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TESTING THE EFFICIENT MARKET HYPOTHESIS OF THE HELSINKI STOCK EXCHANGE
Further empirical evidence based on nonlinear models

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Tiivistelmä – Referat – Abstract

In an Efficient Market prices adjust instantaneously toward their fundamental values, and trading volume contains no information about future price developments. However, the sequential arrival of information model implies a positive causal relation between absolute stock returns and trading volume in either direction, and the mixture model suggests a positive causal relation running from volume to absolute returns. Empirical evidence supports these theories, since large movements in stock prices typically take place on days with high trading volume. Here, we consider the relationship between stock return and trading volume using a nonlinear framework. First, nonlinearity in the Helsinki Stock Exchange data is tested using a STAR-model. Next, we compute nonlinear impulse responses; first to check the stability of the models, and second to scrutinize the persistence of shocks in return and volume series. Linear Granger causality tests indicate bidirectional causality between returns and volume. By contrast, the nonlinear causality tests suggest that only in a few cases can volume be used to forecast returns. Thus, the empirical findings give only slight support to the mixture model. Finally, we exploit the outcome of causality tests to specify a STVEC model in order to take into account the influence of the composition effect and common persistence on the results. We conclude that causality runs mainly from returns to trading volume, corroborating the positive feedback trading hypothesis.

There is a large body of empirical evidence that stock markets perform poorly during inflationary periods. Several explanations have been offered for this so-called “anomaly.” Here, we test the claim that the “spurious” negative correlation between stock returns and inflation is due to counter-cyclical monetary policy. We identify various regimes in the Finnish data using the MS-VAR model. When necessary, the existing long run relation-ships between the model variables are incorporated using the MS-VEC model. Using alternative sets of explanatory variables including measures for monetary policy stringency, we conclude that the sign of the relation between returns and inflation depends especially on the time horizon chosen. In monthly models the statistically significant contempo-raneous correlations between returns and inflation are always negative, but positive in the case of quarterly data. Stocks thus seem to be a good hedge against inflation in the long run. To be more specific, stocks seem to maintain protection against purely monetary inflation but fail to provide a hedge against inflation arising from real output shocks. Last, this is tested using the regime-dependent impulse response function.

Avainsanat – Nyckelord – Keywords

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Habe nun, ach! Philosophie, Juristerei, Theologie und Medizin und leider auch Volkswirtschaft durchaus studiert, mit heißem Bemühn. Da steh´ ich nun, ich armer Tor, und bin so klug als wie zuvor! Heiße Magister, heiße Doktor gar, und ziehe schon and die zehen Jahr´ herauf, herab und quer und krumm meinen Schüler an der Nase herum
- Und sehe, daß wir nichts wissen können!
Das will mir schier das Herz verbrennen.

Aus dem Faust
Johann Wolfgang von Goethe
1749 - 1832

Foreword

This thesis is dedicated to my grandmothers Aune Hakkarainen and Eeva Hytönen. Both of them were very strong women working their way through many obstacles. I hope I have inherited at least some of their strength.

Professor Matti Virén taught me to persist in doing empirical work while I worked as a research assistant for him. Without his example, I would probably have given up this work at some point. I also want to thank Professor Seppo Honkapohja for his personal support ("henkinen tuki"). I will not even try to describe it as we would probably end up arguing about the exact definition, in any case. My special thanks go to Seppo's wife – as who else would have taught him to quarrel in such a pleasant, civilized way? Without the care of the Departmental Administrator Ritva Teräväinen, the Department of Economics of the University of Helsinki would have probably ceased to exist. I am sure that I will also need her valuable help and knowledge about everything going on in the academic world in the future.

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The computations reported in Chapter 3 were carried out using Dr. Hans-Martin Krolzig's (Institute of Economics and Statistics, University of Oxford) MS-VAR for Ox (Doornik, 1998 and Hendry & Doornik, 1999), and the regime-dependent impulse responses computations were based on the Ox procedures by Ehrmann, M., Ellison, M. and N. Valla (European University Institute). I am also grateful for all the help I have received from Hans-Martin Krolzig and Marianne Sensier, Ph. D. (School of Economic Studies, University of Manchester) while working on this Chapter. Special thanks go to Eija Toivanen (Bank of Finland), who has helped me in updating my data set.

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Roderick McConchie, Ph. D., has been of invaluable help in improving my English. His various questions pointed out some of the weaknesses of the manuscript as well.

Any errors that may remain are my own.

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Helsinki 26.3.2002

Carolina Sierimo

Contents

Chapter 1
Introduction

1.1 The motivation of this study

Investors require compensation for the postponement of current consumption as they put their money into a stock market. A market in which prices always fully reflect available information is called "efficient" (Fama, 1965, 1970). In an efficient market an investor gets what he pays for and there are no profit opportunities available to professional money managers or savvy investors. The market genuinely "knows best," and the prices of securities traded are equal to the values of the dividends which these securities pay, also known as fundamental values.

However, one can ask whether hypothetical trading based on an explicitly specified information set would earn superior returns. We would then need to specify an information set first. Under weak-form efficiency the information set includes only the history of prices or returns themselves. Under semistrong-form efficiency the information set includes all information known to all market participants, like the market trading volume. Finally, strong-form efficiency means that the information set includes all information known to any market participant, including private information. (Campbell et al., 1997)

By definition, in an efficient market the path of prices and the return per period are unpredictable.[1] Put more formally, the EMH hypothesis implies that the expected value of tomorrow's price P_{t+1}, given all relevant information up to and including today denoted as Ω_t, should equal today's price P_t, possibly up to a deterministic growth component μ (drift). In other words, $E_t[P_{t+1}|\Omega_t] = P_t + \mu$, where E_t denotes the mathematical expectation operator given the information at time t. (Cuthbertson, 1996) In testing the EMH the model commonly used is $P_t = \mu + P_{t-1} + e_t$, where $e_t \sim$ i.i.d$(0,\sigma^2)$, or returns follow a random walk with drift $\Delta P_t = \mu + e_t$. For a long time these models were maintained as an appropriate statistical model of stock market behavior.

The independence of increments $\{e_t\}$ implies that the random walk is also a fair game, but in a much stronger sense than the martingale. A martingale is a fair game, one which is neither in your favor or your opponent's, or a stochastic process $\{P_t\}$, which satisfies the following condition: $E_t[P_{t+1}|P_t,P_{t-1},...] = P_t$ or $E_t[P_{t+1} - P_t|P_t,P_{t-1},...] = 0$. In a random walk, independence implies not only that increments are uncorrelated, but that any nonlinear functions of the increments are also uncorrelated. Nevertheless, the financial market literature recognizes several forms of the random walk hypothesis. First, relaxing the assumption of identically distributed increments lets us allow unconditional heteroskedasticity in the residuals, which is a useful feature given the empirically observed fact of time-variation in the volatility of many financial asset return series. An even more general version of the random walk hypothesis – the one most often tested in the recent empirical literature – may be obtained by relaxing the independence assumption of the model to include processes with dependent but uncorrelated increments. Tests of random walk may thus be categorized as follows: tests of i.i.d. increments in errors (runs tests), tests of independent increments without assuming identical distributions over time (filter rules and technical analysis) and tests of uncorrelated increments or testing the null hypothesis that autocorrelation coefficients of the first differences of the level of the random walk at various lags are all zero.

The Efficient Market Hypothesis (EMH) has been the cornerstone of financial research for more than thirty years. The first comprehensive study of the dependence in stock prices can be attributed to Fama (1965) as he analyzed the daily returns of the 30 stocks that made up the Dow Jones Industrial average at the time of his study. He found low levels of serial correlation in returns at short lags, and provided evidence concerning the non-Gaussian nature of the empirical distribution of the daily returns. He gave two explanations for these departures: the mixture of distributions and changing parameters hypothesis. The next step in testing the EMH focused on explaining the empirical observation that stock returns are negatively correlated in the long run. For example, the presence of positive feedback traders, who buy (sell) when prices rise (fall), causes prices to overreact to fundamentals. However, at some point in time prices start to revert back to their fundamental values, hence we observe mean reversion in returns. This behavior runs counter to the random walk hypothesis. As shocks are persistent in the case of a random walk, this offers an alternative way to test the EMH. (Cuthbertson, 1996)

Fama & French (1988) report that price movements for market portfolios of common stocks tend to be at least partially offset over long horizons. They found negative serial correlation in market returns over observational intervals of three to five years. Nevertheless, evidence with respect to the presence of long-term dependence in stock returns is still inconclusive (Poterba & Summers, 1988 and Jegadeesh, 1990). At any rate, if the mean reversion hypothesis was rejected, researchers invalidated the asset pricing models based on Brownian motion, random walk and martingale assumptions. We now know many reasons why stock prices deviate from the random walk model. For example, the variance in stock prices is typically not constant over time, since during turbulent times the market reacts to the inflow of new information, beliefs are relatively heterogeneous and volatility is high. During quiet times beliefs are more homogenous, and much of the volatility comes from liquidity trading. This has led to the application of (G)ARCH models in stock returns. Bollerslev et al. (1992) report more than 300 papers related to this topic. Other types of deviation are calendar anomalies, like the January effect, which had already been discovered in the stock market by Wachtel (1942), among others. Similarly, from time to time, large groups of stocks such as Internet stocks trade at prices apparently in excess of their fundamental values, a phenomenon known as price bubbles (Cuthbertson, 1996). Famous documented “first” bubbles include the South Sea share price bubble of the 1720s and the tulip mania bubble (Garber, 1990). It is also typical of the Helsinki stock market that large negative returns appear more often than large positive ones (Knif & Löflund, 1997). Clearly, this justifies using new techniques to test and model stock market data.

The introduction of nonlinear dynamics made researchers realize that zero serial correlation implies statistical independence if and only if the joint probability distribution is normal. The importance of this condition was made clear with the discovery of nonlinear dependences in stock market returns, first reported by Hinich & Patterson (1985). Accordingly, we know that the lack of linear dependence (auto-correlation) does not rule out nonlinear dependence in stock returns, which may even become predictable. Thus, to operationalize the EMH test, we need to add a few features to the regressions[2] we use in the study compared to linear ones. Following Frances & van Dijk (2000) we choose to consider only nonlinear models in substantial detail, and refer the interested reader to Mills (1993), who deals with linear models. To be more specific, any support either for the mixture model or the sequential arrival of information hypothesis (Chapter 2) is taken as evidence against the EMH. Similarly, if investors do not take a rise in inflation into account correctly in making their investment decisions (Chapter 3), this is in conflict with the principles of the EMH. Granger (1992), Bollerslev et al. (1992) and Campbell et al. (1997) give further examples taken from stock-market literature on the Efficient Market Theory.

In this study, we address the following research tasks:

- In an Efficient Market prices should adjust instantaneously toward their fundamental values, and trading volume contains no information about future price developments. Are stock returns related to trading volume at the Helsinki stock exchange? If they are, is the relationship linear or nonlinear?

- Is the view of the persistence of shock in stocks returns or trading volume related to whether we think that these time-series are nonlinear? How does this affect causality between these variables?

Having answered these questions, then we ask whether this evidence suggests that markets are efficient or not. This is the substance of Chapter 2. We then address the following new issues:

- There is a large body of empirical evidence that stock markets perform poorly during inflationary periods. Several explanations have been offered for this so-called “anomaly.” Is the relationship between stock returns and inflation negative in the Finnish data?

- Is the relationship between returns and inflation negative in particular in a regime under which monetary policy is counter-cyclical as already suggested by Bakshi and Chen (1996)?

- In general, stocks seem to maintain protection against purely monetary inflation but fail to provide a hedge against inflation arising from real output shocks. Finally, this is tested using the regime-dependent impulse response function.

These issues are addressed in Chapter 3. The findings should suggest what the relevant information that stock market investors use in rational pricing is. With these results, we can draw conclusions about stock investments as an appropriate inflation hedge.

The switching regression has been widely used, when nonlinearity has been suggested. Roughly speaking, two main classes of regime-switching model can be distinguished: those in which the regimes can be characterized by an observable variable, and those in which the regime cannot actually be observed but is determined by an unobservable underlying stochastic process. In the latter case one can never be certain that a particular regime has occurred at a particular point in time, but only assign probabilities to the occurrence of the various regimes (Frances & van Dijk, 2000). Some special cases of the switching regression models are the threshold models. In the most common case the threshold models may be viewed as a two-regime system, in which a linear model describes each of the regimes. Any change between these regimes is assumed to be abrupt. The smooth transition autoregressive STAR model is a generalization of the two-regime system threshold model, in which the transition between the two extreme regimes is smooth. (Granger & Teräsvirta, 1993) Given the results, both returns and trading volume are best described as nonlinear STAR processes (Chapter 2). Alternatively, the Markov-switching model based on Hamilton (1989) can be used to pick out different regimes in the time-series based on the data alone by attaching probabilities to the different states of the data-generating process. Accordingly, we use the Markov-switching vector autoregressive (MS-VAR) model to illustrate possible dependences between real stock prices and inflation under various monetary policy regimes (Chapter 3). For the links between the STAR and MS-VAR models, see Franses & van Dijk (2000). Besides, van Dijk et al. (2000) discuss extensions which allow for multiple regimes, time-varying properties in conjunction with regime-switching behavior, and modeling several time-series jointly.

Further examples of nonlinear specifications used in this area include polynomial models, piecewise-linear models, the threshold autoregressive TAR model (Tong, 1990) and the Artificial Neural Network (ANN) model advocated by Kuan & White (1994) and Qi & Maddala (1999). Furthermore, nonparametric estimation techniques can be used to capture a wide variety of nonlinearities without recourse to any particular specification of the nonlinear relation. In these models densities, conditional densities and nonlinear regression functions are often estimated by some smoothing operation. The cost of using nonparametric models is that they are highly data intensive and generally not effective for smaller sample sizes. Nonparametric estimation is also prone to over-fitting. (Brock et al., 1991) For these reasons nonparametric methods such as kernel estimators, projection pursuit and cubic spline smoothing are left outside this study.

Since the impulse response function (IRF) summarizes the information in the autoregressive parameters, and the variances and covariances of each regime found in the data, it is easier to illustrate the estimated coefficients of the nonlinear models using the IRF. This is also used to measure the persistence of shocks in a system. Does it however matter what type of shock hits the market at time t? What was the history of the market at time $t - 1$ before the shock hit? What future shocks are assumed to hit the market from $t + 1$ to $t + n$? Answering these questions in the case of nonlinear models allows us to see that current shocks to the system will have a different impact in the future depending on the sign and magnitude of the shock, the regime we were under when the shock hit the market and the point from which we to count the persistence of the shocks. Since the generalized impulse response function (GIRF) is designed to solve this kind of asymmetry problem, we use the GIRF to scrutinize the mean reversion hypothesis of stock prices. As the GIRF can be extended to cases of multivariate models, we also examine whether the source of the shock (real or monetary) affecting the stock market matters. (Koop et al., 1996, Gallant et al., 1993, Potter, 1995, 2000 and Ehrman et al., 2000)

The rest of this introduction is as follows. First, linearity and nonlinearity is defined. This research also describes econometric techniques used in this study, which allow us to take nonlinearity both in and between the model variables, and structural breaks in the data into account (Section 1.2). We then discuss how the generalized impulse response function can be used to illustrate nonlinear models (Section 1.3). The economic calendar is checked to point out extraordinary events (devaluations) in the data. Next, an appropriate econometric model is chosen to describe the patterns in the data. Monthly data is used as information about economic fundamentals like production are only published at longer intervals. Sections 1.4 and 1.5 summarize the main hypothesis of this study. Section 1.6 summarizes the main results of this study in testing the random walk hypothesis against the mixture model, among others, and whether the stocks are a good hedge against inflation.

1.2 New approaches in testing the Efficient Market Hypothesis

The focus in this study is not on the test of market efficiency as such but rather on whether this is a sufficiently good model to describe the characteristics of the Helsinki Stock Exchange. Hence, we place some emphasis on nonlinear models in this introduction despite the contribution of the work being its empirical results. We also justify this by the fact that many aspects of the STAR and MS-VAR models are still under investigation. Therefore, some basic knowledge of these models may help the reader in following the empirical results of this paper.

1.2.1 The motivation for using STAR, STAR-GARCH and MS-VAR models

Linear models have dominated financial market model building. Linear approximations have been successful in empirical work and, instead of abandoning them, very powerful concepts such as cointegrated variables have been built upon the idea of a linear relationship between variables. Nevertheless, since in some cases the underlying economic relationship is nonlinear, if we want to test it using real data, the equations to be estimated are expected to be nonlinear as well. Examples of nonlinearities in economics include capacity constraints restricting production, and asymmetries in cyclical fluctuations of employment due to asymmetric hiring and firing costs. We also know by now that the lack of linear dependence (autocorrelation) in returns does not rule out nonlinear dependence which, if present, would contradict the random walk model.

Granger (1998) defines linearity by considering a single series x_t, which is to be explained by a vector y_t, which may include lagged values of x_t. If the conditional mean of x_t given y_t takes the form $E_t[x_t|y_t] = \beta' y_t + \varphi(y_t)$ then the relationship may be called linear in mean if $\varphi(y_t) = 0$, otherwise the relationship is nonlinear. Note that the linearity is in the variables not the coefficients. Hence, the same definition could be applied to some function of x_t. For example, the ARCH process is linear in u_t^2. However, most accounts of nonlinear processes classify them as nonlinear. A rather more modern version of definition of nonlinearity would also allow the coefficients β and φ to vary with time, the STAR models introduced below being an example. For an overview of both linear and nonlinear time-series specifications in economics, see Granger (1998).

The application of linear models has recently encountered several problems. Tests often reject parameter constancy, implying so-called structural breaks defined as changes in the parameters of a linear model. The solution has often been to dismiss the model or to pad it with dummy variables in order to fix the shortcomings. Simply to apply a set of dummies whenever a break is observed is an ad hoc and unsatisfactory solution. In the case of Chapter 3 it would have resulted as a large number of dummies being required to present changes in monetary policy. Secondly, since monetary policy stringency can be best evaluated by looking at various alternative indicators, and monetary policy typically influences the economy with a lag, the timing of the dummies is not straightforward either. A much more satisfactory way to describe the data is to employ a specification which allows one to estimate different regimes from the data.

Unfortunately, identifying the type of nonlinearity in the data is difficult because of the wide variety of nonlinear models available. At least the following criteria can be used to choose functional forms in the analysis: The form chosen should be capable of possessing the theoretical properties required of the economic relationship. The variables involved should be able to accommodate a wide and appropriate set of possible values. The form chosen should be able to approximate other likely forms for some choice of parameter values. Computational facility and factual conformity set some limits as well. For example, if stock returns are at least partly endogenously determined, it probably pays to use nonlinear models to select this property. But, if returns change because of exogenous shocks, sticking with simpler linear models probably provides the same information as the more complex nonlinear alternatives. (Granger & Teräsvirta, 1993 and Teräsvirta et al., 1994)

A further disturbing property of most of the nonlinear models is that they are all actually or essentially deterministic. In a deterministic model a small policy change may affect values of model parameters in a small way, but may lead to a large change in some important variable. Output from a simple deterministic nonlinear model may lead toward equilibrium or toward a limit cycle or appear to have some properties in common with stochastic processes. The existence of these processes suggests that data taken to be stochastic by the econometrician may be deterministic but chaotic. (Hsieh, 1991) At present, since there is evidence of nonlinearity in economic data but little evidence for this also being chaos, chaotic processes are left outside this study. A review of the literature with respect to the EMH and chaos is given by Barnett & Serletis (2000).

Technically, if some or all time-series under consideration are nonstationary, standard asymptotic theory may not be applicable for the purpose of conducting statistical inference. Henceforth, prior to estimation, we should map the data to *I(0)* series by differencing and cointegration combinations.[3] Tests against stationarity and cointegration are thus routinely done on all the model variables. This is followed by tests against linearity in the data. If the linearity hypothesis is rejected, we try to find a proper nonlinear model to describe the behavior in the time-series/ systems. This study tries to answer, for example, whether some of the conditional volatility in stock prices can be explained by the volatility in its fundamentals or by other variables such as trading volume. The volatility is modeled using the STAR-GARCH model, among others. We discuss the pros and cons of using these alternatives below. STAR models are considered next in more detail.

STAR models

In the switching regression models observations are generated by different regimes, in which the switch point from one regime to another may be either observable or unobservable (Tong, 1990). Some switching regression models are generalized in such a way that the transition from one extreme regime to the other is not discrete but smooth, as it may be more convenient to assume that, for example, instead of varying between boom and recession the economy has a continuum of states between the two extremes. This is an attractive parametrization as the resulting smooth transition autoregression STAR model is locally linear in its parameters and allows easy interpretation. Furthermore, the thresholds are estimated from the data itself. (Granger & Teräsvirta, 1993)

We use STAR models in Chapter 2 to see whether the trading behavior of investors changes after trading volume or returns have crossed a certain threshold value. In particular, we consider the logistic STAR (LSTAR) or exponential STAR (ESTAR) models of order p. These are given in Equation 1.1.

$$y_t = S_t'\Pi + S_t'\theta F(z_t) + u_t, \textit{ where}$$
$$F(z_t) = \begin{cases} 1/(1+\exp(-\gamma(\hat{y}_{t-d} - c))) & LSTAR \\ 1-\exp(-\gamma(\hat{y}_{t-d} - c)^2) & ESTAR, \end{cases} \quad \textbf{\textit{(1.1)}}$$

$S_t = (1, y_{t-1}, ..., y_{t-p})'$, $\Pi = (\pi_0, \pi_1, ..., \pi_p)'$ and $\theta = (\theta_0, \theta_1, ..., \theta_p)'$ are $p + 1$ parameter vectors and $t = 1, ..., T$. The error term $u_t \sim$ n.i.d$(0, \sigma^2)$, $E_t S_t u_t = 0$ and $E_t z_t u_t = 0$. The logistic form of this transition function $F(z_t)$ allows for different effects of positive and negative deviations from the equilibrium. The second type of asymmetry obtained using the exponential transition function in Equation 1.1 distinguishes between small and large equilibrium errors, and the strength of adjustment changes gradually for larger deviations from equilibrium. The slope parameter $\gamma > 0$ indicates how rapid the transition from a linear regime to nonlinear is as a function of the transition variable, which is typically assumed to be the lagged endogenous variable $\hat{y}_{t-d}$. The location parameter c describes the point (the value of $\hat{y}_{t-d}$) where the transition occurs. If $\gamma \to \infty$ Equation 1.1 becomes a two-regime switching regression model with the switching variable $\hat{y}_{t-d}$ (Tong, 1990). Defining $\hat{y}_{t-d} = t$, we obtain a linear model whose parameters change as a function of time. This property offers a way to test for parameter constancy in linear models against smoothly changing parameters (structural breaks).

While the component time-series or vector may have moments such as means, variances and covariances varying with time, some linear combination of these series, which defines the equilibrium relationship, may have time-invariant linear properties. If a linear combination of series has a lower order of integration than any one of them individually, the variables are said to be cointegrated. Granger & Hallman (1991) generalized the concept of cointegration to nonlinear cases. They replaced $I(1)$ by a long-memory concept and cointegration by a possibly nonlinear attractor, so that y_t, x_t are each long-memory but there is a function $g(x_t)$ such that $y_t - g(x_t)$ is stationary. A non-parametric estimator for $g(x_t)$ is proposed. Hendry & Mizon (1998) introduce co-breaking, which prevails if the regime shift alters the mean and the drift of the system such that at least one linear combination remains stationary. Co-breaking is closely related to the idea of cointegration: while cointegration removes unit roots from linear combinations of variables, co-breaking can eliminate the effects of regime shifts by taking linear combinations of variables. (Banerjee et al., 1994)

To take “nonlinear cointegration” or common persistence in the case of STAR models into account, we introduce a smooth transition vector error correction model (STVEC). Short-selling constraints mean that the response of stock prices to negative deviations from equilibrium might be different from the response to positive deviations. Keeping this in mind van Dijk et al. (2000) claim that it is of particular interest to focus on STVEC models in the case of stocks, in which the components of explanatory variables are linked by a linear long run equilibrium relationship, whereas adjustment toward this equilibrium is nonlinear and can be characterized as regime-switching, the regimes being determined by the size and/or sign of the deviation from equilibrium. As an example we consider a case with $Y_t = (r_t, v_t)$, where r_t is returns and v_t trading volume (sales[4]). Here, the multivariate nonlinear system contains only one common nonlinear component $F_j(z_{jt}) = F(z_t)$ for $j = 1,2$, where z_t is one of the $2p$ lagged regressors in Y_t. Hence, a STVEC model can be written as:

$$Y_t = \lambda_0 + \lambda_1 Y_{t-1} + \ldots + \lambda_p Y_{t-p} + \Xi Z_{t-1} + \alpha[\eta_0 + \eta_1 Y_{t-1} + \ldots + \eta_p Y_{t-p} + \Psi Z_{t-1}] F_j(z_{jt}) + \varepsilon_t, \quad \textbf{\textit{(1.2)}}$$

where ε_t is a (2*1) vector of normal errors with mean zero and unknown variance h_t, and ε_t, ε_s are identically distributed and uncorrelated for all $t = s$. The terms λ_0 and η_0 are (2*1) constant vectors, the estimated coefficients λ_i, η_i for lagged Y_{t-i} ($i = 1,...,p$) and α are (2*2) matrixes. Correspondingly, Ξ and Ψ are (2*1) parameter vectors. The long run relationship between returns and volume is introduced to the model using an error correction term $Z_{t-1} = (r_{t-1} - v_{t-1})$. This model also allows that deviations of stock prices from the equilibrium may create arbitrage opportunities that drive the prices back, and market frictions give rise to asymmetric adjustment of such deviations. However, the possibility of distinguishing between logistic and exponential multivariate STAR models is very costly in terms of the number of parameters we need to estimate and, given the typical size of samples, not practical. Alternatively, we could model regime dependences in a system using the MS-VAR model instead, which is the following topic in this study.

Markov-switching vector autoregressive models

The Markov-switching vector autoregressions (MS-VAR) can be used to determine changes in regimes based on the data alone. As the MS-VAR model can be considered as generalizations of the basic finite order VAR model, we start by looking at the p^{th} order autoregression for the k-dimensional time-series vector $z_t = (z_{1t},...,z_{kt})'$ following Krolzig (1997):

$$z_t = \nu + \Pi_1 z_{t-1} + \ldots + \Pi_p z_{t-p} + \varepsilon_t, \qquad \textbf{\textit{(1.3)}}$$

where υ is a constant, Π_j are ($k*k$) parameter matrices for $j = 1,...,p$, $y_0,...,y_{1-p}$ are fixed, and $t = 1,...,T$. Specifying $\Pi(L) = I_k - \Sigma_{j=1}^{p} \Pi_j \lambda^j$ as the $(k*k)$-dimensional lag polynomial, where L is the lag operator such that $L^j z_t = z_{t-j}$, we assume that there are no roots on or inside the unit circle $|\Pi(\lambda)| \neq 0$ for $|\lambda| \leq 1$. If a normal distribution of the error is assumed $\varepsilon_t \sim$ n.i.d$(0,\Sigma)$, Equation 1.3 is known as the intercept form of a stable Gaussian VAR(p). It can be reparametrized as the mean adjusted form of a VAR model:

$$z_t - \mu = \Pi_1(z_{t-1} - \mu) + \ldots + \Pi_p(z_{t-p} - \mu) + \varepsilon_t, \qquad \textbf{\textit{(1.4)}}$$

where $\mu = (I_k - \sum_{j=1}^{p} \Pi_j)^{-1} \upsilon$ is the (k*1) dimensional mean of z_t. As a generalization of Equation 1.4 we consider an MS(M)-VAR(p) model with M regimes:[5]

$$z_t - \mu(s_t) = \Pi_1(z_{t-1} - \mu(s_{t-1})) + \ldots + \Pi_p(z_{t-p} - \mu(s_{t-p})) + \varepsilon_t, \qquad \textbf{\textit{(1.5)}}$$

where $\mu(s_i)$ ($i = 1,...,p$) is a parameter shift function describing the dependence of the parameters μ on the stochastic, unobservable regime variable $s_t \in \{1,..., M\}$, e.g.,

$$\mu(s_t) = \begin{cases} \mu_1 & \text{if } s_t = 1, \\ \mu_2 & \text{if } s_t = 2, \\ & . \\ \mu_M & \text{if } s_t = M. \end{cases} \qquad \textbf{\textit{(1.6)}}$$

Finally, the description of the data-generating mechanisms has to be completed by assumptions regarding the regime-generating process. We assume that the stochastic process generating the unobservable regimes is an ergodic Markov chain defined by the transition probabilities:

$$p_{ij} = \Pr(s_{t+1} = j | s_t = i), \quad \sum_{j=1}^{M} p_{ij} = 1 \ \forall\, i, j \in \{1,\ldots,M\}. \qquad \textbf{\textit{(1.7)}}$$

More precisely, it is assumed that s_t follows an irreducible (no absorbing states) ergodic M state Markov process with the transition matrix P.

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdot & \cdot & p_{1M} \\ p_{21} & \cdot & \cdot & \cdot & p_{2M} \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ p_{i1} & p_{i2} & \cdot & \cdot & p_{iM} \end{bmatrix}. \qquad \textbf{(1.8)}$$

By inferring the probabilities of the unobserved regimes conditional on an available information set, it is then possible to reconstruct the regimes. In principle, all parameters of the conditional model can be made dependent on the state s_t of the Markov chain.

The model, which allows for an immediate one-time jump in the process mean M after a change in the regime, is called an MSM(M)-VAR(p) model. For example, in the case of two regimes the mean could be positive in the first ("expansion") and negative in the second regime ("recession"). Similarly, if we assume that the level of the process smoothly approaches a new level after transition from one state to another, the model obtained is called an MSI(M)-VAR(p).

Similarly, the model variables may have a common cycle, or be "nonlinearly cointegrated." Now, if such a common cycle exists, the inference on dating the cycles can be improved by considering Markov-switching p^{th} order vector autoregression with M regimes and cointegration rank r, i.e., the MSCI(M,r)-VAR(p) introduced in Krolzig (1997) and Krolzig & Toro (1999). In this model both the drift and/or the equilibrium mean of the cointegrating vector are allowed to change. If $z_t \sim I(1)$ and a vector β exists such that $Z_{t-p} = \beta' z_t$ is stationary, then z_t admits an ECM representation, where long run dependences between model variables are given by a singular matrix $\alpha\beta' = I_k - \sum_{j=1}^{p} \Gamma_j = \Gamma(1)$:

$$\Delta z_t = \sum_{j=1}^{p-1} D_j \Delta z_{t-j} + \alpha Z_{t-p} + \nu(s_t) + \varepsilon_t , \qquad \textbf{(1.9)}$$

where Δ is the differencing operator $\Delta z_t = z_t - z_{t-1}$. Indicated by the cointegration rank r, some elements of vector z_t move together over time, such that the "gap" between them is finite and does not grow larger over time. The coefficient matrices are defined by $D_j = -(I_k - \sum_{j=1}^{p} \Pi_j)$ for $j = 1,..., p - 1$. The rank of the matrix $\alpha\beta'$, where $r < k$, is called the cointegration rank. The columns of $\beta(r*k)$ are the so-called cointegrating vectors, and $\alpha(k*r)$ is sometimes called the loading matrix. When $\alpha\beta'$ has full rank, all the variables in z_t are $I(0)$, but if the rank of $\alpha\beta'$ is zero, we continue with differenced data.

Many of the asymptotic aspects of estimation and testing nonlinear cointegrated models are not resolved at this stage, although many promising new directions for future research have been discovered. Meanwhile, the statistical determination of cointegrating rank r and estimation of the cointegration matrix $\alpha\beta'$ of the MS-VAR model is based on the approximation of a non-normal VARMA process by a finite pure VAR, which allows the application of the Johansen maximum likelihood analysis of cointegrated linear systems. In practice, to model long run dependences in the system the standardized cointegrating vectors are used as additional exogenous explanatory variables in the MS-VAR models. Hence, these models are also referred to as MS-VARX models.

Time-series with a changing conditional variance also form an important class of nonlinear time-series models. The popularity of (generalized) autoregressive conditional heteroskedasticity (G)ARCH models in finance applications is probably related in the martingale difference property, which rules out the ability to make point forecasts of security prices. This fact makes (G)ARCH consistent with the weak form of the EMH. (G)ARCH models are discussed in more detail below.

Conditional heteroskedasticity

It is a well reported empirical fact that the (G)ARCH property is found in examining stock returns. Schwert (1989), among others, examined how far the conditional volatility in stock returns depends on its own past volatility as well as on the volatility in other economic variables (fundamentals), such as bonds and the real output. Later, Hamilton & Lin (1996) claimed that recessions are the primary factors that drive fluctuations in the stock return volatility. Furthermore, asset markets are typically characterized by periods of turbulence and tranquillity that is to say, large (small) forecast errors tend to be followed by further large (small) errors. Hence, the variance of the forecast errors is often very persistent, and the duration of market volatility may shed additional light on the market efficiency issue.

The basic idea behind autoregressive conditional heteroskedasticity ARCH models proposed by Engle (1982) is that the second moments of the distribution may have an autoregressive structure. Under rational expectations the forecast error is $u_{t+1} = y_{t+1} - E_t y_{t+1}$, and the conditional distribution of y_{t+1} is assumed to be normal with mean μ_{t+1} and $\mathrm{var}(y_{t+1}|\Omega_t) = h_{t+1} = \alpha_0 + \alpha_1 * u_t^2$, where Ω_t is the information set available at time t. However, the ARCH process has a memory of only one period. To generalize this we could start adding lags of u_{t-i} in the equation for h_{t+1}, $i = 1,...,q$, but then the number of parameters to estimate increases rapidly. People have thus started to focus on the generalized autoregressive conditional heteroskedasticity GARCH(p,q) model instead. For example, in the GARCH(1,1) model the conditional variance depends on lagged variance terms: $h_{t+1} = \alpha_0 + \alpha_1 u_t^2 + \beta_1 h_t = \alpha_0 + (\alpha_1 + \beta_1)h_t + \alpha_1(u_t^2 - h_t)$ in addition to lagged u_t where u_0 is arbitrarily assumed to be fixed and equal to zero. The parameters can be estimated by maximum likelihood techniques. Conditional on time t information Ω_t, $(u_t^2 - h_t)$ has a mean of zero, and can be thought of as the shock to volatility. The coefficient α_1 measures the extent to which a volatility shock today feeds through into the volatility of the next period, while $\alpha_1 + \beta_1$ measures the rate at which this effect dies out over time. Since Engle's seminal work, many generalizations of this original model have been reported. For example, the GARCH(1,1) with $\alpha_1 + \beta_1 = 1$ has a unit autoregressive root so that today's volatility affects forecasts of volatility into the indefinite future. This is therefore known as the integrated GARCH or IGARCH model.

Time dependence at the second moments in returns captured by the (G)ARCH processes is known as volatility clustering, i.e., large changes in price volatility are followed by large changes in either sign. Nevertheless, several studies emphasize that stock market volatility is higher during recessions than during expansions, while mean returns are lower during recessions. Such behavior cannot be properly accounted for using (G)ARCH models since, for example, in the ARCH model negative and positive shocks have same effect on volatility. Hence, to capture asymmetric effects of positive and negative shocks, various nonlinear GARCH models have been proposed. These include the exponential, GJR and smooth transition GARCH models, power GARCH (PGARCH) models and threshold GARCH (TGARCH) models (Franses & van Dijk, 2000).

Leverage terms allow more realistic modeling of the observed asymmetric behavior of stock returns according to which a “good-news” price increase yields lower volatility, while some “bad-news” decrease in price yields an increase in volatility. For example, when the value of (the stock of) a firm falls, the debt-to-equity ratio increases, which in turn leads to an increase in the volatility of the returns to equity. This suggests that returns could also be described by an autoregression whose residual follows an m^{th}-order ARCH-L process, where L stands for the leverage effect (Hamilton & Susmel, 1994). It is also worth mentioning a two-component GARCH which reflects differing short- and long-term volatility dynamics (Ding et al., 1993). The GARCH in mean (GARCH-M) model could be used to capture direct relationships between return and possibly time-varying risk by including the conditional variance in the model for the conditional mean of the variable of interest. For brief descriptions of these models see S+GARCH (1996), and for further details see Engle (1995) and references therein.

Tong (1990) introduced the SETAR-ARCH model that has both a conditional nonlinear mean and a changing conditional variance. Similarly, STAR models could be used to describe the change in the conditional mean, whereas (G)ARCH would pick out heteroskedasticity in the conditional variance. Lundbergh & Teräsvirta (1998) and Lundbergh (1999) thus introduce a smooth-transition GARCH model (STGARCH), by which they attempt to model a structural shift in the conditional variance assuming that the transition between the regimes from one structure to the other is smooth. This approach is employed in Chapter 2. Estimation is done in two stages. In order to avoid mis-specification of the conditional variance in return or volume (sales) we first model nonlinear dependence in the conditional mean of these series.

Scheicher (1999) scrutinizes the daily returns from the Austrian Traded Index for 1986/9 - 1992/5. He finds that stock returns do not follow a Gaussian process with a constant variance, there being some indication of volatility clustering and leptokurtosis.[6] The parametric GARCH and the MS-VAR models following Hamilton (1989) are able to generate linear and nonlinear dependence and allow for leptokurtosis. In the MS-VAR we have a high mean and low volatility in one state and a low (negative) mean and high volatility in the other. This gives us some further motivation to focus on changing volatility in the case of both STAR and MS-VAR models in this study.

When looking at the various ways to test the EMH, an econometrician would also be interested in general diagnostic tests, the outside sample forecasting performance of the equations and the temporal stability of the parameters. Parameter constancy is a key assumption in econometric models. If it is violated, inference about the parameters may be misleading, as well as any policy implications drawn from the model. The accuracy of post-sample forecasting is affected as well. This inclines us to look at the possibility of structural breaks more closely.

1.2.2 Nonlinearity and structural breaks

Regime switches are most likely to appear in long time-series. Despite the large amount of evidence that both nonlinearity and structural changes are relevant for many time-series, to date these features mainly have been analyzed in isolation. Typically, one starts with a linear model, which is routinely subjected to mis-specification tests including a test for nonlinearity and parameter non-constancy. A standard assumption underlying a parameter constancy test is that if the parameters change they change once during the observation period, so that the linear model contains a structural break. Some classical tests for finding such breaks are the Chow test and CUSUM and CUSUMQ tests. When parameter constancy is rejected, testing the alternative time-varying parameter model for nonlinearity is not normally done, despite the fact that it is not at all that difficult to parametrize a nonlinear time-series model so that the resultant time-series resemble series that are subject to occasional level shifts.

In a similar vein, much evidence for nonlinearity in economic time-series might in fact be due to structural change. It may also be difficult to distinguish between an autoregressive process with a structural break and a random walk (a unit root) process, since a regime shift may generate unit-root-like behavior in piecewise stationary autoregressive time-series. A modeler may then have to choose between unit roots and stationarity with structural breaks (Perron, 1990). Hence, finding these breaks is useful for obvious reasons. Increased volatility might be also due to structural breaks in the data. Likewise, it is possible that a time-series might display both nonlinearity and structural instability, which are not necessarily easy to separate (Teräsvirta, 1997). Therefore, before continuing with the modeling cycle in Chapter 2, we test for structural breaks in the data, and if we find any we divide the samples accordingly.[7] (Lundbergh et al., 2000)

However, it is generally not possible to completely grasp the implied properties of time-series generated by the model by trying simply to interpret the model parameters. Therefore, to shed some light on the characteristics of a model it is often useful to consider the effect of shocks on the future patterns of a time-series variable. A convenient tool is the impulse response function, which is the next topic in this study.

1.3 The generalized impulse response function

An equilibrium state is defined as one in which there is no inherent tendency to change. A system may or may not return to its equilibrium state after it has been perturbed, depending on whether the equilibrium has the property of local or global stability. For example, we say that an equilibrium relationship exists between aggregate consumption C_t and income Y_t if C_t tends toward a fraction ζ of Y_t in the absence of shocks. Impulse response functions allow us to scrutinize the extent to which shocks to Y_t represent temporary deviations from a long run stable growth rate in C_t. In other words, we can measure the persistence of shocks in the case of linear systems using the impulse response function (IRF).[8] In spite of the coefficients in a linear VAR not having interpretations as such, the model can be used to show how a variable responds to innovations to another endogenous variable in the system a certain number of periods into the future. A cumulative impulse response of zero implies that the effect of the shock is transitory. If the response is one, the effect of the shock is permanent and reflects the shock in a one-to-one fashion. If the response exceeds one, it implies eventual overshooting. Nevertheless, as the reduced form disturbances are linear combinations of the structural shocks, one needs to know the structure (ordering) of the elements of the VAR to offer any precise interpretation of the shocks. One further problem is in identifying the source of the shock. If there is a single underlying technology shock, the VAR may still decompose this shock into a permanent and a transitory component (Hamilton, 1994 and Cochrane, 1994).

However, linear models restrict the effect of impulses to the same at each stage of the business cycle, contrary to nonlinear models, which have the advantage of being able to capture asymmetries over the cycle. Van Dijk & Franses (2000) suggest that market frictions give rise to asymmetric adjustment of deviations from equilibrium in the case of a stock market. Because of short-selling restrictions, the response of stock prices to negative deviations from the equilibrium may differ from the response to positive deviations. This motivates us to look at the generalized impulse response function (GIRF), which lets us take these properties into account (Koop et al., 1996 & Potter, 1995). Note that in the case of nonlinear models, the shock and history independence of the traditional linear IRF are lost. The three main issues separating GIRF from the traditional IRF are: *i)* the value of the GIRF depends on the types of shock hitting the economy at time *t*, *ii)* the state of the economy at *t - 1* before being shocked and *iii)* the types of shock expected to hit the economy from *t + 1* to *t + n*. To illustrate these claims, the composition of both linear and nonlinear impulse responses are given in Equations 1.10a) and 1.10b).

$$\begin{aligned} &a)\ \mathrm{IRF}(\mathrm{n},\delta,\omega_{t-1}) = E[y_{t+n}|V_t = \delta, V_{t+1} = 0,\ldots,V_{t+n} = 0,\omega_{t-1}] - \\ &\qquad\qquad E[y_{t+n}|V_t = 0, V_{t+1} = 0,\ldots,V_{t+n} = 0,\omega_{t-1}] \\ &b)\ \mathrm{GIRF}(\mathrm{n},\delta,\omega_{t-1}) = E[y_{t+n}|\delta,\omega_{t-1}] - E[Y_{t+n}|\omega_{t-1}]. \end{aligned} \qquad \textbf{\textit{(1.10)}}$$

Here, the upper-case letters are used to denote random variables and lower-case to denote realizations of those variables. The history or information set at *t - 1*, which is used to forecast future values of Y_t, is denoted as Ω_t, with corresponding realizations ω_t. Furthermore, we assume that the conditional expectation E_t exists. By looking at the traditional IRF between *t* and *t + n* we note that the system is hit by a shock V_t of size δ at period *t*, while the second realization, the benchmark, assumes the system is hit by no shocks between *t* and *t + n*. In the GIRF the expectation operator is conditioned on only the history and/or shock; thus the problem of treatment of the future is avoided by averaging out future shocks. Hence, the random variable GIRF is an average of what might happen given the present and past. The baseline is defined as the conditional expectation given only the history. Since in general there are no analytical expressions available for the conditional expectation in the case of a nonlinear model, these are obtained using Monte Carlo simulations by exposing the system to shocks and averaging over all possible realizations of Y_{t+n}. Besides, as the GIRF does not represent the responses to a shock of a certain size and sign but treats the shock itself as a random variable, the GIRF is reported in terms of density functions (the highest density regions), rather than time trajectories as usual.

Additionally, the GIRF can be computed using multivariate models, in which the focus of interest is the same as in univariate models; namely, the time profile of the effect of shocks on the dependent variables. But now the shocks in the first equation may not only have contemporaneous effects on the first dependent variable, but on the other dependent variables in the model as well (the composition effect). Hence it is not appropriate to entertain perturbations in the shock to the first equation while keeping the shocks to other equations fixed. (van Dijk et al., 2000 & Koop et al., 1996 and Pesaran & Shin, 1998)

There has been some related interest in the GIRF in the case of the Markov-switching vector autoregressive model. Krolzig & Toro (1999) introduce the idea that if the unobservable variable in the MS-VAR model is to be interpreted as the state of the business cycle, an alternative procedure to measure persistence of shocks in the system is to look at cyclical fluctuation in terms of the response of the variables to changes in the regime of the state variable. Compared to Koop et al. (1996) the history is now represented by a given state from which we shock the system, whereas the nature of the shock is given by a specific state to which we move. In other words, the dynamics (cyclical shocks) should be seen as shifts in the state of the unobserved variables rather than the traditional Gaussian innovations. One advantage of this methodology is that non-Gaussian innovations might be what some economists have in mind when they refer to "cyclical shocks," that is, investigating the dynamics of some variables in the transition from boom to bust. This gives us a tool with which to analyze MS-VAR models such that we can distinguish between the paths of the variables; for example, when there is a change in the regime such as a shift from regime one to two or any other combination between the existing regimes.

The Ehrmann et al. (2001) approach to measuring the persistence of shocks in the case of the MS-VAR model differs from that of Krolzig & Toro, since they emphasize the response of the economy to changes in particular regimes rather than the IRFs within regimes. Both approaches recognize that the IRF may depend on the point in time and the state of the economy at which the shock occurs. Secondly, what Koop et al. (1996) call "history" is a Markov-switching regime in Ehrmann et al.'s case. They obtain the GIRF first by rewriting Equation 1.3 in a general form (Equation 1.11). There are k endogenous variables z_t and each of the M regimes is characterized by an intercept ν_i, autoregressive terms $\Pi_{1i},...,\Pi_{pi}$ of order p and residuals $A_i\varepsilon_t$, where A_i is a regime-dependent matrix ($i = 1,...,M$):

$$z_t = \left\{ \begin{matrix} \upsilon_1 + \Pi_{11} z_{t-1} + ... + \Pi_{p1} z_{t-p} + A_1 \varepsilon_t & \mathrm{s_t} = 1 \\ . & \\ \upsilon_M + \Pi_{1M} z_{t-1} + ... + \Pi_{pM} z_{t-p} + A_M \varepsilon_t & \mathrm{s_t} = M \end{matrix} \right\}. \tag{1.11}$$

The fundamental disturbances ε_t are assumed to be normally distributed and uncorrelated at all leads and lags. The variance of each ε_t is normalized to unity to give the identity variance-covariance matrix. However, as ε_t are premultiplied by a regime-dependent matrix A_i, the variance-covariance matrix Σ_i of the residuals $A_i\varepsilon_t$ will be regime-dependent, i.e., $\Sigma_i = A_i A_i'$. An identification problem now arises, since the EM algorithm gives only estimates of the variance-covariance matrices Σ_i and not the matrices A_i. Following Sims (1980), Ehrmann et al. (2001) impose restrictions on the parameter estimates to identify these matrices. In addition, the endogenous variables are ordered and it is assumed that the fundamental disturbance to a variable has only contemporaneous effects on the variable itself and on variables ordered below it. Then, using a Choleski decomposition of the matrix Σ_i, we derive A_i, which is now lower triangular and exactly identified.

Estimation of the regime-dependent IRF is done in two stages. First, Ehrmann et al. (2001) estimate an unrestricted MS-VAR allowing means, intercepts, autoregressive parameters, variances and covariances to switch or be constant as desired. At the identification stage restrictions are imposed on the parameter estimates to derive a separate structural form for each regime, from which the regime-dependent IRF can be calculated. Instead of one set of IRF, we then have a set for each regime. However, the validity of regime conditioning depends on the time horizon of the IRF and the expected duration of the regime. As long as the time horizon is not excessive and the transition matrix predicts regimes which are very persistent, then the conditioning is valid and regime-dependent IRFs are a useful analytical tool. The regime-dependent IRF $\theta_{ki,h}$ for regime i can be written as:

$$\left.\frac{\partial E_t z_{t+h}}{\partial \varepsilon_{k,t}}\right|_{s_t=\ldots=s_{t+h}=i} = \theta_{ki,h}, \text{ for h} \geq 0$$

$$\hat{\theta}_{ki,0} = \hat{A}_i \varepsilon_0 \qquad \textbf{\textit{(1.12)}}$$

$$\hat{\theta}_{ki,h} = \sum_{j=1}^{\min(h,p)} \hat{\Pi}_{ji}^{h-j-1} \hat{A}_i \varepsilon_0, \text{ for h} > 0.$$

This shows the expected changes in endogenous variables at time $t + h$ to a one standard deviation shock to the k^{th} fundamental disturbance at time t conditional on regime i. The first response, which measures the impact effect on endogenous variables of the k^{th} fundamental disturbance, can easily be estimated by premultiplying ε_0 by $\hat{A}_i$. The remaining response vectors can be estimated by solving forwards for the endogenous variables in Equation 1.12. The third equation links the estimated response vectors with the estimated parameters.

Dynamic properties of the separate regimes of a time-series provide some means of analyzing the effect of shocks, but even if the process has an explosive cycle in one regime it may be mean reverting in the other, so that the combined dynamics will involve transient shocks as the process may never stay long in the explosive state. Now, by using the GIRF, we can investigate the stability of smooth transition vector autoregressive models, among others (Chapter 2). But before summarizing the main results, a brief introduction to the aims of this study is offered.

1.4 Introduction to Chapter 2

Does knowledge of the behavior of volume improve conditional stock price change forecasts based on past forecasts alone as already suggested by Epps & Epps (1976)? To answer this question, we start Chapter 2 with a survey of papers regarding the nonlinear stock price/return - trading volume relationship. We then discuss some previous empirical results considering nonlinearities in and/or between these variables. For example, changes in trading volume are expected to capture the arrival of new information in the market. Now, if volume is used to measure the disagreement as traders revise their reservation prices based on the arrival of new information, the greater the disagreement the larger the level of trading volume and the larger the absolute price change (the mixture model). In other words, there is a positive causal relation running from trading volume to absolute stock returns.

We also find evidence of structural breaks in the data, and take this into account by dividing the sample into two subsamples. Note that what seems to be a structural break could also be due to nonlinearity, which can be modeled with a constant parameter model. Hence, the null hypothesis of linearity was tested against smooth transition autoregressive STAR models. The null hypothesis is clearly rejected. Granger (1992) has already suggested that regime-switching models are useful in describing both ordinary and exceptional events affecting the stock market (January effects, seasonal patterns). Here, the STAR models let us take differential dynamic behavior of returns and volume (sales) in the estimated regimes into account such that the transition from one regime to another is smooth.

After estimating the STAR models, figures for the transition functions as against the transition variable and over time has been drawn to indicate *i)* whether the form of the transition function has been chosen correctly or *ii)* at what points (months) in time the nonlinear regime is needed to describe the behavior in the data. This is followed by model mis-specification tests, including tests of no linear autoregressive conditional heteroskedasticity in the residuals (Engle, 1982). Various informational efficiency tests of the stock market require that the model residuals be serially uncorrelated. However, the residuals need not be homoskedastic and the variance of errors may vary over time or depend on other economic variables, without violating informational efficiency. However, if the residuals are not homoskedastic, additional econometric problems may arise in testing the EMH. Hence, if we reject homoskedasticity, we model both the "nonlinear" conditional mean and the conditional variance of returns or volume (sales) using the ESTAR- or LSTAR-GARCH model instead.

