector, the latter sectors are highly sensitive to changes in the (US) risk premium. Note that the risk premium sensitivities are positive.[40] We observe both positive and negative responses to oil price changes. As expected, users show negative sensitivities, whereas notably Royal Dutch (also part of the internationals) displays a positive sensitivity. Moody's index appeared no longer relevant.

4.5 SUMMARY AND CONCLUSIONS

This chapter reported empirical investigations into factor models for the Dutch stock market. Referring to the caveat in the introduction, we did not intend to present the multi-factor model for Dutch stocks. The purpose of this chapter was first to illustrate the problems encountered in estimating factor models. Furthermore, we illustrated the process of constructing and estimating a factor model and then linking the empirical results back to the theoretical framework of present value models, as discussed in chapter three. These issues were treated for the case of interest rates. Finally, we introduced additional factors and estimated factor models in a multivariate context. This provides some insight in the nature of factors that work on the Amsterdam stock market. Finally, the estimation results of one of the models will serve as inputs for an illustration of the portfolio selection process, to be presented in chapter five.

The introduction contains reflections on factor models as risk models, and the incorporated factors. We discussed some problems attached to estimating unanticipated factor changes and deriving the identity of relevant factors. We made a distinction between financial market variables and non-financial market variables. The former variables are expected to better reflect economic information since they are traded on

---

40) Fama [1990, p.1091] uses a yield differential as a default spread measure. As a result, he finds **negative** coefficients for the risk premium variable. After all, an increase in the risk premium increases expected returns, hence lowers stock prices, resulting in a negative stock return (and *vice versa*). We use the return version of risk premium changes, which is negatively related to the yield measure.

liquid and competitive markets. Information is immediately processed, so that changes in these variables are largely or completely unanticipated. Furthermore, the data availability is much wider. Still, there are problems attached to these data, and in Appendix 4.C we presented a method to correct for the spurious autocorrelation in a series that emerges from averaging.

A troublesome point is that economic theory does not dictate the identity of the relvant variables. The number of those return generating variables is even still open.

After presenting the (original and derived) stock market data in section 4.2 and Appendix 4.A, we analyzed the relationship between stock returns and interest rates. We focussed on the question how this relationship empirically can be moulded. Using monthly data over the period 1970:1 through 1994:5, we found no evidence on the idiosyncratic influence of either the US long rate or the US and Dutch short rates. All interest rate information seemed to be captured by the Dutch long rate. The sensitivity of the overall weighted index for changes in this rate is about -5.5, with an average explanatory power of over 10%. The overall period results are supplemented with analyses of stability, stationarity, and non-linearities. We discussed several way to capture this asymmetric interest rate response effect. The model we presented in Appendix 3.D adequately accounted for this convexity effect. We finally confronted empirical duration estimates and theoretical estimates.

Section 4.4 enlarged the set of factors with two exchange rates, the US dollar / Dutch guilder exchange rate and a proxy for non-dollar currency effects. In addition, we considered oil prices and commodity prices. For the indices, the proportions explained variance range from 13% to about 30%., the influence of the interest rate variable and both the exchange rate variables being very significant. Oil price changes exert more specific influences on the indices, whereas the significance of Moody's commodity prices is more general, but low.

Limiting ourselves to the most recent 10-year subperiod, we were able to incorporate a risk premium variable in the model. This variable is derived from returns on US high yield bond indices and reflects (default) risk premia. Commodity prices appeared no longer relevant in this period, but the risk premium sensitivities are very significantly positive and quite divers for the various indices.

APPENDIX 4.A: THE STOCK MARKET DATA

This Appendix provides information about the stock market data.

Individual stocks

Table 4.A.1 shows the 36 individual stocks, grouped into CBS sectors. Options are traded on all stocks except Hoek's on the European Options Exchange. Unless stated otherwise, monthly total returns and price returns (corrected for stock dividends and stock splits) are available from 1970:1 through 1994:5 (source: ABN-AMRO Bank). For each month, the dividend yield is computed as the difference between the total return and the price return. Elsevier is only considered in the 1980 - 1994 sample. Some firms have merged during the sample period. To preserve these stocks in the sample, the returns on the individual stocks prior to the merger were weighted according to their market capitalizations immediately before the merger.