We continue by testing nonlinear Granger causality between volume (sales) and returns in order to say more about the joint behavior of these two series. The null hypothesis is that there is no predictive power for returns in lagged values of volume (sales), and vice versa, characterized now by an additive smooth transition component as in the additive STAR model (Eitrheim & Teräsvirta, 1996). Furthermore, the GIRF is used in measuring the persistence of shocks in returns and volume (sales), as well as the stability of the estimated STAR models.

Cochrane (1994) shows that the volume - stock return index ratio is a potent forecaster of long-horizon index growth. He finds that the volume - index ratio is stable over long time periods and concludes that volume and returns are cointegrated, while volume is nearly a random walk. In such a case volume defines a "trend" in returns. We assume that this kind of relationship can be attributed here to a common linear or nonlinear factor. Thus, we expand the analysis to a more general instance of multivariate nonlinear time-series models. Ergo, a smooth transition vector autoregressive model (STVAR) is further modified to let us focus on long run dependences in the system or "nonlinear cointegration." The STVEC model obtained is then used as a basis in computing the multivariate generalized impulse responses (MGIRF).

If shocks to volume (sales) influence returns, observing volume together with prices helps us in explaining the behavior of stock prices. This is in contrast to the EMH. Similarly, many empirical studies imply that stocks are not a good hedge against inflation. The role of counter-cyclical monetary policy in explaining this "anomaly" is considered next.

1.5 Introduction to Chapter 3

Many studies confirm that the real gross domestic product (GDP) is an important indicator of the performance of the economy. Cochrane (1991) showed that the growth rate of the real GDP had a positive effect on stock returns, such that expected returns are high because investment growth is high. By contrast, if increased output causes higher transaction demand for money, the Central Bank is expected to raise the interest rate. A rise in risk-free rates,[9] which investors use to discount the future cash flows of the stocks, increases the required rate of return on equity, and causes a fall in their price. However, inflation expectations may also cause investors to require higher risk premiums for their investment if inflation "eats out" some of their profits. The conventional view suggests that a restrictive monetary environment serves as bad news, and hence investors become more risk averse. This raises the total discount factor they use to discount the future cash flows of stocks, suggesting that one should also scrutinize the role of monetary policy in explaining changes in stock returns. Unfortunately, as stock return patterns are likely to reflect current and expected future economic conditions along with current and expected future monetary conditions, the issue of causation is difficult to determine given that monetary policy is affected by stock returns but also influences it (Choi et al., 1999). Hence, to narrow the study, this thesis focuses on the causation running from monetary policy to returns alone.

Models in monetary economics that assume a role for money and endogenize the price level and inflation together with stock prices typically cite the empirical findings that real stock prices are negatively correlated with inflation, expected or unexpected. This result is contradictory to the traditional view that equities should be a good hedge against inflation. Balduzzi (1996), among others, obtains closed-form solutions for inflation, nominal and real interest rates and stock prices, where monetary uncertainty causes households to respond to tighter monetary policy and lower expected inflation by reducing their demand for real assets and increasing their demand for cash balances. Hence stock returns fall. Bakshi & Chen (1996) have tried to explain the "spurious" negative correlation between inflation and real stock prices. As they studied the endogenous and simultaneous determination of the price level, inflation, asset prices and the real and nominal interest rates, they found that contemporaneous correlation between real stock prices and inflation is negative unless both money growth is pro-cyclical and its covariance with output growth dominates the variance of the latter. From this viewpoint it is reasonable to expect that stock prices are nonlinearly related to inflation or the current state of the business cycle measured by expected inflation (Barnes, 1999 and Boyd et al., 2001). In Chapter 3 we try to find empirical evidence on these claims based on Finnish data.

In a small open economy under fixed exchange rates fiscal policy instruments affect output, but monetary policy has no effect because of forced sterilization through interventions. Hence the question of monetary policy tightness translates into focusing on different exchange rate regimes and the current account balance. If we approximate a current account deficit by the expected change in the interest rate and inflation, we note that agents demand fewer financial assets at given interest differentials as inflation rises. Higher nominal or real interest rates make the rate of return on debt instruments relatively more attractive to investors than equities, which reduces the demand for shares and their prices fall accordingly. (Gärtner, 1997) Alternatively, the Central Bank's goal could be a stable increase in money supply or modest inflation, which could be achieved allowing the exchange rate to float. Under rational expectations and floating exchange rates, an unexpected, permanent increase in the rate of money growth stimulates output temporarily via surprise inflation. However, one period later this effect evaporates, leaving the economy with permanently higher inflation. Inflation is often restrained by increasing interest rates, which should eventually show up as a reduction in stock returns (real activity unchanged).

If devaluation is used to avoid financial crisis, the crisis may be exacerbated because higher expected inflation following devaluation typically results in a rise in interest rates. Similarly, if debt contracts are denominated in foreign currency, devaluation of the domestic currency increases the debt burden of domestic firms. Since assets are typically denominated in the domestic currency, there is no simultaneous increase in the value of the company's assets. The combined result is that a devaluation leads to a substantial deterioration in company's balance sheet and a decline in net worth, which in turn means that effective collateral has shrunk, providing less protection to lenders. In the end, devaluation leads to a decline in stock returns. (Mishkin, 1999)

If the main goal of the Central Bank is to fight inflation and maintain the credibility and stability of the economy, it should choose fixed exchange rates. Yet, despite its inherent advantages, an exchange rate target results in the loss of independent monetary policy, since changes in the anchor country lead to corresponding change in interest rates in the target country. Another disadvantage is that speculators may begin to question whether a country's commitment to the fixed exchange rate peg would hold. A country may thus have to keep its interest rates sufficiently high to fend off their attacks, and this in turn is bad for investment and employment.

A problem in measuring monetary policy stringency in Finland is the gradual deregulation of the financial markets which took place in the early 1980s and continued until the early 1990s. Similarly, a change in monetary policy toward inflation targeting should show up as a regime shift around 1993. Furthermore, with fixed exchange rates and a high degree of capital mobility, the behavior of banks and the characteristics of the credit market also come into play when trying to insulate the effects of monetary policy; i.e., monetary policy affects output only if it changes the availability of loans (Patelis, 1997).

If inflation is fought using monetary policy, what is the right timing of various policy actions? When the monetary authority can correctly foresee a rise in inflation expectations, the need for tighter monetary policy is diminished. But, if the policy actions are taken too late, a much higher rise in interest rates is required to produce the same results. In addition, monetary policy has to be forward-looking, as it takes time for the Central Bank's actions to have any influence on the economy. Consequently, putting a dummy variable in the model when the Central Bank has announced a rise in interest rates does not necessarily tell us when this policy action influences the economy. Therefore, in order to allow for different behavior between real stock prices and inflation under different monetary policy regimes, we use the MS-VAR model. We then look at the signs and magnitudes of the contemporaneous correlations between inflation and returns in the regimes obtained, which we hope to be able to interpret as tight or loose monetary policy regimes.

In spite of mean switches, which may have a natural interpretation as a business cycle, interpreting the estimation results from the MS-VAR models is not always obvious. By contrast, generalized impulse response functions summarize the information in the autoregressive parameters, variances and covariances of each regime, thus making it easier to illustrate the models estimated. Furthermore, several studies describe how the size and magnitude of observed correlation between inflation and returns are affected by the source of fluctuations in the economy; i.e., real or monetary shocks (Marshall, 1992 & Giovannini, 1989 and Lastrapes, 1998). This is tested using the regime-dependent impulse response function. Following Ehrman et al. (2000) we define a separate set of IRF for each Markov regime to show how fundamental disturbances, in particular in output and money, affect real stock prices (returns).

1.6 Contribution

This chapter concludes by presenting the main empirical results of this thesis. The author asked, among other things, whether hypothetical trading based on an explicitly specified information set earns superior returns at the Helsinki stock exchange for 1921 - 1997. In the first case the information set included past stock prices (returns) and trading volume (sales), and STAR models were used to describe the time-series properties of these series. STAR models are also useful as a test against structural breaks. As the sample is large, finding some indication about a structural break in sales series around 1957 was not surprising, especially since the Finnish economy had suffered from a general strike in 1956, and was at the same time opened to foreign trade. In addition, to boost the economy, the paper industry was supported by a 39% devaluation on 15.9.1957. Taking this into account, we divided the sample in two separate time periods. Finally, the analysis has been done using these two sub-samples as well as the whole data period.

Based on the model mis-specification tests, heteroskedasticity seems to be the biggest problem in the analysis. However, informational efficiency tests do not require that the residuals from the random walk model used in testing this hypothesis be homoskedastic. Nevertheless, heteroskedasticity might result from other kinds of model mis-specification such as neglected nonlinearity in the model for the conditional mean. To take this into account we use STAR models as a starting point to pick out the nonconstant conditional mean, and continue by modeling nonconstant error variance using smooth-transition generalized autoregressive conditional heteroskedastic models (STAR-GARCH). There is some indication of a structural break in volatility around 1934 corresponding to the great depression in the 1930s. We also locate a break in 1993/8, which refers to the time when the Finnish economy started to recover from a deep slump, and foreign ownership restrictions were removed. Nevertheless, lack of proper tools for handling these problems means that we have to leave the further implications of these breaks on returns as a topic of future studies.

To be able to completely grasp the implied properties of a time-series generated by the STAR model, we also consider the effect of shocks on the future patterns of returns and sales using the generalized impulse response function (GIRF). The GIRF summarizes the information in the autoregressive parameters, variance and covariance of each regime, which makes it easier to illustrate the estimated model. However, focusing on the persistence of shocks in the stock market is also an interesting problem in itself. If prices follow a random walk, any shock hitting the market has a persistent effect on prices. However, the fact that prices revert back to their fundamental values (mean reversion) after new information has reached it is commonly considered as evidence against the EMH.

The results of the GIRF based on STAR models confirm that shocks to returns at the HeSE in 1957/9 - 1997/11 are not persistent. This also applies when we take into account the possibility that positive and negative shocks may have different effects on the market. Using 50 innovations selected such that they are larger than one standard deviation of the STAR residuals and focusing on “high” return histories, we observe that high returns are generally followed by similar returns or much lower returns. We see this kind of behavior as bimodality, when the highest density regions are used to depict the results from the GIRF. In other words, returns are negatively correlated, or there is mean reversion in stock prices.

After finding a proper STAR model to describe the behavior in returns and sales, we test whether sales contain any information which could be used to get a better idea about the behavior of returns than just looking at returns alone. Recently, Eitrheim & Teräsvirta (1996) have generalized the linear Granger noncausality test to be used for STAR models. As against linear causality tests, which indicate bidirectional causality between returns and sales (volume), we found that causality mainly runs from returns to sales (volume).

The results suggest that changes in returns have affected trading behavior at the HeSE between 1957/9 and 1997/11. These results are used when we fit more parsimonious STVEC models to the data, which allows us to take into account both the possible composition effect and common persistence ("nonlinear cointegration") in the system. Unfortunately, only one of the alternative STVEC models fitted to the data converged such that the calculation of the inverse of the Hessian succeeded. Now, looking at the estimated GIRF, considerable persistence of shocks in both returns and sales is observed, but with particularly low probability. Perhaps the current method does not let us take fluctuations in the variance in the sales into account properly. The results taken together imply that the underlying multivariate dynamics are complicated. We conclude

- that ignoring nonlinearity in stock return and sales (volume) time-series may lead us to make incorrect conclusions about shock persistence, long run dependences (cointegration) and/or Granger causality between these variables. The consequences of using linear methods in testing the sequential arrival of information model - or any other model introducing nonlinearities between sales and stock prices - may therefore be severe.

Thus, to take nonlinearity in the data into account properly, STAR, STGARCH and STVEC models are employed as a basis for measuring persistence of shocks in returns and sales, as well as in testing causality between these variables.

Changes in trading volume alone may not be sufficient to describe the behavior of the stock market. In fact, stock prices are used to some extent to forecast the behavior of the real economy, and vice versa. A rise in interest rates also typically leads to a fall in stock prices. Similarly, we would expect to find positive correlation between stock prices and inflation if stocks are a good hedge against inflation. In particular, the purpose of Chapter 3 was to find empirical support for the results from Bakshi and Chen (1996). They suggest that one finds negative correlation between the real price of an equity and inflation unless both money growth is pro-cyclical and its covariance with output growth dominates the variance of the latter.

Using the MS-VAR model we identify changes in regimes, and tight and loose monetary policy regimes from the data. The regimes obtained are then compared with previous information about monetary policy stringency, devaluation dates in particular. This helps us to determine whether changes in regimes are in fact due to changes in monetary policy.

- After using alternative sets of explanatory variables in the MS-VARs, we conclude that the sign of the contemporaneous correlation between returns and inflation depends on the return horizon chosen: in the monthly models the statistically significant correlations are always negative, but in the case of quarterly data positive - independent of which regime we are in.

The heteroskedasticity of the return series probably affects the nonlinearity characteristics found in the data, and is perhaps one factor driving the regime-switching behavior. Hence, after modeling heteroskedasticity in the data, we also considered whether stock prices keep up with inflation more easily if there are no sudden changes (volatility) in the economy as a whole. Now, in many cases correlations between returns and inflation are statistically significant only in the regime which typically identifies the low volatility periods in the data. Thus we conclude

- that stocks are a good hedge against inflation especially during the steady states in the economy.

However, most of the previous evidence on this latter topic is based on models that do not incorporate any long run relationships that might be present, for example, between the value of equities and movements in goods prices. If the growth process of returns and inflation has contemporaneous regime shifts, then the inference on dating parallel cycles can be improved by considering the Markov switching vector equilibrium model (MS-VECM). This also allows us to pay special attention to the short run dynamics in the system allowing "multiple equilibria." Several cointegration restrictions, like cointegration between inflation and output and between output and returns, are tested and established. From the estimated MS-VEC models we note that in some cases the timing of the estimated regimes is altered compared to the MS-VAR models, but in general the signs of statistically significant correlations between returns and inflation remain unchanged. Thus, the main conclusion that stocks are a good hedge against inflation in the long run holds.

As with STAR models, interpreting individual parameters of the MS-VARs is difficult. Hence, to shed some light on the characteristics of these models it is useful to consider the effect of shocks on the future patterns of a time-series variable. A convenient tool is the multivariate generalized impulse response function (MGIRF). Now, compared to the linear impulse responses, the response of stock returns to a monetary policy shock changes its sign and becomes positive when the MS-VAR includes (in this particular order): y (industrial production), *MCI* (measure of monetary policy stringency), r (stock returns) and *CPI* (consumer price index). The response of inflation to a positive *MCI* shock is also positive. Contemporaneous correlations between *CPI* and r were also positive and statistically significant in this model.

- Thus, it seems that stocks gain briefly following monetary shocks relative to goods prices as already noted by Ely & Robinson (1997).

Finally, when we look at the equation for returns, both output and monetary policy shocks die out quite quickly, in all cases in about five quarters. Note that when we continue by scrutinizing a model with an alternative measure of monetary policy stringency, i.e., the marginal interest rate of funds advanced by the Central Bank to the commercial banks, the response of returns to both output and monetary shock is different in each regime. This confirms the previous findings from Marshall (1992), Giovannini (1989) and Lastrapes (1998) that the source of the shock (real or monetary) to the stock market matters.

The outcomes of tests of the EMH are important in assessing public policy issues such as the desirability of mergers and takeovers, short-termism and regulation of financial institutions. The EMH test results are also useful for derivative market participants, whose success precariously depends on their ability to forecast stock price movements. Similarly, a sharp decline in asset prices can generate systemic concerns when the banks, for example, are affected by stock prices through the risk of a severe reduction in collateral values and of increasing defaults by customers, the risk banks incur as direct investors in the stock markets and/or the risk of an abrupt reduction in overall returns from banking activity. Finally, there is the risk related to adverse changes in the macroeconomic and financial environment possibly associated with a period of declining asset prices. For example, higher asset values in some countries may have caused excessive consumption through wealth effects, which is also reflected in decreased savings and increased indebtedness. Now, a large decline in asset prices may reverse this tendency, slowing economic activity, business investment and the purchase of new property by households, and so on, and thus triggering the classic debt-deflation problem. (European Central Bank, 2000) This kind of behavior has increased the need to supervise the possible risks for the banking sector of such things as sharp changes in stock prices.

A natural question is whether we gain anything if STAR or MS-VAR models are implemented to improve the quality of day-to-day financial activity, or to alter the outlines of public policy. Is there any useful information in addition to stock prices themselves, which investors should follow in trying to beat the market? For example, if changes in monetary policy explain the behavior of stock prices to some degree, should investors or regulators be more concerned about monetary policy announcements? We conclude that as taking into account nonlinearity in the data influences the results considerably, nonlinearity testing and modeling should become a habit when working with financial market data.

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Footnotes

1. Equilibrium expected returns are assumed to be constant. The rational expectations hypothesis holds.

2. As Fama (1991) noted, market efficiency per se is not testable since it must be tested jointly with some equilibrium model. The joint-hypothesis problem requires care in interpreting the

results as evidence for or against market efficiency. Further examples of operationalization of the EMH can be found in Cuthbertson (1996), pp. 116 - 117.

3. If a series has to be differenced *d* times to induce stationarity, it is said to be an *I(d)* series, or integrated to order *d*, denoted $y_t \sim I(d)$. For integrated processes the variance is unbounded, the expected time between crossings of $y_t = 0$ is infinite and the process has a permanent memory. The unit root test is designed to reveal whether H_0: y_t is difference-stationary ($d = 1$) or H_1: y_t is trend-stationary. The components of the vector z_t are said to be cointegrated to order *d,b*, denoted $z_t \sim CI(d,b)$, if *i)* z_t is *I(d)* and *ii)* there is a non-zero vector β such that $\beta' z_t \sim I(d - b)$, $d \geq b > 0$.

4. As the trading volume series is constructed such that it "includes" both turnover and value (price) of trading, we furthermore deflate volume by the actual price index, and call this series sales.

5. Testing the statistical significance of several states is problematic and therefore most authors of applied papers use a model with several states on purely theoretical grounds.

6. It is possible that the GARCH effect disappears with time aggregation at lower frequencies. Scheicher (1999): "GARCH works best with daily data. However, the MS-VAR models offer a framework to investigate topics such as return predictability, which are typically encountered in data with monthly frequency."

7. Some attempt to consider structural breaks and the STAR type of nonlinearity simultaneously has already been made (Lundbergh et al., 2000).

8. See Hamilton (1994).

9. Practitioners frequently simplify the task of pricing derivatives; for example, by assuming that investor risk preferences are zero. This is equivalent to assuming that all stocks and other risky assets have an expected return equal to the risk-free rate and that all cash flows should be discounted at this rate.

Chapter 2

Modeling nonlinearity in the stock return - trading volume relationship

Abstract

In an Efficient Market prices adjust instantaneously toward their fundamental values, and trading volume contains no information about future price developments. However, the sequential arrival of information model implies a positive causal relation between absolute stock returns and trading volume in either direction, and the mixture model suggests a positive causal relation running from volume to absolute returns. Empirical evidence supports these theories, since large movements in stock prices typically take place on days with high trading volume. Here, we consider the relationship between stock return and trading volume using a nonlinear framework. First, non-linearity in the Helsinki Stock Exchange data is tested using a smooth transition autoregressive model. Next, we compute nonlinear impulse responses; first to check the stability of the models, and second to scrutinize the persistence of shocks in return and volume series. Linear Granger causality tests indicate bidirectional causality between returns and trading volume. By contrast, the nonlinear causality tests suggest that only in a few cases can trading volume be used to forecast returns. Thus, the empirical findings give only slight support to the mixture model. Finally, we exploit the outcome of causality tests to specify a smooth transition vector error correction model in order to take into account the influence of the composition effect and common persistence on the results. We conclude that causality runs mainly from returns to trading volume, corroborating the positive feedback trading hypothesis.

2.1 THEORETICAL BACKGROUND FOR THE STOCK RETURN - TRADING VOLUME RELATIONSHIP

Fama (1970) defined an Efficient Market as one in which security prices always fully reflect the available information. When investors are rational, they value each security for its fundamental value or the net present value of its future cash flows discounted for their risk characteristics. According to the Efficient Market Hypothesis (EMH) stock prices change only on the arrival of new information or news about "fundamentals", that is, the future course of either dividends or discount rates. When investors learn something about the fundamental values of securities, they quickly respond to this new information, and prices P_t at time t adjust almost immediately to new levels corresponding to the new net present values of cash flows. Forecast errors $\varepsilon_{t+1} = P_{t+1} - E_t P_{t+1}$, where E_t is the expectation operator, should therefore be zero on average. They should also be uncorrelated with any information Ω_t that was available at the time the forecast was made. Similarly, when the EMH is applied to stock returns, it implies that one cannot earn abnormal profits by buying and selling stocks. Actual returns will sometimes be above and sometimes below expected returns, but on average unexpected returns are zero.[1] Furthermore, as prices already contain all relevant information in the market, other variables such as trading volume, cannot be used to forecast prices either. (Cuthbertson, 1996)

Depending on the information set Ω_t available at time t, the EMH comes in three different forms. The weak form of the hypothesis states that prices efficiently reflect all the information in the past series of stock prices. The semistrong form of the hypothesis states that prices reflect all published information. The strong form of the hypothesis states that stock prices effectively capture all available information (insider information) in the market. In this paper we consider only the first two forms of the EMH.

The EMH has been widely scrutinized, but results have been contradictory. Karpoff (1987) provided a survey of the theoretical and empirical research explaining the relation between price changes and trading volume. There is empirical evidence that increases in prices are positively correlated with trading volume, though the relationship between that and price falls is more ambiguous. Typically, the price-volume relationship depends on the rate of information flow and dissemination to the market, the extent to which market prices convey the information, the size of the market and the existence of short-selling constraints. Price changes ΔP_t can be interpreted as the market evaluation of new information, while the corresponding volume V_t is an indicator of investor disagreement about the meaning of this information. Besides, Karpoff points out that several empirical tests about the price-volume relationship are based on the wrong assumption about the functional relationship between these variables, as well as this relation being monotonic. Tests of linear dependence between volume and returns are thus mis-specified, and we would expect them to yield poor results.

Consequently, two “stylized facts” have emerged from empirical research: first, the correlation between trading volume V_t and the absolute value of the price change, or volatility $|\Delta P_t|$, is positive. In other words, a large increase in volume is usually accompanied by either a large rise or a large fall in prices. This would correspond to a sequential arrival of information model, presented in more detail below. Based on empirical evidence the correlation between volume and returns ΔP_t is also positive. If we assume that we have at least two types of investor in the market (informed and uninformed), then the volume that results when a previously uninformed trader interprets the news pessimistically is less than when the trader is an optimist. Since price decreases with a pessimist (who sells) and increases with an optimist (who buys), it is argued that trading volume is relatively high when the price increases, and low when the price decreases. (Karpoff, 1987)

Nonlinearity in common stock returns was first reported by Hinich & Patterson (1985). Strong evidence of nonlinearity was found in the daily returns of 15 return series using Hinich’s Bispectrum test. Neftci (1991) assumed that investors were following technical trading rules and were modeling returns accordingly. He also found some nonlinearity in returns. Li & Lam (1995) modeled returns using a nonlinear model, where the conditional variance was parametrized as an ARCH process, reporting evidence of nonlinearity of stock returns. Hiemstra & Jones (1994) found evidence of nonlinearity in aggregate trading volume. Gallant et al. (1993) suggested that days with large price changes should also be days with larger than average trading volume. Harris (1984) studied daily data from 479 common stocks and found a positive correlation between volume and the square of the price change. Smirlock & Starks (1988) found that the relation between absolute returns and trading volume was strongest over short periods immediately preceding and following quarterly earnings announcements. The autoregressive conditional heteroskedastic (ARCH) models are also widely used in explaining the sharp falls observed in stock prices. In general, the ARCH literature focuses on the dynamics of the price process alone and investigates its time-varying volatility or risk in the stock market. For example, there is evidence for the "leverage effect;" i.e., changes in the riskiness of equity due to changes in the debt/equity ratio of the firm.[2] Bollerslev et al. (1992) report more than 300 papers related to the application of (Generalized) Autoregressive Conditional Heteroskedastic (G)ARCH models in stock returns.

An extensive survey on the empirical research on Finnish stock markets is given in the special issue of the Finnish Journal of Business (1997). Previous models describing the data were mostly assumed to be linear (autoregressive moving average models) but GARCH models were also used. Several studies suggested that the assumption of market efficiency may not hold in Finland. Significant positive first-order serial correlation was observed in daily, weekly and monthly return intervals. Furthermore, equity research showed that autocorrelation is persistent and related to both friction in the trading process and return predictability. Sierimo & Virén (1995) looked at the behavior of returns and trading volume at the Helsinki Stock Exchange (HeSE) for 1921/1-1996/8, and detected significant causality running from volume to absolute returns in contrast to bidirectional Granger causality found between returns and volume. Furthermore, Finnish stock return distributions are typically negatively skewed and highly leptokurtic, and size and the January effects are observed as in most other countries around the world (Knif & Löflund, 1997).

Granger (1992) summarizes various explanations of the use of regime-switching models in modeling stock returns. For example, if we need to model changes in the mean of returns using an additional explanatory variable; i.e., an indicator variable with a value of unity in January and zero in other months (the January effect), this suggests that the data-generating process itself may be regime-switching, and should be modeled accordingly. For a general survey of nonlinear models, see Tong (1990) or Granger & Teräsvirta (1993). Following this line of research, the EMH is tested using monthly observations of the HeSE general index and trading volume, starting in January 1921 up to November 1997. Nonlinearity in returns and trading volume is tested both individually and together. If linearity is rejected, the volume and return series are modeled using a smooth transition autoregressive (STAR) model. The attempt is to see whether taking nonlinearity or structural breaks in the data into account changes previous results significantly.

The remainder of Chapter 2 is organized as follows: in Section 2.1 some explanations of the presence of a causal relation between stock returns and trading volume are listed based on previous research on this topic. Next, I justify the choice of using a smooth transition autoregressive STAR model instead of a linear model in this study (Section 2.2). Section 2.3 surveys previous empirical evidence about nonlinear relations between stock returns and trading volume. Section 2.4 describes the data. Section 2.5 starts by testing structural breaks in the data, and continues by testing nonlinearity in the HeSE data using STAR models for both returns and trading volume. If I need to model both the "nonlinear" conditional mean and conditional variance of returns and/or volume to improve the fit of the model to the data, I continue by using

STAR-GARCH models instead. Section 2.6 discusses the use of the generalized impulse response function (GIRF) in testing model stability and shock persistence in the case of univariate STAR models. Nonlinear Granger causality between returns and trading volume (sales) is tested in Section 2.7. Finally, Section 2.8 discusses expanding the impulse response analysis to a more general case of multivariate nonlinear time-series models. Here, the shocks in the first equation may not only have contemporaneous effect on the first dependent variable but on the other dependent variables in the system as well (the composition effect). This section ends with empirical results obtained using the smooth transition vector error correction (STVEC) model as a basis in computing the GIRF. Section 2.9 concludes this study.

2.1.1 The no-trade theorem

There is an ongoing debate over the issue of whether "public information" moves stock prices with or without trading (Chen et al., 1999). It has also proved very difficult to find a rational expectations model that breaks the no-trade theorem, according to which diversely informed traders may be extracting information from equilibrium prices so efficiently that, literally, no trading occurs in any equilibrium. Therefore, to explain trading on financial markets we need a model in which the no-trade theorem fails to hold. This has led to studies of asset markets populated by boundedly rational, differently informed agents. For example, some of the market participants may be rule-of-thumb investors, who form their expectations according to some naive rule. Trading occurs until the new information in the market is completely incorporated into prices via the trading of informed investors.

An example of the no-trade theorem that characterizes rational expectations equilibria in a class of models of purely speculative trading can be found in Sargent (1993). He describes how abandoning rationality by allowing least squares learning can temporarily undo the no-trade result and produce a model with trading volume.[3] Furthermore, learning effects explain volatility clustering in stock returns in that if the dividends ("endowment") process underlying stock returns is subject to structural breaks forecasting future dividend streams by market participants potentially becomes a more demanding task. The investor's new estimates of the process parameters immediately after some breaks are potentially volatile since such breaks are different from "ordinary" uncertainty. Since realized stock returns are a function of the parameter estimates of agents, the impact of learning effects is an increase in stock market volatility after a break in the underlying process. If no further breaks are expected, these learning effects should disappear as time elapses and more information arrives. (Timmermann, 1997)

2.1.2 Linear dependences

Large/small trading volume is usually accompanied by a rise/fall in stock returns: corr(V_t,ΔP_t) > 0.

Hiemstra & Jones (1994), among others, provide empirical support for the argument that more can be learned about the stock market through studying the joint dynamics of stock prices and trading volume than by focusing simply on the univariate dynamics of stock prices. DeLong et al. (1990) offer a theoretical background for this kind of analysis. First, it is generally assumed that rational speculators must stabilize asset prices in efficient markets. Nevertheless, the presence of positive feedback traders - who buy when prices rise and sell when prices fall -

together with rational speculators may have the opposite effect. An initial price rise caused by purchases by speculators today stimulates the appetites of uninformed investors, who think that the price rise will continue tomorrow. In anticipation of these purchases, informed rational speculators buy more today, and so drive prices up today higher than fundamental values. Tomorrow, positive feedback traders buy in response to today's price increase and so keep prices above fundamentals even as rational speculators are selling out. In the long run this "truly" temporary component disappears, thus producing mean reversion of stock prices, but in the mean-time prices have already moved more than suggested by the EMH. Note that as positive feedback traders place their market order today in response to a previous price change, and as the purchases of speculators rise in anticipation to a price increase, causality runs from returns to trading volume.

There are several explanations for trading volume tending to be higher when stock prices are increasing than when they are falling. For example, in order to manipulate reported profits, firms may selectively sell winner stocks from their portfolios. As a result trading volume for winner stocks should be high at the end of the fiscal year. But intuition may not always be straightforward: portfolio rebalancing may cause investors to sell stocks even when their prices fall to restore a well-diversified market portfolio. (Shawky & Marathe, 1995 and Bremer & Kato, 1996)

2.1.3 Nonlinear dependences

A large increase in trading volume is usually accompanied by either a large rise or a large fall in stock returns: corr($|\Delta P_t|, V_t$) > 0 or corr($\Delta P_t^2, V_t$) > 0.

Equilibrium prices reflect an averaging of investors' beliefs. Thus, price changes may be small if the revisions of investors' belief largely counterbalance each other. However, the sequential arrival of information hypothesis is supported by the finding that a large movement in prices $|\Delta P_t|$ typically takes place on days with high volume, or vice versa (Copeland, 1976). Now, N traders will in general be split into k optimists, r pessimists and N - k - r uninformed investors at any point in time before all investors become informed. If investors obtain new information only one at a time, trading volume may be high as those who interpret news as good news (optimists) buy from those who think it is unfavorable (pessimists). This kind of behavior tends to push prices up. Note that uninformed investors cannot learn from the actions of informed traders. In addition, volume increases with the degree of homogeneity across investors, and simulation tests indicate that volume is highest when investors are all optimists or pessimists. Once an optimist has traded, a later pessimist has fewer units to sell when it is his turn to trade, whereas a late optimist has fewer units to purchase. On the other hand, an optimist following an optimist has an increased number of suppliers from whom to buy while a pessimist following a pessimist has an increased supply of assets to trade away. Nevertheless, the implication of the model that volume is greatest when all investors agree on the meaning of the information could be criticized, since greater normal trading volume may actually slow down the adjustment of prices to information as, in a market with more uninformed trading, trades from informed traders can be hidden more effectively. (Karpoff, 1987)

If daily returns are not autocorrelated and symmetrically distributed but kurtotic relative to normal distribution, this is explained by their being sampled from a set of distributions with differing variances. This is the mixture of distributions hypothesis. A further implication of this hypothesis is that price data appears to be generated by a conditional stochastic process with changing variance parameters that can be proxied by trading volume, or that transaction price changes are mixtures of distributions with volume as the mixing variable. (Epps & Epps, 1976)

The mixture model states that if trading volume is used to measure the disagreement as traders revise their reservation prices based on the arrival of new information, the greater the disagreement, i.e. the larger the level of trading volume, the larger the absolute price changes. Thus there is a positive causal relation running from trading volume to absolute stock returns. This implies that knowledge of the behavior of volume can marginally improve conditional price change forecasts based on past price change forecasts alone.

Tauchen & Pitts (1983) claim that the variance in the daily price change and the mean daily trading volume depend upon three factors: first, the average daily rate at which new information flows to the market. Second, the extent to which traders disagree when they respond to this new information and, last, the number of active traders in the speculative markets. The first two may be assumed to be constant over time. As to the latter, however, one might conjecture that more traders would tend to stabilize prices. Now, for a fixed number of traders, daily trading volume and the square of the price change are positively correlated but, as the number of traders increases, the mean daily volume of trade increases while the variance in price changes decreases. Tauchen & Pitts conclude that if a rise in the number of traders affects $E_t[\Delta P_t^{\,2}|V_t]$ seriously, one should take this problem in empirical analysis into account by including a trend for volume in the model. Next, we present some previous empirical results concern nonlinearity in return and volume series as well as the nonlinear relationship between these variables.

2.2 PREVIOUS EMPIRICAL RESULTS

Many empirical studies confirm that return and trading volume time-series properties are best described using nonlinear models. For example, the returns data often reveals the volatility clustering phenomenon associated with GARCH of large (small) shocks of either sign tending to follow large (small) shocks. The evidence of nonlinearity in returns and trading volume is not limited to the case in which these series are individually described. Hiemstra & Jones (1994) report unidirectional linear Granger causality from returns to volume in contrast to bidirectional nonlinear causality between these variables. They also filter stock returns with Exponential GARCH to control for volatility persistence, and still find nonlinear causality running from volume to stock returns. Silvapulle & Choi (1999) get similar results focusing on the emerging Korean stock market. Bollerslev et al. (1992) report more than 300 papers related to the application of (G)ARCH models to stock returns. Neftci (1991), Hsieh (1991) and Li & Lam (1995) also reported evidence of nonlinearity. Harris (1984), Smirlock & Starks (1988) and Gallant et al. (1993) find nonlinear relationships between volume and price changes. Lately, Sarantis (2001) finds that STAR models are useful in describing asymmetric cycles in stock price growth rates in most industrial countries (i.e., the USA, Japan, Germany, the UK, France, Italy and Canada).

Campbell et al. (1992) find a negative relation between daily stock index return autocorrelations and trading volume. They assume that two types of investor exist in the market: “non-informational”[4] investors who want to sell stocks for exogenous reasons, and market makers who are willing to buy stocks to accommodate the market selling pressure, but who require compensation for taking the risk in the form of a lower stock price or a higher expected stock return. For such traders stock return reversals tend to cause an abnormally large increase in volume, as prices tend to fall, increasing the trading volume as long as the reallocation of risk between heterogenous traders is completed. Therefore, large trading volume will be associated with relatively large negative serial correlation of returns.

In the case of Finland for 1921/1 to 1996/8, we found significant causality running from volume to absolute returns as distinct from bidirectional causality between stock returns and trading volume (Sierimo & Virén, 1995). The latter results are given in Table 2.1. This suggests that nonlinear models may be useful in describing the behavior of the HeSE.

Table 2.1: Granger causality between returns and trading volume in Finland between 1921/1 and 1996/8.

Direction of causality	Δy_t	Δy_t^2	$\lvert\Delta y_t\rvert$
Return → Volume	8.354	1.717	1.604
Volume → Return	7.419	1.420	**1.795**

Δy_t = the logarithmic difference of returns and trading volume, Δy_t^2 = squared logarithmic difference of returns and volume and $\lvert\Delta y_t\rvert$ = volatility (absolute value of logarithmic difference of returns and volume). Critical value for Granger causality test at the 5% significance level equals 1.750.

Liljeblom & Stenius (1997) scrutinized the relationship between the volatility of macroeconomic variables and stock market volatility in Finland between 1920 and 1991. Significant results are obtained from stock market volatility as a predictor for macroeconomic volatility, as well as the converse. Some evidence of a negative relationship between stock market volatility and trading volume growth was also detected. In the case of non-specialist markets, an increase in trading volume may indicate an increase in the number of traders in the market, in which circumstances the individual trades will probably cancel out, thus reducing the variance in the returns. Berglund & Liljeblom (1990) tested this hypothesis for the Finnish stock market in a high-volume period between 1986 and 1988 and a low-volume period between 1978 and 1980.[5] They expected a lower standard deviation in individual stock returns in the high-volume period than in the low-volume period, but this was not confirmed empirically, even after they excluded the crash in October 1987 from their research. October 1987 is also included in the present study, but before we draw any conclusions about its possible effects on the results, we describe the STAR model and the data in more detail.

2.3 THE CHOICE OF THE TYPE OF NONLINEAR MODEL USED IN THIS STUDY

Here we focus on the models under the heading “regime-switching” theories. For a general survey of nonlinear models see Tong (1990) or Granger & Teräsvirta (1993). First, a general introduction to STAR models is given (van Dijk et al., 2000b). I then show their usefulness in modeling nonlinearities in stock return and trading volume series. Equation 2.1 is the starting point:

$$y_t = S_t^{'}\Pi + S_t^{'}\theta F(z_t) + u_t, \tag{2.1}$$

where $E_t(u_t|\Omega_{t-1}) = 0$, $E_t(u^2_t|\Omega_{t-1}) = \sigma^2$, $E_t S_t u_t = 0$ and $E_t z_t u_t = 0$, where Ω_{t-1} is the history of the time-series up to time $t - 1$, $t = 1,...,T$. The term $S_t = (1, y_{t-1},...,y_{t-p})'$ is the set of explanatory variables including a constant, $\Pi = (\pi_0, \pi_1,..., \pi_p)'$ and $\theta = (\theta_0, \theta_1,..., \theta_p)'$ are $p + 1$ parameter vectors. $F(z_t)$ is a continuous transition function bounded between zero and one allowing the model to change from $E_t(y_t|S_t) = S'_t\Pi$ to $E_t(y_t|S_t) = S'_t(\Pi + \theta)$ with z_t, where $z_t = \gamma(\delta' S_t - c)$ is the indicator function with transition variable $\delta' S_t$, $\delta = (\delta_1,...,\delta_m)'$ and $m = p + 1$. Throughout this work we have assumed that the transition variable is a lagged endogenous variable $\delta' S_t = \hat{y}_{t-d}$ for a certain integer $d > 0$, but it could also be an exogenous variable or a linear time trend. Allowing for exogenous variables as additional regressors included in S_t is also straightforward. These models are known as smooth transition regression (STR) models, which have forms of

$$F(z_t) = \begin{cases} (1 + \exp(-\gamma(\hat{y}_{t-d} - c)))^{-1} \text{ LSTAR} \\ (1 - \exp(-\gamma(\hat{y}_{t-d} - c)^2)) \text{ ESTAR.} \end{cases} \tag{2.2}$$

If a logistic STAR (LSTAR) model of order p is chosen, high and low trading volume/stock returns may have rather different dynamics, and the change in dynamics from one regime to the other is smooth. Parameters change monotonically and the transition variable deviates from a fixed point c, or the “threshold” between the two regimes. In an exponential STAR (ESTAR) of order p, volume/returns may move rapidly between very small and very large values for which local dynamics are stable. The parameter γ determines the smoothness of the change in the value of the transition function, and thus the smoothness of the transition from one regime to the other. We assumed that the conditional variance of u_t is constant in Equation 2.1. Later, we abandon this assumption following Lundbergh & Teräsvirta (1998), and use a model which also allows for the GARCH type of behavior in the error process in addition to a nonlinear mean.

Van Dijk et al. (2000b) recommend a “specific-to-general” strategy for building nonlinear time-series models. This implies starting with a simple or restricted model and proceeding to more complicated ones only if diagnostic tests indicate that the model is inadequate. An additional motivation for this kind of approach here is the identification problems discussed below that prevent us from starting with a STAR model and reducing its size, say, by conducting a series of likelihood ratio tests. Thus, the modeling cycle for STAR models consists of the following steps: *i)* Specify an AR model of order p for the time-series under investigation. *ii)* Test for structural breaks in the data. *ii)* Test the null hypothesis of linearity against the alternative of STAR nonlinearity. If linearity is rejected, select the appropriate transition variable z_t, and the form of the transition function $F(z_t)$. *iii)* Estimate the parameters in the selected STAR. iv) Evaluate the model using diagnostic tests and impulse response analysis. *v)* Modify the model if necessary. *vi)* Use the model for descriptive or forecasting purposes.[6]

Next, we demonstrate why STAR models would be the best for our needs here in modeling the assumed relationship between trading volume and stock returns. Granger (1992) summarizes various explanations for the use of regime-switching models in modeling returns. For example, there is empirical evidence that the mean of returns has regime changes, which are often modeled with an indicator variable taking the value of unity in January and zero in other months. This is known as the January effect. Other seasonal patterns, such as returns being more predictable in the summer months, also exist. Some studies have found that shares that do relatively poorly for more than one period typically perform better in subsequent periods, thus giving price change reversals, even in the long term (Dark & Kato, 1986). Extraordinary movements, like that in October 1987, may also lead to a two-regime model, where one regime includes forecastable "ordinary" excess returns and the other unforecastable extraordinary returns.

Similarly, after volume or returns have crossed a certain threshold value, investors may change their trading patterns and price expectations. For example, naive investors may unexpectedly react to irrelevant news in the market, and this easily produces abnormal jumps in trading volume until prices adjust back to their equilibrium values. Using STAR models allows us to estimate the threshold value from the data itself, and there is no need to set a limit to identify "abnormal" trading. It is also unreasonable to assume that the number of optimists and pessimists in the market remains constant over time (the sequential arrival of information hypothesis). The STAR family allows a smooth transition from one regime to another, which may mean here that the number of types of trader is allowed to change smoothly (reflected in trading volume) but that a quick jump caused by unexpected events is not excluded either.

2.4 DATA DESCRIPTION

The data consists of the monthly Unitas[7] general index and trading volume (million Finnish *markka*) of the Helsinki Stock Exchange between January 1920 and November 1997. Returns are obtained as the first difference of the logarithmic price series (index), and volume is the first difference of the logarithmic trading volume series as given in the Bank of Finland data file. A problem here is how well volume in million Finnish *markka* accounts for the fact that the value of shares as well as the number of shares traded have increased over time. The lack of turnover data has made it impossible for us to take a proper stand on this matter here. As the trading volume series is constructed to include both turnover and value (price) of trading, we deflate volume by the actual price index, and call this series sales.

Unfortunately, in a nonlinear framework deflating the volume series introduces additional difficulties as we test Granger causality between the variables. In contrast to the linear case, in which this transformation has no effect, the STAR model now includes a contemporaneous explanatory variable x_t on both sides of the equation. It is thus difficult to see the consequences of this kind of data transformation. This problem is discussed further later in the text and in Appendix 2.3.[8] To control the possible changes in results due to data transformations, some of the analysis is done using all three series, i.e. returns, volume and sales. The basic statistics for these series can be found in Appendix 2.1. We reject normality in all series, and find excess skewness and kurtosis. The latter may imply that there are outlying observations that the error process is heteroskedastic, and/or that the data would be better described by using a nonlinear time-series model.

Figures for logarithms and differences of logarithmic time-series being studied are presented in Appendix 2.2. Heteroskedasticity is clearly a possible source of problems in all variables as we see from the latter figures. Some outliers can also be detected. We also note that an increasing trend in the logarithm of sales (volume) is interrupted, in particular by the recession at the beginning of 1990 in Finland. This recession had a serious negative influence on the stock market. One should also note the enormous rise in the index after the 1970s, after which prices tend to increase following a growing trend which has major drops in the mid 1970s (the oil crisis) and early 1990 - as already mentioned. Likewise, we want to remind the reader that an increase in sales as a result of growing markets may cause some difficulty here in trying to insulate the effects caused by non-informational investors from a growing trend (Tauchen & Pitts, 1983). Finally, as the long sample includes the Second World War, oil crises and a recession in the 1990s, we expect to find structural breaks in the data. We therefore begin the analysis with formal tests for structural breaks and unit roots (stationarity). Results from the latter tests are given in Appendix 2.1.

2.5 EMPIRICAL RESULTS

The empirical analysis starts with tests for structural breaks in the data. After taking possible breaks into account, an ESTAR or a LSTAR model is fitted to both returns and sales (volume). This is followed by model diagnostics. To characterize the models, graphs of transition functions vs the transition variable and over time are drawn. Next, the local dynamics of returns and sales is summarized by drawing “sliced spectra”. Finally, heteroskedasticity in the data is modeled using the STAR-GARCH model following Lundbergh & Teräsvirta (1998).

2.5.1 Tests for structural breaks

Despite the large amount of evidence that both nonlinearity and structural change are relevant for many time-series, to date these features have mainly been analyzed in isolation. Typically, one starts with a linear model, routinely subjected to mis-specification tests including a test for nonlinearity and parameter non-constancy. When parameter constancy is rejected, testing the alternative time-varying parameter model for nonlinearity is not normally done. Despite this fact, it is not all that difficult to parametrize a nonlinear time-series model such that the resultant time-series resembles series that are subject to occasional level shifts. In a similar vein, much evidence for nonlinearity in economic time-series might in fact be due to structural change. Therefore, before continuing with this modeling cycle, in addition to estimating nonlinear models for the whole data period, we also test for structural breaks in the data and divide the samples accordingly. (Lundbergh et al., 2000)

Looking at the first differences of prices, sales and volume in Appendix 2.2, larger variances than in the surrounding periods suggest that the data may not be generated by the same data-generating process during the whole sample period. However, what looks like a structural break may also be due to nonlinearity, which can be modeled with a constant parameter model. In some cases nonlinearity may be required to describe exceptionally large exogenous shocks in the time-series, like the stock price crash in October 1987. Actually, there have been several changes in the economy that may have affected price behavior at the HeSE. Most notably, foreign ownership has increased due to the abolition of foreign ownership restrictions in 1993. This may have also strengthened the relationship between the Finnish stock market and major markets affecting the behavior of the HeSE. In particular, Finnish equity market volatility tends to spill over from the Stockholm Stock Exchange (Knif & Löflund, 1997 and Kallunki et al. 1997).

As the sample is from 1920 onwards, it is reasonable to assume that we would observe regime shifts in the data. Some motivation for modeling different regimes in the data is given in Figures 2.1 - 2.2, where we have drawn the residuals from a linear model, in which we have regressed the logarithm of the index on a constant and a trend. For long time periods prices and sales have stayed either above or below a trend, and the changes around the trend,[9] especially in the latter period, have been quite abrupt. More formally, the existence of structural breaks is tested by the method proposed by Lin & Teräsvirta (1994). Furthermore, if we expect that the change in model parameters has been smooth, this can be best modeled by a nonlinear STAR model. (Teräsvirta, 1995 and Granger & Teräsvirta, 1993).

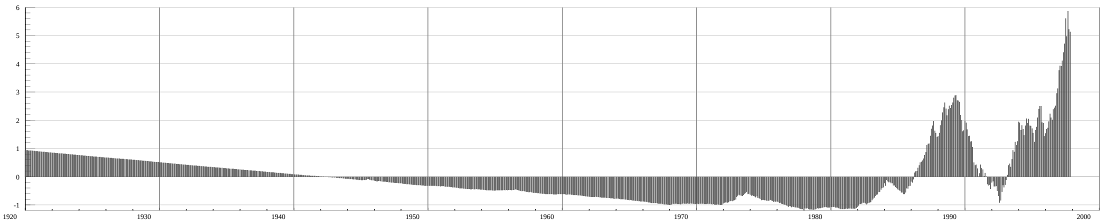


Figure 2.1: The residual from a linear regression model, in which we have regressed the logarithm of the monthly HeSE general index on a constant and a trend.

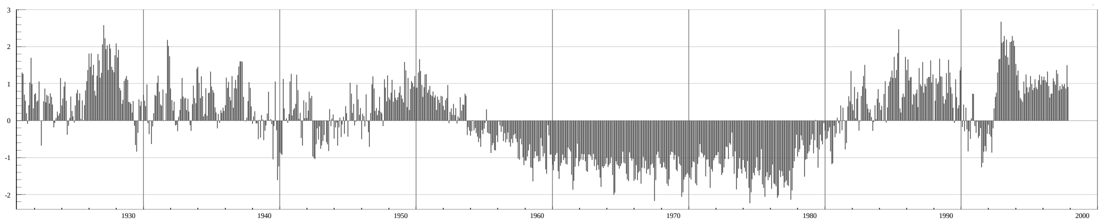


Figure 2.2: The residual from a linear regression model, in which we have regressed the logarithm of monthly sales on a constant and a trend.

The problems of choosing the right lag in the case of nonlinear models is discussed by Frances & van Dijk (2000). Nevertheless, a common approach is to start by specifying an AR(p) model and assume that the order p is appropriate in both regimes of the nonlinear model. Hence, we fit an AR(p) to the data using first differences of the logarithmic sales and price series (Appendix 2.4). First, the stationarity of the data was tested using the augmented Dickey-Fuller unit root test (ADF). The null hypothesis that there is a unit root[10] could not be rejected (Appendix 2.1), but the ADF tests indicate that differencing makes all series stationary. Unfortunately, the final model selection for the whole sample period was ambiguous as large lags proved to be significant in the AR fitted to both series, perhaps because of unmodeled seasonality in the data. However, as many authors have suggested that nonlinear models are best fitted to seasonally unadjusted data so that nonlinearities are not accidentally removed, we leave the data unadjusted. Moreover, given the computationally demanding nature of the estimation, we continue by using a “simple” AR(1-12) as a basis for the later analysis.

The model diagnostics from linear autoregressions for returns, sales and volume from 1921/2 - 1997/11 in Appendix 2.4 indicate that the null hypotheses H_0, model errors are white noise, and H_0, there is no skewness and extra kurtosis in the model residuals, are rejected at the 1% level. Kurtosis is more pronounced in the return series. Substantial excess kurtosis as well as moderate negative (positive) skewness in residuals indicates the presence of mainly negative (positive) outliers in stock return series in the former period (later period). Positive outliers have been more typical of the sales series in the former period than in the latter (negative skewness after 1957/9). As the no-ARCH hypothesis is also rejected at the 1% level, this leads us to assume a nonconstant conditional variance in the error process, but this may also be the first indication of a nonlinear conditional mean (Teräsvirta, 1995). The test for functional form is a general heteroskedasticity test. The null hypothesis is that the errors are homoskedastic or that if heteroskedasticity is present, it is unrelated to the explanatory variables. Based on this test, among others, a modification of the linear models above is required.

Since the RESET test for functional form mis-specification has a significant p-value in the case of the AR(1-12) for stock returns, at least the model for stock returns needs further investigation. Hence, we continue by testing parameter constancy using a "Lagrange multiplier (LM) type" test, which is powerful in detecting structural breaks even when the true alternative to parameter constancy is a random walk. The test is carried out by means of a simple auxiliary regression, hence the name "LM-type." This allows us to focus on cases in which the type and timing of possible parameter changes are unknown. The change in parameters is also allowed to be smooth over time, which may be a more realistic assumption than focusing entirely on a single structural break. To get the LM test we start by assuming that the data has been generated by a STAR model (Equation 2.1). After defining z_t as a function of time, we consider the following cases to fully parametrize $F(z_t)$:

$$F(t,\gamma) = \begin{cases} (1 + \exp(-\gamma(t^k + c_1 t^{k-1} + \ldots + c_{k-1}t + c_k)))^{-1},\ k = 1,3 & \text{a)} \\ 1 - \exp(-\gamma(t-c)^2),\ k = 2. & \text{b)} \end{cases} \qquad \textbf{\textit{(2.3)}}$$

These allow the structural change to be monotonic ($k = 1$) or nonmonotonic but symmetrical ($k = 2$) about c, or the "threshold" between the regimes. To derive a test $F(t,\gamma)$ is modified, replacing it by $F_1(t,\gamma) = F(t,\gamma)$ - 0.5, which makes $F_1(t,0) = 0$ so that H_0: $\gamma = 0$ in Equation 2.3 becomes a natural hypothesis for parameter constancy. The alternative is H_1: $\gamma > 0$ in both cases. However, if the null hypothesis is true, the parameters θ, Π and c in Equation 2.1 remain unidentified, and therefore a suitable approximation for $F_1(t,\gamma)$ is required as a substitute. For other examples of lack of identification of a similar kind, see Luukkonen et al. (1988). Using the first-order Taylor approximation for $F_1(t,\gamma)$ with $k = 3$ and inserting it into Equation 2.1, we obtain Equation 2.4 after recombining some terms. Thus, to test the null hypothesis of parameter constancy we test whether the restrictions H_0: $\lambda_1 = \lambda_2 = \lambda_3 = 0$ and $\varphi_1 = \varphi_2 = \varphi_3 = 0$ are valid in:

$$y_t = s_t'\lambda + (s_t \otimes v_t)'\varphi + e_t, \qquad \textbf{\textit{(2.4)}}$$

where $s_t = (1,t,t^2,t^3)'$, $\lambda = (\lambda_0,\lambda_1,\lambda_2,\lambda_3)'$, $v_t = (y_{t-1},\ldots,y_{t-p})'$, $(s_t \otimes v_t) = (v_t', tv_t', t^2v_t', t^3v_t')'$, $\varphi = (\varphi_0', \varphi_1', \varphi_2', \varphi_3')'$ with $\varphi_0 = (\varphi_{01},\ldots,\varphi_{0p})'$. The remaining error e_t in the Taylor series approximation is equal to u_t under H_0. Lin & Teräsvirta (1994) show that this test has an asymptotic χ^2 distribution under the null hypothesis. In practice they recommend the use of the F-form of this statistic. They call the test statistics LM1, LM2 and LM3 for $k = 1,2,3$ respectively. They are not strictly speaking Lagrange multiplier statistics, but are related in the sense that testing does not require the estimation of Equation 2.4 under the alternative. If theory does not help us to choose k from the three choices given above, we should continue with the following sequence of tests: H_0: $\lambda_1 = \lambda_2 = \lambda_3 = 0$ & $\varphi_1 = \varphi_2 = \varphi_3 = 0$, H_{03}: $\lambda_3 = 0$ & $\varphi_3 = 0$, H_{02}: $\lambda_2 = \varphi_2 = 0 \mid \lambda_3 = \varphi_3 = 0$ and H_{01}: $\lambda_1 = \varphi_1 = 0 \mid \lambda_2 = \lambda_3 = 0$ & $\varphi_2 = \varphi_3 = 0$.

First, we assume that $k = 3$ in Equation 2.3. If the null hypothesis is rejected, we take 2.3a) as the right form for $F(z_t)$ and test H_{03}. Now, if H_{03} is rejected, we choose 2.3a) with $k = 3$, otherwise we continue by testing H_{02}. If H_{02} is rejected, we choose 2.3b) with $k = 2$; accepting means choosing 2.3a) with $k = 1$. In any case we continue by testing H_{01}. This is the original test against $k = 1$. Even if there is no reason to believe that the data has been generated by STR model if the null is rejected, estimating the model parameters of the alternative model and drawing a figure of the corresponding transition function may help us in locating the point in time where simple linear models run into trouble and give us some idea how the parameters change.

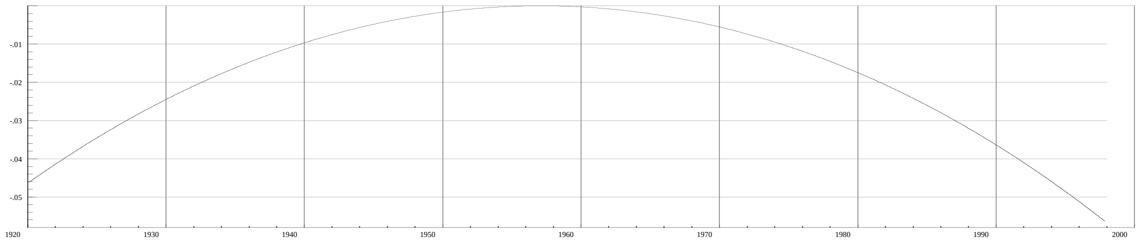


Figure 2.3: Transition function from the monthly sales model 2.3b) with $k = 2$.

Since H_{03} is accepted for the sales series, we continue by testing H_{02}, which is rejected proposing 2.3b) with $k = 2$. (H_{01} is also rejected, or $k \neq 1$.) As we estimated an AR(12) with a transition function 2.3b), we got some evidence about a structural break in sales around 1957 by looking at its estimated transition function (Figure 2.3). The economy was then opened up to foreign trade (Helsinki club) and the currency was devalued on 15.9.1957 by 39%. This may have increased paper industry sales, which has typically had strong influence on the development of the Finnish economy, thus making investment in their stocks more attractive. The general strike in 1956 was another source of damage to the market at that time.

Table 2.2: LM tests of parameter constancy 1921/2 - 1997/11.

Series	**Return**	**d.f.**	**Sales**	**d.f.**
Model	AR(1-12)		AR(1-12)	
H_{03}	1.296 (0.209)	870	1.531 (0.100)	870
H_{02}	0.862 (0.594)	883	2.535 (0.002)	883
H_{01}	2.164 (0.010)	896	1.830 (0.035)	896
H_0	1.444 (0.040)	39,870	1.990 (0.000)	39,870

These results are obtained using monthly data. The following restrictions are tested based on Equation 2.4. H_0: $\lambda_1 = \lambda_2 = \lambda_3 = 0$ and $\varphi_1 = \varphi_2 = \varphi_3 = 0$, H_{03}: $\lambda_3 = 0$ and $\varphi_3 = 0$, H_{02}: $\lambda_2 = \varphi_2 = 0 \mid \lambda_3 = \varphi_3 = 0$ and H_{01}: $\lambda_1 = \varphi_1 = 0 \mid \lambda_2 = \lambda_3 = 0$ and $\varphi_2 = \varphi_3 = 0$. The probability values of the test statistics are given in parentheses; d.f. = degrees of freedom.

Since for stock returns H_{03} is not rejected, we continue choosing transition function 2.3a) with $k = 1$. When we try to estimate a nonlinear model with transition function 2.3a), the model parameters do not converge to reasonable values. In other words, we are unable to find structural breaks in returns. However, the results may be disturbed by either too many outliers[11] in the data or heteroskedasticity (Lundbergh & Teräsvirta, 1998). Besides, in agreement with Lin &

Teräsvirta (1994), sometimes an adequate model may not be found at all, and at any rate tests will have told the investigator that the original linear model is mis-specified.

The estimation results from the linear autoregressions considering the two subsamples are in line with the model fitted to the whole data period (Appendix 2.4). The excess skewness is now particularly high in returns from 1921/2 to 1957/8. The reset test for functional form mis-specification is mainly significant for returns in both periods, and in some cases for sales from 1957/9 to 1997/11. Residual normality, the no-ARCH hypothesis and the hypothesis of no error autocorrelation are also generally rejected. The null hypothesis of no error autocorrelation is rejected at the 5% level in all cases except the AR(1-12) model for stock returns in the former period, and AR(1,6) for the latter period. Model diagnostics thus indicate that some additional problems may have remained in the AR models fitted to both returns and sales, but as estimating nonlinear models is quite a heavy task in itself, we continue by using the "simplest" adequate model.

2.5.2 Testing linearity against STAR models

Despite the fact that parameter nonconstancy is suspected, at least for the sales series, we start by linearity testing using the whole data set. We continue by splitting the sample, taking the possible structural break in 1957/9 (devaluation) into account. If one regime now characterizes standard behavior whereas the other regime describes the response of the system to an unusually large shock, and if the response of the system to such a shock is not completely irregular, its structure can be parametrized. The null hypothesis of linearity[12] can be expressed as equality of the autoregressive parameters in the two regimes of the STAR model. Thus, in Equation 2.1 H_0: $\Pi_j = \theta_j$, whereas H_1: $\Pi_j \neq \theta_j$ for at least one $j \in \{0,...,p\}$ and $F(z_t) = 1$. We also focus on linearity testing against STAR models conditional on delay (d) compared to unknown d as we want to choose a proper transition variable based on these results. Delay is the lag in the transition variable $\hat{y}_{t-d}$ in the STAR model (see Equation 2.2).

As under the null hypothesis the STAR model parameters can take any value, Luukkonen et al. (1988) suggest replacing the transition function by a suitable Taylor series approximation around $\gamma = 0$. As a result we get an auxiliary model without these problems, and obtain LM-type tests with standard χ^2 - distributions. Further advantages are that the model under the alternative hypothesis need not be estimated. Testing linearity against STAR is now done as follows: first, we fit a linear AR for y_t by OLS, obtain residuals $\hat{u}_t$ from this model and compute the residual sum of squares SSR_0. We then regress $\hat{u}_t$ on $S_t y_{t-d}$, $S_t y^2_{t-d}$ and $S_t y^3_{t-d}$ as in the model below, and obtain the residual sum of squares SSR_1.

$$\hat{u}_t = \beta_1' S_t y_{t-d} + \beta_2' S_t y_{t-d}^2 + \beta_3' S_t y_{t-d}^3 + v_t, \qquad \textbf{\textit{(2.5)}}$$

where $t = 1,...,T$ is the sample size, $S_t = (1, y_{t-1},...,y_{t-p})'$, $\beta_j = (\beta_{j0},...,\beta_{jp})'$ ($j = 1, 2, 3$) are functions of the model parameters and p is the lag length of the AR(p). $E_t v_t = 0$, $\text{var}(v_t) = \sigma_v^2$ and $\text{cov}(v_t, v_s) = 0 \;\forall\; s \neq t$. Testing the null hypothesis $\Pi_j = \theta_j$ or $\gamma = 0$ now equals testing $\beta_j = 0$ as $j = 1,2,3$ in Equation 2.5. The LM-type test statistic $T(SSR_0 - SSR_1)/SSR_0$ has an asymptotic $\chi^2(3p)$ distribution under the null hypothesis of linearity. In small samples we use the $F(3p, T - 4p - 1)$-version of the test since it has better size and power properties. The lag d for the transition variable $\hat{y}_{t-d}$ is selected by estimating Equation 2.5 for different d, choosing the one with smallest probability value.

When linearity is rejected in favor of the STAR model, and the transition variable has been selected, the final decision to be made at this stage concerns the appropriate form of the transition function. To choose between LSTAR and ESTAR, we first test H_{01}: $\beta_3 = 0$ in Equation 2.5, then continue with H_{02}: $\beta_2 = 0 \mid \beta_3 = 0$ and H_{03}: $\beta_1 = 0 \mid \beta_2 = \beta_3 = 0$. The decision is based on the probability values of the tests of the sequence. If the p-value of the test of H_{02} is the smallest of the three we choose ESTAR, otherwise we choose LSTAR (Appendix 2.5). Finally, we estimate the models by nonlinear least squares (NLS) and specify the lag structure. (Granger & Teräsvirta, 1993)

2.5.3 Estimation results

STAR models (Equations 2.1 - 2.2) are fitted for the sales and return series for the whole sample period and two sub-samples based on the tests of structural breaks above. To find a proper initial value for γ we standardize the model by dividing the exponential part of the transition function by the standard deviation of $\hat{y}_{t-d}$ (called scaling in Table 2.3).[13] Some results are given below. As all the reported coefficients are statistically significant at the 1% level, we ignore reporting the *p* values for the estimated parameters. March, June, Sept and Nov refer to dummies used to catch seasonal variation in the data.

UW.1 (ESTAR): Returns 1921/2 - 1997/11, base model AR(1 - 12), and transition variable y_{t-1}.

$y_t = 0.08 + 0.20*y_{t-1} - 0.76*y_{t-2} + 0.11*y_{t-3} + 1.51*y_{t-4} + 0.10*y_{t-5} - 1.13*y_{t-6} - 0.89*y_{t-7} - 0.96*y_{t-8} - 2.30*y_{t-9} + 1.29*y_{t-10} - 0.79*y_{t-11} - 0.84*y_{t-12} + (-0.07 + 0.72*y_{t-2} - 1.61*y_{t-4} + 1.15*y_{t-6} - 0.90*y_{t-7} + 0.86*y_{t-8} + 2.43*y_{t-9} - 1.25*y_{t-10} + 1.11*y_{t-11} + 0.86*y_{t-12})*F(\gamma,c).$

UWD.1 (ESTAR): Returns 1921/2 - 1997/11, base model AR(1 - 12) with monthly dummies and transition variable y_{t-1}.

$y_t = 0.09 + 0.03*Jan + 0.02*March + 0.02*June - 0.01*Sept - 0.01*Nov + 0.19*y_{t-1} - 0.76*y_{t-2} + 0.12*y_{t-3} + 1.43*y_{t-4} + 0.10*y_{t-5} - 1.12*y_{t-6} - 0.83*y_{t-7} - 0.93*y_{t-8} - 2.24*y_{t-9} + 1.25*y_{t-10} - 1.04*y_{t-11} - 0.73*y_{t-12} + (-0.09 + 0.72*y_{t-2} - 1.50*y_{t-4} + 1.12*y_{t-6} + 0.85*y_{t-7} + 0.85*y_{t-8} + 2.37*y_{t-9} - 1.21*y_{t-10} + 1.16*y_{t-11} + 0.72*y_{t-12})*F(\gamma,c).$

U57.1 (ESTAR): Returns 1921/2 - 1957/8, base model AR(1), and transition variable y_{t-2}.

$y_t = 0.002 - 1.354*y_{t-1} + (0.002 + 1.692*y_{t-1})*F(\gamma,c).$

U97.1 (LSTAR): Returns 1957/9 - 1997/11, base model AR(1,6), and transition variable y_{t-6}.

$y_t = 2.341*y_{t-1} + (-2.341*y_{t-1} + 0.111*y_{t-2} + 0.124*y_{t-3} + 0.134*y_{t-5})*F(\gamma,c).$

In the U97.1 model constants are restricted to zero, and first lags are restricted to being equal. The latter restriction allows an autoregressive parameter to be canceled out smoothly in the transition between the two regimes.

U97.2 (LSTAR): Returns 1957/9 - 1997/11, base model AR(1,6), and transition variable y_{t-3}.

$y_t = -0.001 + 0.297*y_{t-1} + 0.113*y_{t-6} + (0.023 - 0.514*y_{t-1} + 0.235*y_{t-2})*F(\gamma,c).$

The next natural step is model evaluation. Obvious assumptions to be tested following Eitrheim & Teräsvirta (1996) are the null hypothesis of no remaining nonlinearity (Test 1), no residual autocorrelation (Test 2), and parameter constancy as we assume that parameters are constant when we estimate the models (Test 3). These results are given in Appendix 2.6. An alternative to no remaining nonlinearity is that the data-generating process is an additive STAR model with two (multiple) STAR components instead of a single one. After rejecting H_0 (Test 1) it is desirable to carry out the test sequence H_{03}', H_{02}' and H_{01}' for any given delay *d* as in Section 2.5.2. This helps the investigator to decide whether an LSTAR or ESTAR additive component should be selected to accompany the previous STAR component. Basic model diagnostics are given in Table 2.3 with general definitions of the tests used.

Table 2.3: LSTAR and ESTAR model diagnostics for monthly returns, sales and volume.

Test/Model	**UW.1**	**UWD.**	**U57.1**	**U97.1**	**U97.2**	**WS.1**	**S57.1**	**S97.1**	**V97.1**
c	0.218	0.217	-0.172	-0.125	0.060	0.03	-0.186	0.516	0.738
γ	7.073	7.250	18.62	18.000	1.134	3.868	0.756	440.365	15.297
scaling	18.97	18.97	17.52	21.378	20.56	2.740	2.568	2.925	2.905
RSS	2.032	1.925	1.210	0.932	1.068	97.50	61.552	39.829	39.427
R^2	0.205	0.247	0.133	0.195	0.077	0.206	0.102	0.296	0.313
s	0.050	0.049	0.054	0.226	0.047	0.325	0.378	0.287	0.286
CHI	0.000	0.000	0.000	0.000	0.000	0.000	0.137	0.000	0.0001
skewness	-0.167	-0.179	-0.445	-0.098	0.200	0.018	0.088	-0.306	-0.162
kurtosis	5.146	4.934	7.238	2.051	1.709	1.636	0.399	1.510	0.990
LM1	0.000	0.000	0.001	0.013	0.052	0.056	0.679	0.125	0.093
LM12	0.000	0.000	0.000	0.000	0.000	0.000	0.295	0.001	0.006

The model indicated by, for example, UW.1 refers to that mentioned in the text. To find a proper starting value for γ we standardize the model by dividing the exponential part of the transition function by the standard deviation of $\hat{y}_{t-d}$ and call it scaling. The terms c and γ refer to Equation 2.2. RSS is the residual sum of squares, s the standard deviation and R^2 the goodness of fit measure. CHI is the Doornik & Hansen (1994) test of normality of the errors. Skewness is self-explanatory and kurtosis is the excess kurtosis of the residuals. No linear autoregressive conditional heteroskedasticity in the residuals against ARCH(1) and ARCH(12) is tested using the LM statistic defined by Engle (1982) accordingly called LM1 and LM12. The reported values of the LM1, LM12 and CHI tests are the p-values.

In the case of the UW.1, the U97.1 and U97.2 models tests mainly reject the hypothesis of no remaining nonlinearity. But now the p-values are in general larger than when we tested linearity, which is of course encouraging. In general we ignore significant values of Test 1 unless test statistics are clearly larger than at the first modeling stage. The results show no remaining autocorrelation in U57.1 with the exception of lag 8 (Model U57.1 in Appendix 2.6). In contrast, tests of no remaining autocorrelation are rejected for models UW.1, UWD.1, U97.2 and S57.1 for all lags, but accepted for all lags in the cases of the U97.1 and S97.1.

LM tests of parameter constancy are rejected at the 5% level for the UW.1 and UWD.1, and when the intercept only is tested for the U97.1. As we reject the hypothesis of parameter constancy in a model where intercepts are restricted to zero, this restriction is questionable. In the case of returns for the whole period we continue by adding two different set of dummies to the model. The first set tried to account for years when stock returns had been abnormally high or low. This dummy was not significant (R^2 = .205). Letting a dummy capture possible monthly variation in the data improved the UWD.1 a bit with an R^2 now equal to 0.247. Still, since the model diagnostics indicate that several problems remain, this model is further investigated in Section 2.5.4 in order to capture heteroskedasticity in the data generating process (the LM1 and LM12 tests are rejected, see Table 2.3).

Looking at the graphs of the transition functions over time and against $\hat{y}_{t-d}$ in the case of the UW.1 and UWD.1 models (Appendix 2.7), the former suggests that an LSTAR might have been a better choice in describing returns than an ESTAR. Here the ESTAR mainly identifies possible outliers in the data.[14] However, based on this model another regime is needed to identify the behavior around 1946, the late 1960s and, say, 1971. Finland joined EFTA in 1961 but trade without duty payments first occurred in 1967. In 1967 the world economy was in a slump and pulp and paper exports fell sharply. This was the principal cause of the devaluation in 1967. An earlier structural break in the economy in 1946 shows up in the estimated transition function for U57.1 as well. This is just after the Second World War, in June 1946, when the Finnish government started a TE-KO program, the aim of which was to keep prices and wages constant after some very turbulent years of inflation (Linnarauha). Later, as peaks in the graphs of estimated transition functions over time show, the economy was overheated between 1985 and 1990 because of deregulation of the financial markets (foreign investment, short-term capital movements and foreign exchange borrowing for households was left beyond government control). The recession at the beginning of the 1990s shows as peaks in the estimated transition function over time in 1992/11 and 1994/2 in Figure 2.7.1 as well. This period was followed by a depression between 1991 and 1993, finally leading to recovery of the Finnish economy from 1994 to 1997.

The financial market liberalization, among other things, boosted the economy, and hence stock returns rose considerably in the late 1980s. This boom was followed by a huge recession resulting in an massive fall in prices at the beginning of the 1990s. As the constant term is restricted to zero in both regimes in U97.1, in regime $F = 1$ or "normal times" the positive dependence between returns is smaller than when $F = 0$. A closer look reveals that in the latter regime we have only a few exceptional observations: 1991/3, 1992/3, 1993/2 and 1996/4, which show as peaks in the estimated transition function over time in Figure 2.7.4. The first exceptional observation corresponds to the period after a collapse in the Soviet trade. This caused increased pressure to devalue the exchange rate to improve the competitive position of the Finnish export sector, which was now forced to look for replacement markets. In spite of the first signs of depression, the currency was anchored to the ECU basket on 4.6.1991, but in November *markka* was allowed to float and was finally devaluated by 14% on 15.11.1991. Loose monetary policy is expected to cut back interest rates at least in the short run, and a fall in interest rates is generally expected to cause a rise in returns. Hence it is not surprising that this obvious instability in the Finnish exchange market also shows up in the stock market.

As some of the money invested in the HeSE in the late 1980s was cheap loans from both the domestic and foreign banking sector, a cutback in money available for "making money" in the

1990s due to a slump in the economy may have made the fall in returns on the HeSE even more severe (peaks in the estimated transition functions over time in Figures 2.7.1 and 2.7.2).

The models for sales behave badly as there is still remaining error autocorrelation in the residuals of WS.1 and S57.1 except for the model covering the latter period, S97.1. When parameter constancy is tested, it is rejected in S57.1 when all parameters are tested simultaneously (Appendix 2.4). Estimating an AR(12) for sales with the transition function 2.3a) ($k = 1$) supplies some evidence of a structural break in 1938 which would explain this. This ESTAR nevertheless has a lower R^2 than the linear model. Any further analysis using this nonlinear model instead of a linear one thus needs proper economic justification. Tests of no additive nonlinearity in all the above models are in general smaller than at the first testing stage, which indicates that taking nonlinearity into account improves the models.

Three different nonlinear models fitted for the whole period sales series converged, and we were able to get the parameter estimates. The first had a regime switch around $\hat{y}_{t-d} = 0.6$, but only a couple of observations lie above this number. In the case of an AR(1 - 6,12) with additional lags 1 - 6 and 12 in the nonlinear part, none of the nonlinear parameters were statistically significant. We continued leaving out explanatory variables of the nonlinear part of this model one lag at a time, starting with the highest. None of these models converged either. This is probably due to exceptional behavior in the data around 1938 and 1957. If we look at the WS.1 (Figure 2.7.6 in Appendix 2.7), we note that a nonlinear regime is needed in times when sales are abnormally high or low (mean = 0.005, min = -1.768 and max = 1.712). Furthermore, the negative dependence in sales of the last period values is slightly decreased (the sum of AR coefficients in the linear part of the model being -0.94, and when the nonlinear regime is added -0.84). The estimated transition function against time does not suggest any particular event, but fluctuates quite erratically between the two regimes.

WS.1 (ESTAR): Sales 1921/2 - 1997/11, base model AR(1-6,12), and transition variable y_{t-6}.

$y_t = -0.01 - 0.36*y_{t-1} - 0.28*y_{t-2} - 0.17*y_{t-3} - 0.20*y_{t-4} - 0.14*y_{t-5} - 0.05*y_{t-6} + 0.26*y_{t-12} + (0.04 + 0.10*y_{t-1})*F(\gamma,c)$.

S57.1 (ESTAR): Sales 1921/2 - 1957/8, base model AR(1-6,12), and transition variable y_{t-6}.

$y_t = -0.04 - 0.14*y_{t-1} - 0.15*y_{t-2} - 0.10*y_{t-3} - 0.15*y_{t-4} - 0.22*y_{t-6} - 0.07*y_{t-12} +$
$(-0.17 - 0.37*y_{t-1} - 0.59*y_{t-2} + 0.25*y_{t-5})*F(\gamma,c)$.

S97.1 (LSTAR): Sales 1957/9 - 1997/11, base model AR(1-5,12), and transition variable y_{t-1}.

$y_t = 0.02 - 0.27*y_{t-1} - 0.25*y_{t-2} - 0.09*y_{t-3} - 0.13*y_{t-4} - 0.09*y_{t-5} + 0.33*y_{t-12} + (-0.46 + 0.45*y_{t-1} - 0.56*y_{t-3}$
$- 0.34*y_{t-4} + 0.37*y_{t-12})*F(\gamma,c)$.

V97.1 (LSTAR): Volume 1957/9 - 1997/11, base model AR(1-6,12), and transition variable y_{t-6}.

$y_t = 0.03 - 0.28*y_{t-1} - 0.22*y_{t-2} - 0.12*y_{t-3} - 0.17*y_{t-4} - 0.10*y_{t-5} + 0.36*y_{t-12} +$
$(-1.88*y_{t-1} - 1.40*y_{t-3} - 0.98*y_{t-5} - 0.63*y_{t-6})*F(\gamma,c)$.

For later use, we also need to test and fit (if necessary) a proper nonlinear model for the untransformed trading volume series. The basic statistics of this time-series can be found in Appendix 2.1. The figures for logarithms and differences of logarithmic volume series are in Appendix 2.2. The choice of AR model used in linearity testing is based on results given in Appendix 2.5. Last, model diagnostics can be found in Appendix 2.6. The estimated model (V97.1) and figures for the transition functions versus $\hat{y}_{t-d}$ and over time are displayed in Figure 2.4. This shows that the STAR model is useful in describing the data behavior. Now, Regime 1 identifies time periods in which volume has been abnormally high: around the 1960s, the early and late 1980s and at the beginning of the 1990s.

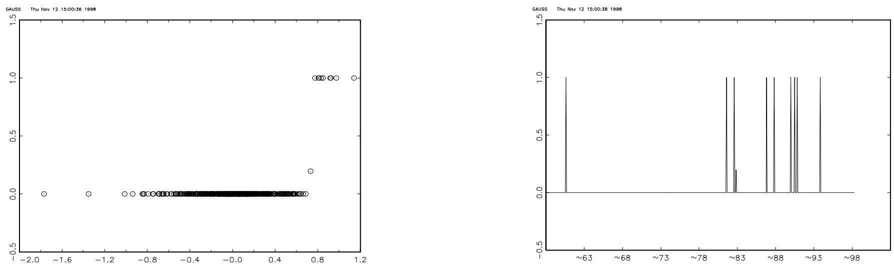


Figure 2.4: Graphs of transition functions vs the transition variable and over time using the first difference of the logarithm of monthly volume, model V97.1.

We continue using these STAR models despite that the AR on which testing nonlinearity was based were not the best possible models in every respect and some problems may therefore have remained. The gain from using nonlinear models should therefore come from better results interpretation than from a statistical point of view. Furthermore, since just looking at the estimated coefficients of the models does not give us much useful information about the dynamic behavior of the processes, we count the roots of the characteristic polynomials of the difference equations at $F = 0$ and $F = 1$. Complex roots indicate fluctuations in the process. The process oscillates or not depending on the sign of the real roots. If the modulus of one root is greater than one the process explodes, and if it is less than one the process is dampened. If the process has an explosive cycle in one regime but is mean-reverting in the other, the combined dynamics involve transient shocks because the process will never stay in the explosive state long. If the moduli of the roots are typically close to one, any mean-reversion of the series will be slow.

Table 2.4: Roots and the nature of the time path for difference equations.

complex (real part negative)	fluctuations	real and negative	oscillatory
complex (real part positive)	fluctuations	real and positive	no oscillations

Baumol, W. (1970). Economic Dynamics, an introduction (3 ed). The Macmillan Company, London.

To characterize the local dynamic behavior one can compute the roots of the characteristic polynomial of the model for given values of the transition function, as above, or use a more economical way to summarize the local dynamics by drawing graphs of the local or "sliced" spectrum of the STAR model (Skalin & Teräsvirta, 1999 and Priestley, 1981, Section 4.12 and 7.8). The "sliced" spectrum describes how the local dynamics of the conditional mean change in the transition between the two extreme regimes in the STAR. A local spectrum of the STAR for $-\pi \le \omega \le \pi$ is defined as:

$$f_{yy}(\omega; y_{t-d}) = \frac{1}{2\pi}\left[\left\{1 - \sum_{j=0}^{p}(\Pi_j - \theta_j F(z_t))e^{-ij\omega}\right\}\left\{1 - \sum_{j=0}^{p}(\Pi_j + \theta_j F(z_t))e^{ij\omega}\right\}\right]^{-1}. \quad \textbf{\textit{(2.6)}}$$

It is a function of $F(z_t)$ and thus of $\hat{y}_{t-d}$. Equation 2.6 is only defined when the estimated STAR model is locally stationary, or for those values of $F(z_t)$ for which the roots of the lag polynomial $1-\sum_j(\Pi_j + \theta_j F(z_t))L^j$ lie outside the unit circle ($j = 0,...p$ and $Ly_t = y_{t-1}$). Furthermore, it needs to be standardized to be comparable with standard spectrum (integrated from zero to π; Equation 2.6 does not integrate to one). In the figures each curve represents a local spectrum and corresponds to a single observation of the transition variable. A peak in the spectrum indicates an important contribution to variance at frequencies in the appropriate interval.[15]

In an ESTAR it is possible for a time-series to move rapidly between very small and very large values for which local dynamics are stable. Here the models UW.1 and UWD.1 for returns for the whole period and U57.1 have complex roots with a modulus greater than one in the regime $F = 0$ (Table 2.5). This means intensified fluctuations with a period of four. In regime $F = 1$ the largest root is real and positive with a modulus of less than one; together these imply transient shocks. In the spectra for models UW.1 and UWD.1 there are peaks at four different frequencies for values of the transition function larger than 0.88, indicating fluctuations. From the U57.1 spectra we see a peak at a frequency corresponding to a period of four or five months when we move from the $F = 1$ regime toward $F = 0$; in addition, the latter regime is needed to describe the data around 1946. Thereafter, we expect to see a cycle of four to five months in a time-series which identifies this kind of behavior. There is also some indication about a trend and very short-term variation, especially in the nonlinear regime.

The real roots of the difference equations U97.1 and U97.2 fitted to returns are positive (except in the U97.2 negative for $F = 1$) indicating no oscillations (oscillations). One unusually large shock or many shocks of the same sign following each other may move the economy into an explosive oscillatory path. When we draw the "sliced spectra" for U97.1 (Figure 2.5) there is some indication of long run dependence shown as a low-frequency tail of the spectrum, which is most prominent for F close to 0.8. Spectra close to regime $F = 0$ with only a few observations have not been drawn, as only nonexplosive cases are selected for the graphs. The U97.2 local spectrum shows a peak in a period of 2 months. This property diminishes as we approach the linear regime. Nonlinearity in the model is mostly needed for returns higher than 0.05 (mean = 0.008) and in particular around 1970, 1973, 1985 and 1995. Since roots in both regimes have a modulus of less than one, any oscillations are dampened.

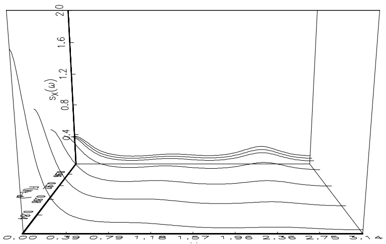


Figure 2.5: "Sliced spectra" for the U97.1 (monthly data).

In the case of S97.1, the roots in the regime $F = 1$ have a modulus greater than one, so that fluctuations in sales in the nonlinear regime are explosive. S97.1 is more like a threshold model (the transition function vs the transition variable changes rapidly from regime $F = 0$ to $F = 1$ as in Figure 2.7.8 in Appendix 2.7). The years when nonlinearity is needed can now easily be pointed out, but there are perhaps too many of them to draw any clear conclusions. Complex roots in regime $F = 0$ but with a modulus of less than one imply dampened fluctuations, which can also be seen in the graphs of the “sliced spectra”. The properties of V97.1 are surprisingly similar to S97.1 (the latter is the volume series deflated by the stock price index). Nevertheless, the “sliced spectrum” is not shown since V97.1 was not locally stationary.

Table 2.5: Roots, modulus and period for monthly returns, sales and volume as $F = 0$ and $F = 1$.

Series	**UW.1**	**UWD.1**	**U57.1**	**U97.1**	**U97.2**	**WS.1**	**S57.1**	**S97.1**	**V97.1**
Roots $F = 0$	$0.067 \pm 1.275i$	$0.062 \pm 1.259i$	$0.001 \pm 1.164i$	2.341	0.756	$-0.240 \pm 0.833i$	$0.599 \pm 0.571i$	$-0.474 \pm 0.814i$	$-0.482 \pm 0.813i$
Modulus	1.277	1.261	1.164	2.341	0.756	0.867	0.828	0.942	0.945
Period	4	4	4	-	-	3	8	3	3
Roots $F = 1$	0.918	0.908	0.583	0.761	-0.816	$0.526 \pm 0.705i$	$-0.685 \pm 0.62i$	$0.610 \pm 0.922i$	$-0.770 \pm 0.849i$
Modulus	0.918	0.908	0.583	0.761	0.816	0.879	0.924	1.106	1.146
Period	-	-	-	-	-	7	3	6	3

The roots of the characteristic polynomials of the difference equations at $F = 0$ and $F = 1$ are obtained numerically by GAUSS (Skalin & Teräsvirta 1999). Roots with a modulus of less than 0.9 are not displayed (in general).

The spectrum for the WS.1 model has three peaks corresponding to frequencies around two and three to four months, and one at six months’ frequency. The S57.1 spectrum is quite similar to the spectrum estimated using the whole sample, but now there is a very small peak in the spectrum at higher frequencies. Since the WS.1 for the whole period and the S57.1 have roots with a modulus of less than one in both regimes, the process is nonexplosive in these cases.

Nevertheless, a proper assessment of the degree of persistence of shocks requires that we analyze the combined dynamics of the process. For example, even though the process has an explosive cycle in one regime, it can be mean reverting in the other, and the combined dynamics will involve transient shocks because the process will never stay in the explosive state long. Besides, analyzing the roots of the characteristic polynomial of the lag operator defined by specific values of the single index of a nonlinear model ignores the possible effect of switching intercepts in the estimated equation and any future movements between regimes. According to Potter (1995) this may be a misleading way to model (business cycle) asymmetry, and he recommends that one should scrutinize the impulse response functions instead. But before this, we fit STAR-GARCH models to the data to identify the possible effects of changes in variances on the properties of the time-series being considered.

2.5.4 Modeling conditional variance using STAR-GARCH models

Various informational efficiency tests of the stock market require that the model residuals must be serially uncorrelated. However, the residuals u_t need not be homoskedastic. Hence, the variance of errors may vary over time or may depend on other economic variables without violating informational efficiency. However, in the latter case additional econometric problems may arise. In particular, it has been found that rejection of the null hypothesis of homoskedasticity might be due to other sorts of model mis-specification such as neglected serial correlation, nonlinearity and omitted variables in the model for the conditional mean. To solve such problems, people started to allow a smooth transition in the conditional mean of the time-series as well as letting the conditional variance follow an ARCH process. Thus, by appropriately modeling the nonlinear dependence in the conditional mean first, they were able to avoid mis-specification of the conditional variance.

For example, Li & Lam (1995) modeled stock returns with a nonlinear threshold autoregressive conditional mean model (TARCH), where the conditional variance was parametrized as an ARCH process. Here, as an attempt to model both the conditional mean and conditional variance, the former using a nonlinear specification, we follow Lundbergh & Teräsvirta (1998), who use a modeling scheme that proceeds from restricted models to more general ones. The statistical rational behind this choice of direction is that if the conditional mean is estimated with a consistent estimator, the conditional variance can be estimated from the residuals of the conditional mean model without loss of asymptotic efficiency, making use of the block-diagonality of the information matrix.[16] Otherwise, the lack of identification leads to lack of consistency in the parameter estimation, which in turn is likely to create numerical difficulties in estimation. Thus, Lundbergh (1999) first tests and parametrizes the conditional mean as a STAR process in order to capture any systematic features in the response of the system to unusually large shocks. The parameters of the conditional mean are estimated assuming that the conditional variance remains constant. He then tests the null hypothesis of no linear (G)ARCH against the (G)ARCH of a given order in the error process of this model. If the hypothesis of no (G)ARCH is rejected, he assumes that the conditional variance follows a low-order standard GARCH, and a STAR-GARCH is fitted to the data. As a first-order GARCH has very often been found to be adequate in practice, it is only expanded if necessary. Once the parameters of the models have been estimated, the validity of the assumptions used in the estimation must be investigated. Hence he tests parameter constancy and that the squared errors of the model are independent and identically distributed, among other things. A summary of the tests used is given by Lundbergh (1999) and Franses & van Dick (2000).

Looking at stock return series we immediately note some large shocks, which may cause a shift in the conditional mean of the series (Appendix 2.2). Besides, we note that volatility appears to be nonconstant over time, and a GARCH may be needed to identify this kind of behavior. The STAR-GARCH used in this study is based on Equations 2.1 - 2.2 (monthly dummies are added when necessary). The error process u_t is now defined as follows:

$$u_t = e_t \sqrt{h_t}, \tag{2.7}$$

where $e_t \sim$ n.i.d(0,1), and the conditional variance $h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}$ is not dependent on e_t. Here α_0 is a constant, and α_1 and β_1 refer to a GARCH(p,q), in which we have set $p = q = 1$. We assume that the moments necessary for the inference exist, and that the parameters are subject to restrictions such that the model is stationary and ergodic. The usual restrictions imposed on the parameters to ensure nonnegative conditional variance are: $\alpha_0 > 0$, $\alpha_1 \geq 0$ and $\beta_1 \geq 0$. If the sum $\alpha_1 + \beta_1$ is close to one, then a shock at time t will persist for many future periods. For $\alpha_1 + \beta_1 = 1$ we have a non-stationary (explosive) series in the conditional variance, and a shock will lead to a permanent change in all future values of h_{t+j}. If $\alpha_1 + \beta_1 < 1$, the influence of h_t on $E_t h_{t+s}$ dies away exponentially. (Nelson, 1990)

Table 2.6: Estimated parameters of the GARCH(1,1) for STAR-model residuals, and model mis-specification test results.

Coeff.	**UWG.1**	**UWDG.1**	**U57G.1**	**U97G.1**	**U97G.2**	**WSG.1**	**S97G.1**	**V97G.1**
φ_0	-0.0002 (0.898)	-0.0003 (0.796)	-0.002 (0.248)	0.004 (0.018)	-0.0006 (0.116)	-0.006 (0.552)	-0.008 (0.483)	-0.004 (0.776)
α_0	0.0001 (0.020)	0.00004 (0.017)	0.00005 (0.031)	0.00004 (0.102)	0.00003 (0.116)	0.003 (0.215)	0.0015 0.139	0.001 (0.159)
α_1	0.126 (0.000)	0.095 (0.000)	0.143 (0.000)	0.094 (0.0003)	0.094 (0.0004)	0.122 (0.044)	0.048 (0.008)	0.065 (0.004)
β_1	0.844 (0.000)	0.888 (0.000)	0.839 (0.000)	0.895 (0.000)	0.898 (0.000)	0.860 (0.000)	0.934 (0.000)	0.925 (0.000)
$\alpha_1 + \beta_1$	0.970	0.983	0.982	0.989	0.992	0.982	0.982	0.990
Li&Mak	0.041 (1)	0.002 (6)	0.005 (4)	0.001 (1)	0.059 (1)	0.014 (6)	0.428 (6)	0.089 (1)
Bollerslev	0.051 (2)	0.025 (7)	0.649 (2)	0.025 (2)	0.044 (2)	0.0004 (2)	0.513 (7)	0.250 (2)
GJR *c* no *c*	0.001 0.016	0.083 0.285	0.011 0.009	0.369 0.459	0.055 0.192	0.0001 0.0001	0.014 0.026	0.0001 0.0003
pconst	0.001 (1)	0.083 (1)	0.011 (1)	0.369 (1)	0.055 (1)	0.0001 (1)	0.014 (1)	0.0001 (1)
CHU break	** obs 160	- obs 164	- obs 252	- obs 104	- obs 74	* obs 339	* obs 432	** obs 424

Tests are based on monthly data. The coefficient for conditional mean is φ_0, α_0, α_1 and β_1 correspond to conditional variances (Equation 2.7). Probability values are given in parentheses, and $\alpha_1+\beta_1$ is the sum of GARCH coefficients. *Li&Mak* is the p-value of the Li & Mak (1994) test for squared and standardized error process not being autocorrelated. It is asymptotically equal to testing for no remaining ARCH in standardized errors against ARCH(m), where m refers to the lag with the smallest p-value of the test. *Bollerslev* (1986) is a test for no remaining serial dependence in the squared residuals. The number in parentheses is m. *GJR* tests whether the response of a shock is due to its size as well as its direction. It is close to a test of standard GARCH against nonlinear GARCH. First row, c = constant included, no c = constant excluded. *Pconst* is a test of parameter constancy against smoothly changing parameters. The number in parentheses is the fixed delay used for parametrization. *CHU* is a Chu (1995) test of parameter constancy, where nonconstancy is parametrized as a single parameter shift. Rejection of the null at the 5% level is indicated by **, at the 1% level by * and " - " means accepting the null hypothesis. *Break* gives the observation number at which the estimated break is located. For more specific definitions of these tests see Lundbergh (1999).

The estimated coefficients of the ESTAR- or LSTAR-GARCH(1,1) are given in Table 2.6. As indicated above, linearity of the conditional mean of returns and sales is rejected, and when we estimate the parameters of the conditional mean assuming that the conditional variance is constant, the null hypothesis of no linear (G)ARCH against (G)ARCH of a given order in these time-series is also rejected. As a GARCH can be adequately approximated by a long ARCH specification, we look particularly at the LM(12) test. We conclude that GARCH(1,1) are needed to identify the behavior of returns and sales, except in the case of model S57.1.

In the UWG.1 model with GARCH(1,1) residuals, the coefficients α_1 and β_1 are significant. Thus, allowing for a nonlinear conditional mean is not sufficient alone to characterize the moments in returns. The sum of the coefficients α_1 and β_1 is also close to one, indicating that a shock at time *t* will persist for many future periods. The same applies to all STAR-GARCH. Besides, as the GARCH(1,1) does not pass the Li & Mak (1994) test, in the optimal case we should expand the GARCH(*p*,*q*) parametrization. The test of no remaining serial dependence in the squared residuals, or no model mis-specification, is also rejected at the 5% level, thus supporting expanding parametrization by increasing either *p* or *q* or both. Finally, parameter constancy is rejected using the pconst and Chu (1995) tests, indicating either smoothly changing parameters or a single structural break. As the GJR test,[17] or a test against a nonlinear GARCH also rejects it, we should continue first taking into account possible structural breaks in this series as well as allowing the response of a shock to be not only due to its size but also its direction. Unfortunately, as most tests also have power against alternatives other than the one for which they are designed, the statistics are not helpful in deciding in exactly which direction one should proceed.

The model with monthly dummies for the whole period (UWDG.1) behaves somewhat better than the UWG.1. Tests indicate a structural break in volatility around 1934, which was a period with very low variance in returns. However, this break is not statistically significant. Or, we were able to catch the break by the correct choice of dummies. Focusing on the period 1921/2 - 1957/8 as in model U57G.1, some problems remain, and a structural break is located at the beginning of 1942 (Second World War), which does not come as a surprise. In the case of the U97G.1 and U97G.2 models there is still some evidence of model mis-specification, since Li & Mak's (1994) test of no remaining ARCH in standardized errors against ARCH(1) is rejected in the former case, and Bollerslev's (1986) test indicates some remaining serial dependence in the squared residuals. The structural break is now located in the 1960s (1963/10 or 1966/4), i.e., a period of recession in Finland.

We conclude that modeling both nonconstant conditional variance and mean seems to improve the accuracy of the results. This should be kept in mind when looking at the results of the following chapters. All models behave similarly, and even though not statistically significant, the breaks in volatility located using the Chu (1995) test also have an economic interpretation.

Next, we focus on the models for sales (WS.1 and S97.1) and volume (V97.1) series. The WSG.1 model behaves in much the same manner as the previous models for stock returns, but now the structural break located in 1948 is statistically significant. Recovery from the Second World War may have increased the importance of the stock exchange as an efficient marketplace, thus increasing sales and hence the volatility of the market. The test statistics are significant in the case of the S97G.1, when we test against nonlinearity, which is either a combination of a generalized GJR model and QGARCH, or nonlinearity in the spirit of Teräsvirta. Parameter constancy is also rejected at the 1% level, and a break is located around 1993/8. This is the time when foreign ownership restrictions were abolished, and the Finnish economy started to recover from a deep slump. These results are confirmed using the V97G.1, except that the structural break is located somewhat earlier in December 1992.

Nevertheless, (G)ARCH models are symmetric: while the size of the shock matters, the sign does not. Schwert (1989), among others, offers empirical evidence that stock returns are more volatile during recessions than during booms. In periods of high volatility one typically observes considerable persistence in volatility, and it also seems to influence the expected equilibrium returns. In contrast, in periods of low volatility persistence seems to be much lower and a relatively low value for the conditional variance does not have a perceptible impact on equilibrium returns. In an attempt to demonstrate this kind of nonlinear behavior in stock returns Li & Li (1996) allowed the conditional variance process to characterize asymmetric responses to shocks using the double threshold autoregressive heteroskedastic model (DTARCH). Recently, Lee & Li (1998) generalized the DTARCH by allowing the transition between the first and second regimes to be smooth. They called this model the Smooth Transition (ST) Double Threshold model (STDT). Hagerud (1997) estimated a smooth transition ARCH model (STARCH) for Swedish asset returns.

Hence, the next natural step would be modifying the above models as in Lundbergh & Teräsvirta (1998). Linearity of the conditional variance should be tested against a nonlinear specification that allows for asymmetric responses in variance to shocks. If rejected, STAR-STGARCH models should be estimated to characterize nonlinear behavior both in the conditional mean and the conditional variance. Further examples of nonlinear GARCH are given in Franses & van Dijk (2000). This would be a good topic for future studies.

Interpreting the parameters of estimated STAR- and STAR-GARCH models is not always easy. This led the people to use the generalized impulse response function (GIRF). In rational expectations models the definition of GIRF is equivalent to the revision in forecast function, for example, a movement in stock prices in response to news about dividends. GIRF allows one to focus on asymmetric shocks as well. Thus, after filtering out nonlinearity in the mean (and variance[18]) of sales and stock returns, the next step is to focus on measuring the persistence of shocks in these series.

2.6 THE GENERALIZED IMPULSE RESPONSE FUNCTION: UNIVARIATE MODELS

It is generally not possible to completely grasp the implied properties of time-series generated by a model by simply trying to interpret the model parameters. Therefore, to shed some light on the characteristics of a model it is often useful to consider the effect of shocks on the future patterns of a time-series variable. The impulse response functions are a convenient tool for measuring such effects of shocks. However, in the case of nonlinear models shock and history independence of the traditional linear impulse response function are lost. Current shocks will have a different impact on future observations depending on the sign and magnitude of the shock, the regime we were under when the shock hits the market as well as the point from which to count impulse responses. In other words, the customary tests for classifying shocks as permanent or transitory based on linearity lose their meaning. Hence, following Granger & Teräsvirta (1993), Boswijk & Franses (1996), Koop et al. (1996), Gallant et al. (1993) and Potter (1995, 1999, 2000), we use the adequate nonlinear model fitted to the data as a basis for simulations to obtain generalized impulse response functions (GIRF). These are used to scrutinize model stability and the persistence of shocks in return and sales series. In the case of a multivariate model we must add the composition effect to the list of GIRF properties (Section 2.7).

2.6.1 Measuring the persistence of shocks in the stock market

Traditional (IRF) and generalized impulse response functions are defined in Equation 2.8. Throughout, we use upper-case letters to denote random variables and lower-case to denote realizations of these random variables. For example, the "history" or information set at $t - 1$, which is used to forecast the future values of y_t, is denoted as Ω_{t-1}, with corresponding realizations denoted as ω_{t-1}.

$$\begin{aligned} IRF(n, v_t, \omega_{t-1}) &= E[y_{t+n} | V_t = v_t, V_{t+1} = 0, \ldots, V_{t+n} = 0, \omega_{t-1}] - E[y_{t+n} | V_t = 0, V_{t+1} = 0, \ldots, V_{t+n} = 0, \omega_{t-1}] \\ GIRF(n, v_t, \omega_{t-1}) &= E[y_{t+n} | V_t = v_t, \omega_{t-1}] - E[y_{t+n} | \omega_{t-1}]. \end{aligned} \qquad \textbf{(2.8)}$$

Looking at the traditional impulse response $IRF(n,v_t,\omega_{t-1})$, we note that the system is hit by a shock v_t at t, while the second realization, the benchmark, assumes that the system is hit by no shocks between t and $t + n$. All shocks in intermediate periods between $t + 1$ and $t + n$ are set at zero in both realizations. Traditional IRF is also symmetric, a shock of size $-v_t$ having an effect exactly opposite to that of a shock of size $+v_t$. The IRF is also proportional to the size of the shock and history-independent since, for example, it follows that $IRF(n,v_t,\omega_{t-1}) = \pi_1^n v_t$, $n = 0,1,2,...$ in the case of an AR(1) model $y_t = \pi_0 + \pi_1 y_{t-1} + u_t$.

In the nonlinear case, the expectation operator is conditioned only on the specific history ω_{t-1} and the random initial V_t, and the problem of dealing with shocks occurring in intermediate time periods is handled by averaging them out. Given this choice, the natural benchmark profile for the GIRF is the expectation of y_{t+n} conditional only on the history of the process ω_{t-1}. Thus current shocks together with intermediate shocks are averaged out as well. As the GIRF do not represent the responses to a shock of a certain size and sign but treats the shock itself as a random variable, the GIRF are reported in terms of density functions, rather than time trajectories. In other words, Potter (1995, 2000) and Koop et al. (1996) suggest that the dispersion of the distribution of the GIRF at finite horizons can be interpreted as a measure of the persistence of shocks. A shock $V_t = v_t$ is said to be transient at history ω_{t-1} if the $GIRF(n,v_t,\omega_{t-1})$ approaches zero as $n \to \infty$. Otherwise, the shock is said to be persistent. For stationary and ergodic time-series processes the effects of all shocks eventually converge to zero for all possible histories of the process. By contrast, for nonstationary time-series the dispersion of the distribution of the $GIRF(n,V_t,\Omega_{t-1})$ is positive for all n.

As the GIRF is defined as a function of v_t and ω_{t-1}, which are realizations of the random variables V_t and Ω_{t-1}, Koop et al. (1996) conclude that the GIRF is itself a realization of a random variable. However, it can still be interpreted as a random variable if parameter uncertainty is taken into account. This latter interpretation allows various conditional versions which are of potential interest to be defined (Koop, 1995). For example, one might want to consider only those histories ω_{t-1} for which the transition function of the estimated STAR is either smaller or larger than a specific threshold value, and treat the GIRF as a random variable with respect to shocks V_t.