CBS (sector) indices

In addition to data on individual stocks over a long time period, we have data on stock market reinvestment and price (sector) indices over the period 1980:1 through 1993:12 (source: Central Bureau of Statistics, CBS). This allows us to compute total returns, price returns and dividend yields on these indices. In the set of CBS indices, there are 9 sector indices. We combined the sub-indices of 'Banking and Financial Services' and 'Insurance' into one single financial sector index, according to the folowing procedure. Using monthly returns over the period 1980:2 - 1992:1, we computed the composition of the portfolio of the initial 9 sector indices, whose return exhibits maximum correlation with the return on the overall index, the CBS-General Index (excluded Royal Dutch).[1)] The correlation between this tracking portfolio and the general index is 99.81% and the portfolio weights of 'Banking' and 'Insurance' are 14.57% and 12.89%, respectively. Hence, we combined 'Banking' and 'Insurance' according to the proportions 53.07% and 46.93% into the sector index 'Banking & Insurance'. This leaves us with 8 sector indices. We add Royal Dutch as representative for the oil sector.[2)]

---

1) We used the tracking procedure as developed in Hallerbach [1994b].
2) The CBS does not compute an index for the Oil & Mining sector.

Table 4.A.1: The 36 individual stocks, grouped into CBS sectors, and the composition of the derived sector indices. Internationals are indicated by an asterisk.

CBS sector / stock:	symbol:	derived sector indices: weights (%):	derived sector indices: correlation (%):
1. **Consumer goods industries:**	**·W1**		
1.1 ACF Holding	ACF	2.57	99.58
1.2 (Royal) Bols Wessanen	BSW	3.88	
1.3 CSM	CSM	2.27	
1.4 Gist-Brocades	GIS	4.10	
1.5 Heineken	HEI	15.52	
1.6 Nutricia	NUT	2.50	
1.7 Unilever*	UNI	69.16	
2. **Capital goods industries:**	**·W2**		
2.1 Fokker Aircraft	FOK	5.62	98.74
2.2 Océ - van der Grinten	OCE	5.99	
2.3 Philips Electronics*	PHI	81.75	
2.4 Stork	STO	6.64	
3. **Basic goods:**	**·W3**		
3.1 Akzo Nobel*	AKZ	58.54	98.67
3.2 Hoek's Machineries & Oxygen Factories	HOE	4.88	
3.3 (Royal) Hoogovens*	HO	15.94	
3.4 Hunter Douglas[a]	HDG	10.62	
3.5 (Royal) KNP BT	KKB	10.01	
4. **Construction & Building:**	**·W4**		
4.1 BAM	BAM	18.64	85.04
4.2 HBG	HBG	81.36	
5. **Transport & Communication:**	**·W5**		
5.1 KLM (Royal Dutch Airlines)	KLM	40.62	97.33
5.2 (Royal) Nedlloyd	NED	23.21	
5.3 (Royal) Pakhoed	PAK	15.80	
5.4 (Royal) Van Ommeren	VO	20.37	
6. **Non-financial services:**	**·W6**		
6.1 Telegraaf[a]	TEL	19.60	94.18
6.2 VNU	VNU	34.69	
(6.3 Elsevier)[b]	ELS	45.71	
7. **Trade:**	**·W7**		
7.1 (Royal) Ahold	AH	43.54	95.96
7.2 (Royal) Borsumij Wehry	BW	16.55	
7.3 Hagemeyer	HGM	10.10	
7.4 Internatio - Muller	IM	16.97	
7.5 (Royal) KBB	KBB	12.84	
8. **Banking & Insurance:**	**·W8**		
8.1 ABN-AMRO Bank	AAB	40.35	99.55
8.2 AEGON	AGN	11.89	
8.3 AMEV	AMV	11.21	
8.4 ING	ING	33.27	
8.5 Stad Rotterdam	SR	3.28	
9. **Oil:**			
9.1 Royal Dutch*	RD	-	-

* Internationals. [a] Available from 1971:11. [b] Available from 1979:1.

Derived indices

Apart from the explicit CBS indices, as discussed above, we constructed two sets of alternative sector indices by combining the information on the individual stocks and the sector (index) information. This allows us to extend the sector information to the period 1970 - 1979.

According to sector membership, we combined the individual stocks into equally-weighted sector indices for the period 1970 - 1994. These indices are denoted by **EW#**, where # indicates the sector number. In addition, we combined the five internationals (Akzo, Hoogovens, Philips, Royal Dutch and Unilever) into an equally-weighted internationals index, indicated as **EWint**. We combined all 36 stocks into an equally-weighted overall index, **EWall**.