Since in general there are no analytical expressions available for the conditional expectation in the case of the STAR models, they are obtained using Monte Carlo simulations by exposing the system to shocks and averaging over all possible realizations of y_{t+n}. The Monte Carlo technique of forming the GIRF for a single time-series is presented in Skalin & Teräsvirta (2002). Furthermore, since for the nonlinear models conditional distribution can be asymmetric and even contain multiple modes, the symmetric interval around the mean is no longer the most appropriate forecast of the confidence region. By contrast, the highest density forecast region is that in which future observations will probably fall, and thus they also portray asymmetry and multi-modality. Hence, to be able to interpret the results more clearly, we use the results of the GIRF to form the basis of the highest density regions, which are then used for a graphical representation. Following Hyndman (1995,1996) and King (1996)[19] the 50% and 95% highest density regions are estimated using the density quantile method (Appendix 2.8).

2.6.2 Stability of the estimated STAR models

Stability of the estimated models was already discussed in Section 2.5.3. Using the GIRF we may also investigate the stability of the estimated STAR models from another perspective. Consequently, the GIRF is simulated using all observations from the time-series as "history" and shocks are drawn from all residuals of the STAR model under consideration. If density converges to one point in time, the model is stable. If the density becomes flatter over time, stability can no longer be assumed, and the model is best used for very short-term forecasting.

Since we are more interested in the behavior of the HeSE in recent history, with more developed financial markets, we now focus on the period 1957/9 - 1997/11 only. In Figure 2.6 below we have drawn the 50% and 95% highest density regions (HDR) for the simulated GIRF based on U97.1 up to 24 months. We use "random history" (a random draw using all observations from the time-series as history), 50 random shocks per history drawn from all residuals of the model, and the number of replications is R = 1000. The results indicate that shocks are transient in contrast to some long run dependences in regime $F = 1$, which was already observed in the corresponding "sliced spectra" (Figure 2.5). However, persistence of shocks in the variance of this process indicated by the STAR-GARCH above may have disturbed these results. We observe similar mean reversion in the case of the U97.2 model using "random history" and drawing shocks from all model residuals (Figure 2.8.10 in Appendix 2.8). Prices adjust back to their fundamental values in less than a year.

Shocks should also be formed from all residuals greater or less than one negative residual standard error since considering only one realization of the future shocks could easily lead to misleading situations. For example, positive shocks may have a big influence in a recession but no effect in a boom (Koop et al., 1996 and Potter, 2000). The HDRs are thus simulated using both positive and negative shocks greater than one residual standard deviation drawn from the residuals of the STAR model under consideration. In the case of U97.1 the effect of both fifty positive and negative shocks dies out quite quickly, as can be seen in Figures 2.8.8 and 2.8.9 in Appendix 2.8.

The behavior of the UW.1 model is described in Figures 2.8.4 - 2.8.6 in Appendix 2.8. The roots of the characteristic function for the UW.1 and UWD.1 models were complex with a modulus greater than one, indicating intensified fluctuations and very slow mean reversion. Shock persistence was also confirmed by the STAR-GARCH results. All this is in line with the current finding that the 50% highest density regions only approach zero in the very short run.

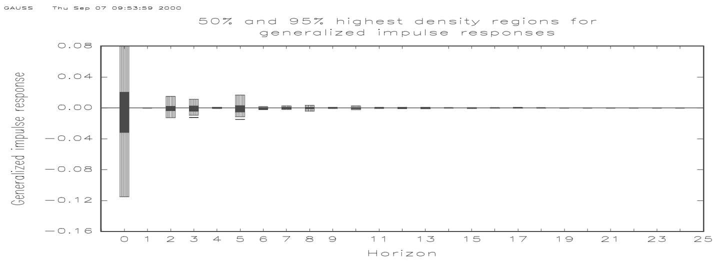


Figure 2.6: Model U97.1 (LSTAR) for 1957/9 - 1997/11. The 50% (black) and 95% (white) highest density regions for the generalized impulse responses.

Next, we look at the HDRs using differenced trading volume data and 50 random shocks per "random history" with R = 1000 replications (Figure 2.7). Observed fluctuations confirm the local nonstationarity of the V97.1, which prevented drawing graphs of the "sliced spectra". Similarly, the previous results suggest that we should expect to see some exploding fluctuations in the case of the S97.1 model. Using 50 random shocks per "random history", the HDRs prove this assumption (Figures 2.8.1 - 2.8.3 in Appendix 2.8).

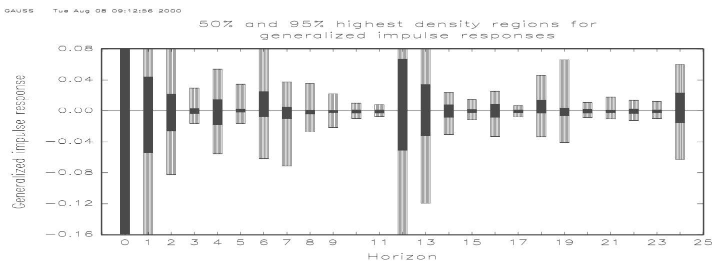


Figure 2.7: Model V97.1 (LSTAR) for 1957/9 - 1997/11. The 50% (black) and 95% (white) highest density regions for the generalized impulse responses.

We then divide the set of selected histories to include either all histories (unconditional) or those histories for which the transition functions $F(z_t)$ in Equation 2.2 are larger and smaller than the threshold value c = 0.5. We do this because the effect of a shock may be different depending on which history we were in when the shock hit the economy. It could also matter if a positive shock hits the market when returns are low/high or a negative shock hits the market when returns are low/high. The results in the case of S97.1 are given in Figures 2.8.2 & 2.8.3 in Appendix 2.8. These results are similar to those obtained using "random history". The process fluctuates and behaves in much the same way as in Figure 2.7.

Empirical studies show that returns tend to increase if the trend in returns has been upward-sloping, but eventually there has to be a drop in returns as they cannot grow forever. Hence high returns are generally followed by similar returns or much lower returns, and we expect to see this kind of behavior as bimodality when the highest density regions are used to depict the stock returns behavior. To see whether this kind of behavior also applies here, the HDRs are drawn based on the U97.2 (Figure 2.8) using 50 innovations larger than one standard deviation of the model residuals, and focusing on those histories for which $F(z_t) > 0.5$ corresponding to the years 1970, 1973, 1985 and 1995. The effect of a positive shock is now both positive and negative in the next period; i.e., there is slight evidence of multimodality in this model. The persistence of shocks is mostly positive, but dies out quite quickly. The reverse pattern arises in the case of negative shocks (Figure 2.8.12 in Appendix 2.8).

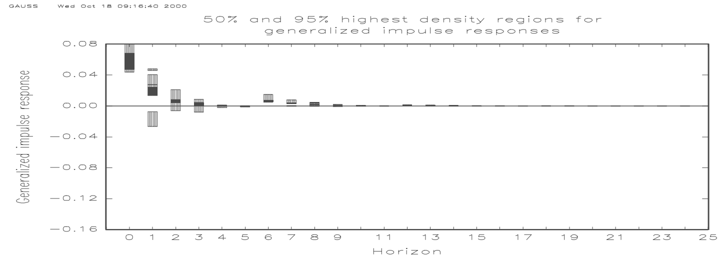


Figure 2.8: The 50% (black) and 95% (white) highest density regions for the GIRFs in the two-regime STAR model that is effective when $F(z_t)$ in U97.2 is larger than 0.5.
Innovations are larger than one standard deviation of the corresponding model residuals.

To scrutinize the significance of asymmetric effects of positive and negative shocks, Potter (1994) uses the following formulation:[20]

$$ASY_y(n, v_t, \omega_{t-1}) = GIRF(n, v_t^+, \omega_{t-1}) + GIRF(n, -v_t^+, \omega_{t-1}), \qquad \textbf{(2.9)}$$

where $n = 1,2,3,...$, and v_t^+ indicates the set of all positive shocks. If positive and negative shocks have exactly the same effect with the opposite sign, ASY_y should almost certainly be zero. Or, more generally, if ASY_y has a symmetric distribution with a mean of zero, we say that shocks have a symmetric effect on average. As the corresponding graph for the negative shocks in Figure 2.8.12 is not quite a mirror image of the one for positive shocks in Figure 2.8.11, this implies that some asymmetry is built into the U97.2 model (Appendix 2.8). In Figure 2.8 we have drawn the highest density regions for the sum of the GIRFs of these two cases. ASY_y falls to zero in about six months, confirming this assumption.

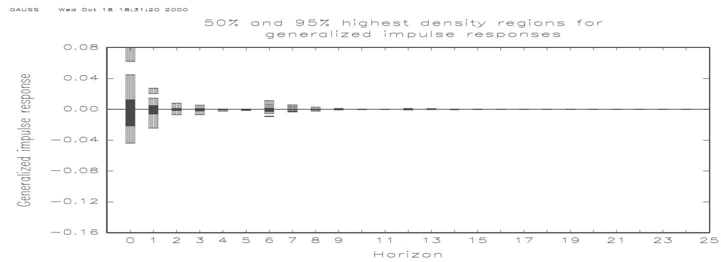


Figure 2.9: The 50% (black) and 95% (white) highest density regions for the difference of the generalized impulse response functions in the two-regime STAR models effective when $F(z_t) > 0.5$ in the U97.2.
If positive and negative shocks have exactly the same effect with the opposite sign, ASY_y should almost certainly be equal to zero, or the GIRF should equal zero.

Finally, we test nonlinear causality to find out whether knowledge about past trading volume helps us to predict movements in current stock returns, or vice versa. We could ask, whether volume causes returns in a bad state of the economy in contrast to no causal relation in a boom. Volume changes could be interpreted more seriously in a recession since information gathering costs are relatively lower then than in a boom.

2.7 GRANGER CAUSALITY

The basic rules behind Granger noncausality are that the future cannot predict the past and it is only meaningful to discuss causality for a group of stochastic variables. Here, volume is said to "cause" stock returns if taking account of past changes in volume enables better return predictions to be made. Formally, Granger's definition of causality states that v_t causes r_t if the variance of the one-step-ahead prediction error for r_t is smaller when history $\omega_t = (v_{t-1}, v_{t-2}, \ldots, v_{t-n})$ $n = 1,2,3,\ldots$ is included in information set Ω_t than when it is excluded, i.e., MSE$(r_t|\Omega_t)$ < MSE$(r_t|\Omega_t - \omega_t)$. Volume does not cause stock returns if these prediction error variances are equal. Unfortunately, in the case of forward-looking behavior of the variables of interest, returns may be an excellent predictor of the future, but this does not necessarily mean that a change in returns (prices) is the cause of trading volume. Consequently, the causality test is one way to assess the efficient markets views and, strictly speaking, one must be careful in using it as a means of inferring a direction of causation. (Hamilton, 1994, Skalin & Teräsvirta, 1999, Baek & Brock, 1992, Bell et al. 1996, Warne, 1996 and Hiemstra & Jones, 1994.)

2.7.1 Are increased returns followed by increased trading volume?

First, we try to find out whether the data supports the fact that periods with large price movements are also periods with larger than average trading volume, and vice versa (Karpoff, 1987 and Tauchen & Pitts, 1983). Do we observe strong contemporaneous negative correlation between volume and price volatility movements as suggested by Gallant et al. (1993)? In other words, can we observe a triangular shape as we draw a scatter plot $(\Delta P_t, T_t)$, where ΔP_t is returns and T_t is the adjusted logarithm of sales?

The case where volume is in its positive half and ΔP_t is different from zero can be interpreted to mean that information is diffused and incorporated into prices via the trading of informed investors (points A- and A+ in Figure 2.10). Uninformed investors observe the arrival of information through a price movement on higher than average volume. When scaled volume is equal to zero but returns are different from zero (B- and B+), new information arrives as common knowledge. This implies early consensus and a price movement on average (zero) volume. When volume is in its negative or positive half and returns are zero there is no consensus and trade results from disparate beliefs (C- and C+).

All time periods share the common property of a triangular shape in these figures. To take into account increased stock market trading, Figure 2.10 is redrawn such that sales is measured as deviations from a quadratic trend (Figure 2.13). The triangular shape in the picture remains unchanged, supporting the hypothesis that the relation between trading volume and price changes is nonlinear, and should therefore be modeled accordingly.

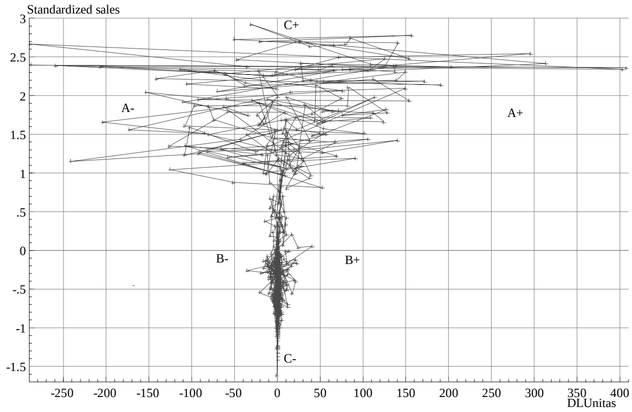
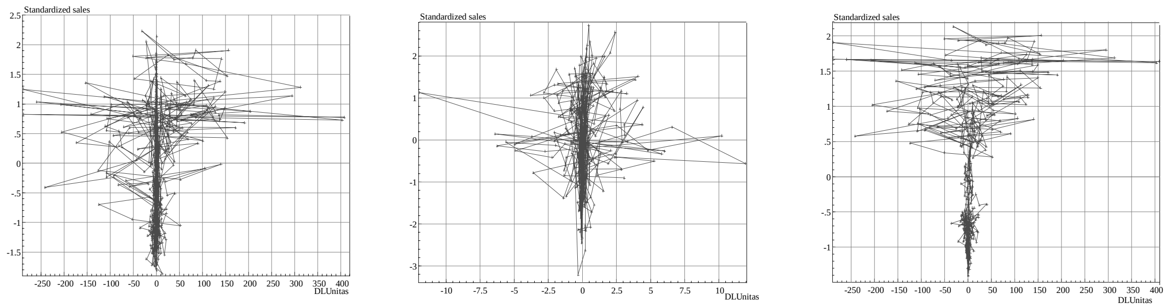


Figure 2.10: A scatter plot ($\Delta P_t, T_t$) for 1921/2 - 1997/11.
The y-axis plots logarithms of standardized[21] monthly sales and the x-axis monthly logarithmic price change (returns).

Additionally, the figures show that the logarithmic returns are first quite small, and increase considerably after a certain point in time. This suggests that there is at least one structural break in the relation between return volatility and trading volume. In Figure 2.13 this break is located[22] around 1991/8 (standardized sales ≈0.5 and returns ≈0). Hence, we continue by scrutinizing the causal relation between returns and sales following Skalin & Teräsvirta (1999).



Figures 2.11 - 2.13: A scatter plot ($\Delta P_t, T_t$) for 1921/2 - 1957/8, a scatter plot ($\Delta P_t, T_t$) for 1957/9 - 1997/11 and a scatter plot ($\Delta P_t, T_{trend}$) for 1921/2 - 1997/11, where sales is measured as deviations from a quadratic trend. *The y-axis plots logarithms of monthly standardized sales[25] and the x-axis monthly logarithmic price change.*

2.7.2 Linear Granger causality

The Granger representation theorem states that cointegration[23] entails Granger (1969) causality in at least one direction. Thus we continue with the cointegration test, since the Augmented Dickey-Fuller unit root tests for the whole period and the two subsamples of logarithms of returns, sales and volume indicate that these time-series are *I(1)*. Two series, v_t and r_t are cointegrated to order *d*, *b*, denoted as *CI(d,b)* if they are both integrated to order *d*, *I(d)*, and there is a linear combination of them which is *I(d - b)*, where *b* > 0. This means that there is some kind of steady-state relationship between the two series as against time-series integrated of different orders, which are drifting apart in time. Using a VAR for volume and returns for 1958/3 - 1997/11, we calculated the maximum eigenvalue statistics suggested by Johansen (1991). The null hypothesis is H_0: there are no cointegrating vectors, and the alternative is H_1: there is one cointegrating vector. Based on the results, H_0 is rejected at the 5% significance level (p = 6 and 12), and for lag $p = 1$, when the constant is entered unrestricted and the trend is entered restricted into the cointegration relation. This implies that since these two series are cointegrated, volume should cause returns, or vice versa. This is considered next in more detail. However, the results from unit root and cointegration tests are also used later in Section 2.8, when we scrutinize multivariate nonlinear impulse responses based on the smooth transition vector error correction (STVEC) models.

2.7.3 The parametric nonlinear Granger causality test

After checking the cyclical properties of univariate series we scrutinize temporal relations between sales and stock returns. The main interest lies in finding out whether sales is informative about the next state stock returns, and vice versa. Analogically to the linear Granger causality test, Skalin & Teräsvirta (1999) base their nonlinear parametric causality test on testing the null hypothesis of the nonexistent predictive power for y_t of lagged values of another variable x_t characterized now by an additive smooth transition component as in the additive smooth transition regression model. The test procedure itself is a modification of the test for no additive nonlinearity as in Eitrheim & Teräsvirta (1996). The model is thus $y_t = S_t'\Pi + S_t'\theta F(z_t) + K(x_t) + \eta_t$, where y_t and x_t are assumed to be stationary and ergodic. $S_t = (1, y_{t-1}, ..., y_{t-p})'$ is a $p + 1$ vector of explanatory variables, $\Pi = (\pi_0, \pi_1, ..., \pi_p)'$ and $\theta = (\theta_0, \theta_1, ..., \theta_p)'$ are $p + 1$ parameter vectors, and $F(z_t)$ is the transition function in Equation 2.2. Under the null hypothesis $\eta_t \sim$ i.i.d$(0, \sigma_\eta^2)$ the parameters can be estimated consistently by nonlinear least squares. The identification problem under H_0 is avoided by approximating the second transition function $K(x_t)$ by its Taylor series approximation. The third-order expansion as in Luukkonen et al. (1988) is used, and we obtain the model $y_t = S_t'\Pi + S_t'\theta F(z_t) + \sum x_{t-j} + \sum\sum x_{t-j}x_{t-i} + \sum x^3_{t-j} + \eta_t$. The corresponding auxiliary regression used in testing the null hypothesis is:

$$\hat{\eta}_t = \beta_0' g_t + \sum_{j=1}^{q} \delta_j x_{t-j} + \sum_{i=1}^{q}\sum_{j=1}^{q} \varphi_{ij} x_{t-i} x_{t-j} + \sum_{j=1}^{q} \psi_j x_{t-j}^3 \qquad \textbf{\textit{(2.10)}}$$

where $\hat{\eta}_t$ are independent, identically distributed errors estimated under H_0, g_t is the gradient vector of the parameters of the STAR model under H_0, and β_0, δ_j, φ_{ij}, ψ_j are $p + 1$ parameter vectors. The hypothesis "x_t does not Granger cause y_t" can be written as H_0: $\delta_j = 0$, $\varphi_{ij} = 0$ and $\psi_j = 0$, where $i,j = 1,...,q$. The LM-type test can be carried out as before if all the necessary moments for x_t exist. The degrees of freedom of the approximating F-statistic are $q(q + 1)/2 + 2q$ in the numerator and $T - n - q(q + 1)/2 - 2q$ in the denominator, where T is the number of observations and n is the dimension of the gradient vector.

As some of y_{t-d} $(d = 1,...,p)$ are missing after fitting the best STAR model to the data, we include these lags in the causality tests, and report results both with and without missing y_{t-d}. As we cannot assume that d in the additional nonlinear part is known, causality testing is done using x_{t-q}, $q = 1,2,...,6$ as a transition variable. Another drawback in allowing a general form for $K(x_t)$ is that the dimension of the null hypothesis increases quickly with q. This may easily lead to a situation in which the test is not likely to have very much power (Skalin & Teräsvirta, 1999). This should be kept in mind when looking at the following results.

Nonlinear causality tests are done for both returns and trading volume, and for sales obtained after deflating the original trading volume series by the HeSE general index. The reason for using both series is explained more carefully above and in Appendix 2.3. The results are then compared to find out whether the inclusion of contemporaneous x_t has affected them seriously. Nevertheless, a proper analysis of how deflating alters the results would have required simulations, as the local nonstationarity observed in returns based on the V97.1 model may have partly affected the results here.

TABLE 2.7: Nonlinear Granger causality tests 1957/9 - 1997/11: sales and returns.

return → sales	**return → sales**	**sales → returns**		**sales → return**		**q**
S97.1	**S97.1**	**U97.1**	**U97.2**	**U97.1**	**U97.2**	
0.988	**0.027**	0.562	0.999	0.506	0.373	1
0.983	**0.000**	0.471	0.999	0.415	0.340	2
0.964	**0.003**	0.451	0.998	0.481	0.394	3
0.999	**0.014**	0.464	0.995	0.259	0.278	4
0.996	0.179	0.176	0.994	0.693	0.677	5
0.961	**0.010**	**0.025**	0.746	0.551	0.430	6

Only p-values are reported. The q = delay in the second transition function $K(c_2,x_{t-q})$. **Note: first and third columns:** missing lags of the dependent variable are included among explanatory variables (see Section 2.5.3). Model S97.1 includes lags $y_{t-1},...,y_{t-6}$ and $x_{t-6},...,x_{t-11}$, U97.1 lags $y_{t-6},x_{t-1},...,x_{t-6}$ and U97.2 lags $y_{t-2},...,y_{t-5},x_{t-1},...,x_{t-6}$. **Second and fourth columns:** missing lags of the dependent variable are not included among explanatory variables. Model S97.1 includes lags $x_{t-6},...,x_{t-11}$, U97.1 and U97.2 lags $x_{t-1},...,x_{t-6}$.

We also test linear causality between returns and sales (volume). The p-values for testing linear causality running from returns to sales using lags 6 and 12 are: 0.000 (F(6,477)) and 0.0098 (F(13,444)). Correspondingly, when we test causality running from sales to returns, the p-values are 0.002 (F(7,476)) and 0.0003 (F(13,444)). This indicates bidirectional causality between returns and sales in contrast to the rejections of nonlinear causality in either direction shown in many cases in Tables 2.7 and 2.8.

Nonlinear causality tests were first done without including missing dependent variable lags among explanatory variables in the linear part of the equation. In this case we find nonlinear causality running from returns to sales using *q = 1,2,3,4* and *6* but not vice versa. After including the excluded dependent variable lags among the explanatory variables, causality can only be found running from sales to returns (the base model is U97.1, the first lag of sales and its powers are tested, the transition variable is sales_{t-6}). Hence, choosing the information set has an essential role in testing causality, as usual.

When we focus on the tests of causality between volume and returns, we find causality from returns to volume in the case of the model V97.1 with *q = 6*, but vice versa using U97.2. Using *q = 2* in V97.1, causality again runs from returns to volume. Nevertheless, after expanding the autoregression with missing lags of dependent variables, no causality is found between these variables. To conclude, the results depend somewhat on the data transformation; for example, we reject causality running from returns to sales in the case of S97.1 with *q = 1*, but the same result does not apply to V97.1. Unfortunately, we may get this result because of the properties of the underlying models as well.

Nevertheless, compared to linear causality tests, which indicated bidirectional causality, the direction of causality is now easier to point out. Based on the results in Tables 2.7 and 2.8, nonlinear causality mainly seems to run from returns to sales or volume. Whether high returns attract more investors to the market or the investors leave the market on a fall in stock prices, causing increased trading, remains to be answered.

TABLE 2.8: Nonlinear Granger causality tests for 1957/9 - 1997/11: Volume and returns**.**

return → volume	**return → volume**	**volume → return**		**volume → return**		**q**
V97.1	**V97.1**	**U97.1**	**U97.2**	**U97.1**	**U97.2**	
0.959	0.077	0.705	0.999	0.586	0.772	1
0.855	**0.006**	0.611	0.999	0.505	0.621	2
0.824	0.027	0.763	0.999	0.730	0.531	3
0.947	0.059	0.417	0.999	0.367	0.239	4
0.963	0.419	0.749	0.999	0.696	0.175	5
0.939	**0.041**	0.705	0.999	0.615	**0.010**	6

Only p-values are reported. The q = delay in the second transition function $K(c,x_{t-q})$. **Note: first and third columns:** missing lags of the dependent variable included among explanatory variables (see Section 2.5.3). Model V97.1 includes lags $y_{t-6},\ldots,y_{t-11}$ and $x_{t-1},\ldots,x_{t-6}$, U97.1 lags $y_{t-6},x_{t-1},\ldots,x_{t-6}$ and U97.2 lags $y_{t-2},\ldots,y_{t-5},x_{t-1},\ldots,x_{t-6}$. **Second and fourth columns:** missing lags of the dependent variable are not included among explanatory variables. Model V97.1 includes lags $x_{t-1},\ldots,x_{t-6}$, U97.1 $x_{t-1},\ldots,x_{t-6}$ and U97.2 lags $x_{t-1},\ldots,x_{t-6}$.

To avoid the influence of cointegration, causality and/or the composition effect on the GIRF, we continue by focusing on measuring the persistence of shocks in the case of smooth transition vector autoregressive models (STVAR) or smooth transition vector error correction models (STVECM). The GIRF in the case of STVECM models are also formed assuming that the shocks to returns equation has some effect on the sales (volume) equation, but the reverse is not likely.

2.8 THE GENERALIZED IMPULSE RESPONSE FUNCTION: MULTIVARIATE MODELS

In the standard error correction model, adjustment toward the long run equilibrium is linear. In other words, it is always present and of the same strength under all circumstances. Recently, several attempts have been made to allow nonlinear adjustment or to make a distinction between adjustment of positive and negative or between adjustment of large and small deviations from an equilibrium. Van Dijk & Franses (2000) suggest that market frictions give rise to asymmetric adjustment of deviations from equilibrium in the case of a stock market. For example, short-selling restrictions mean that the response to negative deviations from the equilibrium can be different from the response to positive deviations. Alternatively, transaction costs prevent adjustment of equilibrium errors as long as the benefits from adjustment, which equal the price differences, are less than the costs.

Hence we simulate the multivariate generalized impulse response function (MGIRF) to pick up the possible asymmetry in the persistence of shocks in stock returns and trading volume. The generalized multivariate impulse response function is formally defined as:

$$MGIRF(n, v_{jt}, \omega_{t-1}) = E(Y_{t+n} | V_{jt} = v_{jt}, \omega_{t-1}) - E(Y_{t+n} | \omega_{t-1}), \qquad \textbf{(2.11)}$$

where Y_{t+n} is a (2*1) matrix $n = 1,2,3,...$ and v_{jt} (ω_{t-1}) are realizations of random shocks V_{jt} (history Ω_{t-1}). This section concludes with results from GIRF based on STVECM fitted to sales and returns, where the direction of causality runs from returns to sales as already indicated in Section 2.7.

2.8.1 The composition effect and nonlinear cointegration

Expanding the analysis to a more general case of a multivariate nonlinear time-series model is not straightforward. The focus of interest in multivariate models is the same as in univariate models, namely, the time profile of the effect of shocks on the dependent variables, but now the shocks in the first equation may not only have contemporaneous effects on the first dependent variable, but on the other dependent variables in the model as well. Hence, it is not appropriate to entertain perturbations in the shock to the first equation while keeping the shocks to other equations fixed. This property is referred to as the composition effect. To avoid the composition effect one may want to transform the model so that the covariance matrix of the transformed shocks is a diagonal matrix, but in general such a transformation is not unique. Another solution is to let the GIRF be conditional not on all shocks at time *t* but on just one of them. This means considering fixing the i^{th} shock from the vector of all shocks V_t, and then integrating out the effects of the other shocks at time *t* given its value v_{it}. (Koop et al., 1996 and Pesaran & Shin, 1998)

In other words, as the GIRF in the case of multivariate models depends on the composition of shocks, to measure the persistence of shocks in returns and trading volume series - assuming that these two series are related - we need to look at a properly adapted VAR. The intuition to add an error correction term in the nonlinear part of the VAR is that if the system is very far from its long run equilibrium, the adjustment process back to equilibrium may no longer be properly described by a linear Taylor series approximation. By contrast, additional nonlinear terms need to be included to achieve a proper fit. Loosely speaking, the error correction term gives a “weight” for adding these nonlinear terms in the model. Furthermore, following Pesaran & Shin (1998) and van Dijk et al. (2000) we restrict the interest in measuring the response of Y_{t+n} to a shock v_t at time *t* in the j^{th} equation only ($j = 1,2$), while integrating out the effects of shocks to the other equations.

Hence we use the STVECM, in which $Y_t = [r_t, v_t]'$. Nonlinearities are described by the same nonlinear factor given either by $F_j(z_t) = (1 + exp[-\gamma(z_{t-d} - c_j)])^{-1}$ or $1 - exp(-\gamma(z_{t-d} - c_j)^2), j = 1,2,$ in both explanatory variables. Here, z_{t-d} is one of the $2p$ lagged regressors in Y_t, $\gamma_j > 0$, $c_j = c$, and the transition function is standardized by dividing it by the standard deviation of z_{t-d} to get γ scale free. Since the second type of asymmetry distinguishes between small and large equilibrium errors, the strength of adjustment changes gradually for larger deviations from equilibrium.

However, the possibility of distinguishing between logistic and exponential STAR models is very costly as it requires including additional higher-order terms in the Taylor-series expansion. Given the typical size of macroeconomic samples, this is not practical, so that the choice is made more or less based on economic intuition. The next step would be applying the generalized method of moments test for common nonlinear components in multiple time-series as suggested by Anderson & Vahid (1998).

The STVEC model for $Y_t = [r_t, v_t]'$ is defined as:

$$Y_t = \lambda_0 + \lambda_1 Y_{t-1} + \ldots + \lambda_p Y_{t-p} + \Xi Z_{t-1} + \alpha[\eta_0 + \eta_1 Y_{t-1} + \ldots + \eta_p Y_{t-p} + \Psi Z_{t-1}] F_j(z_{jt}) + \varepsilon_t, \quad \textbf{(2.12)}$$

where ε_t is a (2*1) vector of normal errors with mean zero and unknown variance h_t, and ε_t, ε_s are identically distributed and uncorrelated for all $t = s$. The λ_0 and η_0 are (2*1) constant vectors, λ_i, η_i, $i = 1,...,p$ and α are (2*2) parameter matrixes. Ξ and Ψ are (2*1) parameter vectors. Cochrane (1994) shows that the volume - stock return index ratio is a potent forecaster of long horizon index growth. He finds that the volume - index ratio is stable over long periods and concludes that volume and returns are cointegrated, while volume is nearly a random walk. In such a case volume defines a “trend” in returns. Following Cochrane, we assume that this kind of relationship can be attributed here to a common nonlinear factor. Hence, the error correction term in Equation 2.12 is defined as $Z_{t-1} = [r_{t-1} - v_{t-1}]$.

2.8.2 Measures of shock persistence based on a smooth transition vector autoregressive model

We should remark that since the interest in multivariate nonlinear modeling has started to develop only very recently, the relevant statistical theory has by no means been fully developed, and is still a topic of much current research. Multivariate nonlinear modeling is difficult. An obvious way to proceed is to consider whether economic reasoning and the data would allow us to simplify the modeling process. Given the nonlinear structure of the model and the computationally demanding nature of the estimation, we restrict the analysis to a few “simple” choices of model parametrization. Some tricks are also used to help solve the nonlinear estimation problem. For example, we have standardized the right-hand side variables. This is important for the nonlinear estimation, because we are using numerical derivatives, and the magnitudes of the right-hand side variables (the ECMs vs lagged growth rates) are different. However, since we have not standardized the dependent variables, the residuals are of the same unit. We have also multiplied sales by ten to avoid dealing with very small numbers.

Based on the previous results sales and returns are linearly cointegrated. The error correction term used here is thus $Z_{t-1} = (r_{t-1} - 3897.3{*}v_{t-1} + 41.193{*}\text{trend})$, as illustrated in Figure 2.14. Unfortunately, looking at this graph we may suspect that the error correction series is not stationary. Interpreting the estimated coefficients may also be difficult, partly because the variables in the error correction term are also included as an explanatory variable in the nonlinear part of this equation. Fortunately, despite all these difficulties in estimation, we are more interested in seeing whether taking the composition effect into account changes the previous results of shock persistence much.

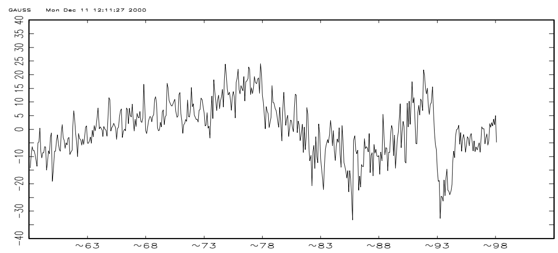


Figure 2.14: Cointegrating relation for 1957/9 - 1997/11 between returns and sales**.**

Estimation results from the bivariate STVECM model fitted to returns and sales are given in Table 2.9, where we have replaced the transition variable z_t in $F_j(z_{jt}) = F(z_t)$, $j = 1,2$, by the estimated error correction term following Teräsvirta & Eliasson (1998). Furthermore, we focus on cases in which we assume that the system is hit by a particular shock at time *t* in the stock return equation. Finally, we have used this model to simulate the MGIRF, which is described in Appendix 2.9.

TABLE 2.9: Estimation results from a STVECM for returns and sales 1957/9 - 1997/11, when a shock hits the equation for returns.

parameters	**estimates**	**s.e.**	**Est./s.e.**	**probability**
λ_{10}	19.238	29.470	0.653	0.257
CI_1	3.734	6.737	0.555	0.290
λ_{11}	2.300	0.701	3.282	0.001
λ_{12}	-0.822	1.136	-0.723	0.235
λ_{20}	0.594	0.286	0.208	0.418
CI_2	0.066	0.067	0.991	0.161
λ_{21}	0.024	0.029	0.832	0.203
λ_{22}	-0.056	0.016	-3.479	0.0003
η_{10}	10.950	34.622	0.316	0.376
CI_3	6.200	10.950	0.566	0.286
η_{11}	4.187	8.002	0.523	0.301
η_{12}	-0.598	1.303	-0.458	0.324
γ	0.461	0.195	2.363	0.009
c	-4.186	0.944	-4.432	0.000
α_{11}	-0.865	1.680	-0.515	0.303
α_{12}	0.003	0.009	0.320	0.375

The parameters λ_{1i}, $i = 0,1,2$ and CI_1 refer to the stock return equation, λ_{2i}, $i = 0,1,2$, and CI_2 to the sales equation and η_{1i}, $i = 0,1,2$ to the common nonlinear part. Parameters c and α (α_{11} and α_{12}) refer to Equation 2.12. S.e. is the standard error of the estimates, Est./s.e is the *t*-value, and probability is the significance of the estimated coefficient. The variables of the right-hand side of the equation are standardized, because we use numerical derivatives to estimate the model parameters. The covariance matrix of parameters is computed using the inverse of the computed Hessian. The mean of the log-likelihood is -9.014, and the number of cases is 481.

By adding up the coefficients in the two different regimes from Table 2.9, we observe that when shocks hit the return equation and when we are away from the long run equilibrium (F = 1), returns are negatively related to the cointegrating relation and lagged returns (mean reversion) as against positive dependence between these variables close to equilibrium (F = 0). Only the latter relationship is statistically significant at the 1% level. Similarly, an increase in sales diminishes returns more seriously when we are away from the long run equilibrium (an increase in sales brings bad information to the market?). Lagged returns have a small (statistically insignificant) positive effect on sales in both cases. We also observe a small significant negative dependence in sales.

The first column in Appendix 2.9 represents the estimated MGIRF based on the stock return equation followed by the MGIRF for sales (second column) and the error correction term. The second and third rows of graphs correspond to a situation in which shocks have arrived when $F(z_t)$ is either below or above 0.5. The scales of these estimated MGIRF shows that shocks are very persistent in all cases, but with remarkedly small probabilities. In other words, some problems in the STVECM remains.

Other attempts to produce stable models were not successful and, even when the sales series was replaced by volume, the model did not solve for a reasonable number of experiments with the data. We assume that these problems are related to structural breaks or increases in volatility, which the current approach may not be able to take into account. For example, focusing on STAR-GARCH(1,1) model S97.1 we located a structural break around 1993/8, which is the time when trading at the HeSE increased rapidly as a result of abolition of foreign ownership restrictions. Furthermore, the HDR drawn for S97.1 indicated problems in modeling sales (exploding fluctuations). Hence, to our regret, the results on how the composition effect influences measures of shock persistence remain inconclusive at this stage of the study.

Further attempts to split the data into smaller periods have been avoided as we want to show how the methods used in this study influence testing the EMH even when the data includes structural breaks. The STAR models describe the behavior of the HeSE fairly well between 1921/1 and 1997/11. Accordingly, this study concludes by repeating the main results. Nevertheless, the many ways to approach the data have pinpointed several remaining problems, which are all equally important for further research.

2.9 CONCLUSIONS

The results show that we need nonlinear models to describe the time-series properties of stock returns and trading volume at the Helsinki Stock Exchange between February 1921 and November 1997. To demonstrate nonlinearity in the data we use smooth transition autoregressive models (STAR), smooth transition generalized autoregressive conditional heteroskedastic models (STGARCH) and smooth transition vector error correction models (STVECM). These models are applied as a basis for measuring the persistence of shocks in stock returns and trading volume, as well as testing whether changes in volume contain any information which could be used in forecasting returns, and vice versa.

STAR models can also be exploited as a test against structural breaks. As the data starts from February 1921, finding some indication about a structural break in sales around 1957 was not surprising, especially as the Finnish economy had suffered from a general strike in 1956, and the economy was finally opened up to foreign trade. In addition, to boost the economy the paper industry was supported by a 39% devaluation on 15.9.1957. Taking this into account, the sample is divided in two parts. Linearity against STAR is then tested using the whole sample and the two subsamples. Finally, the STAR models indicated by the test results are fitted to the data.

The next natural step was model evaluation. Based on the model mis-specification tests, heteroskedasticity seemed to be the biggest remaining problem in the analysis. To take this into account we continued as follows: informational efficiency tests do not require that the residuals from the model used in testing this hypothesis be homoskedastic. Nevertheless, rejection of the null hypothesis might be due to other kinds of model mis-specification such as neglected nonlinearity in the model for the conditional mean. Hence, I first modeled nonlinear dependence in the conditional mean in order to avoid mis-specification of the conditional variance. In other words, STAR models are used to identify the nonconstant conditional mean. Only then is nonconstant variance modeled using the STAR-GARCH to improve the accuracy of the results.

STAR-GARCH fitted to returns for 1921/1 - 1997/11, 1921/1 - 1957/8 and 1957/9 - 1997/11 behaved in a similar manner. Some indication of a structural break in volatility around 1934 corresponding to the Great Depression was given. When we fitted a similar model to the volume series using the whole sample, the model behaved much as the model for returns, but now without any structural breaks. However, we rejected the null of homoskedasticity against nonlinearity in the spirit of Teräsvirta based on the model for sales for 1957/9 - 1997/11. Parameter constancy in the sales model was also rejected, and we located a break in 1993/8, which is the time when the Finnish economy started to recover from a deep slump. The results using volume confirmed this behavior, except that the structural break is located somewhat earlier, in December 1992.

It is generally not possible to completely grasp the implied properties of time-series generated by a model by only trying to interpret the model parameters. Therefore, to characterize the models estimated we considered the effect of shocks on the future patterns of returns and volume. A convenient tool is the generalized impulse response function (GIRF). Using this we are able to take into account, that the effect of a shock depends on the history of the time-series up to the point where the shock occurs, that the effect of a shock is not proportional to its size, and that the effect of a shock depends on shocks occurring in periods between that at which the impulse occurs and the moment at which the response is measured. As in the case of nonlinear models, the conditional distribution may be asymmetric and even contain multiple modes, the highest density regions being best used for a graphical representation of the GIRF densities obtained.

Since in the case of returns for 1921/1 - 1997/11 the highest density regions graphed only narrow toward zero in the very short run, this model can best be used for very short-term forecasting. This observation of model instability is not surprising, as the tests for functional form mis-specification had already been significant. In contrast, returns for 1957/9 - 1997/11 show that shocks are not persistent; this also applies when we take into account the possibility that positive and negative shocks may have different effects on the process. Based on the HDR for the U97.2 model using 50 innovations such that they are larger than one standard deviation of the model residuals, and focusing on those histories for which returns are typically higher than 0.05, we observe bimodality, or mean reversion. In other words, large returns are generally followed by similar returns or much smaller returns. When we look at the HDR based on the V97.1, we observe fluctuations confirming local nonstationarity due to which we could not depict the “sliced spectra” as we did for other models reported above. This kind of behavior is also observed in the case of sales (S97.1), when we draw fifty random shocks per “random history”, and when histories where the transition function obtains values both above and below one are used in simulating the HDRs. Stability of the STAR models estimated was also scrutinized using the GIRF. Fortunately, the results of model stability were generally in line with those obtained calculating the roots, modulus and period for the estimated models both in linear and nonlinear regimes.

Causality between returns and sales (volume) is tested using parametric nonlinear causality tests. By contrast with the linear causality test, which indicated bidirectional causality between these variables, we found that causality mainly runs from returns to sales (volume). This indicates that changes in returns have affected the trading behavior at the HeSE, especially between September 1957 and November 1997. These results are also used when we fit a STVECM to the data, which allows us to take into account both the possible composition effect and “nonlinear cointegration” or common persistence in the system.

The focus of interest in multivariate models is the same as in univariate models; namely, the time profile of the effect of shocks on the dependent variables. But now the shocks in the first equation may not only have contemporaneous effects on the first dependent variable, but on the other dependent variables in the system as well. However, only one STVECM of the several parametrizations which we tried to fit to the data for 1957/9 - 1997/11 converged such that calculating the inverse of the Hessian succeeded. Now, looking at the estimated GIRF, large shock persistence in both returns and sales is observed but with particularly low probability. This may be partly because using the current methods we are not able to take fluctuations or large changes in variance into account properly, especially in sales. Together, the results imply that the underlying multivariate dynamics are complicated.

Previous studies of the Finnish stock market report persistent serial correlation in monthly returns. The results based on generalized impulse response functions for 1957/9 - 1997/11 indicate that since shocks to returns are not persistent, prices adjust back to their fundamental values as they should according to the EMH. Next, linear Granger causality tests indicate bidirectional causality between returns and sales (volume). However, since the nonlinear causality tests used in this study suggest that only in a few cases can sales (volume) be used to forecast stock returns, we can give only slight support to the mixture model. Causality runs mainly from returns to sales, supporting the positive feedback trading hypothesis. We must conclude that ignoring nonlinearity in returns and sales may lead us to draw incorrect conclusions about the persistence of shocks in these series, and causality between these variables. Therefore, taking nonlinearity into account clearly makes a difference in testing whether market efficiency is a good enough model to describe the characteristics of the HeSE. With this we conclude that nonlinearity testing should become a habit when working with financial market data.

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Appendix 2.7: Graphs of transition functions and "sliced spectra" using the first difference of the logarithm of the series under consideration.
Appendix 2.8: The 50% (black) and 95% (white) highest density regions for GIRFs in the two-regime STAR models.
Appendix 2.9: The generalized impulse response functions in the case of the STVECM.

Footnotes

1. To test the EMH we also need a model of how investors form a view about expected returns.

2. Gallant et al. (1993) find that "leverage effect" is a weak transient phenomenon.

3. All insurance and consumption smoothing reasons for trading are absent.

4. If a fall in stock prices is due to exogenous selling pressure by non-informational traders who have become more risk-averse, market makers buying stock will require a higher expected return, and so there will tend to be price increases on subsequent days. Hence, low returns accompanied by high trading volume are probably due to a rise in risk aversion, while those observed with low trading volume are probably due to bad public news. (Gallant et al., 1993) In practice large and sudden changes in risk aversion are not likely, as transaction costs partly offset the willingness of naive investors to change the composition of their portfolios. There is however an increasing interest in the idea that risk aversion may vary over time with the state of the economy because of habit formation, trading based on irrational expectations or the existence of heterogenous agents.

5. Trading at the HeSE starts with a calling out, where the price range for trades is determined, and continues with an aftermarket, where the rest of the trade occurs. Now, an increase in trading frequency in the calling out probably decreases the offer price range, and the price in the aftermarket is more likely to be driven beyond the range specified at calling out, and trade in the stock is halted. The price pressure will then produce price changes next day in the same direction, i.e., returns will be serially correlated between these particular days.

6. Evaluating forecasts from nonlinear time-series models is a topic of much current research, and at the time of writing no conclusive results have been obtained. Sarantis (2001) finds that STAR can improve upon the linear autoregressive and random walk models in forecasting stock price growth rates at both short-term and medium-term horizons.

7. Beginning in January 1991 this is the HeSE general index, aggregated last observation. Returns do not include dividends either. See also Appendix 2.1.

8. Markku Rahiala has helped me in solving this problem.

9. Note that if prices follow a random walk, this type of behavior in the time-series is not unexpected. A further modification would be the application of an exponential model to identify possible nonlinearity in the data.

10. We included a constant and a linear trend in the Augmented Dickey-Fuller regression.

11. If a linear time-series is contaminated by outliers, the LM type of nonlinearity test may indicate nonlinear structures (van Dick & Frances, 2000).

12. Since Lundbergh & Teräsvirta (1998) assume constant conditional variance in their linearity test, it is not robust against conditional heteroskedasticity. However, based on simulation studies they do not recommend robustification. Robust estimation methods for STAR models are discussed in van Dijk et al. (2000).

13. For large γ, $F(z_t)$ is close to a step function. To obtain an accurate estimate of γ one then needs many observations in the immediate neighborhood of the threshold, because even large changes in γ only have a small effect on the shape of the transition function. The estimate of γ may therefore be rather imprecise and often appear to be insignificant when judged by its *t*-statistic. There is no idea in testing whether the *c* coefficient is different from zero since it describes where the transition function changes in the sample.

14. We were unable to solve the LSTAR model fitted to the data.

15. The “global” dynamics of STAR models are better characterized by a “model” spectrum.

16. The maximum likelihood estimator is consistent, but it is hard to prove that it is asymptotically normal, which is often ignored by empirical researchers. The disadvantages of two-step estimation are discussed in Lundbergh & Teräsvirta (1998).

17. The GRJ-GARCH model is $h_t = \gamma + \alpha\varepsilon_{t-1}^2 + \omega S^-_{t-1} e_{t-1}^2 + \beta h_{t-1}$, where $S^-_{t-1} = 1$ when $\varepsilon_{t-1} < 0$ and zero otherwise.

18. GAUSS procedures used to obtain the GIRF do not allow for estimating STAR-GARCH models in two stages.

19. Testing zero persistence using the GIRF requires the construction of standard deviation to reflect both estimation uncertainty and Monte Carlo sampling variation.

20. Potter (2000) utilizes the definition of second-order stochastic dominance in comparing the GIRF densities: if two variables involved have the same mean, then one distribution dominates the other in the second-order stochastic dominance sense if it is more compactly placed around the mean than the other distribution, remembering that any form of distribution can occur. For a more detailed definition of stochastic dominance see Granger (1999).

21. $T_t = 1$ is achieved when sales is one standard deviation above its mean (T_t = mean + standard deviation), $T_t = -1$, when sales is one standard deviation below its mean, and $T_t = 0$, when sales is equal to its mean.

22. To determine break points, the graphs were drawn such that each point in them was indicated by its time label. These quite messy graphs are not reported here, but are available from the author on request.

23. Boswijk & Frances (1996) claim that common persistence of nonlinear time-series corresponds to the concept of cointegration for linear time-series.

APPENDIX 2.1: Data sources and basic statistics.

Helsinki Stock Exchange (HeSE) general index

1920/1 - 1928/12 Panu Poutvaara, Pörssikurssien kehitys Suomessa 1896 - 1929: Uudet indeksisarjat ja niiden tulkinta. Bank of Finland Working Paper, 1996.

1929/1 - 1990/12 Unitas index, Bank of Finland data file. Multiplied by 2.76 to be comparable with the rest of the data.

1991/1 - 1997/11 HeSE general index, aggregated last observation. Bank of Finland data file.

Trading volume at the HeSE

1920/1 - 1996/9 Trading at the HeSE, million Finnish *markka*. Bank of Finland data file. The missing value 1939/12 is replaced by -2.650 in log(volume) and -4.687 in log(sales) series.

Basic statistics 1921/2 - 1997/11 (*N = 922*)

Series	mean	Std.	skewness	kurtosis	min	max	normality	ADF(i)
Index (log)	4.156	1.979	0.236	-1.086	1.178	8.225	0.000	-0.977 (10)
Return	0.007	0.053	0.153	5.609	-0.326	0.352	0.000	-9.029 (8) **
Sales (log)	-2.376	1.631	1.227	0.297	-5.004	2.392	0.000	-1.344 (12)
Dsales	0.005	0.365	-0.103	1.403	-1.768	1.712	0.000	-11.402 (11) **
Volume (log)	1.779	3.418	0.837	-0.432	-3.219	10.117	0.000	-1.467 (12)
Dvolume	0.012	0.37	-0.073	1.431	-1.770	1.741	0.000	-10.268 (11) **

Basic statistics 1921/2 - 1957/8 (*N = 439*)

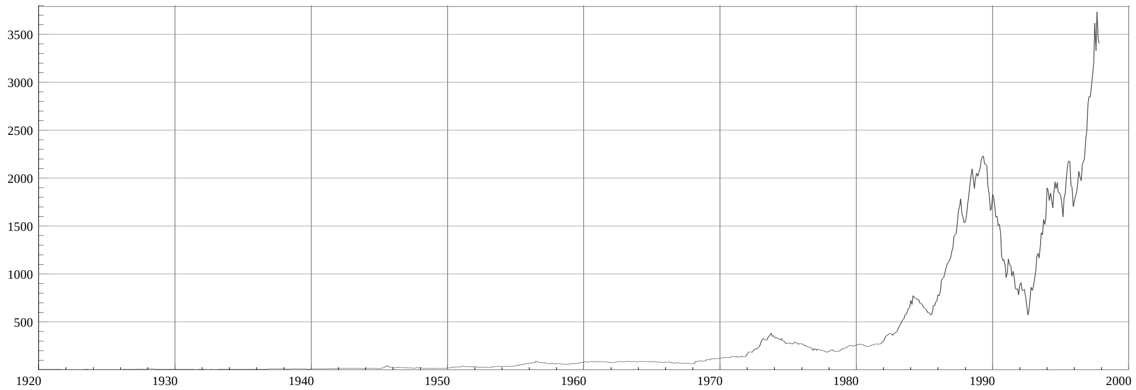
Series	mean	Std.	skewness	kurtosis	min	max	normality	ADF(i)
Index (log)	16.555	17.096	2.057	4.106	3.250	89.320	0.000	-1.428 (1)
Return	0.006	0.056	0.146	7.661	-0.326	0.352	0.000	-8.613 (7) **
Sales (log)	-3.262	0.543	0.013	-0.190	-5.004	-1.783	0.828	-2.424 (10)
Dsales	-0.002	0.388	0.117	0.999	-1.361	1.712	0.0002	-11.746 (9) **
Volume (log)	-0.858	1.112	0.181	-1.113	-3.219	1.281	45.863	-2.603 (10)
Dvolume	0.003	0.395	0.167	1.052	-1.321	1.741	0.0001	-18.967 (1) **

Basic statistics 1957/9 - 1997/11 (*N = 483*)

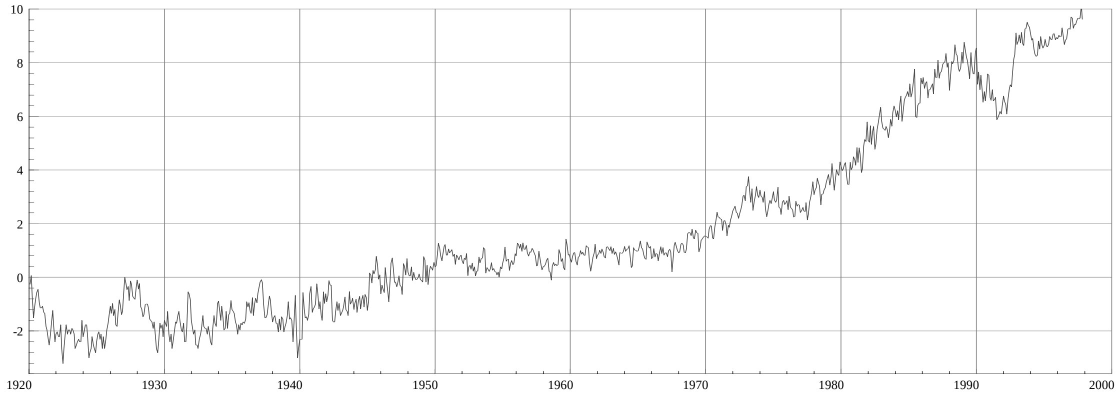
Series	mean	Std.	skewness	kurtosis	min	max	normality	ADF(i)
Index (log)	637.723	757.61	1.543	1.771	56.680	3732.140	0.000	-0.340 (2)
Return	0.008	0.049	0.185	1.904	-0.186	0.205	0.000	-4.947 (8)**
Sales (log)	-1.572	1.856	0.415	-1.304	-4.185	2.392	0.000	-2.794 (12)
Dsales	0.010	0.342	-0.377	1.881	-1.768	1.095	0.000	-7.097 (11) **
Volume (log)	4.177	3.018	0.358	-1.353	-0.105	10.117	0.000	-3.2220 (2)
Dvolume	0.019	0.344	-0.381	1.876	-1.77	1.141	0.000	-6.265 (11)**

N is the number of observations, Std. = standard deviation. For normal distribution skewness and kurtosis are equal to zero. Normality = Doornik & Hansen (1994) normality test p-value. ADF(i) is the augmented Dickey-Fuller unit root test, where *i* is the lag used in the test. The null hypothesis is that there is a unit root. Two ** (*) indicate that the null hypothesis is rejected at the 5% (1%) level. See also Pc-Give manual 8.0.

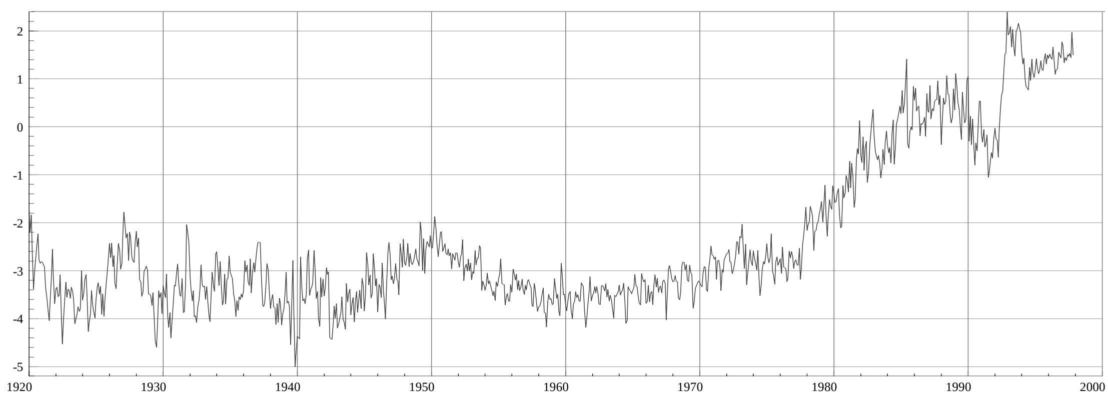
APPENDIX 2.2: Graphs of the data.



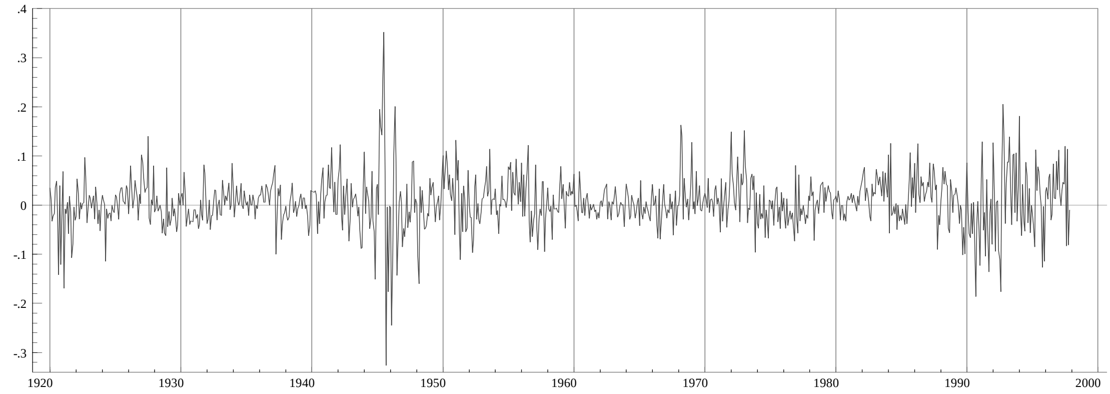
A: Stock prices (logarithm),1920/1 - 1997/11.



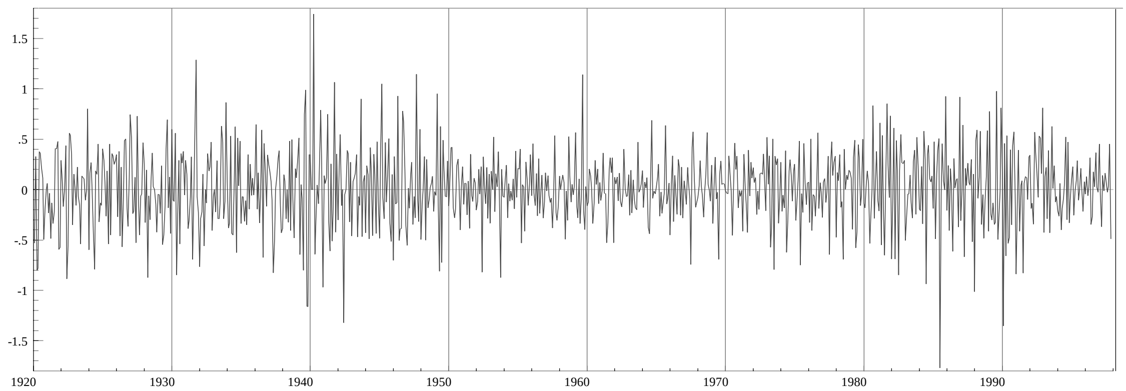
B: Trading volume (logarithm),1920/1 - 1997/11.



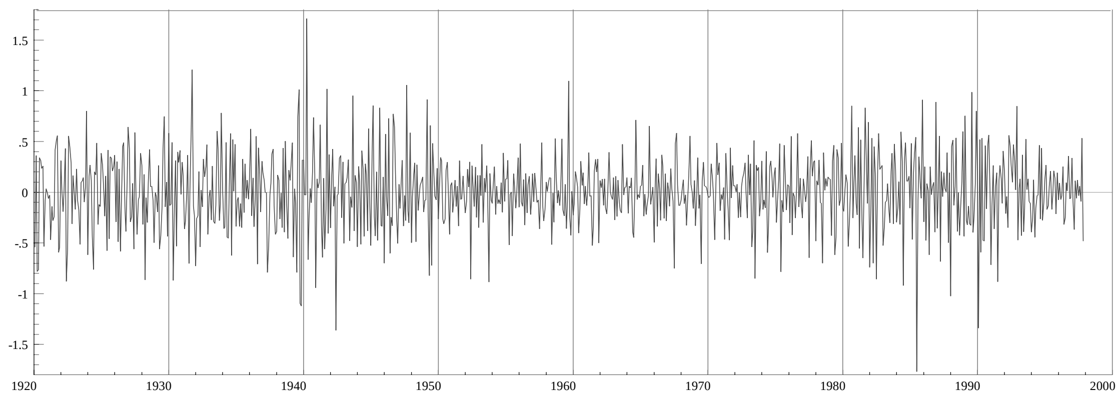
C: Sales (logarithm),1920/1 - 1997/11.



D: Difference of logarithmic stock returns, 1920/1 - 1997/11.



E: Difference of logarithmic trading volume, 1920/1 - 1997/11.



F: Difference of logarithmic sales, 1920/1 - 1997/11.

APPENDIX 2.3: The effects of data transformation on Granger causality.

We consider Granger causality between the following variables both in a linear and nonlinear framework ($t = 1,...,T$).

y_t = log(returns$_t$)
x_t = log(volume$_t$) - log(returns$_t$)
x_t* = log(volume$_t$).

A VAR for y_t and x_t (x_t*) is written as

(A) $Y_t = (y_t,x_t)' = \mu + \phi_1 Y_{t-1} + ... + \phi_p Y_{t-p} + \varepsilon_t$, where $\varepsilon_t \sim$ n.i.d.$(0,\Sigma)$.

The hypothesis "x_t does not Granger cause y_t" now corresponds to parameter restrictions according to which all matrices $\phi_1,...,\phi_p$ would be lower triangular matrix.

If on the other hand we consider a vector $Y_t* = (y_t,x_t*)'$ we immediately see, that

(B) $Y_t = \begin{vmatrix} 1 & 0 \\ -1 & 1 \end{vmatrix} (y_t,x_t*)' = AY_t*$; model A can then be rewritten as:

(C) $Y_t* = A^{-1}\mu + A^{-1}\phi_1 AY_{t-1}* + ... + A^{-1}\phi_p AY_{t-p}* + \varepsilon_t*$, $\varepsilon_t \sim$ n.i.d.$(0,A^{-1}\Sigma A^{-1}{}')$.

If matrices $\phi_1,...,\phi_p$ are lower triangular, transformed matrices also have this property. Thus, it does not affect our results whether we use transformed data or not to test for Granger causality. The same result applies to different types of Granger causality tests as well as if the differences of the data Δy_t, Δy_t* and Δx_t are used to obtain stationarity. (Note that if y_t and x_t* are $I(1)$ and cointegrated, then x_t may be $I(0)$.)

Next, we assume that nonlinearity can be modeled as follows:

(D) $Y_t = \Pi' W_t + F(\gamma_0 + \gamma' Y_{t-d})\theta' W_t + e_t$,

where $e_t \sim$ n.i.d.$(0,\sigma^2)$ and $e_t \perp W_t$, $W_t = (1,y_{t-1},...,y_{t-p},x_t,x_{t-1},...,x_{t-p})'$, $Y_t = (y_t,x_t)'$, d is a delay, $\Pi \in R^{2(p+1)}$, $\theta \in R^{2(p+1)}$ and $\gamma = (\gamma_1,\gamma_2)' \in R^2$. Within this general framework testing Granger causality is equal to testing the parameter restrictions H_0: $\pi_{p+2} = ... = \pi_{2(p+1)} = \theta_{p+2} = ... = \theta_{2(p+1)} = \gamma_2 = 0$. Thus, the model is estimated using nonlinear least squares "freely" (SSR_0) and then again by taking into account the parameter restrictions as in H_0 (SSR_1). The likelihood ratio obtained $LR = [(SSR_0 - SSR_1)/(4p + 5)]/[SSR_1/(T - 4p - 5)]$, is asymptotically $\chi^2(4p + 5, T - 4p - 5)$, where T is the number of observations. Unfortunately, the results are now affected by the way the data is transformed because of the contemporaneous explanatory variable x_t included in W_t. Therefore, to get some idea about the severity of this problem we test Granger noncausality using both x_t and x_t* against y_t.

APPENDIX 2.4: Estimated AR models for different time periods.

Results for the period 1921/2 - 1997/11.

Series	**Sales**	**Sales**	**Sales**	**Returns**	**Returns**	**Returns**
lags	1-6	1-6,12	1-12	1-6	1-6,12	1-12
Schwarz	-2.111	-2.184	-2.177	-5.920	-5.915	-5.916
Hannan	-2.134	-2.210	-2.219	-5.943	-5.941	-5.958
ρ	0.000	0.000	0.000	0.000	0.001	0.017
Normality	0.000	0.000	0.000	0.000	0.000	0.000
ARCH	0.000	0.000	0.000	0.000	0.000	0.000
Heterosked.	0.000	0.000	0.000	0.000	0.000	0.000
Skewness	-0.017	0.054	0.125	-0.141	-0.125	-0.156
Kurtosis	1.384	1.649	1.585	5.257	5.182	4.665
FUNC	0.000	0.000	0.000	0.000	0.000	0.000
RESET1	0.394	0.571	0.599	0.237	0.506	0.006
RESET2	0.182	0.731	0.628	0.317	0.488	0.013
RESET3	0.313	0.818	0.777	0.411	0.695	0.000
R^2	0.137	0.203	0.227	0.080	0.082	0.116
RSS	106.04	97.867	94.979	2.350	2.346	2.258

The reported values of these tests are p-values: ρ = error autocorrelation test (F-form) with the null hypothesis that model errors are white noise (Harvey, 1981), Normality = tests on whether the skewness and kurtosis of the model residuals correspond to normal distribution, ARCH = LM test for autocorrelated squared residuals (Engle, 1982), Heterosked. = test for heteroskedastic errors with the null hypothesis of unconditional error homoskedasticity (White, 1980), skewness = model residual skewness, kurtosis = model residual kurtosis. For normal distribution skewness and kurtosis are equal to zero. FUNC = a general heteroskedasticity test, while test of functional form (F-form) and RESET1, RESET2 and RESET3 are tests of adding $\hat{Y}^2$, $\hat{Y}^2,\ldots,\hat{Y}^3$ and $\hat{Y}^2,\ldots,\hat{Y}^4$ to the model. (For more information about the tests, see PC-GIVE manual 8.0.)

Results for the period 1921/2 - 1957/8.

Series	**Sales**	**Sales**	**Sales**	**Returns**	**Returns**	**Returns**
lags	1-5,12	1-6,12	1-12	1	1-2,6	1-12
Schwarz	-1.975	-1.970	-1.960	-5.828	-5.807	-5.759
Hannan	-2.015	-2.015	-2.033	-5.840	-5.829	-5.833
ρ	0.018	0.000	0.0112	0.011	0.005	0.064
Normality	0.000	0.000	0.000	0.000	0.000	0.000
ARCH	0.034	0.012	0.004	0.000	0.000	0.000
Heterosked.	0.330	0.016	0.036	0.000	0.000	0.000
Skewness	0.314	0.276	0.369	-0.450	-0.298	-0.228
Kurtosis	1.694	1.391	1.258	7.192	6.360	5.087
FUNC	0.035	0.000	0.000	0.000	0.000	0.000
RESET1	0.628	0.601	0.151	0.006	0.001	0.010
RESET2	0.890	0.719	0.317	0.018	0.006	0.037
RESET3	0.873	0.844	0.228	0.010	0.014	0.085
R^2	0.165	0.172	0.219	0.100	0.105	0.172
RSS	55.273	54.817	51.670	1.257	1.249	1.156

Results for the period 1957/9 - 1997/11.

Series	**Sales**	**Sales**	**Sales**	**Returns**	**Returns**	**Returns**	**Volume**	**Volume**
lags	1-5,12	1-6,12	1-12	1,6	1-6	1-12	1-5,12	1-6,12
Schwarz	-2.357	-2.345	-2.301	-6.046	-6.009	-5.983	-2.244	-2.299
Hannan	-2.393	-2.387	-2.370	-6.062	-6.046	-6.051	-2.312	-2.341
ρ	0.016	0.0186	0.035	0.499	0.001	0.005	0.039	0.056
Normality	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ARCH	0.002	0.0011	0.000	0.000	0.000	0.000	0.000	0.000
Heterosked.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Skewness	-0.385	-0.359	-0.294	0.134	0.175	0.160	-0.352	-0.361
Kurtosis	1.699	1.618	1.856	1.627	1.673	1.511	1.766	1.642
FUNC	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
RESET1	0.486	0.462	0.740	0.028	0.121	0.552	0.615	0.5
RESET2	0.721	0.691	0.931	0.027	0.036	0.047	0.877	0.048
RESET3	0.335	0.326	0.073	0.066	0.018	0.002	0.024	0.048
R^2	0.261	0.261	0.276	0.049	0.063	0.109	0.244	0.237
RSS	41.839	41.796	40.948	1.100	1.085	1.031	43.374	43.751

APPENDIX 2.5: Results of linearity testing.

delay	WS	S57	S97	UW	UWD	U57	U97	V97
1	0.006	0.177	0.0003	2.812e-13	2.8e-13	0.010	1.301	0.339
2	0.587	0.741	0.068	0.000	0.000	5.572e-06		0.105
3	0.047	0.795	0.010	0.000	2.781e-13	0.132		0.174
4	0.018	0.085	0.181	1.191e-12	2.808e-13	0.389		0.361
5	0.001	0.120	0.406	1.191e-12	2.806e-13	0.002		0.022
6	0.001	0.0008	0.047	2.813e-13	2.797e-13	0.045	5.563	0.000
7				6.358e-9	4.073e-10			0.033
8				1.984e-11	1.191e-12			
9				2.572e-10	2.893e-11			
10				0.000	2.71e-13			
11				2.345e-6	1.411e-6			
12	0.007	0.406		1.101e-5	2.351e-6			
H_{01}	0.521	0.078	0.039	0.093	0.000	0.006 0.001	0.057	0.455
H_{02}	0.013	0.001	0.059	1.061e-12	6.002e-13	0.058 0.001	0.374	0.230
H_{03}	0.002	0.135	0.002	0.0003	0.044	0.067 5.572e-06	4.516e-06	0.000
lag	6	6	1	1	1	1 and 2	6	6
type	LSTAR	ESTAR	LSTAR	ESTAR	ESTAR	ESTAR	LSTAR	LSTAR

To choose between LSTAR and ESTAR, we first test H_{01}: $\beta_3 = 0$ in Equation 2.5, then continue with H_{02} and H_{03}. The decision is based on the probability values of the test of the sequence, which are given above. If the p-value for H_{02} is the smallest of the three we choose ESTAR, otherwise LSTAR. The lag *d* for the transition variable y_{t-d} is selected by estimating Equation 2.5 for different *d*, and the one with smaller probability value is chosen indicated as “lag”. The last column shows the type of model estimated. WS = sales for the whole period, S57 = sales for 1921/2 - 1957/8, S97 = sales for 1957/9 - 1997/11, UW = stock returns for the whole period, UWD = returns for the whole period (model with monthly dummies), U57 = returns for 1921/2 - 1957/8, U97 = returns for 1957/9 - 1997/11 and V97 = volume for 1957/9 - 1997/11.

APPENDIX 2.6: Model diagnostics.

LM test of no remaining nonlinearity (Test 1) and LM test of no error autocorrelation (Test 2). Reported values are the p-values of the tests. Following Eitrheim and Teräsvirta (1996) after rejecting the H_0 of no remaining nonlinearity, it is possible to carry out the test sequence H_{03}, H_{02} and H_{01} for any given delay *d* in a similar manner to Chapter 2.5.2. This helps the investigator to decide whether an LSTAR or an ESTAR additive component should be selected to accompany the previous STAR component (Test 1). In the case of Test 2, df is the degrees of freedom.

Model UW.1:

S_t/lag	Test1/H_0	Test1/H_{03}	Test1/H_{02}	Test1/H_{01}	Test2	df
1	0.001	0.003	0.027	0.171	0.001	906
2	0.000	0.661	0.000	0.395	0.001	905
3	0.000	0.000	0.390	0.000	0.001	904
4	0.000	0.007	0.022	0.000	0.000	903
5	0.000	0.000	0.125	0.000	0.000	902
6	0.000	0.000	0.007	0.285	0.000	901
7	0.000	0.077	0.001	0.000	0.000	900
8	0.000	0.033	0.000	0.453	0.000	899
9	0.000	0.000	0.721	0.036		
10	0.001	0.636	0.001	0.008		
11	0.012	0.391	0.062	0.012		
12	0.065	0.013	0.445	0.450		

Model UWD.1

S_t/lag	Test1/H_0	Test1/H_{03}	Test1/H_{02}	Test1/H_{01}	Test2	df
1	3.279e-6	0.023	0.000	0.003	0.011	901
2	1.926e-13	0.001	0.000	9.368e-8	0.004	900
3	7.357e-13	0.001	1.082e-10	0.007	0.007	899
4	5.283e-12	0.003	1.077e-9	0.004	0.007	898
5	7.357e-13	0.000	0.001	9.982e-9	0.011	897
6	2.807e-13	1.168e-5	3.674e-10	0.038	0.022	896
7	1.668e-9	0.016	0.000	9.730e-7	0.005	895
8	7.031e-11	0.010	2.120e-8	0.001	0.008	894
9	4.464e-10	9.433e-6	0.001	0.000		
10	2.804e-13	0.307	4.930e-8	5.662e-10		
11	6.101e-7	0.003	0.002	0.001		
12	0.000	0.006	0.031	0.041		

Model U57.1

S_t/lag	Test1/H_0	Test1/H_{03}	Test1/H_{02}	Test1/H_{01}	Test2	df
1	0.000	0.000	0.082	0.004	0.743	434
2	0.000	0.298	0.000	0.000	0.191	433
3	0.000	0.016	0.000	0.000	0.346	432
4	0.000	0.018	0.024	0.001	0.328	431
5	0.000	0.000	0.000	0.000	0.093	430
6	0.000	0.000	0.000	0.457	0.134	429
7					0.123	428
8					0.007	427

Model U97.1

S_t/lag	Test1/H_0	Test1/H_{03}	Test1/H_{02}	Test1/H_{01}	Test2	df
1	0.003	0.093	0.442	0.001	0.929	476
2	0.000	0.002	0.026	0.000	0.996	475
3	0.000	0.000	0.033	0.288	0.9998	474
4	0.043	0.090	0.096	0.172	0.99999	473
5	0.068	0.827	0.454	0.007	0.999999	472
6	0.026	0.159	0.166	0.030	0.986	471
7					0.973	470
8					0.986	469

Model U97.2

S_t/lag	Test1/H_0	Test1/H_{03}	Test1/H_{02}	Test1/H_{01}	Test2	df
1	0.170	0.922	0.102	0.096	0.002	476
2	0.000	0.013	0.021	0.000	0.006	475
3	0.046	0.007	0.848	0.219	0.000	474
4	0.000	0.002	0.526	0.001	0.000	473
5	0.040	0.184	0.413	0.020	0.000	472
6	0.000	0.007	0.096	0.011	0.000	471
7					0.000	470
8					0.000	469

Model WS.1

S_t/lag	Test1/H_0	Test1/H_{03}	Test1/H_{02}	Test1/H_{01}	Test2	df
1	0.058	0.030	0.275	0.351	0.063	911
2	0.236	0.567	0.657	0.042	0.004	910
3	0.743	0.221	0.963	0.658	0.002	909
4	0.226	0.413	0.461	0.112	0.006	908
5	0.001	0.348	0.001	0.046	0.011	907
6	0.000	0.018	0.000	0.806	0.000	906
7	-	-	-	-	0.000	905
8	-	-	-	-	0.000	904
12	0.009	0.019	0.185	0.091		

Model S57.1

S_t/lag	Test1/H_0	Test1/H_{03}	Test1/H_{02}	Test1/H_{01}	Test2	df
1	0.060	0.011	0.934	0.167	0.0005	428
2	0.270	0.508	0.636	0.069	0.000	427
3	0.050	0.076	0.107	0.297	0.000	426
4	0.627	0.561	0.746	0.290	0.000	425
5	0.192	0.604	0.024	0.741	0.000	424
6	0.539	0.778	0.278	0.400	0.000	423
7	-	-	-	-	0.000	422
8	-	-	-	-	0.000	421
12	0.481	0.204	0.778	0.427		420

Model S97.1

S_t/lag	Test1/H_0	Test1/H_{03}	Test1/H_{02}	Test1/H_{01}	Test2	df
1	0.083	0.143	0.056	0.467	0.080	475
2	0.113	0.235	0.248	0.099	0.112	474
3	0.014	0.775	0.283	0.001	0.086	473
4	0.750	0.291	0.988	0.622	0.077	472
5	0.005	0.058	0.286	0.005	0.135	471
6	-	-	-	-	0.193	470
7	-	-	-	-	0.254	469
8	-	-	-	-	0.158	468
12	0.211	0.506	0.072	0.411		

Model V97.1

S_t/lag	Test1/H_0	Test1/H_{03}	Test1/H_{02}	Test1/H_{01}	Test2	df
1	0.032	0.268	0.018	0.270	0.522	472
2	0.408	0.080	0.104	0.520	0.372	471
3	0.286	0.759	0.768	0.025	0.542	470
4	0.608	0.387	0.976	0.213	0.111	469
5	0.003	0.426	0.089	0.001	0.162	468
6	0.435	0.200	0.453	0.692	0.213	467
7	-	-	-	-	0.120	466
8	-	-	-	-	0.111	465
12	0.014	0.039	0.053	0.266		

LM tests of parameter constancy (Test 3), when the constancy of all parameters is tested simultaneously (first three columns) and when only the intercept is tested (last three columns).

Model	**UW.1**	**UWD.1**	**U57.1**	**U97.1**	**U97.2**
Test	F-statistic (df)	F-statistic (df)	F-statistic (df)	F-statistic (df)	F-statistic (df)
LM_3 LM_2 LM_1	1.837** (874) 1.82** (890) 2.421** (906)	1.668** (859) 1.564* (880) 2.043** (901)	1.125 (429) 1.404 (431) 1.146 (433)	1.245 (15) 1.469 (10) 0.550 (5)	0.692 (465) 0.572 (469) 0.250 (473)
LM_3* LM_2* LM_1*	2.187* (916) 3.017** (918) 5.128** (920)	2.284* (916) 3.021* (918) 4.976** (920)	0.698 (432) 0.707 (433) 1.254 (434)	3.286* (474) 4.497* (475) 1.681 (476)	0.218 (474) 0.274 (475) 0.494 (475)

Model	**WS.1**	**S57.1**	**S97.1**	**V97.1**
Test	F-statistic (df)	F-statistic (df)	F-statistic (df)	F-statistic (df)
LM_3 LM_2 LM_1	0.488 (895) 0.522 (904) 0.562 (913)	1.406 (24) 1.816* (16) 2.579** (8)	1.126 (21) 1.290 (14) 1.991 (7)	- - -
LM_3* LM_2* LM_1*	0.148 (916) 0.219 (918) 0.111 (920)	0.108 (3) 0.140 (2) 0.240 (1)	0.668 (3) 0.751 (2) 1.108 (1)	- - -

Model refers to the models presented in the text. LM test values of parameter constancy when the constancy of all parameters is tested simultaneously are shown in the first three rows with their significance indicated by ** at the 1% level and * at the 5% level. The LM test values of the constancy of the model intercept (LM*) are shown in the last three rows. The number in parenthesis (df) is the degrees of freedom of the test.

Appendix 2.7: Graphs of transition functions and "sliced spectra" using the first difference of the logarithm of the series under consideration.

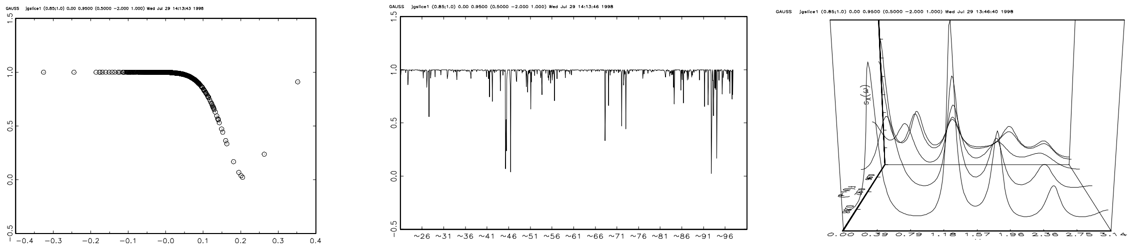


Figure 2.7.1. Stock returns, model UW.1.

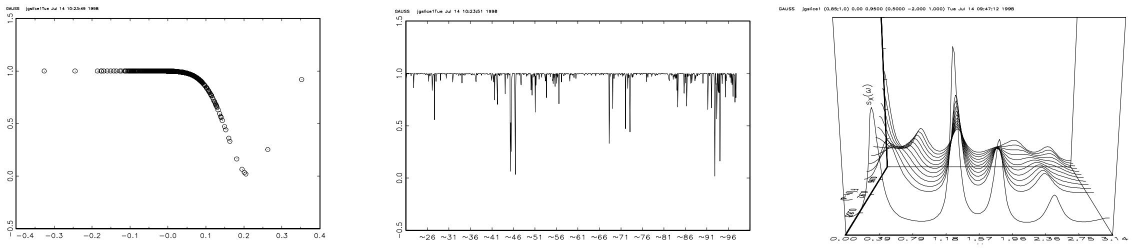


Figure 2.7.2 Stock returns, model UWD.1.

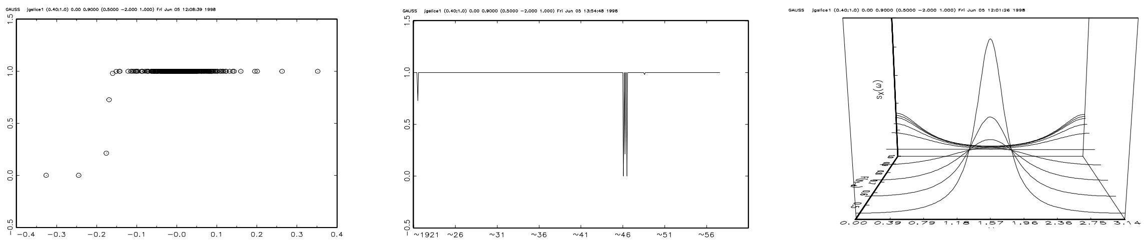


Figure 2.7.3 Stock returns, model U57.1.

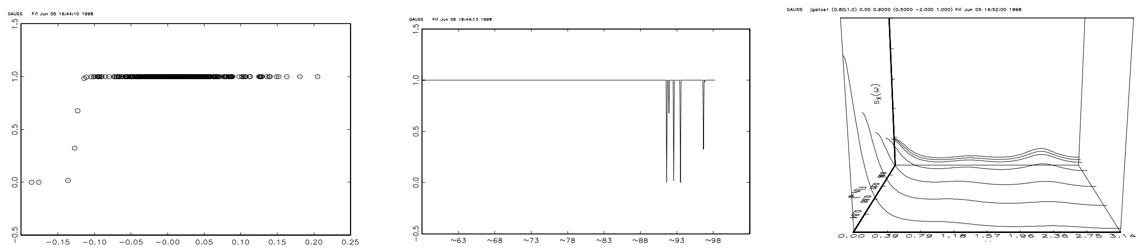


Figure 2.7.4 Stock returns, model U97.1.

The figures are in the following order: first estimated transition function vs the transition variable and over time, followed by "sliced spectra."

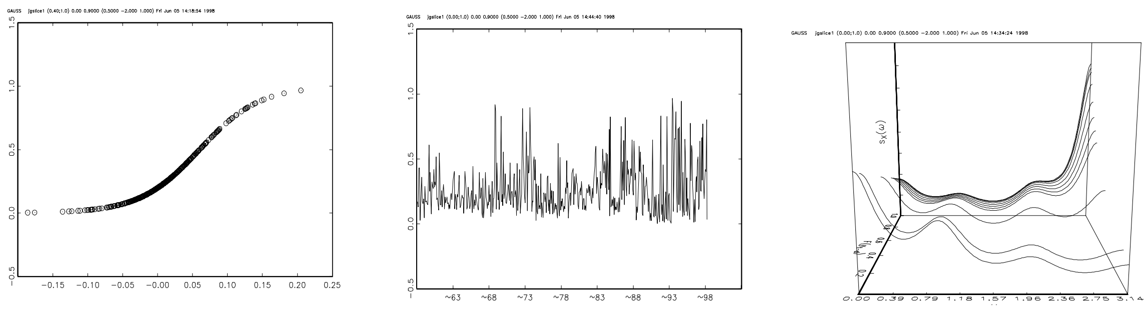


Figure 2.7.5 Stock returns, model U97.2.

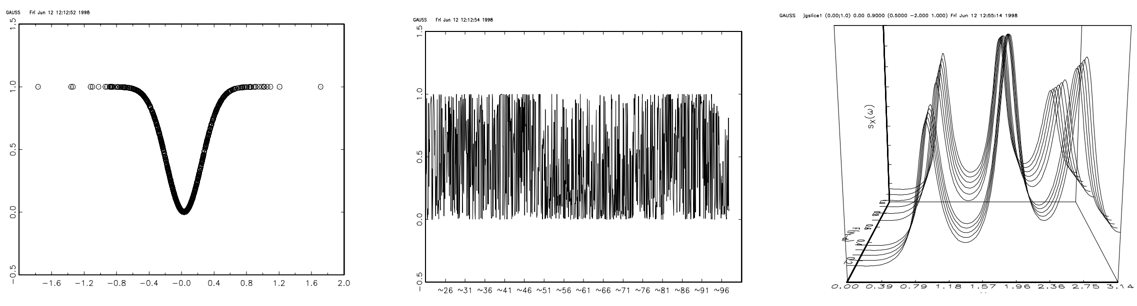


Figure 2.7.6 Sales, model WS.1.

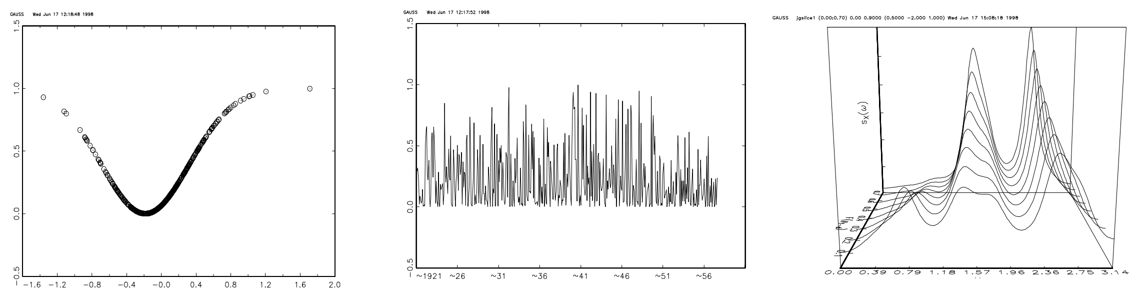


Figure 2.7.7 Sales, model S57.1.

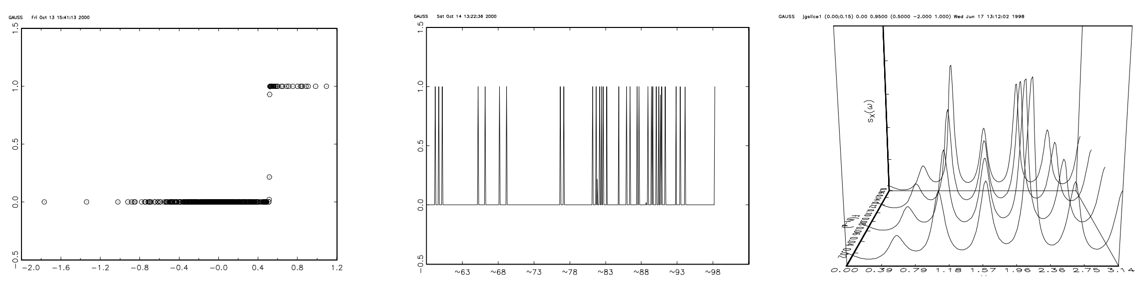


Figure 2.7.8 Sales, model S97.1.

The figures are in the following order: first estimated transition function vs the transition variable and over time, followed by “sliced spectra.”

Appendix 2.8: The 50% (black) and 95% (white) highest density regions for GIRF's in the two-regime STAR models. (R is the number of simulations.)

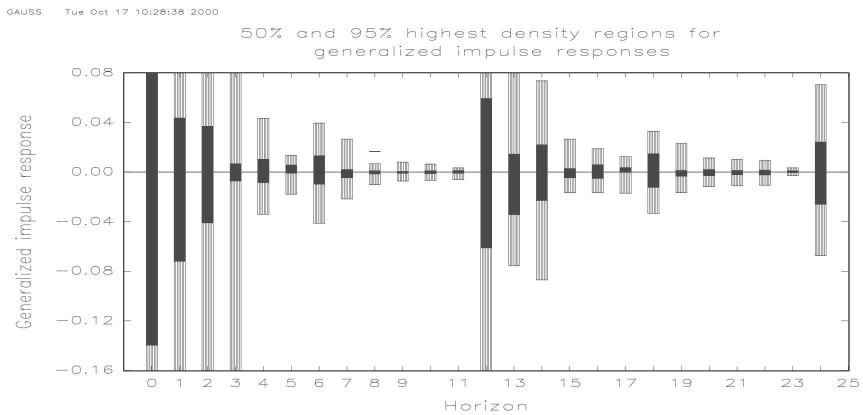


Figure 2.8.1 Model S97.1, 50 shocks per random history, R = 1000.

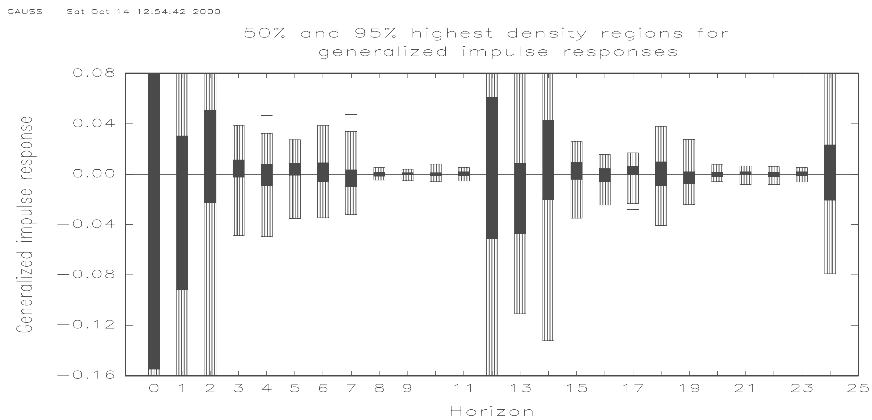


Figure 2.8.2 Model S97.1, 50 random shocks per $F(z_t) > 0.5$ history, R = 1000.

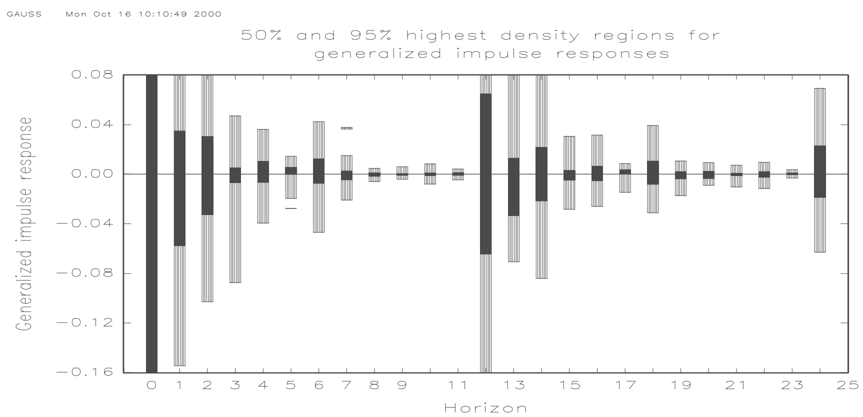


Figure 2.8.3 Model S97.1, 50 random shocks per $F(z_t) < 0.5$ history, R = 1000.

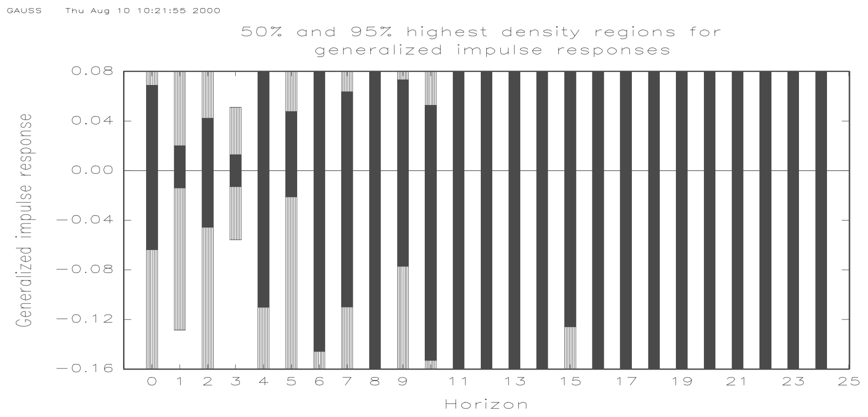


Figure 2.8.4 Model UW.1, 50 random shocks per random history, R = 1000.

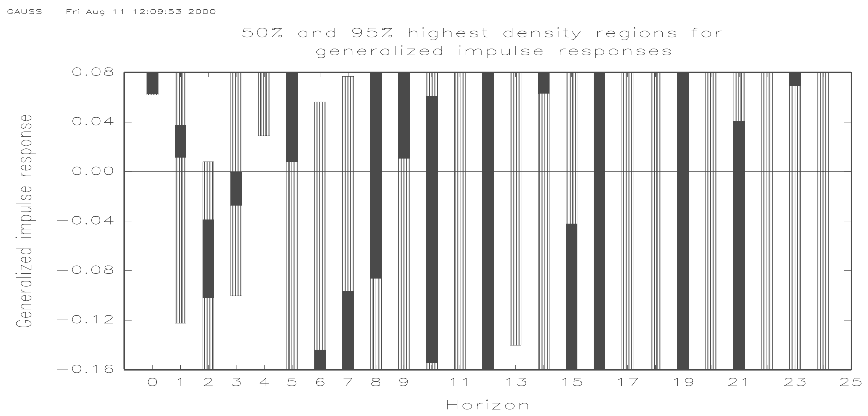


Figure 2.8.5 Model UW.1, 50 positive shocks per random history, R = 1000.

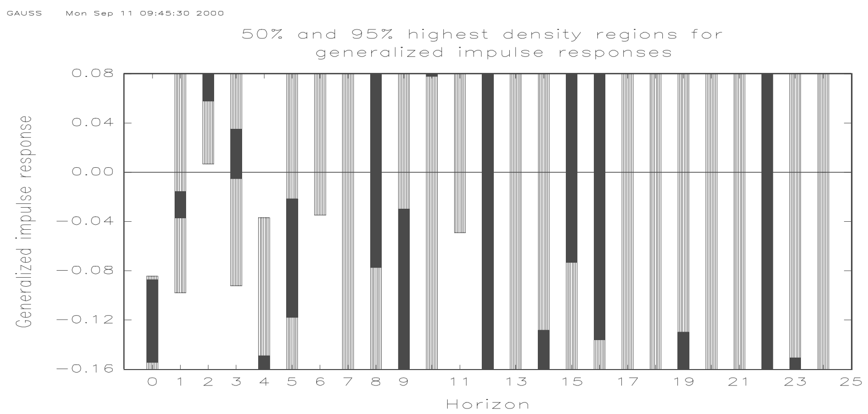


Figure 2.8.6 Model UW.1, 50 negative shocks per random history, R = 1000.

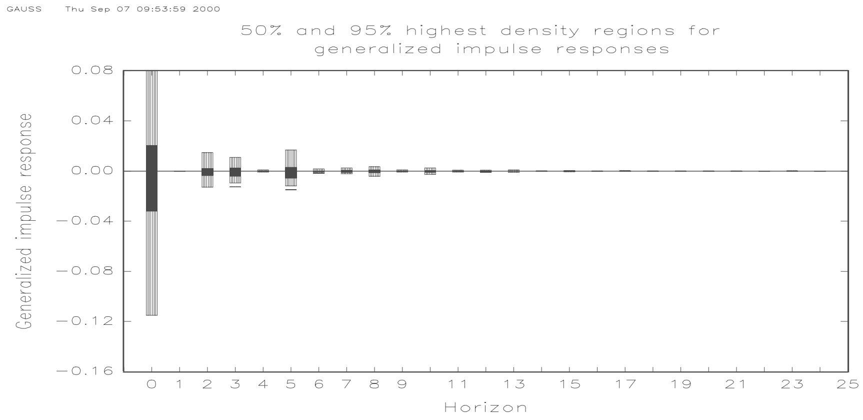


Figure 2.8.7 Model U97.1, 50 random shocks per random history, R = 1000.

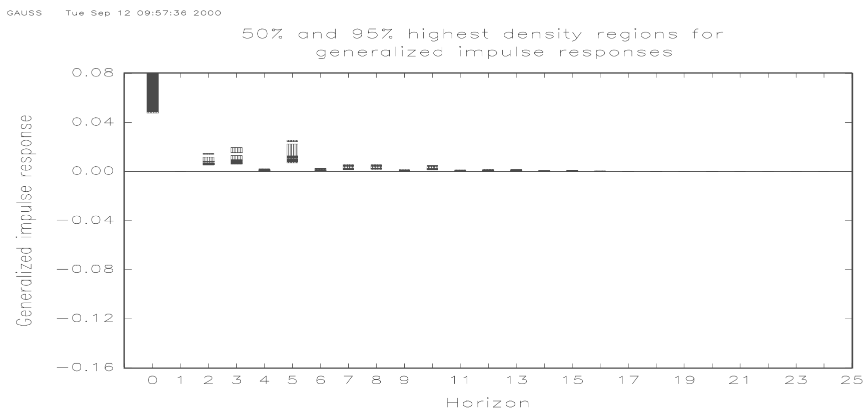


Figure 2.8.8 Model U97.1, 50 positive shocks per random history, R = 1000.

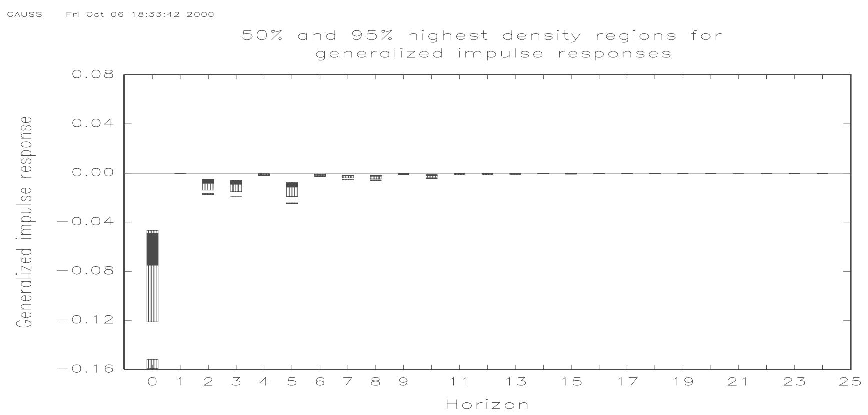


Figure 2.8.9 Model U97.1, 50 negative shocks per random history, R = 1000.

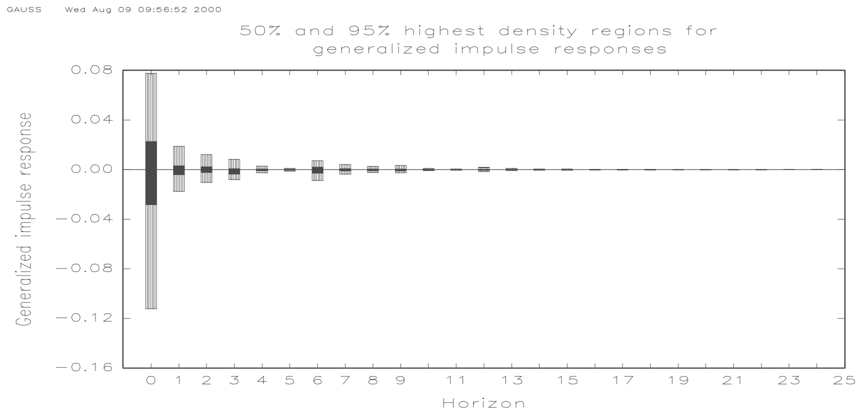


Figure 2.8.10 Model U97.2, 50 shocks per random history, R = 1000.

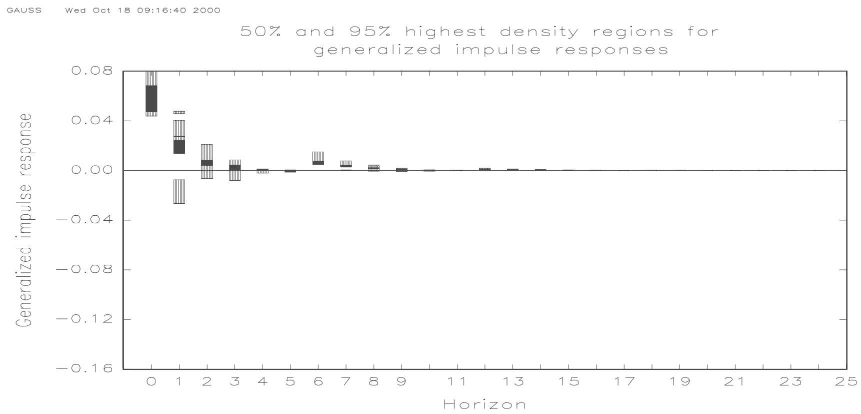


Figure 2.8.11 Model U97.2, 50 positive shocks per $F(z_t) > 0.5$ history, R = 1000.

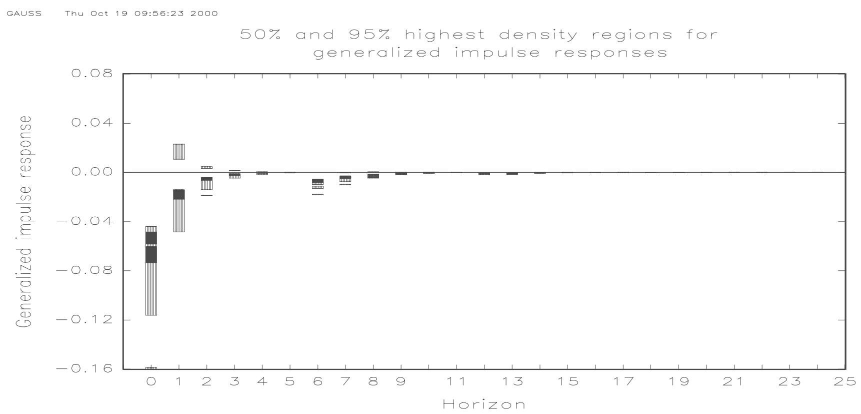


Figure 2.8.12 Model U97.2, 50 negative shocks per $F(z_t)> 0.5$ history, R = 1000.