Furthermore, we constructed weighted sector indices. Using (monthly) returns over the period 1980:2 - 1992:1, we computed for each sector the composition of the stock portfolio whose return exhibits maximum correlation with the return on the CBS sector index.[2)] Holding these portfolio weights constant, we constructed the time series of returns for the derived sector indices over the period 1970:1 - 1994:5. The derived ('value weighted') indices are denoted by **VW#**, where # again indicates the sector number. The portfolio weights and the correlation between the tracking portfolio and the sector index (over the period 1980:2 - 1992:1) are contained in Table 4.A.1. Except for sector 4, these correlations are very high. This indicates that the selected individual stocks and the derived sector indices are representative for the sectors.

Likewise, we constructed a weighted internationals index, **VWint**. This portfolio shows maximum correlation with the CBS Internationals index over the period 1980:2 - 1992:1. The derived portfolio of the internationals (portfolio weights between parentheses) Akzo (4.00%), Hoogovens (1.17%), Philips (9.28%), Royal Dutch (67.88%) and Unilever (17.67%) exhibits a correlation of 99.47% with the CBS Internationals index.

Finally, we computed a weighted overall index by combining the weighted sector indices in a way that the correlation with the CBS-General Index (excluded Royal Dutch) is maximized. This portfolio is indicated by **VWall**. The sector weights are presented in Table 4.A.2. Note the importance of the consumer goods industry and the financial sector. Over the period 1980:2 - 1992:1, the correlation of this derived portfolio with the actual general market index is only a fraction lower than the maximum attainable correlation between the actual sector indices and the actual general index (99.81%). So from the perspective of correlation, the weighted sector and overall indices are representative for the actual sector indices and the actual general index.

---

2) See footnote 1.

Table 4.A.2: The composition of the derived overall stock market index.

CBS sector	symbol:	weights (%):	correlation (%):
1. Consumer goods industries	VW1	32.11	99.38
2. Capital goods industries	VW2	13.67	
3. Basic goods	VW3	9.21	
4. Construction & Building	VW4	2.40	
5. Transport & Communication	VW5	4.99	
6. Non-financial services	VW6	6.76	
7. Trade	VW7	5.30	
8. Banking & Insurance	VW8	25.57	

APPENDIX 4.B: RETURN DEFINITIONS AND BIASES

This Appendix belongs to section 4.2.2: Choosing a return definition.

Discretely and continuously compounded returns

In portfolio theory (continuous time theory excepted), investment returns are measured by discretely compounded returns. These returns, also referred to as 'simple returns', 'percentage returns', 'holding period returns', 'investment relatives' or 'price relatives'[1)] , are defined by:

$$1 + r_{i,t} \equiv \frac{P_{i,t} + Div_{i,t}}{P_{i,t-1}}$$

where $P_{i,t}$ is the price of stock i at the end of month t and $Div_{i,t}$ the cash dividend, paid in month t.

The characteristic of percentage returns is that they can be aggregated linearly in cross-section: the return on a portfolio equals the weighted average of the returns on the included securities. This implies that when the individual random returns are drawn from a distribution that is closed under addition (i.e. a stable distribution like the normal), then the portfolio returns will follow the same distribution. Due to limited liability, however, the actual distribution of percentage returns will be truncated on the left by -100% and we expect it to be skewed to the right.

The emergence of continuous time models has shifted emphasis from discrete time random variables to continuous time diffusion processes, with lognormality for security prices in the stationary case. By the central limit theorem, lognormality of prices and price relatives is the only regular solution to any continuous space, infinitely-divisible (finite variance) process in time (Merton [1971, pp.387-388]). It implies that the log of one plus the percentage return is normally distributed. Furthermore, lognormality does invoke limited liability. The continuous compounded total stock return is computed as:

$$R_{i,t} = \ln\left[\frac{P_{i,t} + Div_{i,t}}{P_{i,t-1}}\right]$$

The log transformation of one plus the percentage returns, emanating from the continuous compounding, distributes the returns over the interval $(-\infty,+\infty)$ and is expected to yield a more symmetric distribution (i.e. a better approximation to the normal distribution).

---

1) Including cash disbursements in the numerator for total returns.