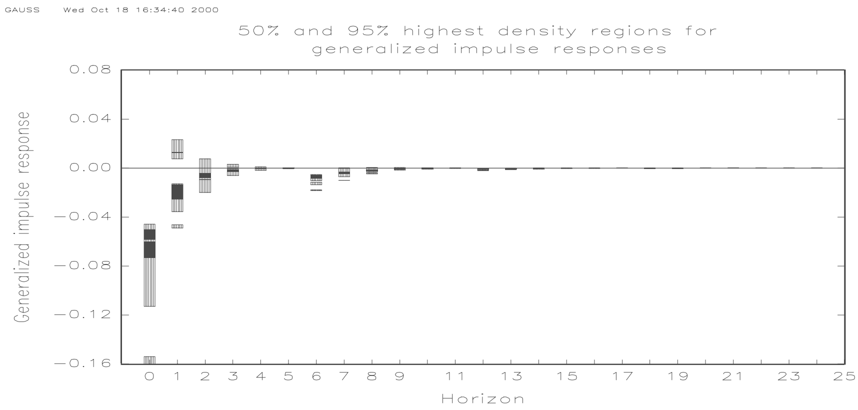
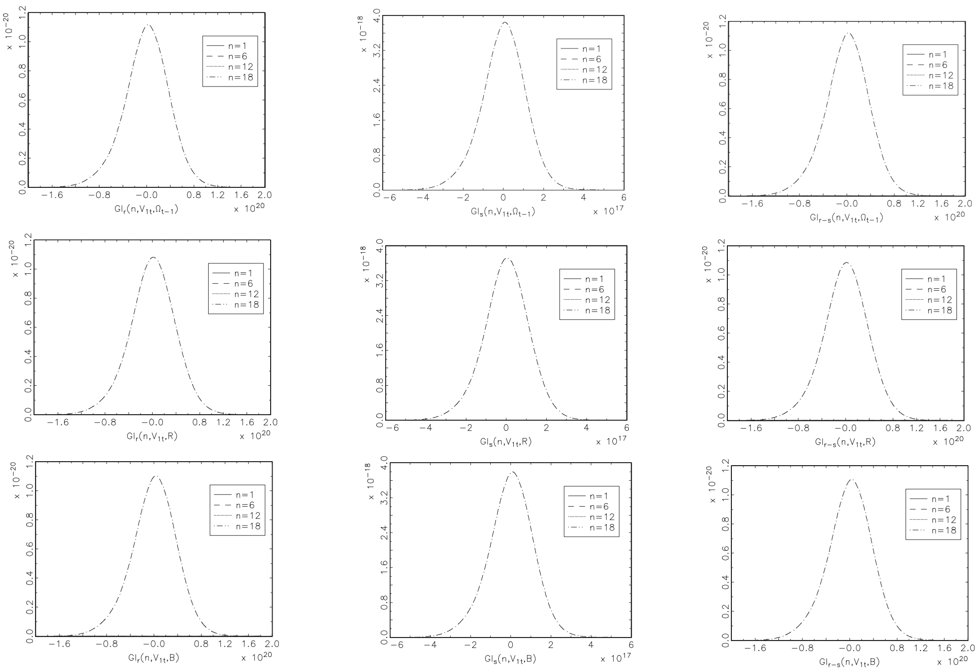
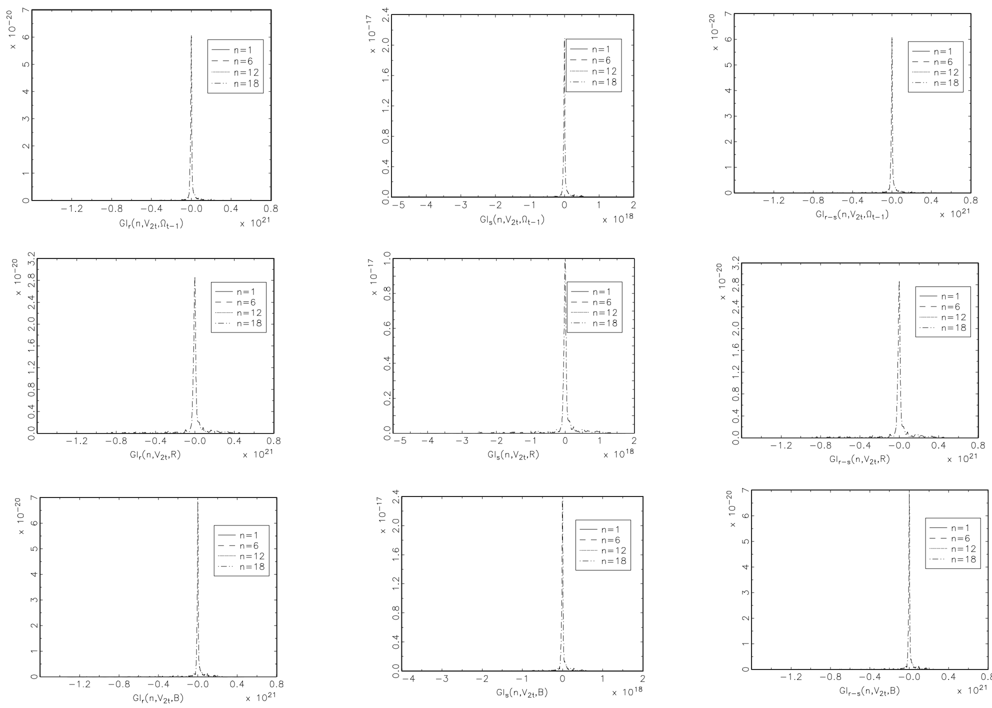


Figure 2.8.13 Model U97.2, 50 negative shocks per $F(z_t) < 0.5$ history, R = 1000.

Appendix 2.9: The generalized impulse response functions in the case of the STVECM.



A shock to returns equation: all shocks, shocks in regime $F(z_t) < 0.5$ and $F(z_t) > 0.5$.



A shock to sales equation: all shocks, shocks in regime $F(z_t) < 0.5$ and $F(z_t) > 0.5$.

Chapter 3

Is the “spurious” negative correlation between the real price of an equity and inflation due to counter-cyclical monetary policy? Further evidence based on Markov-switching vector autoregressive models

Abstract

There is a large body of empirical evidence that stock markets perform poorly during inflationary periods. Several explanations have been offered for this so-called “anomaly.” Here, we test the claim that the “spurious” negative correlation between stock returns and inflation is due to counter-cyclical monetary policy. We identify various regimes in the Finnish data using the Markov-switching vector autoregressive model. When necessary, the existing long run relationships between the model variables are incorporated using the Markov-switching vector error correction model. Using alternative sets of explanatory variables including measures for monetary policy stringency, we conclude that the sign of the relation between returns and inflation depends on the time horizon chosen rather than the monetary policy regime. In monthly models the statistically significant contemporaneous correlations between returns and inflation are always negative, but positive in the case of quarterly data. Stocks thus seem to be a good hedge against inflation in the long run. To be more specific, stocks seem to maintain protection against purely monetary inflation but fail to provide a hedge against inflation arising from real output shocks. Last, this is tested using the regime-dependent impulse response function.

3.1 ARE STOCKS A GOOD HEDGE AGAINST INFLATION?

In contrast to financial economists, who want to know whether an equity is a good hedge against inflation, macro economists are interested in finding out whether money has any effect on real stock prices. After all, assets as such are claims on future economic output, so that if monetary policy has any real effect,[1] then shifts in monetary policy should affect stock prices (Patelis, 1997). Models in monetary economics that assume a role for money and endogenize the price level and inflation together with stock prices typically cite the empirical findings that real stock prices are negatively correlated with inflation, expected or unexpected. This is contradictory to the traditional view that equity shares should be a good hedge against inflation. Besides, Bakshi & Chen (1996) show that the correlation between the real price of an equity and inflation is clearly negative unless both money growth is procyclical and its covariance with output growth dominates the variance of the latter. Besides, more inflation in a low-inflation environment is not matched by greater nominal equity returns, but in high-inflation economies equity returns move

Table 3.7: Cointegration analysis for 1953/2 - 1998/11, where $z = [y\ M1\ r\ CPI]'$.

Maximum Eigenvalue Test			**Trace Test**
rank (r)	Eigenvalue	Likelihood ratio test	Likelihood ratio test
r = 0		75.97**	107.3**
r ≤ 1	0.129	26.02*	31.37
r ≤ 2	0.046	3.457	5.355
r ≤ 3	0.006	1.899	1.899

The null hypothesis under Johanssen's maximum eigenvalue test for cointegration rank is: H_0 rank = r against H_1: rank = $r + 1$, and in the trace test: H_0: rank = r versus H_1: $r <$ rank $\leq K$, where K is the number of variables in the VAR. The significance of the tests is marked by asterisks: * indicates rejecting the null hypothesis at the 5% level, ** at the 1% level. The results are from the model with $z = [y\ M1\ r\ CPI]'$, where lag $p = 2$ derives from information criteria. Variables entered unrestricted (restricted) in the cointegration space are constant and dummies $R1$ = {1992/3} & $Y1$ = {1974/12,1991/1} (trend). Other results are available from the author on request.

Note that if the system is vulnerable to deterministic breaks or regime shifts, valid cointegration analysis requires using dummy variables to capture these effects.[13] Note also that domestic variables are not expected to influence the long run stationary relationships of the foreign variables. Thus, all foreign variables are set as exogenous explanatory variables in the MS-VECM.[14]

Table 3.8: Some restrictions on the cointegration vectors.

H_i	*y*	*M1*	*r*	*p*	*e*	*i*	*i**	*p**
H1	1		1					
H2	1			-1				
H3			1	-1				
H4	-1	1		-1				
H5				-1		1		
H6			-1		1			
H7					-1	1	-1	
H8				-1	1			1
H9						1	-1	
H10				1	-1	-1		-1
H11	1				1			

H_i refers to the cointegration restriction to be tested, $i = 1,...,11$. For example, in H2 we test the cointegration restriction $y - p$. Here y refers to industrial production, *M1* and *MCI* refer to monetary policy stringency, r to stock returns, i to domestic and i^* to a German interest rate, e to exchange rates (e_{DEM} or e_{USD}) and p and p^* are price indices (*CPI*) both home and abroad. Restrictions H1 - H3 are based on the real activity hypothesis (Fama, 1981). H4 tests the quantity theory of money $m - y$, where inflation adjusts to deviations from this steady state. H5 is included to test the one-for-one adjustment of the nominal interest rate i to the inflation rate p (the Fisher effect). Granger et al. (1998) find a negative relation between exchange rates and returns (the traditional approach). Whether this relation also holds in the long run is tested in H6. A domestic interest rate i reflects changes in a foreign interest rate i^* and expectations about the changes in a domestic exchange rate: $i = i^* + E_t e_{t+1} - e$ (the open Fisher parity H7). The real exchange rate $\dot{e} + p^* - p$ is also assumed to be stationary (H8). H9 links domestic and foreign interest rates $i - i^*$ (Jacobson et al., 1998). The index of monetary conditions (H10) combines the exchange rate and interest rates in the long run: $MCI = (e + p^* - p) + \beta i$. Finally, cointegration between output and exchange rates is tested (H11).

at least one-for-one with marginal increases in inflation rates.[2] From this viewpoint it is reasonable to expect that stock prices (returns) are nonlinearly related to inflation or the current state of the business cycle measured by expected inflation. (Barnes, 1999 and Boyd et al., 2001) Sellin (1998) offers an extensive survey of how changes in monetary policy affect the stock market.

As monetary policy is constantly used as a means of fighting inflation, we attempt to take into account the effects of policy changes on the relation between returns and inflation. To be more specific, we try to interpret various regimes arising from changes in monetary policy from the estimated Markov-switching vector autoregressive models (MS-VAR). Alternatively, we could have concentrated on asset prices as leading indicators of economic activity or on the optimal response of monetary policy to unexpected changes in stock returns (Estrella & Mishkin, 1995). Similarly, it is not easy to distinguish between shocks in the supply and demand for money even though we consider several measures of monetary policy stringency.

Since most of the evidence for stock markets performing poorly during inflationary periods is based on models over relatively short periods, these models do not incorporate any long run relationships that might be present in the data. Keeping this in mind, Ely & Robinson (1997) use recent advances in the theory of cointegration in their study. First, they test whether stock prices move one-for-one with goods prices. If this is accepted, they include a coinciding cointegration vector in their system. Using various parametrizations to form a system, and even after controlling for the source of the shock to the economy, they conclude that stocks maintain their value relative to goods prices in the long run. Following this approach, we fit Markov-switching p^{th} order vector autoregressions with M regimes and cointegration rank r called an MSCI(M,r)-VAR(p) model, or its equilibrium correction form MS(M)-VECM(p - 1) following Krolzig (1997) to the Finnish stock market data. This allows us to pay special attention to the short run dynamics of these models while allowing for “multiple equilibria”.

The remainder of this paper is organized as follows: in Section 3.2.1 how Bakshi & Chen (1996) explain the spurious negative correlation between real stock prices and inflation focusing on monetary policy stringency is illustrated. This study continues by giving a brief summary of the literature regarding both theoretical models and empirical findings considering these matters. Section 3.3 focuses on the special characteristics of conducting monetary policy in a small open economy. The main ideas behind cycle dating following Hamilton (1989) and the MS-VAR models are scrutinized in Section 3.4. Section 3.5 describes the Finnish stock market and the data, where also the major problems in measuring monetary policy stringency are outlined, as well as the major changes in exchange rate regimes, as devaluations have been an important element of monetary policy in Finland. Several short- and long run MS-VAR and MS-VEC models, which also allow for heteroskedasticity, are estimated. The main empirical results are given in Section 3.6. To describe how the size and magnitude of the observed correlation between inflation and returns are affected by the source of fluctuations in the economy (real or monetary shocks) we use a regime-dependent impulse response function. Finally, Section 3.7 concludes this study. To begin, we conduct a literature survey on the interaction between (real) stocks returns, inflation and money growth with a special emphasis on how monetary policy affects stock returns.

3.2 MODELING INFLATION, STOCK RETURNS AND MONETARY POLICY TIGHTNESS

According to the Fisher hypothesis (1930, 1965) the expected nominal return on an asset should equal the expected real return plus expected inflation. However, Mundell (1963b), Ram & Spencer (1983), Marshall (1992), Ali & Hasan (1993) and Crowder & Hoffman (1996), among others, find a negative relationship between realized inflation and ex post real asset returns against our expectations that equities ought to act as an inflation hedge. Fama (1981) explains the spurious negative correlation between stock prices and inflation by the negative relationship between real activity and inflation. He suggests that both inflation and stock prices are determined by real activity. Higher expected future output leads to higher current stock prices. Hence, real activity is positively correlated with stock prices, which even seem to forecast the real sector. Second, for a given growth rate in money supply an increase in expected future output must lead to lower inflation for the quantity theory to hold (the proxy hypothesis). Alternatively, we find a negative correlation between inflation and real activity coming out from the monetary sector. For example, expected inflation (increased demand for money) raises interest rates and thus reduces investment as loans become more costly for firms. Thereafter output, and accordingly the value of the firm, are reduced. Correspondingly, the firm's stock becomes less desirable to investors, and its price falls. These combined effects induce a spurious negative correlation between inflation and stock prices.

Fama's claims have been criticized since they are contrary to the Phillips curve analysis. Nevertheless, the negative relationship between inflation and stock prices seems to hold. The main findings of the Bakshi & Chen model (1996), which they use to determine the endogenous and simultaneous price level, inflation, asset prices, and the real and nominal interest rates serve as an example.

3.2.1 The Bakshi and Chen model (1996)

The Bakshi & Chen (1996) approach integrates asset pricing theory with models from monetary economics and, in contrast to the consumption-based CAPM of Cox et al. (1985), money now has a specific role in their system. Their setup is an intertemporal representative agent monetary economy, which incorporates fiat money for transaction purposes and where investors find it useful to hold cash balances. There is a single perishable consumption good, and the agent's instantaneous utility function depends on both consumption and cash balances. Production (output) and money supply are the two underlying state variables. First, they assume that consumption, money demand, and portfolio adjustment decisions take place at discrete time intervals of length *Δt*. Later, they take the model to its continuous time limit. The infinitely long-lived agent chooses consumption, money demand and portfolio holding at each point of time in order to maximize her lifetime utility:

$$\max_{c_t, M_t^d : t=0,\Delta t, 2\Delta t,\ldots,\infty} = \sum_{t=0}^{\infty} e^{-\rho t} E_0\{u(c_t, \frac{M_t^d}{P_t^c})\}\Delta t, \qquad \textbf{(3.1)}$$

where E_t is the expectation conditional on all time t information, c_t denotes the consumption flow during $[t, t + \Delta t]$, M_t^d is the nominal money demand from time $t - \Delta t$ to t, P_t^c is the price of the consumption good, and ρ represents the discount factor. Uppercase letters refer to nominal variables and lowercase letters to real variables. They furthermore assume that the utility function is twice continuously differentiable and concave in both real money demand and consumption.

There is one equity share traded whose holder is entitled to all the output of a single production technology. This technology produces the sole consumption good. Its output in terms of units of the good y_t is governed by:

$$\frac{\Delta y_t}{y_t} = \mu_{y,t}\Delta t + \sigma_{y,t} B_{y,t}\sqrt{\Delta t}, \qquad \textbf{(3.2)}$$

where $\mu_{y,t}$ and $\sigma_{y,t}$ are the conditional expected value and standard deviation of output growth per unit of time, and $\{B_{y,t}: t = 0, \Delta t, ...\}$ is an i.i.d. standard normal process. The time t nominal price of the equity is denoted by $P_{z,t}$. One risk-free real bond and one nominal bond, and $N - 2$ financial assets are traded. The real (nominal) interest rate at time t, $r_t(R_t)$ is simply the real (nominal) rate of return on the real (nominal) bond. At time t the nominal cum dividend price for every other financial asset i is denoted by $P_{i,t}$, for $i = 3,...,N$. Using this information, they construct the intertemporal budget constraint:

$$\begin{aligned} & M_t^d + (P_{z,t} + P_t^c y_t \Delta t)z_t + P_t^c \alpha_{1,t} + \alpha_{2,t} + \sum_{i=3}^{N} P_{i,t}\alpha_{i,t} = \\ & P_t^c c_t \Delta t + M_{t+\Delta t}^d + P_{z,t} z_{t+\Delta t} + P_t^c \frac{\alpha_{1,t+\Delta t}}{1 + r_t \Delta t} + \frac{\alpha_{2,t+\Delta t}}{1 + R_t \Delta t} + \sum_{i=3}^{N} P_{i,t}\alpha_{i,t+\Delta t}. \end{aligned} \qquad \textbf{(3.3)}$$

“Expenses” are equal to total nominal value of wealth carried over from the past. Here z_t is equity holdings (shares) and $\alpha_t = (\alpha_{1,t},...,\alpha_{N,t})'$ are financial holdings, where $\alpha_{i,t}$, for $i = 1,...,N$ is the number of units of a financial asset i held from $t - \Delta t$ to t.

Monetary policy is conducted in this economy such that money supply M_t^s is defined by the following stochastic process over time:

$$\frac{\Delta M_t^s}{M_t^s} = \mu_{M,t}\Delta t + \sigma_{M,t} B_{M,t}\sqrt{\Delta t}, \qquad \textbf{(3.4)}$$

where $\{B_{M,t}: t = 0, \Delta t, ...\}$ is again an i.i.d standard normal process, and $\mu_{M,t}$ and $\sigma_{M,t}$ are the conditional expected value and standard deviation of money growth rate per unit time respectively. Money supply and output processes are allowed to be correlated. Furthermore, to characterize equilibrium relations they assume that real asset prices are defined as:

$$\frac{\Delta P_{i,t}}{P_{i,t}} = \mu_{i,t}\Delta t + \sigma_{i,t} B_{i,t}\sqrt{\Delta t}, \qquad \textbf{(3.5)}$$

where $\{B_{i,t}: t = 0, \Delta t, ...\}$ is an i.i.d standard normal process, and $\mu_{i,t}$ and $\sigma_{i,t}$ are the conditional expected value and standard deviation of the real rate of return per unit time on an asset i.

In general equilibrium the following conditions have to be met: $c_t = y_t$, $M_t \equiv M_t^s = M_t^d$, $z_t = 1$, $\alpha_{i,t} = 0$, $\forall\, i = 1,...,N$, for each t. First-order conditions for the representative agent problem are derived under these market clearing conditions. In addition, two transversality conditions must be met. Solving this system, Bakshi and Chen (1996) conclude that the real price of the stock market is proportional to real output, the inflation process is driven by both real and monetary shocks and, finally, the expected inflation is increasing in expected money growth and decreasing in expected output growth. Furthermore, the real money demand is proportional to output but unrelated to nominal money supply. Doubling money supply will nevertheless double the nominal prices of both the good and the stock market, but will not affect real prices.

To be able to say more about the price and the expected inflation process, they need more specific restrictions on the parameters of the production and money supply processes. They also derive closed form solutions of this model in continuous time, which gives them a way to understand and predict how changes in the real and monetary variables may affect the money, the stock and the bond markets. Output and money growth processes are then described using geometric Brownian motions as follows:

$$\begin{aligned} \frac{dy_t}{y_t} &= \mu_y dt + \sigma_y dw_{y,t} \\ \frac{dM_t}{M_t} &= \mu_M dt + \sigma_M dw_{M,t}, \end{aligned} \qquad \textbf{\textit{(3.6)}}$$

where y_t is real output, M_t is money supply, μ_y, μ_M, σ_y, σ_M are all positive constants, $dw_{y,t} \equiv B_{y,t}\sqrt{dt}$ and $dw_{M,t} \equiv B_{M,t}\sqrt{dt}$. Now, both output and money growth are i.i.d., monetary policy has no impact on real output and does not accommodate economic growth. The equilibrium conditions can then be further modified to achieve the following results (Equations 3.7 - 3.8):

$$\mathrm{cov}_t\left(\frac{dp_{z,t}}{p_{z,t}}, \frac{dP_t^c}{P_t^c}\right) = \mathrm{cov}_t\left(\frac{dy_t}{y_t}, \frac{dM_t}{M_t}\right) - \mathrm{var}\left(\frac{dy_t}{y_t}\right). \qquad \textbf{\textit{(3.7)}}$$

Hence, the correlation between the real price of an equity and the price of the consumption good (inflation) is clearly negative, unless both money growth is procyclical and its covariance with output growth dominates the variance of the latter.[3] Finally, the correlation between stock prices and money growth depends on that between output growth and money growth as indicated below:

$$\mathrm{cov}_t\left(\frac{dp_{z,t}}{p_{z,t}}, \frac{dM_t}{M_t}\right) = \mathrm{cov}_t\left(\frac{dy_t}{y_t}, \frac{dM_t}{M_t}\right). \qquad \textbf{\textit{(3.8)}}$$

Since similar results have been obtained by various authors trying to explain this relationship, we expect that for many types of monetary economies stock prices will be negatively correlated with inflation and positively correlated with money growth. We continue by giving a brief summary of studies focusing on this matter.

3.2.2 General results

Boyle & Peterson (1995) suggest that the primary source of the mechanism by which money affects stock prices is the interaction between real and monetary sectors. In their model monetary policy affects returns by changing the required returns, or the expected future real dividends of the underlying stocks. Under weakly pro- or counter-cyclical monetary policy they find a negative correlation between inflation and returns as higher output growth decreases inflation more than the associated higher money growth increases it, and the higher purchasing power of the dividend sum carried over to the next period makes equity more valuable and raises stock prices. By contrast, equity returns are positively correlated with inflation under strongly procyclical monetary policy. The mechanism is straightforward: increases in real output raise real equity prices, and simultaneously loose monetary policy raises nominal goods prices.

The empirical findings of negative correlation between real stock returns and inflation under counter-cyclical monetary policy are further supported by Kaul (1987, 1990), who found that the negative relation between returns and changes in expected inflation was significantly stronger in the USA during interest rate regimes (counter-cyclical policy) than under money supply regimes. By contrast, there was no change in the relation between returns and inflation in countries that only experienced one type of policy regime during the period studied. Kaul's results (1990) were further confirmed by Graham (1996), who regressed real stock returns on inflation and conducted a series of searches for break points, enabling him to divide the data into three subperiods. He concluded that monetary policy is neutral during periods with a negative returns-inflation relation, and counter-cyclical when this relation is positive.

Kearney (1996) shows how efficient financial markets should respond to ex post money supply changes, and how the size and direction of the response depends on how the government is expected to react to unanticipated money. The monetary authority may have either an interest rate or a money supply target. These policies influence stock prices in that after a positive portfolio shock at time *t* under interest rate targeting, prices will remain unchanged since policymakers are expected to offset the rise in interest rates (procyclical policy), assuming that the increased supply of nominal money balances is willingly held. In contrast, monetary policy has the largest effect under the money stock targeting rule. Agents now expect real interest rates to rise, reflecting an offsetting contraction by the government (counter-cyclical policy), which has a negative impact on the price level and results in a large fall in stock prices. Unfortunately, Kearney's findings cannot be used as a basis for the empirical study as we are not able to form expectations about an unobserved, unofficial, unpublished Bank of Finland monetary policy rule, a key variable in her model. Nevertheless, she points out that there is a link between monetary policy and announcements of certain key economic variables. Hence, instead of forming expectations about the monetary policy changes, investors may start to respond to unanticipated changes in such things as unemployment based on what they have learned about the government's reactions to such news. We would then find a causal relation between unemployment and stock prices.

Since unexpected inflation indicates an economic shock, and has a positive effect on inflation uncertainty, unexpected inflation raises nominal interest rates. If investors erroneously use these higher rates to discount their investments, the result is an undervaluation of stocks (negative correlation between inflation and stock prices). However, if investors are rational, they should not be misled by this Money Illusion. The link between stock prices and unexpected inflation has also been explained by the equity value of the firm reducing with a positive level of nominal contracts (the nominal contracting hypothesis) and inflation-induced wealth transfers. For example, if the real value of government liabilities held by the public is reduced by unexpected inflation, this leads to an unexpected decrease in real after-tax personal income, which causes negative wealth effects.[4] This in turn may affect the investment decisions of the public if they are trying to smooth their consumption by reducing savings. As a result the value of equities falls. In other words, the source of the shock may also matter. This is considered in Section 3.2.3, which focuses on real and monetary shocks.

3.2.3 The effects of real and monetary shocks on stock prices

General equilibrium models explaining the relationship between stock returns and inflation predict that the source of the inflation shock is a key variable in determining whether stocks offer a hedge against inflation or not. Marshall (1992) describes how the size and magnitude of observed correlations between inflation and asset returns are affected by whether inflation is caused by fluctuations in real economic activity or fluctuations in the money growth rate. Danthine & Donaldson (1986) argue that stocks provide protection against purely monetary inflation, but fail to provide a hedge against inflation arising from real output shocks. Giovannini (1989) points out that the effect of unexpected inflation depends on both its source and persistence. First, changes in uncertainty about future consumption affect asset prices through changes in desired savings as a shift toward those assets which are better suited to consumption smoothing. If intertemporal substitution is low, precautionary demand for money increases when the next period's dividend risk increases (dividends = gross national product), and investors substitute stocks for money. As a result, nominal interest rates rise and stock prices fall. If the shock in dividends is permanent, stock prices remain unaffected. If the shock is due to permanent nominal disturbances, the expected liquidity value of money decreases with an increase in uncertainty about money growth at $t + 1$. Consumers then start to accumulate assets, which can be changed into money at $t + 1$, since the real returns on money balances are expected to be higher at $t + 2$ as a result of the increase in money growth uncertainty. In other words, stock prices increase relative to money because the current liquidity value of money balances decreases. Giovannini's model also predicts that temporary nominal disturbances leave long-term interest rates and thus stock prices unaffected.

Ely & Robinson (1997) calculated impulse response functions from VEC models including output, money, stock and goods prices to assess the response of share and goods prices to innovations in both the money supply and real output over several years. This allowed them to estimate the extent to which stocks maintain their value relative to inflation for several countries, and whether this relationship depends on the source of the shock. They discover, for example, that stocks gain briefly relative to goods prices following monetary shocks in Finland. However, in the USA stocks fail to maintain their value relative to goods prices following real output shocks. Nevertheless, with these few exceptions they conclude that stocks maintain their value in the long run relative to goods prices following both real and monetary shocks.

TABLE 3.1: Responses of real stock prices to monetary and real innovations.

Shocks	**Real innovation: dividend risk**	**Nominal disturbances**
permanent	prices unaffected	prices rise
temporary	prices fall	prices unaffected

These results are based on Giovannini's general equilibrium cash-in-advance model (1989).

In practice the monetary authority is likely to respond quickly to monetary shocks, thus negating their influence on the economy. However, identifying monetary shocks is difficult. If they can be identified at all, they are likely to show up as innovations in interest rates. These identification problems induce people to try to use various alternative measures of monetary policy stringency in their studies to get a better idea of the real effects of nominal disturbances.

3.2.4 Empirical results based on VARs

Next, we give a brief summary of the empirical studies focusing on the relationship between stock returns and monetary policy stringency. Various combinations of both domestic and foreign explanatory variables in vector autoregressions have been applied, and short run and long run returns are utilized. Lastrapes (1998) estimates the short run responses of interest rates and equity prices to money supply shocks over the postwar monthly period for the G-7 countries and Holland. His empirical results are based on a VAR including the yield on medium to long-term government bonds, an index of the real equity price, the interest rate, output, price level and nominal money stock. He identifies money supply shocks by imposing long run monetary neutrality on the system: permanent changes to the money supply are assumed to have no effect on real variables at infinite horizons. This suggests that returns are quite sensitive to money supply shocks and this relation is mostly positive. He concludes that the negative relationship between inflation and stock returns is more likely because of the importance of real shocks. In other words, he claims that stocks are a good hedge against inflation when changes in price level are caused by money supply shocks.

Thorbecke (1997) measures US monetary policy shocks by narrative indicators; i.e., shocks are identified by using Federal Reserve Statements and other historical documents, and by an event study of Federal Reserve policy changes as reported in the Wall Street Journal. Using this information, he finds a positive link between expansionary monetary policy and ex-post stock returns. Similarly, he shows that monetary tightening is expected to reduce the small firm equity prices, as tighter monetary policy lifts interest rates and makes it harder for firms to borrow from the market.

Canova & De Nicoló (1997) analyze interdependences among asset returns, real activity and inflation from a multi-country and international point of view. Their results are based on closed and open economy VARs including a measure of nominal stock returns, the slope of nominal term structure (which is considered to be a good predictor of the real activity), real activity (industrial production) and inflation, as well as the bilateral nominal exchange rate in multi-country models. They use monthly data from 1973/1 to 1993/12. When international influence is allowed for, stock returns have little connection with the domestic bond market, real activity or inflation outside the USA. US shocks however have important real and informational effects on other countries. Innovations in the US nominal stock returns are instantaneously transmitted across the world and induce a statistically significant and positive median response in nominal foreign stock returns. Similarly, an appreciation in the dollar gives a (temporary) boost to production growth to some extent in all countries. However, an innovation in the US production growth which occurs close to full capacity increases both short-term interest rates and inflation, causing a decline in nominal and real stock returns both at home and abroad. Still, when they allow interdependences among countries, the negative link between production growth and inflation beyond the USA seems to be missing. The inflationary pressure coming from the USA is possibly neutralized by the responses of local monetary authorities, thus leaving domestic output unaffected. Canova & De Nicoló conclude that the primary source of disturbances at the national and international levels appear to be shocks originating in real activity, whereas those originating in financial markets or attributable to a restrictive view of monetary policy have a secondary role in generating significant cyclical fluctuations.

Groenewold et al. (1997) use a model including nominal stock returns, real income, real government expenditure, the real exchange rate, real tax revenues, a nominal interest rate on foreign bonds, an expected rate of exchange rate depreciation and money to test whether the spurious negative relationship observed between stock returns and inflation depends on pro- or counter-cyclical monetary policy. A dummy variable obtained by multiplying expected inflation by zero for periods of counter-cyclical policy and one otherwise is included in each equation in the model. The full system results suggest that monetary policy stringency is not significant in explaining the puzzle. After estimating the reduced form, the negative sign between inflation and stock returns survives, and the source of the "spurious" negative correlation between returns and inflation is found in the macroeconomic interactions (through real income).

As previous results of negative relations between stock returns and inflation are generally obtained from models structured to estimate short run relationships, Ely & Robinson (1997) continue this line of research by using a reduced-form approach and recent advances in the theory of cointegration. Their vector error correction (VEC) model consists of output, money, the nominal stock price and goods prices, in this order.[5] They use quarterly data for 1957/1 to 1992/3 from Australia, Austria, Belgium, Canada, Finland, France, Germany, Italy, Japan, the Netherlands, Norway, Spain, Sweden, Switzerland, the UK and the USA. First, to impose long run equilibrium constraints, any cointegration relationship detected is introduced into the model through an error correction term. They also check whether stock and goods prices enter the cointegration relationship with statistically significant coefficients. In the case of Finland, stock and goods prices do not appear to exhibit any long run relationships. Similar results were obtained for most countries. Is this because stock prices outpace increases in the general price level or that in the long run dividends compensate for the failure of stock prices to keep up with inflation? In any case, rational risk-averse investors should require higher returns for stocks if their covariance with inflation is negative, as such assets are not desirable for inflation hedging. In fact, with few exceptions, they conclude that in the long run stocks maintain their value relative to goods prices following both real shocks (except for the USA) and monetary shocks.

Gjerde & Sættem (1999) utilize a VAR approach to Norwegian data to see whether stocks are a good hedge against inflation. Consistent with the US and Japanese findings, they establish that real interest rate changes affect both stock returns and inflation, and the stock market responds accurately to oil price changes, one of the most important sources of inflation in Norway. However, the negative inflation - stock return relationship cannot be explained by the link between real activity and inflation. Furthermore, the stock market shows a delayed response to changes in domestic real activity. Nevertheless, note that Norway's economy is very sensitive to the world market prices of its natural resources, that a small stock market may easily be manipulated, and that short-selling of stocks is prohibited, which together implies that negative information is less effectively incorporated into stock prices. Frennberg & Hansson (1993) considered long-horizon returns in Sweden regressed on expected and unexpected inflation. They found that at long horizons stocks are good hedges against inflation. To see whether this also holds in Finland, we continue by discussing some papers trying to explain the dependences between stock returns and the macroeconomy in the case of the Helsinki Stock Exchange (HeSE).

3.2.5 Previous research focusing on the Finnish stock exchange

Junttila et al. (1997) provide a survey of the relations between the stock market and the macro economy in Finland. Their main focus is on the Arbitrage Pricing Theory and the intertemporal version of the Capital Asset Pricing Model (CAPM) of Sharpe (1964). To mention some findings, the term structure of interest rates seems to be an essential factor affecting the discount rate of future cash flows, and thus stock returns. Furthermore, as asset prices reflect expectations of future earnings, they are expected to be influenced by the real activity (GNP, employment or exports). Examining the relation between stock returns and expected as against unexpected changes in the money supply produces mixed results. Some studies corroborate the convention that a rise in money supply boosts stock prices. But contrary findings also exist. For example, Lahti & Pylkkönen (1989) find that the unanticipated part of the real money supply is insignificant in explaining changes in stock prices.

Järvinen (1998) examines the responses of disaggregated stock prices to macroeconomic shocks. He computes impulse response functions based on a VAR including Finnish data on industrial production, *M1* (money), the three-month Helibor (Helsinki Interbank Offered Rate) interest rates, inflation, exchange rates (nominal trade-weighted exchange rates deflated by the price levels ratio between foreign and domestic price levels) and stock returns for the period 1987/1 - 1996/12. Money supply and interest rate shocks are expected to capture the impact of monetary policy on returns. He finds that in the long run stock prices respond to non-monetary shocks, while in the short run monetary shocks are also important. The responses are mainly uniform between industries. After taking into account the long run dependences (cointegration) between the model variables, interest rate shocks have a significant and persistent effect on stock prices. Furthermore, his findings suggest that the reaction of stock returns to macroeconomic news is neither constant nor symmetrical, but varies with business conditions, the qualitative nature of the news variable, and the monetary policy regime chosen.

Although various specifications of the VAR and estimation procedures were used to determine the linear impulse responses, Järvinen (2000) finds that the inflation rate shocks are the most successful variable in explaining stock returns. The sign of the stock return response to inflation shocks is positive in the short run, but after two to three months returns fall below their pre-shock levels. In principle this slow adjustment of returns to inflation shocks should indicate profit opportunities for rational investors, who base their trading strategies on the initial stock market response.

Löflund & Nummelin (1997) point out that changes in expected asset returns, or discount rates following changes in production growth and risk, are a function of investors' time-varying preferences. Hence, higher predicted economic growth and lower perceived real uncertainty may affect asset returns differently from time to time, depending on the state of the economy. For instance, when the economy is depressed, investors are generally cautious and tend to react to price changes, expected real economic growth and risk in asset markets accordingly. Using monthly data for 1971/1 - 1994/12 they illustrate that expectations of industrial production growth affect asset returns over the whole business cycle, and in particular when business conditions are very strong or very weak. A negative relationship between returns and growth emerges, especially in good economic conditions. This is explained by the implied fear that high expected one-period future growth is not persistent and signals lower future multi-period growth.

Moreover, Järvinen (2000) suggests that a stronger relationship between news and stock returns pertains when the reactions are allowed to vary depending on asymmetries such as the sign and/or the size of the news. Mainly positive and major news jointly have significant effects on stock returns, and the sign (size) effects relate to non-monetary (monetary) news. However, some industry-specific differences in reactions can be found.

Fortunately, the econometric tools used in this study allow us to take into account differences in stock return behavior under alternative economic states, but first we have to adjust the theories described above to fit to the case of a small open economy. We start by scrutinizing a small open economy model. This is followed by a brief introduction to theories explaining causal relations between stock returns and exchange rate regimes since during the period of this study devaluations have been an important part of conducting monetary policy in Finland.

3.3 MODELING INFLATION, STOCK RETURNS AND MONETARY POLICY IN A SMALL OPEN ECONOMY

The literature is full of basically similar open economy models, the core of which is the structure established by Dornbush (1976), who built on the work of Mundell (1962, 1963a) and Fleming (1962). Including stock returns in these macro-models has led to two categories of work: first, there are papers which examine the returns - inflation question within the context of the dynamic stochastic optimization model based on analyzing the behavior of a single representative household. Second, there are some structural macro-economic models: Lächler (1983) presents an ISLM-based model which pays particular attention to the effects of US tax structure. Klotz & Meinster (1986) combine the CAPM with an ISLM. In Groenewold et al. (1997) the model structure is motivated by the Rational Expectations Hypothesis, and could also be interpreted as an ISLM augmented by a stock return equation. In formulating the empirical models we try to follow these traditions, adding a few features. However, the main focus is now on the effects of monetary policy stringency on stock returns and not vice versa.

3.3.1 The influences of fiscal and monetary policy under floating and fixed exchange rates

Basic monetary policy elements are the exchange rate, monetary and/or inflation targeting and monetary policy with an implicit but not an explicit nominal anchor, i.e., a constraint on the value of domestic money. Monetary targeting is mainly used in countries where exchange rate targeting is not an option because the country is too large or has no obvious country whose currency could serve as the nominal anchor. By exchange-rate targeting we mean fixing the value either of the domestic currencies to a commodity such as gold or the exchange rate of a large, low-inflation country. The exchange rate target fixes the inflation rate for internationally traded goods and thus directly contributes to keeping inflation under control. It also forces a tightening of monetary policy when there is a tendency for the domestic currency to depreciate. However, if the main goal of the central bank is a stable increase in money supply or modest inflation, this could be achieved by allowing the exchange rate to float.

The question of monetary policy tightness translates into focusing on different exchange rate regimes and the current account balance in a small open economy like Finland. We start by analyzing relations between real activity and inflation under different exchange rate regimes. We follow the monetary approach of the exchange rate, where a rule for the money supply will make the exchange rate endogenous, and vice versa. The Mundell-Fleming model explaining how policy instruments affect output and hence returns under different exchange rate regimes then indicates the following rules: under a fixed exchange rate regime, fiscal policy instruments affect output, corporate profit and interest rates, but monetary policy has no effect (forced sterilization through intervention). Only devaluations may be used to restore the price competitiveness of the economy in order to improve aggregate demand and employment. Under floating exchange rates an unexpected, permanent increase in the rate of money growth stimulates output temporarily via surprise inflation. This effect finally evaporates, leaving the economy with permanently higher inflation. Inflation is often fought back by increasing interest rates, which should eventually show up as a reduction in returns in the long run (real activity unchanged).

Wage and price stickiness is often the key assumption needed to make monetary policy effective. Since the price level does not respond to a monetary shock in the short run, the interest rate will have to adjust to equilibrate the money market. The more sticky prices are, the slower the real money stock and hence profits and real interest rates will return to their previous level after a shock, which also causes a higher initial jump in the stock market (Blanchard, 1981).

However, the empirical VAR literature has not been successful in providing evidence for the theoretical models of the monetary transmission mechanism in the economy. In the open-economy literature we find examples of depreciation of the domestic currency against the US dollar due to a restrictive monetary policy shock at home, which is called the exchange rate puzzle. This puzzle has been explained by the inability of VARs to distinguish exogenous monetary shocks from the endogenous reaction of monetary authorities to exchange rate fluctuations, or the wrong exclusion of a commodity price index as a leading indicator of inflation in the VAR. (Bagliano et al., 1998) The traditional and portfolio approaches also link exchange rate changes with stock returns. These are discussed below in Section 3.3.2.

3.3.2 The traditional and portfolio approaches

Granger et al. (1998) show that under fixed and even flexible exchange rates, an appreciation of the local currency will lessen the competitiveness of the firm’s product and its profit, thus lowering its stock price. From this viewpoint, exchange rates lead the stock price change. This is known as the traditional approach.

An inverse relation between stock returns and exchange rates is known as the portfolio approach in which causality runs from returns to exchange rates. For example, a decrease in stock prices reduces wealth of the domestic investors, which in turn leads to lower demand for money followed by lower interest rates. The lower interest rates encourage capital outflows ceteris paribus, which is the cause of currency depreciation. However, as capital markets are nowadays increasingly integrated, changes in stock prices and exchange rates may reflect the capital movements more than current account imbalances. If both traditional and portfolio approaches influence the economy simultaneously, the stronger effect determines the sign and order of causality.[6]

3.3.3 The lending channel

Since under fixed exchange rates the Central Bank is obliged to buy and sell currency at a predetermined fixed price, money supply depends on the balance of payments. Limits on conducting monetary policy set by the current account balance and the degree of monetary policy independence are measured by a spillover multiplier. As prices are fixed in the short run, big changes in policy are needed to produce changes in output as monetary expansion reduces interest rates to some extent, but the side-effect of this policy is a capital outflow. The larger the response of foreign capital movements to an interest rate change, the higher the effect on the current account and the smaller the effect on domestic interest rates, i.e., the higher the spillover multiplier. A large multiplier and loose monetary policy may lead to speculative attacks if investors expect the country to devalue to prevent its balance of current payments from falling any further. Current account deficits have thus typically been controlled by regulating deposit interest rates and the amount of credit available to the public. Hence, in a small open economy with fixed exchange rates and a high degree of capital mobility, the behavior of banks and the characteristics of the credit market come into play when trying to isolate the effects of monetary policy.

In booms credit and liquidity may be readily available and thus it is likely that monetary policy shocks will be neutral. In recessions firms and consumers may find it harder to obtain funds for investment or consumption, and monetary policy may have real effects through the credit and liquidity channels. For instance, if tighter monetary policy forces banks to curtail the availability of bank loans, private expenditures may fall if the private sector is not able to offset the fall in loan availability in public capital markets. In practice, adverse selection and moral hazard virtually prevents small and medium sized firms from funding themselves in public capital markets. (Ravn & Sola, 1996 and Ees et al., 1994) Macroeconomic shocks may also be propagated depending on the financial health of the corporate sector. A monetary shock during a tight monetary period has a larger effect than during an easy money period, since during the previous corporate financial health has already declined through both a worsening balance sheet income and reduced bank loan availability. (Patelis, 1997)

Credit rationing in Finland has created possible problems in using *M1* as a measure of monetary policy stringency. If liquidity is constrained, *M1* may be a fairly uninteresting variable, while the availability of credit may be more important. However, as output is measured by industrial production instead of total output, which also depends on more heavily rationed households, credit rationing may have a less severe effect. Nevertheless, alternative measures such as total credit advanced to the public and the marginal interest rate of funds advanced by the Central Bank to commercial banks as an indicator of the monetary policy stance should be considered (Starck,1990).

3.3.4 Deregulation of the financial markets

Money market regulation started during the Great Depression, and has since then been typical of the Finnish economy. In the 1930s it was necessary to control the deposit interest rates of the commercial banks. In the 1940s reconstruction and war indemnities forced the Government to continue this policy. In the 1960s the stock market was very small, and interest rates for loans and deposits were still under control. Currency exchanges were also limited. However, deregulation started in small steps, because in the 1970s the amount of credit not directly under the Central Bank's control gradually increased. To fight against this "black money market", a new means of supplying funds to the banks was introduced in 1975, a call money market on which both the commercials and the Central Bank operated. However, money market regulation continued in practice until 1985, by which time there were both regulated and deregulated financial markets due to pressure from the outside world with increased international capital movements. In fact, regulated interest rates meant that some short-form credit was still provided outside the banking system.

Finland finally went through deregulation of financial markets in the eighties. The negative aspect of this was that the economy was no longer insulated from the effects of speculative capital movements. As a result, monetary authorities were bound to sustain fixed exchange rates, and the responsibility of conducting counter-cyclical economic policy became part of fiscal policy. Bordes writes about the 1984 - 88 period as follows: first of all the whole period seemed quite ordinary; only ex post do these years show all the ingredients of a coming crisis. The liberalization of the financial system disrupted the economy and led to extraordinarily high inflation in shares and houses prices fueled by speculation and an increased use of leverage encouraged by tax incentives. The boom was mainly financed by the banking sector, whose supervision and regulation were not sufficiently adapted to the new financial environment. At the same time the demand for goods and services expanded rapidly. Given these developments, fiscal policy was not tight enough to curb demand and all the monetary authorities could have done would have been to revalue the *markka*.[7] (Bordes et al., 1993)

There were also severe currency regulations between 1930 and 1970, and the *markka* first became convertible in 1957 - 58, when some foreign trade regulations were abolished. The remaining foreign capital controls were eased as late as 1986. Some economists thus claim that this period should be scrutinized taking into account constrained capital mobility, i.e., the ability to conduct independent monetary policy as in a closed economy (Tarkka, 1993). Together, these changes in policy suggest that we will probably find some regime switches in the data. This naturally implies that the models we use in the empirical analysis should be chosen accordingly. The benefits of using the Markov-switching vector autoregressive model to pick out this kind of behavior are considered next.

3.4 THE MARKOV-SWITCHING VECTOR AUTO-REGRESSIVE MODEL (MS-VAR)

The Markov-switching vector autoregressive (MS-VAR) model is a useful way of dealing with changes in the data constantly occurring because of changes in government policy and economic institutions (Krolzig, 1997). In this case, we try to estimate changes in monetary policy regimes from the data alone using these models. We ask whether the sign of the contemporaneous correlation between stock returns and inflation depends on monetary policy stringency, or whether it is only affected when the policy change is strong enough to cause a state switch in the economy. The background to the need for this kind of analysis was explained above (Geske & Roll, 1983, Kearney, 1996 and Bakshi & Chen, 1996).

3.4.1 General definition of the MS-VAR model

The Markov-switching vector autoregressive MS(M)-VAR(p) model of order p and M regimes[8] can be considered as a generalization of the basic finite order VAR model. Compared to the VAR model, this model allows for an immediate one-time jump in the process mean M after a change in the regime, or:

$$z_t - \mu(s_t) = \Pi_1(z_{t-1} - \mu(s_{t-1})) + \ldots + \Pi_p(z_{t-p} - \mu(s_{t-p})) + \varepsilon_t, \qquad \textbf{\textit{(3.9)}}$$

where $z_t = (z_{1t},...,z_{kt})'$ is a k-dimensional time-series vector ($t = 1,...,T$) and Π_j are ($k*k$) parameter matrices ($j = 1,...,p$). Let $\Pi(L) = I_k - \Sigma_{j=1}^{p} \Pi_j \lambda^j$ be a ($k*k$)-dimensional lag polynomial, where L is the lag operator such that $L^j z_t = z_{t-j}$. We assume that there are no roots on or inside the unit circle $|\Pi(\lambda)| \neq 0$ for $|\lambda| \leq 1$. The errors of this model are normally distributed $\varepsilon_t \sim$ n.i.d.$(0,\Sigma)$, and $y_0,...,$ y_{1-p} are fixed. The $\mu(s_t)$ is a parameter shift function describing the dependence of the mean μ on a stochastic, unobservable regime variable $s_t \in \{1,...,M\}$ e.g.,

$$\mu(s_t) = \begin{cases} \mu_1 & \text{if } s_t = 1, \\ & . \\ \mu_M & \text{if } s_t = M. \end{cases} \qquad \textbf{\textit{(3.10)}}$$

The description of the data-generating mechanisms has to be completed by assumptions regarding the regime-generating process. Here, we assume that the stochastic process generating the unobservable regimes is an ergodic[9] Markov chain (Equations 1.7. and 1.8 in Chapter 1). Note that the assumptions of ergodicity and irreducibility are essential for the theoretical properties of MS-VARs, such as their property of being stationary (Krolzig, 1998a). Also of interest in the MS-VARs are the unconditional probabilities (prob. L/T) that the process is in in each of the regimes, that is, $P(s_t = i)$ for $i = 1,...,M$ (Hamilton, 1994 and Krolzig, 1997).

In the MSM(M)-VAR(p) model the regimes are associated with different conditional distributions of z_t. For example, in the case of two regimes, the mean could be positive in the first ("expansion") and negative in the second regime ("recession"). Similarly, if we assume that the level of the process smoothly approaches a new level after transition from one state to another, the following model with a regime-dependent intercept term $\upsilon(s_t)$ may be used. Correspondingly, it is called an MSI(M)-VAR(p):

$$z_t = \nu(s_t) + \sum_{j=1}^{p} \Pi_j z_{t-j} + \varepsilon_t, \qquad \textbf{\textit{(3.11)}}$$

where $\nu(s_t) = (\nu_1(s_t),..., \nu_k(s_t))'$.

The MS-VAR allows for a great variety of specifications. In principle, all parameters of the conditional model can be made dependent on the state of the Markov chain. Allowing state dependent heteroskedasticity gives $\varepsilon_t|s_t \sim$ n.i.d.$(0,\Sigma(s_t))$. However, throughout this paper we assume that the autoregressive coefficients Π_j are independent of the state s_t. In other words, the model is linear in its coefficients, since the number of parameters would otherwise grow rapidly and shrink the number of observations usable for estimating the regime-dependent parameters. For these reasons a specific-to-general approach is preferred in general. Hence, in empirical research only some parameters will be conditioned on the state of the Markov chain, while the others will be made regime invariant. Various alternatives are presented in Table 3.2 below.