For this reason, almost without exception log returns (or 'growth rates') are used in empirical work. The characteristic of log returns is that they can be aggregated over time: the return over some multi-period time interval equals the sum of the returns over the spanned periods. This implies that when the single-period log returns are drawn from a distribution that is closed under addition, then the multi-period returns follow the same distribution.[2)]

Unfortunately, log returns cannot be aggregated linearly in cross-section: the log return on a portfolio does not equal the simple weighted average of the log returns on the included securities. The log return $\underline{R}_p$ on a portfolio p with investment weights $\{x_i\}_{i\epsilon p}$ can be computed by transforming security log returns $\underline{R}_i$ into percentage returns $\underline{r}_i$, aggregating the percentage returns into a discrete portfolio return $\underline{r}_p$ and then converting this back into a log return:

$$(4.B.1) \qquad \underline{R}_p \equiv \ln(1+\underline{r}_p) = \ln\{ \textstyle\sum_{i\epsilon p} x_i (1+\underline{r}_i) \}$$

$$= \ln\{ \textstyle\sum_{i\epsilon p} x_i \exp[\underline{R}_i] \}$$

(cf. eq.(2.16) section 2.2.2.C). This is clearly a non-linear function of the log returns of the component securities.[3)] The simple aggregation of the log returns,

$$(4.B.2) \qquad \underline{R}'_p = \textstyle\sum_i x_i \underline{R}_i$$

will understate the true portfolio log return: $\underline{R}'_p < \underline{R}_p$. After all, as the logarithmic function is strictly concave, we have by analogy with Jensen's Inequality that $\ln[E(\cdot)] > E[\ln(\cdot)]$. Eq.(4.B.1) and (4.B.2) are only equal up to a first order approximation.

In fact, we recognize the analogy with the issue of arithmetic mean indices versus geometric mean indices. Eq.(4.B.1) can be considered as the log return on a (value weighted) arithmetic mean index, whereas (4.B.2), the weighted average of log returns, reflects the log return on

---

2) Note that, with regard to the stability of return distributions, one must distinguish between the (linear) combination of returns over time and the (linear) combination of returns over some cross-section of securities. See also chapter two, footnote 18 (p.57).

3) Only under continuous portfolio rebalancing will lognormally distributed security price relatives be consistent with lognormally distributed portfolio price relatives (Merton [1971, pp.384-386]). Although Elton & Gruber [1974, p.1270 fn.12] recognize that security log returns are not additive in cross-section, they simply assume that the lognormal distribution is closed under addition. Ohlson & Ziemba [1976] and Schaible & Ziemba [1985] explicitly employ this simplifying assumption as a basic approximation. The empirical results of Dexter, Yu & Ziemba [1980] and Schaible & Ziemba [1985] lend support to the appropriateness of the approximation. Note that these authors are not concerned about the additivity of log returns (since they use simple returns in the portfolio analysis) but about additivity within lognormal distributions.

a (value weighted) geometric mean index. The percentage return on the latter index equals the (weighted) geometric average of the percentage returns of the component securities. Hodges & Schaefer [1974] argued that the arithmetic mean of log returns cannot be interpreted as a potentially attainable return on a continuously rebalanced, equally weighted portfolio. Modest & Sundaresan [1983, pp.17-20] and Brennan & Schwartz [1985] independently formalize this notion and explicitize the negative bias in the expected return on the geometric mean index.

Differences between discretely and continuously compounded returns

Given the dilemma between using percentage returns for portfolio analysis and using log returns for empirical work, we would like to know the relevant difference between the expressions (4.B.1) and (4.B.2). For analytical convenience, we assume that the security log returns $\underline{R}_i$ are distributed normally, with mean and variance:

$$(4.B.3) \qquad E\{\underline{R}_i\} = E\{\ln(1+\underline{r}_i)\} = \mu_i$$

$$(4.B.4) \qquad Var\{\underline{R}_i\} = Var\{\ln(1+\underline{r}_i)\} = \sigma^2_i.$$

Hence, one plus the percentage security returns are distributed lognormally with mean and variance:

$$(4.B.5) \qquad E\{1+\underline{r}_i\} = m_i = \exp(\mu_i + \tfrac{1}{2}\sigma^2_i)$$

$$(4.B.6) \qquad Var\{\underline{r}_i\} = s^2_i = m^2_i\,[\exp(\sigma^2_i)-1]$$

The negative bias from $m_i - 1 > \mu_i$ for $\sigma_i > 0$, as discussed above, is obvious. The difference in variance depends on the mean percentage return.

In general, it is contended that percentage returns and log returns are approximately equal when the range is limited to $-15\% \le \underline{r} \le 15\%$, and Fama [1976, pp.27,35-36] states that for daily and monthly data, the distributions of both returns have the same general properties. Nevertheless, serious differences can be observed between portfolio returns computed according to (4.B.1) or (4.B.2). To illustrate the bias that occurs when log returns are linearly combined to compute portfolio returns, Table 4.B.1 reports the means and standard deviations of the total returns on the all-sample equally-weighted return portfolio as well as their squared correlation coefficients. We see that the simple return exceeds the log return. As we expected, the aggregation of the log returns seriously understates the true portfolio log return. The volatility is slightly overstated. This implies that feeding a portfolio optimization program with log returns —so that eq.(4.B.2) is used— can lead to quite different 'solutions' compared to using percentage returns.

Table 4.B.1: Comparing monthly (total) portfolio returns: portfolio percentage return, portfolio log return and linearly aggregated log returns. Equally weighted portfolio (x_i=1/N). N = 36. Numbers in % over 1989:1 - 1993:12 (60 months).

	$r_p = \sum x_i r_i$	$R_p = \ln[\ 1 + \sum x_i \exp(R_i)\ ]$	$R'_p = \sum x_i R_i$
Mean:	1.296	1.174	0.973
Std dev.:	4.779	4.777	4.813
$(Corr)^2$:			
r_p		.999	.998
R_p			.999

The correlation between discretely and continuously compounded returns

However, when (cor-)relating security returns to other variables, as we intend to do, it is relevant to know how much variance is shared by log returns and percentage returns. This information is provided by the squared correlation coefficient. The covariance between both types of returns can be computed as:

$$\begin{aligned} (4.B.7) \qquad Cov\{1+\underline{r}_i, \underline{R}_i\} &= Cov\{\ \exp(\underline{R}_i), \underline{R}_i\ \} \\ &= E\{\exp(\underline{R}_i)\} \cdot Cov\{\underline{R}_i, \underline{R}_i\} \\ &= m_i \sigma^2_i \end{aligned}$$

where the second and third equality follow from applying Stein's Lemma (cf. Appendix 3.B to chapter 3) and applying eq.(4.B.5), respectively. Using eqs.(4.B.4) and (4.B.6), the correlation coefficient readily follows as:

$$(4.B.8) \qquad \rho(\underline{r}_i, \underline{R}_i) = \frac{\sigma_i}{[\exp(\sigma^2_i) - 1]^{1/2}}$$

(By definition, the correlation is corrected for the different means and standard deviations of the return types.) When the distributional assumptions are not satisfied, eq.(4.B.8) holds as an approximation.

For reasonable values for σ, ρ will be very close to one. For a security (or portfolio) with σ = 35% per year (i.e. 10% per month), for example, it follows that as much as 99.5% of the variance is shared by simple and log returns. Due to the high correlation, we can use the log security returns $\underline{R}_i$ to approximate (with negative error) the simple returns $\underline{r}_i$, compute their weighted average $\underline{r}_p$ and use this simple portfolio return as an approximation (but now with positive error) for

the portfolio log return $\underline{R}_p$. From Table 4.B.1 it appears that, from a **correlation** point of view, eq.(4.B.1) is indeed very well approximated by (4.B.2). In the rest of chapter 4, we will therefore use log returns (changes in logs).[4)]

---

4) It can be argued that a linear relationship between the logs of the price relatives and the logs of the other variables implies a multiplicative relationship between the price relatives and these other variables. Non-linearities are discussed in section 4.3.5.

APPENDIX 4.C: A CORRECTION FOR SPURIOUS SERIAL CORRELATION FROM AVERAGING.

This Appendix belongs to section 4.3.3.A and presents a method to correct for a spurious first order moving average component in the first differences of an averaged time series.