Table 3.2: Specification of the Markov-switching vector autoregressive models.

		Markov-switching mean (M)	Markov-switching intercept (I)		
		μ varying	μ invariant	ν varying	ν invariant
Π_j invariant	Σ invariant	MSM-VAR	linear MVAR	MSI-VAR	linear VAR
	Σ varying	MSMH-VAR	MSH-MVAR	MSIH-VAR	MSH-VAR
Π_j varying	Σ invariant	MSMA-VAR	MSA-MVAR	MSIA-VAR	MSA-VAR
	Σ varying	MSMAH-VAR	MSAH-MVAR	MSIAH-VAR	MSAH-VAR

Π_j ($j = 1,...,p$) refers to autoregressive coefficients (Equation 3.9), which are regime invariant (or varying). Σ invariant (varying) is the (regime-dependent) variance-covariance-matrix (H stands for heteroskedasticity). The ($k*1$) dimensional mean of z_t is given by $\mu = (I_k - \sum_{j=1}^{p} \Pi_j)^{-1} \nu$, and ν is an intercept (Equation 3.11). To distinguish models with time-invariant mean and intercept, we denote the mean-adjusted form of a VAR as MSM-, and the latter by MSI-VAR. Changes in regime need not always show in estimated means or intercepts. As an example we give the MSAH-VAR model, which is a Markov-switching heteroskedastic autoregressive vector model.

The notation we follow for each MS-VAR model, also given in Table 3.2, is:

M Markov-switching mean
I Markov-switching intercept term
A Markov-switching autoregressive parameters
H Markov-switching heteroskedasticity.

To conclude, a one-time jump in the process mean is assumed in an MSI- as against an MSM-VAR, where the adjustment is smooth. In MSIH- and MSMH-VARs the variance is no longer regime-invariant. In fact, changes in regimes can be important sources of persistence in the conditional variance of a time-series. Finally, we consider estimation and specification testing of the MS-VAR models in more detail.

3.4.2 Estimation of the MS-VAR model

Estimation of the two components in the MS-VAR model, i.e., the Gaussian VAR model as the conditional data-generating process and the Markov chain as the regime-generating process, is based on maximum likelihood estimation; to be more specific, a version of the Expectation Maximization (EM) algorithm introduced by Dempster et al. (1977). The EM algorithm is designed for a general class of models in which the observed time-series depends on some unobservable stochastic variable such as the regime variable s_t. Each iteration of the EM algorithm consists of two steps. The expectation step involves a pass through the filtering and smoothing algorithms using the estimated parameter vector of the last maximization step in place of the true unknown parameter vector θ. This delivers an estimate of the smoothed probabilities $\Pr(s_t|z_t, \hat{\theta})$ of the unobserved states s_t. In the maximization step, an estimate of the parameter vector θ is derived as a solution of the first-order conditions associated with the likelihood function, in which the conditional regime probabilities $\Pr(s_t|z_t, \theta)$ are replaced by the smoothed probabilities derived in the first expectation step. Equipped with a new parameter vector, the filtered and smoothed probabilities are updated in the next expectation step, and so on, guaranteeing an increase in the value of the likelihood function. Some details are given in Kim & Nelson (1999).

The estimation results include filter probabilities $\Pr(s_t = i|z_t)$, $i = 1,...,M$, which provide information about which regime the series is most likely to have been in at every point in the sample. However, filtered probabilities represent an optimal inference using only the current information up to time $t = 1,...,T$. Smoothed probabilities $\Pr(s_t = i|z_T)$ are based on full information about the sample. The estimated transition probability $\Pr(s_t = i|s_{t-1} = j)$ is essentially the number of times state i seems to have been followed by state $j = 1,...,M$ divided by the number of times the process was in state i.

3.4.3 The vector equilibrium correction model with Markov-switching regimes

A variable which is integrated to order one is said to have a stochastic trend since (some) shocks to it have permanent effects. Variables which are cointegrated are said to have common stochastic trends. In econometrics, the cointegration relationships are often interpreted as the long run equilibrium of the system. Technically, if some or all variables in a VAR are non-stationary, standard asymptotic theory may not be applicable to the purpose of conducting statistical inference. Henceforth, prior to estimation, we should map the data to $I(0)$ series by differencing and cointegration combinations.

If we want to pay special attention to the short run dynamics of the MS-VAR models but allow "multiple equilibria" or Markovian shifts in the equilibrium mean and/or the drift of the system at the same time, we can use the MSCI(M,r)-VAR(p) with M regimes and cointegration rank r; or its equilibrium-correction form MS(M)-VECM(p - 1) following Krolzig (1997). The VAR(p) with Markov-switching intercepts is given in Equation 3.11. If the reverse characteristic polynomial of this equation $|\Pi(\lambda)| = |I_k - \Pi_1\lambda - ... - \Pi_p\lambda^p|$ has one or more roots for $\lambda = 1$, $|\Pi(1)| = 0$, and all other roots are outside the complex unit circle, $|\Pi(\lambda)| \neq 0$ for $|\lambda| \leq 1$, $\lambda \neq 1$, the z_t variables are integrated and possibly cointegrated. If $z_t \sim I(1)$ and there is a vector β such that $Z_{t-p} = \beta' z_{t-p}$ is stationary, then z_t admits error correction representation. Subtracting z_{t-1} from both sides and rearranging terms, the system in Equation 3.11 can be written in its vector equilibrium correction form as:

$$\Delta z_t = \sum_{j=1}^{p-1} D_j \Delta z_{t-j} + \alpha Z_{\text{t-p}} + \nu(s_t) + \varepsilon_t, \qquad \textbf{(3.12)}$$

where the coefficient matrices are defined by $D_j = -(I_k - \sum_{j=1}^{p-1}\Pi_j)$ for $j = 1,...,p-1$, Δ is the differencing operator $\Delta z_t = z_t - z_{t-1}$, and the matrix $\alpha\beta' = I_k - \sum_{j=1}^{p}\Gamma_j = \Gamma(1)$ is singular.

The estimation is done in two stages. As cointegrated systems with Markovian regime shifts can be characterized as a non-Gaussian cointegrated VAR of infinite order, this property allows us to base the cointegration analysis on procedures available for these models. Hence we use Johansen's (1988, 1991) methods to test and estimate the cointegration vectors. We first test for unit roots in the time-series under consideration. If we find $I(1)$ processes, we then test for the number of unique cointegrating vectors in the system. Finally, we try to identify a corresponding number of cointegration vectors from the data. Conditional on the estimated cointegration matrix, the remaining parameters of the model are estimated using the EM algorithm for ML estimation. In practice, before introducing the cointegration vectors as exogenous variables X to the MS-VAR, i.e., the MS-VARX models, they had to be normalized such that $E_t(Z_{t-p}) = 0$.

Alternative specifications of these models are possible depending on whether we have unrestricted shifts in the intercept $\nu(s_t)$, in the state-dependent equilibrium mean $\mu(s_t)$ and/or shifts in the drift $\delta(s_t)$. Suppose, that each regime $i = 1,...,M$ is associated with a particular attractor (μ_i, δ_i). Then, if $j = 1$, the MS-VECM can be written as

$$\Delta z_t - \mu(s_t) = \sum_{j=1}^{p-1} D_j(\Delta z_{t-j} - \mu(s_t)) + \alpha(Z_{t-1} - \delta(s_t)) + \varepsilon_t, \qquad \textbf{(3.13)}$$

where $\nu(s_t) = (I - D_1)\delta(s_t) - \alpha\mu(s_t)$, and the notation is otherwise the same as in Equation 3.12 above. In other words, both Δz_t and Z_{t-1} are expressed as deviations about their regime- and time-dependent means $\mu(s_t)$ and $\delta(s_t)$ (Krolzig, 2001). Later, we consider only the simplest case, cointegrated VAR with Markovian regime shifts in the intercept. For example, if we let the autoregressive coefficients depend on the regime process, the stationarity condition for a VAR is not valid and, hence, the existing unit root tests may not be meaningful. Moreover, we would need further guidance on how to relate the idea of cointegration to the MS-VAR under these circumstances. (Krolzig, 1997, Krolzig & Toro, 1999 and Artis et al., 1999)

In general, cointegration entails Granger causality (Granger, 1969) in at least one direction. As a cause must precede an effect; i.e., the future cannot cause the past, if v_t causes r_t it should also help to predict r_t. Note that if the VAR coefficients are allowed to depend on the regime, causality may change from regime to regime. Hence, in order to study causality in the MS-VAR it is not sufficient to check its AR coefficients. Even if there is no linear interrelation, the second group of variables may reveal information about the actual regime and thus improve the forecast of the first group if the regime matters. Thus there are still many unsolved problems in testing causality in the case of regime-switching models but, at least in the case of stationary MSM- and MSI-VAR, causality can be checked on the basis of their finite-order VARMA representations. (Krolzig, 1998a).

3.4.4 Specification testing of the MS-VAR model

Tests for omitted autocorrelation, omitted ARCH, mis-specification of the Markovian dynamics and omitted explanatory variables in the MS-VAR models are suggested by Hamilton (1989, 1990, 1996), Hamilton & Perez-Quiros (1996) and Engel & Hamilton (1990). Hamilton shows how a variety of specification tests can be based on the score statistics based on the work of Newey (1985), Tauchen (1985) and White (1987). The problem with these tests is not calculating them - as a matter of fact the building blocks for these tests are derived as a by-product of the general estimation of the smoothed probabilities - but their small sample properties are quite poor. Andrews' test for structural change could also be implemented (Andrews, 1993).

Another way to approach testing problems is to use graphical evaluation. The MS-VAR procedure for Ox provides the following figures together with the general estimation results of the MS-VAR models:

- Correlograms and distributions of the standardized residuals and prediction errors of the MS-VAR models estimated.
- Spectral densities; i.e., smoothed functions of the model autocorrelations. Peaks indicate cyclical or seasonal behavior in the series (Hendry & Doornik, 1999).

- Density and QQ plots (cross probability plots) $P_x(X > x)$ can be used to test the normality of the standardized residuals and prediction errors of the model. Standard normal distribution is used for comparison.
- Plots of the smoothed and prediction errors in the MS-VAR models.

These latter alternatives are considered in the empirical part of the paper.

3.4.5 Forecasting the performance of the MS-VAR model

Would we benefit from using the nonlinear models in forecasting stock returns? Probably not, since if we focus solely on forecasting, the models themselves may behave poorly. The lack of forecast gain of nonlinear over linear models is often explained by nonlinearity not necessarily persisting into the future. Nonlinear models may also fail to forecast even when the null hypothesis of linearity is rejected because detected nonlinearity may be an outcome of outliers or structural breaks in the series and these offer no gain in improved out-of-sample series performance. Inappropriate nonlinear models may also have been used in trying to capture nonlinearity in the data. (Granger & Teräsvirta, 1993)

Clements & Krolzig (1998) investigate the empirical forecasting ability of the Markov-switching autoregressive (MS-AR) model. If the time-series includes changes in the regime in the stochastic process generating the data, these models can yield some improvement over the constant parameter, linear model. Nevertheless, there is no guarantee that the nonlinear features which causes the MS-AR to fit the data in the sample better than linear models also characterize the out-of-sample period. However, even though the model may prove to be linear, we might still want to generate turning point forecasts by using the Hamilton filter. This model could then be evaluated by looking at the fraction of the time in which the model correctly anticipates the phases of the business cycle. For further limitations and extensions in forecasting in the case of the MS-VAR models see Krolzig (1998b).

3.5 DATA DESCRIPTION

Various empirical studies suggest that it takes years for changes in monetary policy to affect output and inflation. Hence, in order to prevent inflation from getting started, monetary policy needs to be forward-looking and needs to act before inflationary pressures appear in the economy. In other words, to test whether the spurious negative correlation between inflation and stock returns is possibly due to changes in monetary policy, we need to allow for the fact that policy changes are slow. It is thus proper to use monthly and quarterly data in the study in spite of the fact that the Efficient Market Hypothesis (EMH) implies that (intra) daily quoted stock prices should reflect all relevant new information reaching the market. We start by introducing the monthly and quarterly data. Next, we consider the typical problems of measuring monetary policy tightness. As devaluations have been an important part of conducting monetary policy in Finland between 1939 and 1999, we conclude by representing the major changes in the value of the *markka* against the US dollar and the German *mark*.

3.5.1 Defining the variables in the MS-VAR models

In the augmented small open economy MS-VAR beginning in January 1921 and ending in November 1989 the variable of interest is the monthly HeSE general index *r*, which is the weighted Unitas price index with weights based on the trading volume of the individual stocks adjusted for cash and stock dividends, splits and rights issues. It is available up to December 1991, after which we use the value-weighted HEX index. Other variables are money[10] *M1*, the Government bond rate over 4 - 5 years in percentages *b*, a short-term interest rate (*i* = the three-month Helibor interest rate, *i** = the German three-month interest rate), industrial production both home *y* and abroad *y** (Germany), exchange rates against the German *mark* e_{DEM} and the US dollar e_{USD} and consumer price index *CPI*. The data is obtained from the Bank of Finland data bank. The Bank of Finland has also constructed a measure of monetary policy stringency[11] to be used in their macro model, but unfortunately this monetary condition index (*MCI*) is only available on a quarterly basis. However, we use it in the quarterly analysis. The other quarterly variables are obtained by picking out the observations related to the months of February, May, August and November from the data. The variables are graphed in logarithms (interest rates are measured in percentages) in Appendix 3.1. Note that from here on we use the time subscripts only when they differ from "*t*", for example, CPI_{t-2}.

The real stock returns are deflated using the *CPI*. Unfortunately, only price indices are available rather than total return indices, i.e., dividends are overlooked. Given the reluctance of firms to cut dividends however, real or monetary shocks to the economy will be more likely to impact total stock returns through price changes than changes in dividend yields (Ely & Robinson, 1997). Changes in money supply are also assumed to explain stock returns, and not vice versa, regardless of the Central Bank following the stock market trend while making its monetary policy decisions. In addition, money supply may be so strongly correlated with both inflation and interest rate changes that one of these variables becomes redundant in the VAR. Moreover, in spite of the possibility that the Finnish economy may be weakly dependent on the US or German output shocks, the reverse is not likely. This suggests that foreign variables in these models may be taken as given (exogenous).

3.5.2 Measuring the tightness of monetary policy

Researchers have obtained poor results in measuring monetary policy either because it influences the economy in a different way than the theory suggests or because it has not been successfully identified (Cushman & Zha, 1997 and Bagliano & Favero, 1998). Very different approaches ranging from narrow to broad monetary aggregates, credit aggregates, interest rates and interest rate spreads have thus been used to measure monetary policy tightness. The problem with *M1* as a measure of monetary policy stringency is that changes in it may be a result of either changes in money demand or supply. Furthermore, this series is basically constructed in Finland for research purposes only. Alternatively, we could use the interest rate, but the only interest rate data available for a longer sample period in Finland is the long-term government bond rate. Unfortunately, monetary policy has contributed little to the trends in bond rates in recent years. The credibility of the Finnish Government and international long rates seem to be more substantial. Hence, other variables are needed. To cover for the floating exchange rate period starting 1992/9 we could, as suggested by Redward & Saarenheimo (1996), use the short one-month Helibor interest rate. Another problem in measuring monetary policy stringency in

Finland is the gradual deregulation of the financial markets, which began in early 1980 and continued until the early 1990s.

Bank borrowing from the Bank of Finland played a major role in monetary policy from 1950 to 1984. The Central Bank controlled the credit market by specifying limits up to which each bank could borrow from it at a basic discount rate. Hence, we use a variable constructed from the average interest rate for Central Bank credit to commercial banks c_i 1950 - 1984 as one explanatory variable in the MS-VAR (Saarinen, 1986) and continue this series using the marginal interest rates for Central Bank credit 1985 - 1986. The latter are calculated for research purposes only, since after 1984 the Bank of Finland stopped regulating credit and a new interest rate, overnight interest, was established. Beginning from 1987 the interest rate used is the yield of the Government bond rate over 4 - 5 years in percentages.

3.5.3 Exchange rate regimes in Finland 1926 - 1999

It is a general belief that monetary policy should be effective only under flexible exchange rates. In the case of Finland this would mean 1921 - 25, 1931 - 33 and 1992/9 - 1996/10. In Table 3.4 below we list all currency regimes 1926 - 96 including devaluation dates, which are later used as a benchmark in the attempts to explain the spurious negative relation between stock returns and inflation. Unfortunately, if we believe that stock returns predict changes in monetary policy, the regimes listed in Table 3.4 are no longer valid in dating changes in returns due to changes in monetary policy. Stock returns would have already predicted these changes, which would be fully anticipated when the actual change occurs.

Table 3.3: Economic growth in Finland 1949 - 1980.

1949	**1950**	**1953**	**1954-55**	**1956**	**1957-58**	**1961**	**1962**	**1966-67**	**1969-70**	**1971**	**1972-74**	**1975-78**	**1979**
R	B	r	b	R	R	b	r	R	B	r	B	R	b
	KW			GS	D	EFTA					infl.	Oil	

B/b = boom/recovery, R/r = recession/mild recession. KW = Korean war upturn, GS = general strike and international slump, D = devaluation, EFTA = joining EFTA, infl. = cost inflation, Oil = oil crisis. (Ahvenainen et al., 1982)

Under the Pound standard, money supply in Finland remained constant, and there was no change until the Korean War broke out in June 1950, followed by a worldwide economic boom. Other extraordinary events in the sample are the Vietnam War upturn in 1967/8 - 1967/11 and general strikes in 1956, 1971 and 1976, which created inflationary pressure. The impact of the oil crises in 1974 - 75 and at the beginning of 1980 on domestic demand may have remained modest because of bilateral trading with the Soviet Union,[12] as an increase in oil prices automatically boosted exports to the Soviet Union.

Since the paper industry has played a major role in Finnish exports throughout its history as an independent country, changes in wood and pulp prices in international markets have given rise to aggregate demand disturbances for the paper industry, producing considerable pressure to use devaluations to restore its price competitiveness. Nevertheless, current account surpluses obtained by sudden devaluations typically remained temporary as they were usually followed by increased inflation. We may even talk about inflation - devaluation cycles, especially in the 1970s. Repeated devaluations kept inflation at high levels, and as nominal interest rates were regulated by the Government, real interest rates were low. Furthermore, the Government aimed for low real interest rates because it wanted to support private housing investment. Hence, we observe several periods with negative real interest rates in Finland.

TABLE 3.4: Exchange rate regimes in Finland for 1926 - 1999.

Period.	**Exchange rate regime.**	**Description of the peg.**
1926 - 1931	Gold standard.	Fixed exchange rates.
1931 - 1933	Floating currency.	Floating exchange rates.
1933 - 1939	Pound standard.	Fixed exchange rates.
1939 - 1949	Dollar standard. Devaluations:	"War economy" and deals between two countries. 31.5.1945 75.0% 27.6.1945 40.4% 16.10.1945 12.5%
1949 - 1971	Bretton Woods system . Devaluations:	17.6.1949 17.7% 19.9.1949 44.4% 16.9.1957 39.1% 12.10.1967 31.3%
1972 - 1973	Smithson system.	Deals between Central Banks (devaluation 7.1%).
1973 - 1977	A currency basket.	Unofficial peg.
1978 - 1991	A currency basket. Devaluations: Revaluations:	Official peg. 5.4.1977 5.7% 1.9.1977 3.0% 17.2.1978 8.0% 6.10.1982 4.0% 11.10.1982 6.0% (Floating: 14.11.1991 - 15.11.1991) 15.11.1991 14.0% 5.8.1979 -1.5% 21.9.1979 -2.0% 25.3.1980 -2.0% 27.3.1984 -1.0% 17.3.1989 -4.0%
1991/6 - 1992/9	Ecu standard.	
1992/9	Floating currency.	8.9.1992 - 11.10.1996
1996/10	Joining the EMS.	Fixed exchange rate 14.10.1996.
1999/1	Euro.	Floating, common EMU exchange rate policy.

Data sources: Kiander & Vartia (1998) and Helsingin Sanomat 13.10.1996. The EMS stands for the European Monetary System.

A small survey of macroeconomic indicators after 1985 is given in Table 3.5. The period 1985 - 90 can be described as an overheating period, followed by depression 1991 - 93, finally leading to recovery between 1994 and 1997. The *markka* was revalued in 1989 since increased capital mobility foreign investors had started to disrupt the Bank of Finland's efforts to conduct an effective monetary policy. It thus changed its fixed exchange rate policy and started to create uncertainty about the level of exchange rates. Increased uncertainty was expected to prevent further speculative attacks on Finnish markets. Later, the “hard currency” policy and deregulating the financial markets together with the collapse of the Soviet Union caused several problems. In spite of this development, the currency was anchored to the ECU-basket at 4.6.1991, but, by November *markka* was allowed to float and was finally devalued on November 15th by 14%. This caused many bankruptcies as high domestic interest rates had created markets for foreign loans and investors did not see that domestic interest rates remained high mainly because of the devaluation risk. This finally led to a banking crisis which continued until 1998. This crisis made banks more risk-averse, and the tight monetary policy was accompanied by a fall in domestic credit. Bank lending decreased around 1992 - 95, and barely increased for the two years following the low point reached in 1995. Thus private expenditures fell as the private sector was not able to completely offset the fall in the availability of bank loans in public capital markets. This may show up in the empirical results as a regime shift.

Table 3.5: Macroeconomic indicators for Finland 1985 - 1997.

Indicator	**1985 - 1990**	**1991 - 1993**	**1994 - 1997**
Real gross domestic product (*GDP*)	3.4	-11.4	4.8
A private consumption deflator	4.7	4.7	1.2
Current account/*GDP*	-2.9	-3.8	3.7
Stock market	17.2	4.1	29.1
Total lending	17.7	-4.8	-0.5
Unemployment %	4.4	11.1	14.8
Money stock	12.4	1.8	2.4
Credit losses, % of bank lending	0.3	4.1	2.5

Annual average growth unless indicated otherwise. Source: Honkapohja & Koskela (1999).

To get rid of its bad reputation for using devaluation to support the export sector of the economy, Finland adopted inflation targeting in 1993. This policy has the potential to reduce the likelihood that the Central Bank will fall into the time-inconsistency trap, in which the Central Bank announces that it will try to stabilize output and employment by pursuing restrictive monetary policy. However, the Central Bank is always tempted to break its own rules, thus boosting the economy by a sudden increase in the money supply. If people foresee this change in policy, they adjust their wage demands accordingly, so that this policy has only led to higher inflation. Today, all inflation targeting countries try to taper off inflation gradually in order to minimize output declines by lowering medium-term inflation targets toward the long run goal slowly. It has helped countries to avoid inflation-devaluation cycles, as inflation targeting seems to ameliorate the effects of inflationary shocks. (Mishkin, 1999) Since the Bank of Finland has maintained an explicit inflation target, changes in exchange rates are assumed to have real effects only if they affect the target. In order to gain further credibility for the new anti-devaluation policy, Finland joined the European Union in 1995, and became a member of the European Monetary System in 1996. Nevertheless, to avoid further difficulty in defining monetary policy regimes in this study we end the sample in 1998. Starting from January 1st 1999, the *markka* has been bound to the euro.

Before we continue with the empirical results, we must mention some specific events in the history of the HeSE. Trading at the HeSE remained low until the end of the 1960s. Investors had kept their money in bank accounts benefitting from interest rates paid on savings, which followed inflation. The interest rate for savings and Government bonds was not taxed either, which meant a "tax" on investments at the stock exchange (Ahvenainen et al., 1982). Typically high housing prices due to private ownership in Finland may also have led to lower prices of alternative assets like equities. This is called the alternative assets hypothesis (Summers, 1981). In 1980 the general optimism and increased credit availability generated views of higher expected property levels than before. Integrating financial markets induced investors to believe that undervalued stocks at the HeSE would rise to a higher "real" fundamental level. At the same time foreign investors arrived. This may partly explain why the stock market overheated, and finally collapsed in 1987/10, despite the real side-effects of this crash remaining small. It is reasonable to expect that the rise in stock prices in the late 1980s partly resulted from the availability of cheap loans, which explains the modest price decreases after the outset of the banking crisis. A peak in asset prices was still achieved in 1989, but high interest rates in 1989 - 92 together with devaluation eventually encouraged investors to abandon the Finnish market. The change in exchange rates made the fall in stock returns from spring 1989 until fall 1992 by 71% even more pronounced, as the drop in ECUs was as high as 78% (Kiander & Vartia, 1998). Investor interest in investing in equities increased again in 1994 - 95, mainly as a result of diminishing interest rates. Finally, in 1995 - 1997 the stock market reached its previous level of annual average growth rates after the recession, and went on to almost double it. The ability of the MS-VAR models to identify these events is considered next in more detail.

3.6 EMPIRICAL RESULTS

Tightening of monetary policy seems to have a severe effect on output when used in a recession, but a weaker effect in periods of growth. An easing of monetary policy, on the other hand, has a neglible effect on the economy both in the downswing and upswing phases (Sensier, 1996 and Garcia & Schaller, 1995). Variables which are major indicators of business cycles very often affect stock returns as well. For example, equity risk premiums seem to be higher at business cycle troughs than they are at peaks (Sadeghi, 1992). Here, applying the MS-VAR models to the data, we try to show how the contemporaneous correlation between inflation and stock returns may depend on different monetary policy regimes. In spite of the main focus being on the possibly asymmetric relation between money, inflation and stock returns, other variables are also included to make the small open economy model more realistic. This model should also be thought of as a general framework within which the empirical analysis will be made as only a small number of variables can be included and only a minimum amount of a priori structure can be imposed. The model is general from the theoretical point of view as well. We consider the most appropriate monetary policy stringency measures as explanatory variables: *M1*, total credit advanced to the public, and the marginal interest rate of funds advanced by the Central Bank to commercial banks. Devaluation has also been an important part of monetary policy in Finland. Hence, if changes in estimated regimes can be interpreted as changes in monetary policy, then, even on its own, it is very interesting to see how well the estimated regimes coincide with the observed exchange rate regimes.

3.6.1 The MS-VAR and MS-VEC models

The simplest way of cycle dating is to explain the dependent variable with a constant and a trend, and use residuals from this model as a cyclical component (Hamilton, 1989). Such a plot of e_{DEM}, e_{USD}, *M1*, domestic long run interest rates, *MCI*, *CPI* and returns is provided in Appendix 3.2. Now, since we can clearly observe long run cycles in the behavior of *M1*, *CPI* and returns, the MS-VAR models are employed to identify this behavior in the data.

3.6.1.1 Cointegration testing

To consider the short run dynamics of the system in particular but allow for "multiple equilibria" we modify the MS-VAR such that it explicitly takes into account any long run relationships between the model variables. We start by testing the stationarity of individual time-series using the Augmented Dickey & Fuller (1979, 1981) unit-root test (ADF). The null hypothesis is H_0: there is a unit root. To check for possible *I(2)*:ness we also test H_0 using first differences of logarithms of the data. Some results of the ADF tests are given in Table 3.6 below. Test results for additional variables used in this study are available from the author on request. We cannot reject H_0 for the levels of the series, but differences of the logarithms of the data are generally stationary apart from *CPI*, where some problems remain. This is followed by Johansen's (1988) trace and maximum eigenvalue tests for cointegration rank *r* to select the number of cointegration vectors to be used in the MSCI(*M*,*r*)-VAR(*p*) model.

Table 3.6: Augmented Dickey-Fuller unit root tests
for 1962/4 - 1998/3 (quarterly data).

	MCI	***ΔMCI***	***CPI***	***ΔCPI***	***r***	***Δr***	***y***	***Δy***
T-adf	-2.078	-11.75**	0.91	-2.92	-3.12	-6.269**	-1.884	-12.521**
lag	2	1	1	2	3	1	2	1

All variables are in logarithms. *MCI* = monetary conditions index, *CPI* = inflation, *r* = returns, and *y* = industrial production. Δ is a difference operator such that $\Delta x_t = x_t - x_{t-1}$. A constant and a trend are included in testing the null hypothesis of a unit root. Rejecting the null hypothesis implies that the time-series is stationary. T-adf is the test value, and lag indicates the lag used in unit root test autoregression. The significance of the ADF tests is marked by asterisks: * indicates rejecting the null hypothesis at the 5% level, ** at the 1% level.

The unrestricted cointegration analysis determines the cointegration rank (dimension of the cointegration space), but any linear combination of the cointegration vectors is also admissible, since restrictions are needed to make the resulting parameters unique. Hence, the next step is to test over-identifying restrictions on the cointegration vectors implied by the restrictions proposed in Table 3.8. If the probability value of the χ^2- test statistic is significant, we save the restricted cointegration vectors, and do a quick ADF test to check for their stationarity. Finally, accepted cointegration vectors need to be normalized before entering them into the MS-VECM.

3.6.1.2 Results using quarterly data

In Appendix 3.3 we report the results from the MS-AR for *MCI*, *CPI* and return series individually using quarterly data for 1962/3 - 1998/3. Fairly large LR test statistics support the presence of two regimes in returns and the *CPI*. Looking at Figure 3.1 we note that in the MSMH(2)-AR(4) model *CPI* typically identifies the periods of high inflation (the oil crisis), and suggests that the Finnish economy suffered from inflation - devaluation cycles until 1980. After that inflation stays in Regime 1. Whether this results merely from joining the European Monetary System needs further investigation. The crash in October 1987 can be seen in the MSM(2)-AR(4) for returns, and a number of revaluations (r) and devaluations (d) can be pointed out by looking at changes in regimes in the *MCI* based on the MSM(2)-AR(4).

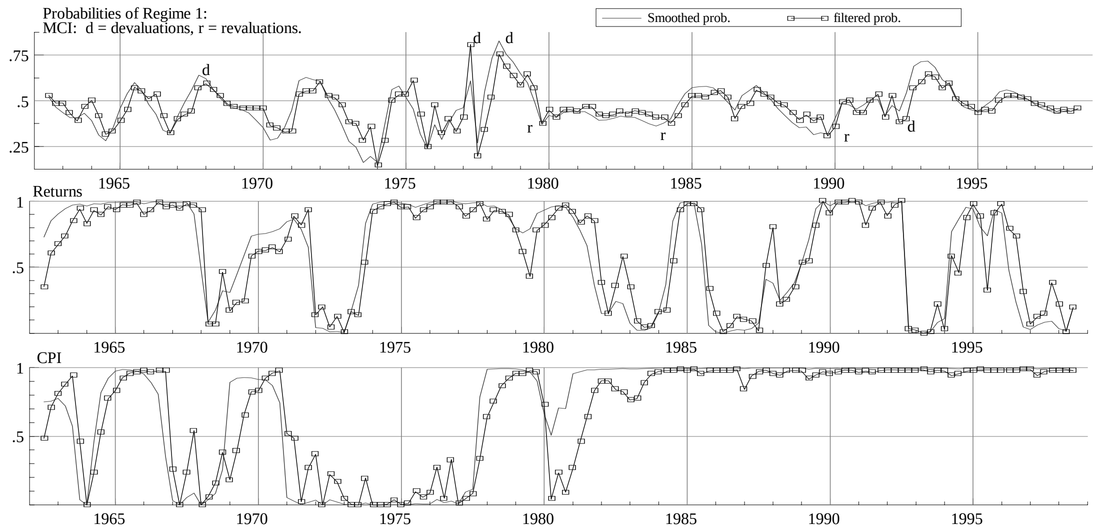


Figure 3.1: Smoothed and filtered probabilities from the quarterly MS-AR models for 1962/4 - 1998/3 focusing on the monetary conditions index, stock returns and inflation separately. *Filtered probabilities represent an optimal inference using only the current information up to time t. Smoothed probabilities of being in state one or two are based on the full information in the sample; i.e., t = 1,...,T.*

Our previous study on the cross correlations between the *CPI* and stock prices in Finland in 1920/1 - 1996/9 indicated a clear lead-lag relationship between these variables with a different sign pattern. Stock prices were positively related to lagged consumer prices and negatively related to leading consumer prices. Thus consumer prices influenced stock prices positively and stock prices affected the price level negatively. The former effect is intuitively obvious but the latter is somewhat obscure. (Sierimo & Virén, 1995) When we look at the MS-VAR models to get more information about this relationship, we expect to find negative contemporaneous correlations between *r* and *CPI* only under counter-cyclical monetary policy regimes for the reasons already given above.

We start with a simple model with only three variables of the main interest as, strictly speaking, any long-term relations between the model variables are not included in the studies above. Results from the quarterly MS-VAR models for 1962/4 - 1998/3 including *CPI*, *MCI* and returns (in this order) can be found in Appendix 3.3. In the MSI- and MSM-VAR(2), Regime 1 mainly identifies periods of high interest rates or tight monetary policy, and Regime 2 occurs at the time of devaluations (loose monetary policy) with a probability of one. Furthermore, we reject the hypothesis[15] that variances are regime-invariant; i.e., $\Sigma_1(s_t) \neq \Sigma_2(s_t)$. In the corresponding MSIH-VAR and MSMH-VAR Regime 1 arises with a probability of one after 1980 indicating a permanent change in regimes. Contemporaneous correlation equals 0.104 in Regime 1 and 0.152* in Regime 2 in the former model. In the latter model the corresponding values are 0.147* and 0.178*, both being statistically significant at the 5% level. From here on statistically significant coefficients in estimated models as well as correlations are marked with an asterisk: * at the 5% level and ** at the 1% level. We refer to transition probabilities as p_{LL}/p_{TT} and to unconditional probabilities as prob. L./T.[16] The estimated duration of both regimes is reported as well. As in the case of two regimes the graphs for smoothed and filtered probabilities are symmetric, we continue by presenting smoothed and filtered probabilities from Regime 1 only.

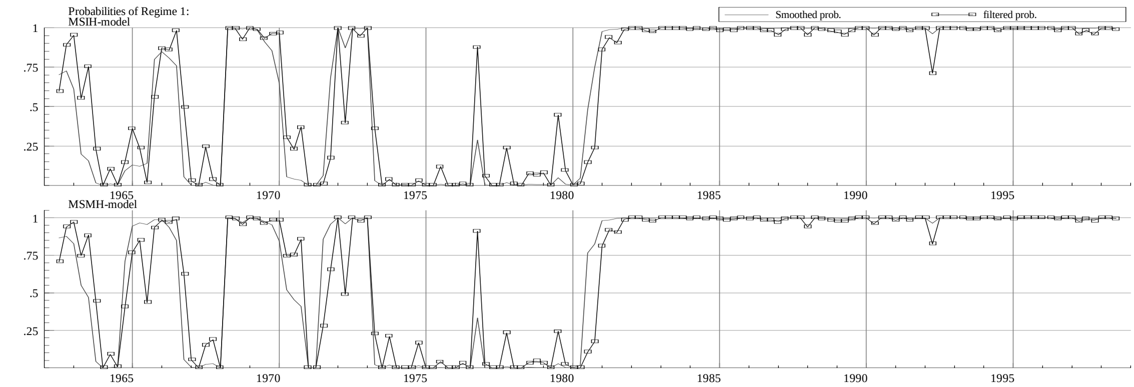


Figure 3.2: Smoothed and filtered probabilities from the quarterly MS-VAR model for 1962/4 - 1998/3, where z = [*y MCI r CPI*]´.

Next, following Ely & Robinson (1997), we add *y* to the set of explanatory variables above; *z* = [*y MCI r CPI*]´. This allows us to "test" the real activity hypothesis. Does a fall in real activity lower stock prices and increase the Government budget deficit, hence typically leading to increased money creation and higher inflation? This could explain the "spurious" negative correlation between inflation and stock returns. We start by testing whether the estimated variance covariance matrix $\Sigma(s_t)$ is in fact regime-dependent. Homoskedasticity is rejected, and we continue by looking at the MSIH(2) and MSMH(2)-VAR(3) instead. The figures for smoothed and filtered regime probabilities again show a permanent change in the regime in the 1980s (Figure 3.2). In addition to a change in the regime in the *CPI* alone (Figure 3.1), liberalization of the financial markets, abandonment of credit constraints and rapid development in trading systems at the stock exchange characterized this period. Later these models have a minor peak by the time the Finnish economy was in recession, which finally led to a floating currency regime in 1992/9 - 1996/11. Regime changes before 1980 are around the big devaluation and the Vietnam War upturn in 1967, oil crises in 1974 and 1980, and so on.

In the MSMH-VAR contemporaneous correlation between *CPI* and *r* is positive in both regimes: 0.202* in the "low volatility" regime,[17] which is needed mainly after financial liberalization starting in 1980, and 0.218* in the "high volatility" "loose monetary policy" regime, which is most typical around recessions leading eventually to devaluations in 1964, 1967, 1971 and 1973 - 80. In the MSIH-VAR contemporaneous correlations are of the same sign, equal to 0.136* in

Regime 1 and 0.227* in Regime 2. Reordering the variables and adding an additional explanatory variable *y* this did not alter the previous results much.

In addition, returns seem to "forecast" output in the sense that its estimated mean from the MSIH(2)-VAR(3) first starts its upward and downward movements compared to the output mean as shown in Figure 3.3. The graph of the means of *r* and *y* also reveals some seasonality in *y* before 1980. Note that we have not seasonally adjusted the data, as this might erroneously eliminate important nonlinear properties from the data.

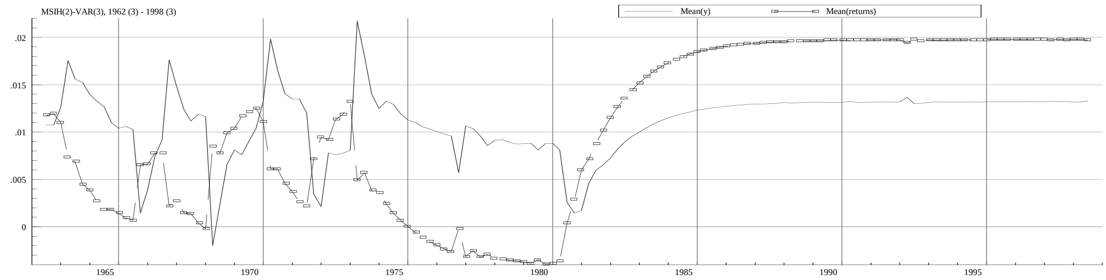


Figure 3.3: Means of quarterly returns and output based on the estimated MSIH(2)-VAR(3) model, where $z = [y\ MCI\ r\ CPI]'$ for 1962/4 - 1998/3.

In general, high inflation in the past is expected to lower present stock returns as high inflation typically leads to higher inflation expectations. Rational investors would then require compensation for this when making their investment decisions. To check further whether stocks provide a good hedge against inflation, we look at the estimated coefficients for lagged CPI in the stock return equation of the MS-VAR model. In the MSIH- and MSMH-VAR they are mainly negative but statistically insignificant at conventional levels. By contrast, the measure of monetary policy stringency has a statistically significant negative coefficient in the stock return equation: higher past interest rates, i.e., tighter monetary policy indicate a fall in today's returns. Higher interest rates make corporate borrowing more costly, and hence its output and the value of the stock falls. Finland's history of inflation - devaluation cycles may make people interpret tighter monetary policy as a sign of higher inflation to come; first leading to a recession (a fall in stock prices) and, finally, to a devaluation of the *markka* to get the economy out of a slump.

All the models estimated have gone through the model diagnostics briefly described above. Nevertheless, to save some space, these results are reported only when we want to stress the statistical problems which may have remained in the analysis. In the above case the model diagnostics showed some outliers in the distributions of standardized residuals and smoothed and prediction errors of the MSIH-VAR (Appendix 3.4). Residual correlograms do not have any marked peaks, and residuals are not autocorrelated. Furthermore, flat spectral densities indicate that there is no regular behavior in the series (the model successfully distinguishes seasonality in *y*). When we test the normality of the standardized residuals and the prediction errors, we observe flat tails and some extra kurtosis. This may indicate the presence of ARCH effects. Hence, strictly speaking, some statistical problems have remained in these models. However, regarding the presence of ARCH effects, changes in regimes can be important sources of persistence in the conditional variance of a time-series. Later, we test whether adding an additional regime to describe the behavior of the data improves the results.

We continue by cointegration tests. As the data-generating process is assumed to have regime switches, the model used in testing cointegration is only an approximation. Different lag lengths *p* in the VAR should thus be considered. Here, based on the maximum eigenvalue and trace test, the cointegration rank is two when $p = 1$, and the system has full rank when $p = 3$. The constant plus the dummies *Y1* = {1971/1} and *R1* = {1992/3} are entered in the cointegration space unrestricted. The former allows for a non-zero drift in any unit-root processes found by the cointegration analysis. As a quadratic deterministic trend in levels of economic variables is not usually a sensible long run outcome, the trend is entered restricted, or is forced to lie in the cointegration space, thus restricting the system to at most a linear deterministic trend in levels. The trend reflects such things as the long run growth in trading as well as technical progress in the stock market. Several cointegration restrictions introduced in Table 3.8 are established. Using $p = 1$ we find cointegration between the *CPI* and *y* (H2) in the first β eigenvector and between *y* and *r* (H1) in the second. A general cointegration test or testing rank = 2 is accepted: the $\chi^2(1)$ test has a *p*-value of [0.756]. Setting the coefficient for *y* equal to one and the *CPI* equal to minus one (H2) and trend to zero in the first β eigenvector and correspondingly one for *r* and minus one for the *CPI* (H3) in the second, rank = 2 is also accepted (α unrestricted). In practice, before introducing these cointegration vectors in the system as exogenous variables *X*, they had to be normalized such that $E_t(Z_{t-p}) = 0$. Hence, the MS-VECM are also cited as MS-VARX models.

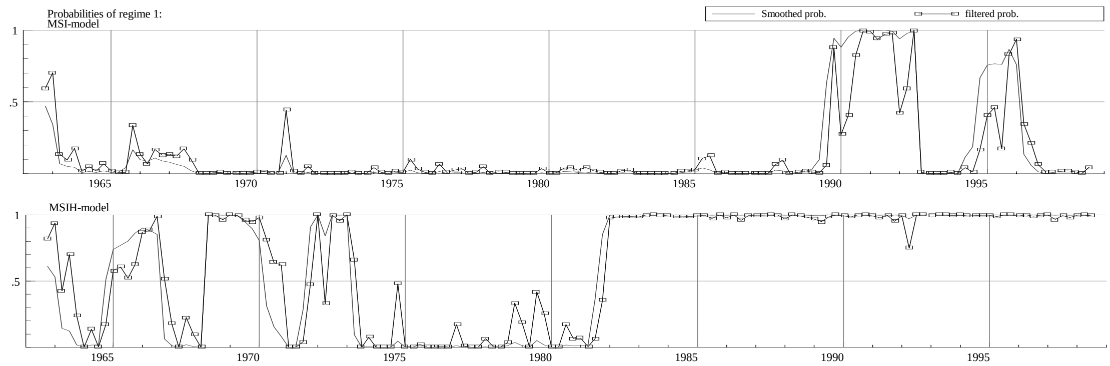


Figure 3.4: Smoothed and filtered probabilities from the quarterly MS-VARX models for 1962/4 - 1998/3, where $z = [y\ MCI\ r\ CPI]'$ with cointegration vectors $CI_1 = [1\ b_{12}\ b_{13}\ -1]'$ and $CI_2 = [b_{21}\ b_{22}\ 1\ -1]'$.

The results from the cointegrating Ely & Robinson model for 1962/4 - 1998/3 are reported in Appendix 3.5. In the MSI(2)-VARX(1) with the cointegration vectors $CI_1 = [1\ b_{12}\ b_{13}\ -1]'$ and $CI_2 = [b_{21}\ b_{22}\ 1\ -1]'$ Regime 1 identifies the recession in 1963 and especially that in 1990 - 93 (Figure 3.4). Regime 1 also has a high probability in 1995, when Finland was still suffering from the banking crisis. These are also periods of tight monetary policy. The only coefficient which is now clearly statistically significant in this model is the coefficient of CI_1. Secondly, the LR linearity test value is quite small, and information criteria suggest that a linear system should be preferred. Since the results from the MSM(2)-VARX(1) are quite similar, we continue by looking at the MSIH- and MSMH-VARX instead.

In the MSMH(2)-VARX(1) Regime 1 identifies devaluations, and there is a permanent regime switch after 1980. Once again, corr(*CPI,r*) is positive in both regimes (0.091 and 0.167*). Similar results apply to the MSIH(2)-VARX(1). The contemporaneous correlation is 0.097 (0.143*) in Regime 1 (Regime 2). As correlations are statistically significant only in Regime 2, which typically distinguishes the low volatility periods in the data, we conclude that stocks are a good hedge against inflation during the steady states in the economy. Both cointegration vectors are also significant in the equation for *r*, indicating that the long run dependences of the economy matter to investors. Nevertheless, the coefficient for CPI_{t-1} in the return equation is almost minus one in both models: -0.968* (-0.999*). We try to explain this by the results of the unit root tests (Table 3.6) as there was some evidence of the *I(2)*:ness of inflation. Taking the first differences of the logarithm of *CPI* may therefore be insufficient to achieve stationarity of this series. Besides, model diagnostics show that some cyclical variation is still left in the model.

The regime shifts based on MS-VARX with $CI_1 = [1\ b_{12}\ b_{13}\ -1]'$ and $CI_2 = [1\ b_{22}\ 1\ b_{24}]'$ do not differ much from those given in Figure 3.4. The linearity test has a small value in the case of both the MSM(2)- and MSI(2)-VARX, and all coefficients for lagged explanatory variables in the equation for returns are statistically insignificant (Appendix 3.6). In contrast, cointegration coefficients and (negative) coefficients for lagged *CPI* are significant in the case of the MSIH- and MSMH-VARX. These latter coefficients are again close to one, which warns us of possible I(2):ness of inflation. Once again contemporaneous correlations are statistically significant in Regime 2, which identifies steady periods in the economy. This indicates that stocks are a good hedge against inflation during low volatility periods.

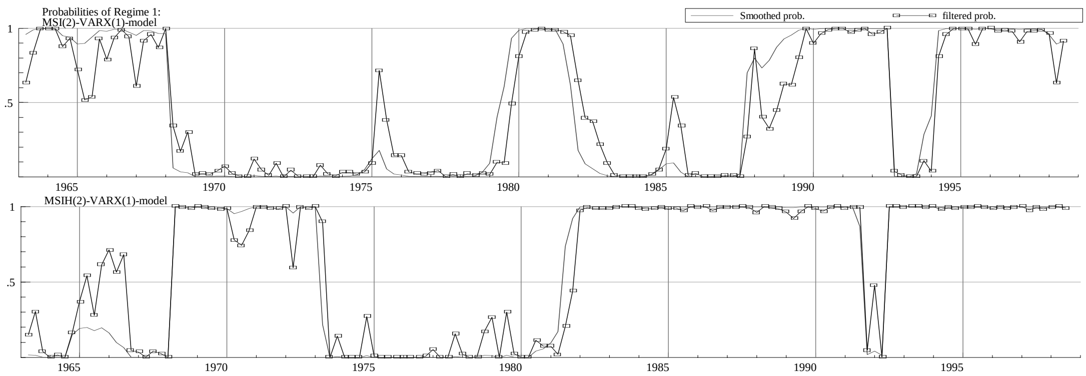


Figure 3.5: Smoothed and filtered probabilities from the quarterly MS-VARX models for 1963/2 - 1998/3, where $z = [y_r\ MCI\ r_r\ CPI]'$ with cointegration vectors $CI_1 = [1\ b_{12}\ b_{13}\ -1]'$ and $CI_2 = [b_{21}\ b_{22}\ 1\ -1]'$.

The MS-VAR are also estimated using real returns r_r and real output y_r to see whether the results differ much from nominal variables. The main reason for using nominal variables has been already explained above (see Chapter 3.5.1 and Endnote 3). First, we test for cointegration including the dummies *R1* and *Y1* and find evidence of two cointegrating vectors. The cointegration restrictions H2 and H3 are accepted, and the corresponding cointegration vectors are included in the system (Appendix 3.5). This changes the previous results as follows: first, these models seem to identify periods following revaluations in Regime 1 and devaluations in Regime 2. In contrast with models estimated using nominal values, we can also see the shift into a floating exchange rate regime in 1992/9 as a change in regimes. Regime 1 is also characterized by smaller *y*, *MCI* and *CPI* variances than in Regime 2. Now, contemporaneous correlation between r_r and *MCI* is positive in Regime 1; i.e., the tight monetary policy and low volatility regime, and changes its sign in Regime 2. Furthermore, lagged MCI_{t-1} has a positive and statistically significant coefficient in the MSMH-VARX equation for returns. In contrast to what we are used to expect; i.e., that higher interest rates make stock prices fall, a rise in interest rates now seems to have a positive effect on the stock market. Perhaps this rise in interest rates was needed to stop the economy from overheating.

The above models clearly need to be modified further. The main reason for using quarterly data was that the Bank of Finland measure of monetary policy stringency is available only on a quarterly basis. However, to get the benefits of increased sample size, we continue by using monthly data. Furthermore, the Ely-Robinson model is expanded using information about exchange rates against the US dollar and the German *mark*, foreign interest rates and foreign inflation following the outlines set by the small open economy models.

3.6.1.3 Results using monthly data

In the monthly model following Ely & Robinson (1997), monetary policy stringency is first measured using $M1$; i.e., $z = [y\ M1\ r\ CPI]'$ in 1953/3- 1998/11. For reasons given above this series is different from the MCI constructed by the Bank of Finland. First, we test cointegration in the data, since modeling the long run relationships between y and CPI (CI_1) or r and CPI (CI_2) may help us to locate the regimes in the data more precisely. The maximum eigenvalue test and trace test imply that cointegration rank is equal to one or two when $p = 2$, or one or zero when $p = 13$ based on the Akaike Information Criteria (AIC). The dummies $R1$ and $Y1$ are used similarly as in the quarterly model.[16] Testing the cointegration restriction H2 lets us accept that the cointegration rank is one: $\chi^2(1) = 3.299$ [0.069]. The cointegration restriction $[b_{11}\ b_{12}\ 1\ -1]'$ is also accepted. These cointegration vectors are stored for use in subsequent analysis. Similarly, we tested the cointegration restrictions H1 and H4 but in all cases rank = 1 is rejected.

In the resulting MSI(2)- and MSM(2)-VARX(2) (Appendix 3.7), where $CI_1 = [1\ b_{12}\ b_{13}\ -1]$, shifts into Regime 1 are located around 1956 - 59 (general strike, devaluations), 1964 - 68 (recession), 1974 - 78, 1980 - 82 (the oil crises), 1985 and 1989 - 93 (hard currency policy and deregulation of financial markets). Thus this regime seems to pick out recessionary, high inflation/high interest rate periods, which were typically followed by devaluations (μ_L is negative in Regime 1 whereas μ_T is positive in Regime 2, and both are statistically significant in each model). Furthermore, returns depend positively on lagged returns, and the coefficient of CPI_{t-2} is positive and statistically significant in the MSI-VARX as well. When cointegration is found between r and CPI, or $CI_2 = [b_{11}\ b_{12}\ 1\ -1]$, Regime 1 still identifies recessionary, high interest rate periods. Contemporaneous correlations are positive but statistically insignificant as in the case of CI_1. However, these models are not considered here in more detail as it is hard to explain the erratic smoothed and filtered probabilities obtained. Hence we modify these models to get a better figure of the relationship between returns, inflation and monetary policy stringency.