Averaging and spurious correlation

Over the sample period from 1970 to 1994, parts of the two Dutch interest rate series and all of the two US interest rate series consist of monthly averages of daily observations. As Working [1960] has shown, this averaging introduces a spurious first order serial correlation in the first differences of the time series. Now assume that the first differences of daily observations on an interest rate series are white noise with constant variance. When the interest rates are averaged over d trading days in each month, the first order serial correlation ρ_1 between these monthly differences $\Delta\underline{i}'_t \equiv \underline{i}'_t - \underline{i}'_{t-1}$ equals:

$$(4.C.1) \qquad \rho_1 = \frac{d^2 - 1}{2(2d^2+1)}$$

As Working [1960, p.918] notes, higher order serial correlation coefficients remain zero.

From Working's results, we infer that the differenced interest rate series $\Delta\underline{i}'_t$ follows a MA(1)-process:

$$(4.C.2) \qquad \Delta\underline{i}'_t = \underline{\varepsilon}_t + \alpha\underline{\varepsilon}_{t-1} = \underline{\varepsilon}_t[1+\alpha L]$$

where Δ is the backward difference operator, $\underline{i}'_t$ is the average of daily interest rates in month t, $\underline{\varepsilon}_t$ is a zero mean, serially uncorrelated and constant variance disturbance term, α is the moving average parameter and L is the lag operator, $L\Delta\underline{i}'_t = \Delta\underline{i}'_{t-1}$. Inverting the MA(1) into a AR(∞)-process[1], we have:

$$(4.C.3) \qquad \underline{\varepsilon}_t = \frac{\Delta\underline{i}'_t}{1+\alpha L} = \Delta\underline{i}'_t[1 - \alpha L + \alpha^2 L^2 - .....]$$

The variate $\underline{\varepsilon}_t$ now represents the monthly interest rate change, corrected for the spurious first order serial correlation:

---

[1] The first order serial correlation for the MA(1)-process (4.C.2) is $\rho_1 = \alpha/(1 + \alpha^2)$. As d has a lower bound of 2, it follows from (4.C.1) that $1/6 \leq \rho_1 < 1/4$. This in turn implies that $-.1623 \leq \alpha < .2679$. As $|\alpha| < 1$, invertibility of the MA(1) is guaranteed.

(4.C.4) $\quad \underline{\epsilon}_t = \Delta \underline{i}_t$

A correction[2)]

In order to perform this correction, we first determine the theoretical expected value of the spurious first order serial correlation. Assuming that there are on average d=21 trading days in a month, we have from eq. (4.C.1) $\rho_1 = .2492$.[3)] As the first order serial correlation for the MA(1)-process (4.C.2) is $\rho_1 = \alpha/(1 + \alpha^2)$, we have $\alpha = .2670$. We then compute the corrected series $\Delta \underline{i}_t$ according to eq. (4.C.3), truncated after five lags:

$$(4.C.5) \qquad \Delta \underline{i}_t = \Delta \underline{i}'_t - .2670 \cdot \Delta \underline{i}'_{t-1} + .0713 \cdot \Delta \underline{i}'_{t-2} - .0190 \cdot \Delta \underline{i}'_{t-3} + \\ + .0051 \cdot \Delta \underline{i}'_{t-4} - .0014 \cdot \Delta \underline{i}'_{t-5}$$

After applying this filter, the actual first order serial correlation of $\Delta \underline{i}_t$ is zero.

In our data, we started from the earliest available ultimo interest rate (or the last average rate for the US) and worked back using the corrected interest rate changes to construct the corrected interest rate level series $\underline{i}_t$. For the Dutch rates, we then combined the corrected averaged series over 1970:1 to 1974:12 (or 1979:12) with the ultimo series over 1975:1 (or 1980:1) to 1993:1.

As we use continuous compounded stock returns, we will also use continuous compounded interest rates $\underline{R}\cdot_t \equiv \ln(1+\underline{i}_t)$. The relative change in one plus the discretely compounded interest rate, $\Delta \underline{i}_t / (1+\underline{i}_{t-1})$, is thus proxied by the absolute change in the continuous compounded rate, $\Delta \underline{R}\cdot_t = \Delta \ln(1+\underline{i}_t)$.

---

2) It came later to our attention that Working's [1960] result inspired Praetz [1982, p.67] to perform some similar correction of his monthly averaged stock price index data.

3) The actual first order serial correlations for the Dutch long and short rates are .276 (.09) and .181 (.13), and for the US long and short rates .319 (.06) and .259 (.06), respectively (standard deviations between parentheses). As we only want to correct for the correlation that is induced by averaging, we used the theoretical value of ρ_1.