When we consider y_r and r_r the results change as follows (Appendix 3.7): first, cointegration was tested but rejected. Next, we test whether the variance covariance matrices $\Sigma_i(s_t)$, $i = 1,2$, are in fact regime independent. In the case of testing the MSI- against the MSIH-VAR model, LR = -2*(5269.04 - 5026.03) = -486.02**. Similar results are obtained when we test the MSM- against the MSMH-VAR. Hence, we reject homoskedasticity, and continue by looking at the MSIH-VAR. In the mid-1990s Finland adjusted its monetary and fiscal policy to be able to join the European currency union. In practice this meant tighter monetary policy as Finland wanted to be rid of its bad reputation for using devaluation to restore the price competitiveness of its open sector. Based on both the MSIH- and MSMH-VAR the process stays in Regime 2 after 1992, confirming a change in policy. Nevertheless, contemporaneous correlations between r_r and *CPI* are still significantly negative, except in the case of the MSMH(2)-VAR(3). In the MSMH- and MSIH-VAR the coefficients of CPI_{t-3} in the equation for r_r are also negative, -0.567* and -0.336* respectively. According to Bakshi & Chen (1996) this latter correlation is negative only when monetary policy is counter-cyclical. The coefficients of $M1_{t-3}$ are positive and statistically significant in these models as well. Nevertheless, as we have difficulty in interpreting the graphs of the estimated regime probabilities, we choose to continue with the analysis.

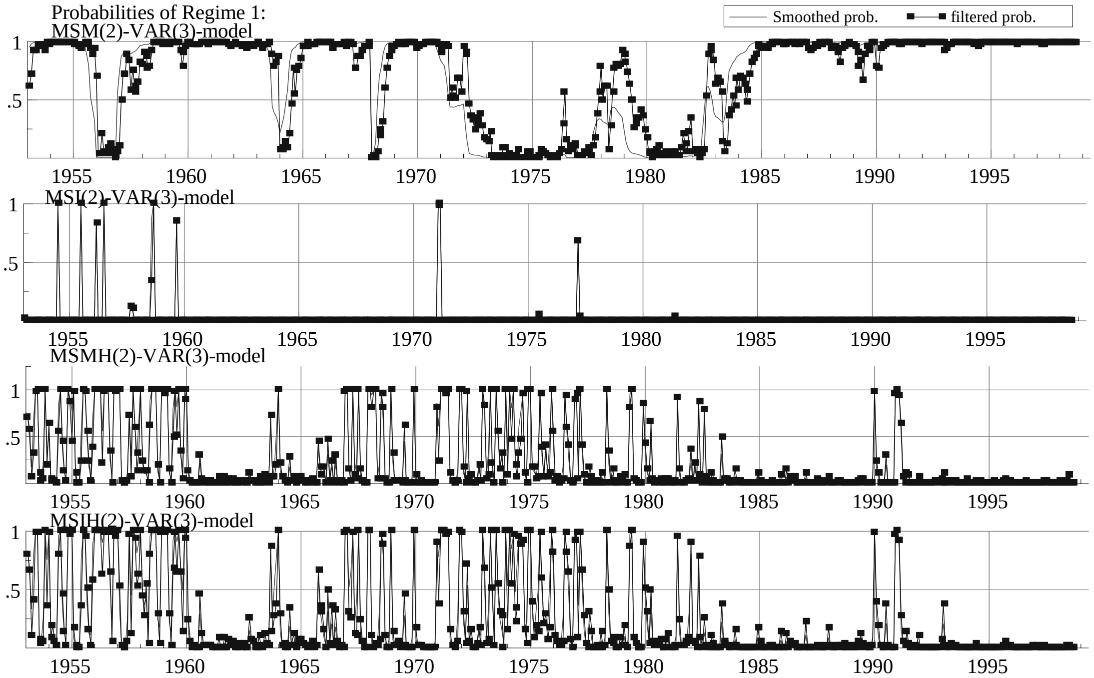


Figure 3.6: Smoothed and filtered probabilities from the MS-VARX models for 1953/2 - 1998/9, where z = [y_r *M1* r_r *CPI*]′.

Next, we test weak exogeneity in the Ely-Robinson model. Output, for example, is weakly exogenous for the long run equilibrium if an unanticipated shock to *y* has a significant long run impact on a system. If the null hypothesis is accepted, one stochastic trend in the system is probably given by *y* (a real trend). Nevertheless, weak exogeneity of output is rejected. Finally, this model is augmented by adding domestic interest rates and the exchange rate to the set of explanatory variables.

Under fixed exchange rates domestic inflation follows foreign inflation and the only monetary variable which affects the real economy is the exchange rate. Small changes in the exchange rate are now expected to have little influence on returns as long as the current account balance is not threatened. Following Järvinen (1998) we add new explanatory variables in the VAR, i.e., *z* = [*y M1 i CPI* e_{USD} *r*]′, but use e_{USD}, instead. The first estimation period is 1973/2 - 1998/11. First, we test cointegration in the system. Now, depending on which information criterion we use, we focus on lags *p* = 1, 2 or 12 in the VAR, and the cointegration rank obtained is in the same order: 3, 3 and 2. When *p* = 1 or *2* we cannot identify the cointegration vectors based on the restrictions given in Table 3.8. Similarly, testing weak exogeneity of *y* leads to the rejection of rank = 3. Selecting the restrictions based on the estimated β led us to draw the same conclusion that cointegrating vectors remain unidentified. We therefore now fit the MS-VAR as such to the data.

Similarly, the LR tests indicate that modeling heteroskedasticity improves the models considerably. Based on the MSIH- and MSMH-VARs, the contemporaneous correlation between *r* and *CPI* is however statistically insignificant at conventional levels. Nevertheless, in the MSMH-VAR the coefficient for $e_{USD(t-1)}$ is positive, and significant together with the coefficient for r_{t-1}. Hence, an appreciation of the exchange rate decreases returns, which is in line with the traditional approach. Model diagnostics from this model show some fluctuations or slight peaks in spectral densities, which indicate regular cyclical or seasonal behavior in the corresponding time-series. This may also be due to ARCH effects remaining in the model residuals. This makes us ask to what extent the regime-switching approach actually manages to describe the nonlinearity of the relationship.

The above model has also been estimated for the shorter time period of 1987/1 - 1996/12. Cointegration tests produced the following results: the real activity hypothesis is rejected,[18] as is the weak exogeneity of *y*. Other cointegration restrictions were also tested but without any success. Only $CI_1 = [b_{11}\, b_{12}\, b_{13}\ {-1}\ 1\ b_{16}]'$ is accepted based on the maximum eigenvalue test. This vector, which possibly describes the inflation/devaluation cycle, is stored for further analysis. The results from the MS-VARX using this cointegration vector are given in Appendix 3.8.

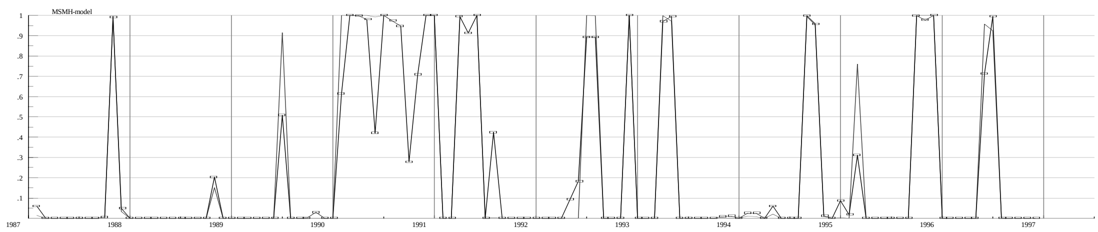


Figure 3.7: Smoothed and filtered probabilities from the MSMH(2)-VARX(2) model for 1987/1 - 1996/12, where $z = [y\ M1\ i\ CPI\ e_{USD}\ r]'$ with a cointegrating vector $CI_1 = [b_{11}\ b_{12}\ b_{13}\ {-1}\ 1\ b_{16}]'$.

Judging by the LR test the MSIH- and MSMH-VARX should be preferred. Figure 3.7 of the smoothed and filtered probabilities of the MSMH(2)-VARX(2) indicates that Regime 2 now takes place at high probability except around 1987/10, 1988/10, 1989/6 (revaluation in 1989/3), 1990 - 91 (a drop in returns), 1991/3 - 1991/5, 1992/6 - 1992/7, 1993/3 - 1993/4, 1994/8 - 1994/9, 1995/9 - 1995/11 and 1996/6. Typical of these dates is that they all occur close to times when negative shocks have hit the Finnish economy. Note that the smoothed and filtered probabilities fluctuate, with durations of the estimated regimes of around a year or six months. Perhaps it has taken some time for the market to adjust to the regular introduction of shocks to the economy, which would explain this kind of behavior. CPI_{t-1} now has a positive, statistically significant coefficient in the stock return equation. The cointegration vector has a significant coefficient as well. Hence, after including cointegrating vectors to identify the long run behavior of the system and after being able to capture negative shocks to the Finnish economy with these models, we conclude that investors adjust their required returns to inflation in about a month. The coefficient for e_{USD} is also positive, i.e., appreciation of the exchange rate against the US dollar reduces returns. Appreciation of the domestic currency reduces the competitiveness of the firms' products abroad, which could explain this. During the estimation period the *markka* appreciated before it was devalued in 1989, at the beginning of 1990, and after the Bank of Finland set its inflation target in 1993.

We also try to control the role of interest rates in the system by adding both domestic and foreign interest rates to the set of explanatory variables, i.e., $z = [y\ M1\ i\ r\ CPI\ e_{USD}]'$. For example, tighter monetary policy increases interest rates and makes corporate borrowing more costly, thus causing the price of the stock to fall. The coefficients for interest rate are now not significant in any of the models estimated. Only in the case of MSIH(2)-VAR(3) are the coefficients for CPI_{t-3} and $e_{USD(t-3)}$ in the equation for r negative and statistically significant. Unfortunately, it is not clear why changes in CPI and e_{USD} would show in returns with a lag of three months. Contemporaneous correlations between r and CPI are not statistically significant in these models either.

Finally, the dependences of the economy on neighboring countries are imported into the analysis using German data following Starck (1990).[19] Germany is and has been an important trading partner of Finland, and it is therefore sufficient to assume that changes in German output, for example, influence the Finnish economy. The results from the models for 1976/5- 1998/1, where $z = [y\ CPI\ M1\ r\ i^*\ e_{DEM}]'$ or $z = [y\ CPI\ i\ r\ e_{DEM}\ y^*\ CPI^*\ i^*]'$ are given in Appendix 3.9.

First, we test against the cointegrating vectors $y + e_{DEM}$ and $y + CPI - M1$ using the first set of explanatory variables. We also use dummies to capture Black November and the devaluations *(D1)*. The results suggest that there are two cointegrating vectors. Unfortunately, clear upward trends, that is nonstationarity in these vectors are apparent, and hence have been omitted from further analysis. Instead, only i^* and e_{DEM} have statistically significant coefficients as explanatory variables in the MSI(2)-VAR(2) equation for r. Similarly, in the MSIH CPI_{t-2}, $M1_{t-1}$, r_{t-1} and $e_{DEM,t-1}$ have positive statistically significant coefficients. Finally, all significant contemporaneous correlations between r and CPI are negative. However, giving economic interpretation to regimes is difficult because of erratic fluctuations in both smoothed and filtered probabilities.

Using the second set of explanatory variables the MSM- and MSI-VAR models identified the structural break in the Finnish economy after the recession in the 1990s. The probability of staying in Regime 1 is now 1.0, and the duration of staying in this regime is also very high. This suggests that the other regime is only needed to pick up a few exceptional periods in the data. We also found evidence of four cointegration vectors, but were unable to identify them. This is not surprising, as the system was close to full rank based on the trace test. However, the LR tests indicate once again that we should rather focus on models in which we have taken heteroskedasticity into account.

Since 1993 Finland has had an explicit inflation target, and the main goal of monetary policy has clearly been to get rid of inflation - devaluation cycles. Accordingly, in the MSMH-VAR Regime 1 has a high probability after 1993. Furthermore, since the 1990s compensation for inflation may not have been as important to stock market investors as before. Shorter holding periods of stocks and global diversification of investor portfolios make the economic fundamentals of an individual country matter less. Still, since we detect statistically significant negative correlations between CPI and r in Regime 1, we conclude that Finland's new anti-inflationary policy may not have convinced investors after all. Inflation expectations may have remained high causing upward pressure on the interest rates used in discounting stock prices (stock prices fall). Besides, in the MSIH- and MSMH-VAR r_{t-1} and $e_{DEM(t-1)}$ have positive and statistically significant coefficients in the equation for r. In other words, easing monetary policy by letting the exchange rate devalue has increased returns (the traditional approach).

So far we have assumed that we only need two regimes to describe the behavior of the data. However, sometimes three may be needed to describe the behavior of the economy, for example, tight or loose monetary policy regimes, and one regime to describe periods of neutral monetary policy. The previous models have been therefore slightly modified to allow for three different regimes.

3.6.1.4 The MS-VAR model with three regimes

As an example of how including a third regime may influence the results we consider the MSM(3)- and MSI-VAR(3) models,[20] where $z = [y\ M1\ i\ CPI\ e_{USD}\ r]'$ for 1987/1- 1996/12. Now, the estimated transition matrix and unconditional probabilities together with duration in Table 3.9 give us information similar to the figures for the filtered and smoothed probabilities. The unconditional probability of being in Regime 2 is highest [0.877] of these three regimes. Its duration is around a year and a half (17 months). In contrast, we have only approximately four observations in Regime 3 and if the process ever reaches this regime, it stays in it only for a month. Moving from Regime 1 to Regime 3 is more likely than moving into Regime 2. Once we have reached Regime 3 we move back into Regime 1 with a probability of [0.086] and to Regime 2 with a probability of [0.028].

Table 3.9: Estimated transition matrix with unconditional probabilities and duration from the MSI(3)-VAR(2) model, where $z = [y\ M1\ i\ CPI\ e_{USD}\ r]'$ for 1987/1 - 1996/12.

Regime	**Regime 1**	**Regime 2**	**Regime 3**	**Nobs**	**Prob.**	**Duration**
Regime 1	0.626	0.03	0.231	11.6	0.091	2.671
Regime 2	0.289	0.942	0.769	104.45	0.877	17.156
Regime 3	0.086	0.028	0.000	3.945	0.032	1.0

The values of the first three columns correspond to transition probabilities from Regime *m* to Regime *n*, where *m =1,2,3 & n = 1,2,3*. Nobs= number of observations in Regime *m(n)* and Prob. = unconditional probability. Duration gives the expected time the process stays in Regime *m(n)*.

Figure 3.8 shows that Regime 1 in the MSI(3)-VAR(2) identifies the drop in stock returns due to the recession in 1990 and the period of high interest rates following a revaluation in 1991. Regime 2 mainly describes the "normal periods" with, for example, rising returns for 1987 - 89. The system stays mainly in Regime 2. Regime 3 identifies some peaks in 1990, 1991/3, 1992/8 (just before the *markka* was forced to float as Finland failed to defend its currency) and in 1992/12. Thus, the third regime seems to pick out extraordinary periods in the economy. We are most likely to reach this regime after normal times (Regime 2). This suggests that shocks to the Finnish economy may have arrived as a surprise (exogenous foreign shocks).

Regimes one and three have significant means/intercepts in these models. Contemporaneous correlation in the MSI(3)-VAR(2) (MSM-VAR) between *r* and *CPI* is again negative -0.106 (-0.174*). But now, in the MSI-VAR, CPI_{t-1} has a positive coefficient of 3.445* together with positive statistically significant coefficients for e_{USD} and r_{t-1}. In other words, if inflation rises, stock returns adjust accordingly but with a lag. Similarly, exchange rate appreciation causes a fall in returns as suggested by the traditional approach, and returns themselves are positively correlated.

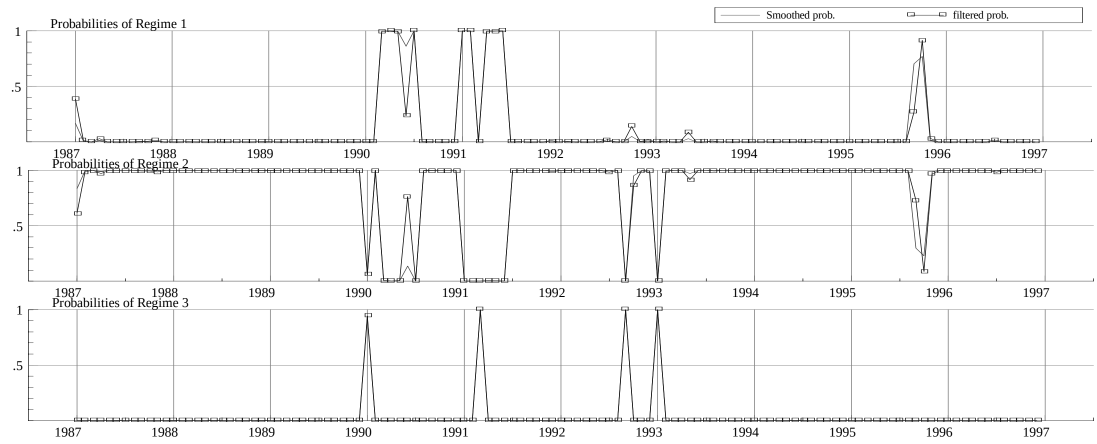


Figure 3.8: Smoothed and filtered probabilities from the MSI(3)-VAR(2) model for 1987/1 - 1996/12, where $z = [y\ M1\ i\ CPI\ e_{USD}\ r]'$.

These results confirm that various forms of the MS-VAR are useful in finding changes in regimes in the data. Unfortunately, it is not easy to tell whether changes in regimes are due to changes in monetary policy or in the structure of the economy as a whole. Some of the "spurious" results reported in the literature may suffer from this kind of identification problem as well, which should be kept in mind. The set of explanatory variables used in the study alters the results slightly as well. Finally, remembering that evaluating monetary policy stringency is not straightforward, we expand the basic model by an alternative monetary policy stringency measure, i.e., the interest rate set on bank borrowing from the Central Bank.

3.6.1.5 The role of the credit control

Bank borrowing from the Central Bank played a major role in the monetary policy pursued by the Bank of Finland for 1950 - 84 (Saarinen, 1986). Until 1985 the Bank of Finland controlled the tightness of the credit market by regulating the terms of the Central Bank debt of the banks and interest rates. Hence, either the total credit advanced to the public by commercial banks c_p (a million Finnish *markka*) or the marginal interest rate for funds advanced by the Central Bank to commercial banks c_i is used in the place of *M1* in the following MS-VAR models. The pros and cons of using these variables have been already discussed in Section 3.3 above.

First, we conduct Dickey-Fuller unit root tests using logarithms and differences of logarithmic c_p (c_i). The null hypotheses of a unit root cannot be rejected in the former, but differencing the data makes it stationary. Unfortunately, taking differences leaves nonlinearity in the c_p series unattached, as we can see from Figure 3.9. Furthermore, the variance of y and r is much higher than in the *CPI* and c_p series. Together, these properties of the data may explain the problems in solving the MS-VAR models. As we know from recent economic history, the late 1980s was also the period of extra liquidity, or a rise in c_p in Finland, which eventuated as a rise in housing and equity prices. In other words, there was a period of high liquidity followed by a deep recession, when total credits advanced to the public dropped dramatically. People even started to pay back their debts and, because of the poor record of bankruptcies, a higher share of personal financing for investments in equities or housing markets was required from the banks. Therefore, the problems in estimating the MS-VAR could also be due to a structural break which the two-regime models are unable to take into account.

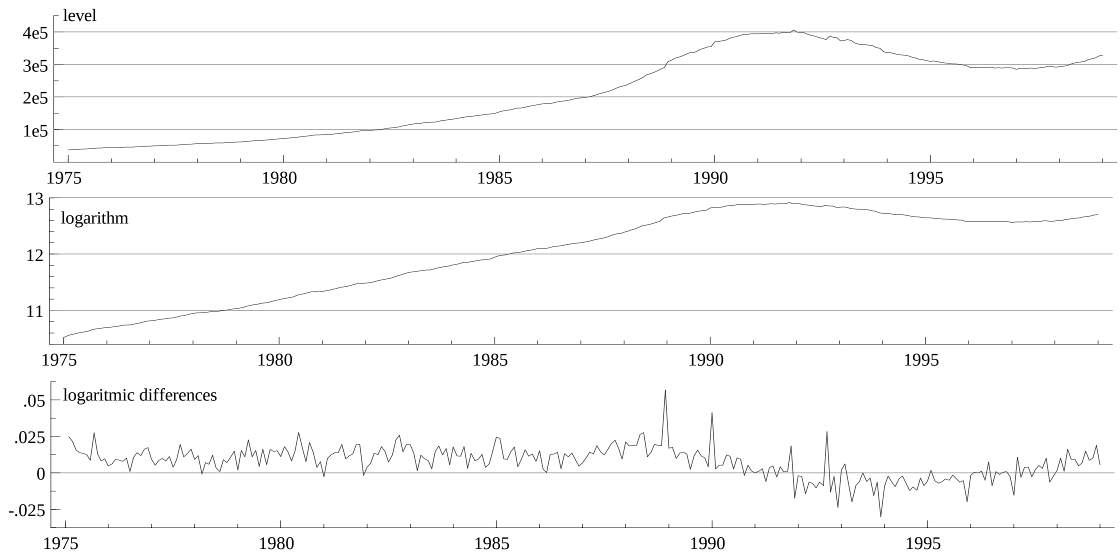


Figure 3.9: Total credit advanced to the public in levels, logarithms and differences of logarithmic credits for 1976/4 - 1999/1 (monthly data).

In the model $z = [y\ c_p\ r\ CPI]'$ for 1976/4 - 1999/1 we test cointegration between y - CPI, y - r, y - c_p, etc. The only cointegrating restriction which we accept is $CI_1 = [b_{11}\ b_{12}\ 1\ {-1}]'$ when $p = 7$. Solving large MS(M)-VAR(p) takes time and, since the results are typically only as good as when we use shorter lags, further analysis is carried out without focusing on the long run relationships (Krolzig, 1997). When c_p in this model is replaced by c_i, the most obvious cointegration restrictions are rejected.

Using c_i to measure monetary policy stringency in the model $z = [y\ c_i\ r\ CPI]'$ for 1953/2 - 1998/9, we get the following results (Appendix 3.10). Based on the LR test, heteroskedasticity should be modeled. As the MSMH-VAR(2) did not solve, we estimated an MSH(2)-VAR(2) instead. Negative contemporaneous correlation applies between r and CPI (-0.079*), but otherwise only lagged returns have explanatory power for r. Compared to the model with $M1$ as a measure of monetary policy stringency, lagged CPI has positive coefficients more often. In the end, the results change when we replace $M1$ by variables describing credit rationing in Finland. But, as c_i (c_p) may not be sufficient in describing monetary policy stringency alone, the system is further expanded by adding e_{USD} to it. CPI_{t-2} now gets a positive statistically significant coefficient only in the case of the MSI-VAR, and contemporaneous correlations are no longer statistically significant.

In order to find regularities in the results, we present below a summary of the contemporaneous correlations between stock returns and inflation obtained from all the estimated MS-VAR models. As interpreting the estimated parameters from these models is not always easy, we conclude this study with some results from the regime-dependent impulse response functions.

3.6.2 Summary of the results

Looking at the survey given by Sellin (1998), it seems clear that money can help predict stock returns to some extent (Appendix 3.11). In Table 3.10 we have gathered the contemporaneous correlations corr(*CPI,r*) based on the MS-VAR models with different sets of explanatory variables, and using both quarterly and monthly data for various periods. Now, all significant positive contemporaneous correlations are related to quarterly data, where we have used *MCI* as a measure of monetary policy stringency. In contrast, in the case of monthly data significant correlations between returns and inflation are all negative. This is also the case with the monthly models, including the main components of *MCI*, i.e., the exchange rate, domestic and foreign prices and domestic interest rates. When we use real output and real returns or include cointegrating vectors in the system, the results remain unaltered. Hence we conclude that stocks are a good hedge against inflation in the "long run," i.e., a period of more than four months.

TABLE 3.10: Contemporaneous correlation between inflation and stock returns: a summary.

Quarterly data				
Model	**period**	**variables**	**cointegration**	**corr(*CPI,r*)**
MSI(2)-VAR(2) MSIH(2)-VAR(2) MSMH(2)-VAR(2)	1962/4- 1998/3	*CPI, MCI, r*	Estimated without cointegration vectors.	-0.135 0.104/0.152* 0.147*/0.178*
MSI(2)-VAR(3) MSM(2)-VAR(3) MSIH(2)-VAR(3) MSMH(2)-VAR(3)		*y, MCI, r, CPI*	Estimated without cointegration vectors.	-0.109 0.080 0.136*/0.227* 0.202*/0.218*
MSI(2)-VARX(1) MSM(2)-VARX(1) MSIH(2)-VARX(1) MSMH(2)-VARX(1)		*y, MCI, r, CPI*	H2 H3	0.004 0.008 0.097/0.143* 0.091/0.167*
Monthly data				
Model	**period**	**variables**	**cointegration**	**corr(*CPI,r*)**
MSI(2)-VARX(1) MSM(2)-VARX(1) MSIH(2)-VARX(1) MSMH(2)-VARX(1)	1962/4- 1998/3	*y, MCI, r, CPI, R1,Y1*	H2 H3	0.004 0.008 0.097/0.143* 0.091/0.167*
MSI(2)-VARX(2) MSM(2)-VARX(2)	1953/2- 1998/11	*y, M1, r, CPI, R1,Y1*	H3	0.030 0.023
MSI(2)-VARX(2) MSM(2)-VARX(2)		*y, M1, r, CPI,R1,Y1*	H2	0.021 0.013
MSI(2)-VARX(1) MSM(2)-VARX(1) MSIH(2)-VARX(1) MSMH(2)-VARX(1)		*y, M1, r, CPI, R1,Y1*	H1 H2	0.005 0.008 0.098/0.143 0.096/0.163

Model	**period**	**variables**	**cointegration**	**corr(*CPI,r*)**
MSI(2)-VARX(3) MSM(2)-VARX(3) MSIH(2)-VARX(3) MSMH(2)-VARX(3)	1953/2 - 1998/9	y_r, $M1$, r_r, CPI	Tested, but rejected.	-0.169** -0.165** -0.350**/-0.084* -0.0003/-0.00001
MSI(2)-VAR(1) MSM(2)-VAR(1) MSIH(2)-VAR(1) MSMH(2)-VAR(1)	1973/2- 1998/11	y, $M1$, i, CPI, e_{USD}, r	Estimated without cointegration vectors.	-0.142** -0.21 -0.070/-0.015 -0.067/-0.035
MSI(2)-VAR(1) MSM(2)-VAR(1) MSIH(2)-VAR(1) MSMH(2)-VAR(1)	1987/1- 1996/12	y, $M1$, i, CPI, e_{USD}, r	Estimated without cointegration vectors.	-0.129 -0.189* -0.263**/0.000 -0.220*/-0.058
MSI(2)-VARX(2) MSM(2)-VARX(2) MSIH(2)-VARX(2) MSMH(2)-VARX(2)	1987/2- 1996/12	y, $M1$, i, CPI, e_{USD}, r	H8	-0.003 -0.178* -0.099/0.032 -0.086/-0.000
MSI(3)-VAR(2) MSM(3)-VAR(2)		y, $M1$, i, CPI, e_{USD}, r	Three regimes, not tested.	-0.106 -0.174*
MSI(2)-VAR(2) MSM(2)-VAR(2) MSIH(2)-VAR(2) MSMH(2)-VAR(2)	1976/5- 1998/11	y, CPI, $M1$, r, i*, e_{DEM}	H4, H11rejected among others.	-0.117* -0.099* -0.140*/0.045 -0.097*/-0.001
MSI(2)-VAR(1) MSM(2)-VAR(1) MSIH(2)-VAR(1) MSMH(2)-VAR(1)		y, CPI, i, r, e_{DEM}, y*, CPI*, i*	Tested but rejected.	-0.021 -0.02 -0.115*/-0.010 -0.132*/0.061
Not solved (lag = 7)	1976/2- 1998/9	y, c_p, r, CPI	H3	-
MSI(2)-VAR(2) MSM(2)-VAR(2) MSIH(2)-VAR(2) MSH(2)-VAR(2)		y, c_p, r, CPI	Estimated without cointegration vectors.	0.022 0.04 -0.041/-0.005 -0.079/0.013
MSI(2)-VAR(2) MSM(2)-VAR(2) MSIH(2)-VAR(2) MSH(2)-VAR(2)	1953/2- 1998/9	y, c_i, r, CPI	Tested but rejected.	0.022 0.040 -0.041/-0.005 -0.079*/0.013
MSI(2)-VAR(2) MSM(2)-VAR(2) MSIH(2)-VAR(2)		y, c_i, r, CPI, e_{USD}	Tested but rejected.	0.032 -0.032 -0.066/-0.011

The H_i in the ´cointegration´ column refers to Table 3.8. Corr(*CPI,r*) is the contemporaneous correlation between *CPI* and stock returns based on the model given in the first column. Statistically significant correlations are marked with an asterisk, * at the 5% level and ** at the 1% level. The system variables are described in Section 3.5.1.

When we model heteroskedasticity in the data, the contemporaneous correlation between inflation and returns is more often statistically significant than based on the “simple” MSI- or MSM-VAR models. This is not surprising since, if the data is in fact heteroskedastic, and we have succeeded in modeling this behavior, the results become more precise. It is a well-known fact that estimated coefficients from mis-specified models are both inefficient and biased. After successfully modeling heteroskedasticity, we have also tried to see whether the contemporaneous correlations have different signs depending on whether the process is in a low or high volatility regime. It is intuitively clear that stock prices may keep up with inflation more easily if there are no sudden changes (volatility) in the economy as a whole. However, in all cases, when the correlation changes its sign in the two regimes, the positive correlation is insignificant. In many cases correlations are statistically significant only in Regime 2, which typically identifies the low volatility periods in the quarterly data. Thus we conclude that stocks are a good hedge against inflation in the long run and especially during the steady states in the economy.

3.6.3 The regime-dependent impulse response function

In spite of mean switches, which may have a natural interpretation as a business cycle, interpreting the estimation results from the MS-VAR models is not always straightforward. However, impulse responses[21] summarize the information in the autoregressive parameters, variances and covariances of each regime, thus making it easier to illustrate the model estimated. Hence, following Ehrmann et al. (2001) we define IRFs for each Markov regime to show how fundamental disturbances, in particular in output and money, affect the variables in the model dependent on the regime. Instead of one set of IRFs we now have a set for each regime.

Regime-dependent IRFs are obtained in two stages (Equation 1.12 in Chapter 1). First, MS-VAR models are estimated as described above. Next, restrictions (if necessary) are imposed on the parameter estimates to derive a separate structural form for each regime, from which the regime-dependent IRFs can be computed. The identification problem is solved as in Sims (1980). Endogenous variables are thus ordered, and it is assumed that since the fundamental disturbance to a variable has only contemporaneous effects on the variable itself and on variables ordered below it, a shock in one variable may be accompanied by a shock in another simultaneously. The results from IRFs must however be interpreted with care because the covariance matrix of the error term is regime-dependent, and hence the orthogonalized IRFs will differ across regimes. Thus, for each of the orderings of the variables, we get different IRFs describing the response of those variables dependent on the state of the system when the shock occurs. Furthermore, the validity of regime conditioning depends on the time horizon of the IRF and the expected duration of the regime. As long as the time horizon is not excessive and the transition matrix predicts regimes which are highly persistent the conditioning is valid, and the regime-dependent IRFs are a useful analytical tool.

Keeping these “warnings” in mind, the regime-dependent IRFs are now computed for some models, which we have already found useful in describing the data for illustrative purposes. We start with linear IRFs, which are computed for one standard deviation impulse to the innovations for each of the variables, without orthogonalizing[22] the variables. This is done for simplicity, and because we want to focus on possible differences in the responses between models and across regimes (Figure 3.10).

First, we consider the quarterly VAR model for 1962/3 - 1998/3, where $z = [y\ MCI\ r\ CPI]'$. Using this set of explanatory variables in the MS-VAR models contemporaneous correlations between r and CPI were positive and statistically significant in both regimes. Figure 3.10 shows that a positive output shock increases returns, and the effect is highest after a year. Tightening monetary policy on the other hand reduces returns, and also has its strongest effect after a year. Tighter monetary policy typically implies higher interest rates, which is expected to cause a fall in returns. In all cases the effect of a shock dies out in about eighteen months. In the case of orthogonalized impulse responses, this ordering of variables means that after applying the identification restrictions returns react to all variables except *CPI* within the same month.[23] However, the results suggest that orthogonalization has no influence in this case.

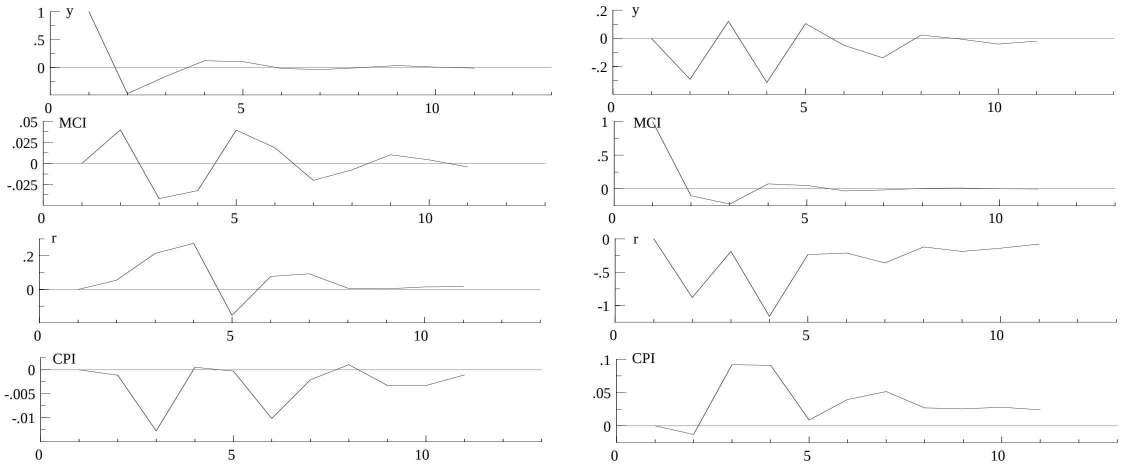


Figure 3.10: The unit linear impulse responses based on the quarterly VAR(3) model for 1962/3 - 1998/3, where z = [*y MCI r CPI*]´.
The first column represents output shock, and the second monetary shock.

Finally, we compare Figure 3.10 with the regime-dependent IRFs obtained from the corresponding MS-VARs (Figures 3.11 & 3.12). We are especially interested in finding out whether output and money shocks affect stock returns differently, even after taking the separate regimes into account. Giovannini (1989) has already shown that temporary dividend innovations (dividends = GNP) make stock prices fall. If the dividend risk for next period increases, precautionary demand for money increases, and investors substitute stocks for money to smooth consumption. This raises nominal interest rates, and hence stock prices fall. By contrast, if the shock is due to nominal disturbances, or there is uncertainty in money growth, stock prices should increase relative to money because the current liquidity value of money balances decreases (Table 3.1). We would also like to remind the reader about the difficulties in identifying monetary shocks. Besides, as MCI is derived from the goods market equilibrium condition, it is a long run relation, and should therefore be considered with caution when we try to describe the mechanism of shock transmission in these models.[24]

From Figures 3.11 & 3.12 we note that the effect of the one standard deviation shock conditional on the prevailing regime is quite similar in both estimated regimes (left-hand diagrams represent Regime 1 whilst right-hand diagrams represent Regime 2). In other words, the response to both output and monetary shocks are similar in both regimes. Nevertheless, compared to linear IRFs the response of returns to a positive monetary shock now changes its sign and becomes positive. The response of *CPI* to a positive *MCI* shock is also positive. As the contemporaneous correlations between *CPI* and *r* were also positive and statistically significant based on this model, it seems that stocks gain briefly relative to goods prices following monetary shocks as already found by Ely & Robinson (1997). Finally, both shocks die out quite quickly, in all cases in about five quarters.

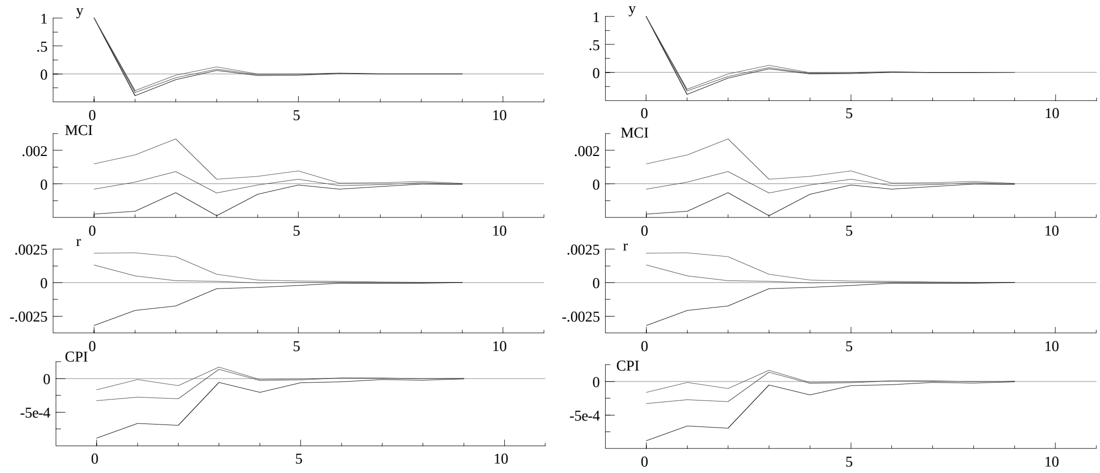


Figure 3.11: Responses to a one percentage point shock in output in the quarterly Ely-Robinson MSIH(2)-VAR(3) model for 1962/3 - 1998/3.
The confidence intervals indicated by dashed lines in the figures are obtained by employing standard bootstrapping techniques (5000 replications).

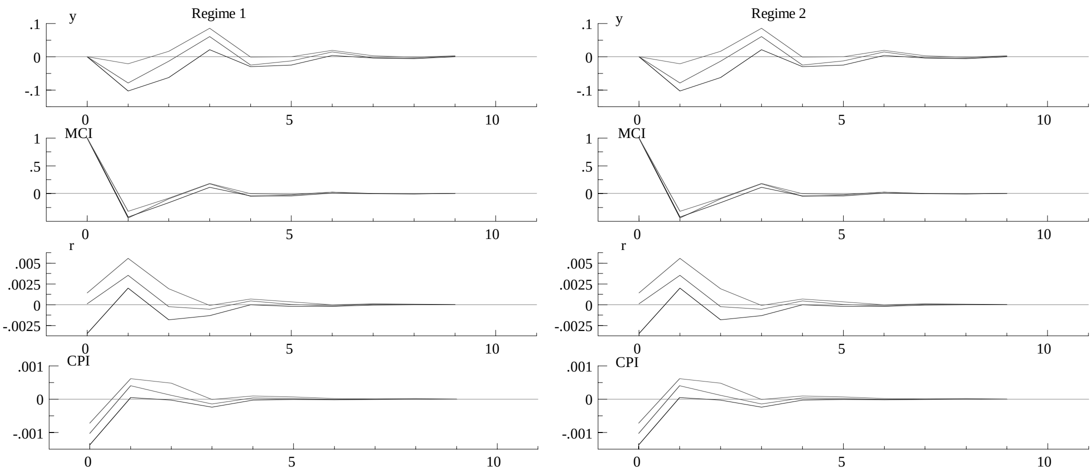


Figure 3.12: Responses to a one percentage point shock in *MCI* in the quarterly Ely-Robinson MSIH(2)-VAR(3) model for 1962/3 - 1998/3.
The confidence intervals indicated by dashed lines in the figures are obtained by employing standard bootstrapping techniques (5000 replications).

To see whether the choice of the set of explanatory variables or the sampling interval affects these results, we continue by scrutinizing a monthly model with an alternative measure of monetary policy stringency $c_{i,}$ or the marginal interest rate of funds advanced by the Central Bank to the commercial banks. The IRFs are given in Figures 3.13 and 3.14 ($z = [y\ c_i\ r\ CPI]'$). Now, in Regime 1 a positive output shock has positive influence on stock returns, but returns adjust back to their mean level in two months. An increase in output has only a minor effect on inflation, and the interest rates show a small temporary increase as well. To conclude, all variables respond to a positive output shock in an expected way. Furthermore, a positive interest rate shock influences stock returns negatively, but the response is quite small (Figure 3.14).

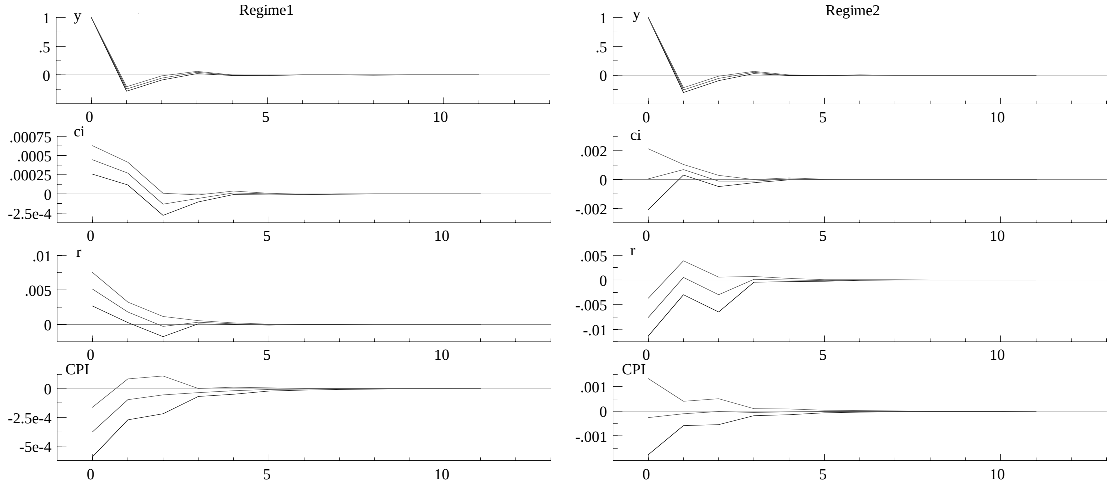


Figure 3.13: Responses to a one percentage point shock in output in the monthly MSH(2)-VAR(2), where z = [y c_i r CPI]´ for 1953/2 - 1998/9.
The confidence intervals indicated by dashed lines in the figures are obtained by employing standard bootstrapping techniques (5000 replications).

However, as against the previous results, the behavior in Regime 2 is no longer similar to that of Regime 1. For example, in Regime 2 returns respond to a positive output shock negatively (the response at lag one is basically zero) before returning back to their mean level in about three months. The response to a monetary or interest-rate shock also changes its sign, being clearly positive at lag 2. The magnitude of this shock is also larger than in Regime 1. We remember that Regime 1 was needed to identify the behavior in the system, especially after 1987. The probability of being in this regime is also very high (0.83).

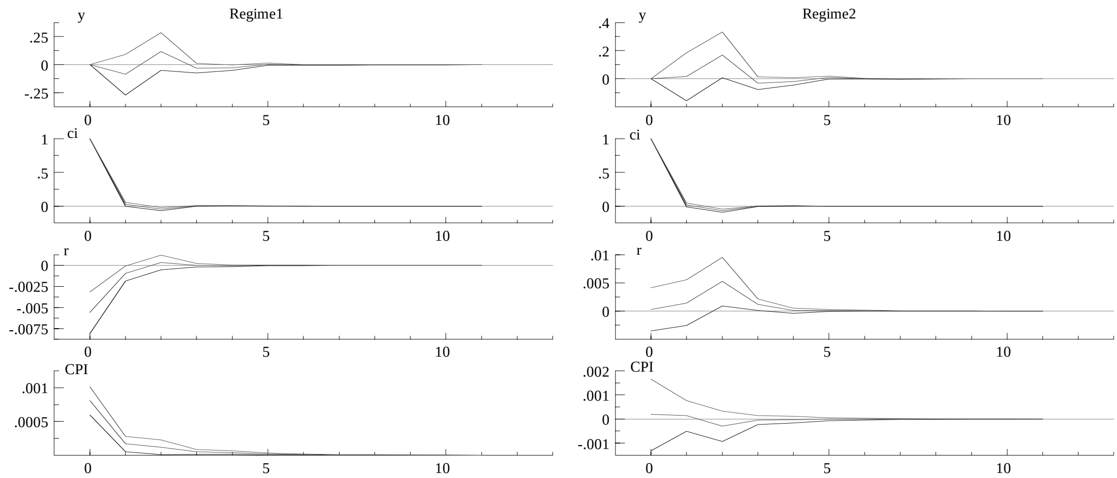


Figure 3.14: Responses to a one percentage point shock in c_i in the monthly MSH(2)-VAR(2), where z = [y c_i r CPI]´ for 1953/2 - 1998/9.
The confidence intervals indicated by dashed lines in the figures are obtained by employing standard bootstrapping techniques (5000 replications).

Since Regime 2 is mostly needed to pick out regime switches for which the duration is about 2 months, the positive response of returns to tighter monetary policy is linked to a few “exceptional” periods in the economy. For example, if loose monetary policy has led to high inflation and higher inflation expectations, stock returns are expected to fall owing to higher expected real interest rates. Similarly, stock returns would rise if tight monetary policy caused investors to reduce their inflation expectations. These results from the regime-dependent IRFs conclude this study. The source of the shock clearly matters.

3.7 CONCLUSIONS

We would normally expect positive correlation between real stock prices and inflation if stocks are a good hedge against inflation, an expectation often violated in reality. Furthermore, as equities are claims on future economic output, if monetary policy has real economic effects then shifts in it should affect stock prices. Consequently, we would like to know whether the negative relation between stock prices and inflation can be explained by counter-cyclical monetary policy. Does a fall in real activity lower stock prices and increase government budget deficits, typically leading to loose monetary policy and finally to higher inflation (Fama, 1981)? After all, this theorem has been supported by a number of studies. Note that if we accept this theorem, the “spurious” negative relation between returns and inflation can no longer be said to be a puzzle.

After giving special emphasis to monetary policy, many studies have found unambiguous evidence that monetary easing leads to higher equity prices. Furthermore, monetary policy seems to exert an influence on stock prices both independently of and together with the state of the business cycle. Boyle & Peterson (1995) show that if the monetary authority conducts a counter-cyclical monetary policy this implies a negative relation between expected inflation and stock prices, while if it conducts a pro-cyclical policy this relation becomes positive instead. First, since counter-cyclical policy in a recession is usually aimed at increasing output, stock prices should rise. As long as the country remains in a slump, inflation is not expected to rise. However, in a boom the Central Bank raises the interest rates, trying to prevent the economy from overheating, and higher interest rates typically cause a fall in stock prices. Tighter monetary policy is often pursued because of higher inflationary expectations. Finally, as a result of higher inflation expectations current inflation rises as well.

These results motivate us to use the multi-regime MS-VAR model in this study. However, we cannot directly apply the theories presented above to the case of Finland, since we first need to modify these models to take into account the special features of a small open economy. We characterize “cycles” as common regime shifts in the stochastic process of some macroeconomic time-series based on an MS-VAR. We then try to interpret the estimated regimes from these models being as due to pro- or counter-cyclical monetary policy. In an attempt to measure monetary policy tightness, we also focus on different exchange rate regimes and the current account balance. Theoretical models imply that the only monetary variable which should affect the real economy under fixed exchange rates is the exchange rate. Additionally, with fixed exchange rates and a high degree of capital mobility, the behavior of banks and the characteristics of the credit market also come into play when trying to insulate the impact of monetary policy. Under perfect capital markets a change in domestic money supply is completely offset by a change in the foreign component, and has no effect on the real economy. Hence, monetary policy influences output only if it changes the availability of loans (Patelis, 1997).

As we estimated models with the same set of explanatory variables and for different time spans, statistically significant contemporaneous correlations between inflation and stock returns were always negative when we used monthly data, compared to positive correlations obtained using quarterly observations. Thus it seems to take some time to discount changes in goods prices on the stock market. Heteroskedasticity is obviously one factor underlying the regime-switching behavior. Either changes in regimes may be important sources of persistence in the conditional variance of a time-series, or the empirically obtained regimes may describe different types of volatility levels. After modeling heteroskedasticity, we sought to establish whether stock prices keep up with inflation more easily if there are no sudden changes (in volatility) in the economy as a whole. Now, in many cases correlations are statistically significant only in the regime which typically identifies the low-volatility periods in the data. Thus we conclude that stocks are a good hedge against inflation in the "long run" and especially during the steady states in the economy. Using alternative measures of monetary policy stringency, and replacing output and returns by real output and real returns in the system does not substantially change the results. Even after permitting "multiple equilibria or nonlinear cointegration" in the system as in Ely & Robinson (1997), we note that the main results remain unaltered.

Hence, we get new information about the relationship between real stock prices (returns) and inflation under different monetary policy regimes using the MS-VAR models. These models are consequently used to obtain regime-dependent impulse response functions to measure the persistence of shocks in the system, and to check whether the source of the shock to the system matters. Compared to the linear impulse responses, the response of stock returns to a monetary shock changes its sign and becomes positive in the case of the Ely & Robinson (1997) model. The response of inflation to positive monetary shock is also positive. As the contemporaneous correlations between inflation and stock returns were also positive and statistically significant, it seems that stocks gain briefly relative to goods prices following monetary shocks as already found by Ely and Robinson (1997). Finally, both output and monetary shocks die out quite quickly, in all cases in about five quarters. A monthly model using the marginal interest rate of funds advanced by the Central Bank to the commercial bank as a measure of monetary policy stringency shows that the response to both output and monetary shocks is different in each of the estimated regimes. This confirms the previous findings from Marshall (1992), Giovannini (1989), Lastrapes (1998) and Järvinen (2000) that the source of the shock (real or monetary) to the stock market matters.

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Endnotes

1. The finding that money is irrelevant, particularly in the long run, is known as monetary neutrality. All variables in the economy can be divided into nominal variables, which are measured in monetary units such as the price of a stock, and real variables, which are measured in physical units such as the number of stocks in a portfolio. This division is called the classical dichotomy. It is useful in analyzing the economy because various forces influence real and nominal variables. Nominal variables are affected by money changes, while real variables are not. However, the value of nominal variables is proportional to the quantity of money: if the money supply in an economy doubles, prices double and wages double. However, real variables remain unchanged.

2. Boyd et al. (2001) suggest that the threshold is set at an inflation rate of 15% per year, which is quite high compared to the normal reported goals of 2 - 3% in developed countries.

3. Cov(r,p) = E_t[((R - P) - (mean(R) - mean(P))(P - mean(P))] = cov(R,P) - var(P), where R is returns and P is inflation, and upper case letters indicate nominal values and lower case letters real values. The difference cov(r,P) - cov(R,p) is small being -0.0002 based on quarterly data for 1962/3 - 1998/3, for example.

4. Taxes are normally levied on nominal income and asset returns. Negative correlation between r and CPI may be due to over-taxation of corporate profits during inflationary periods (Fama, 1981). If the inflation tax is offset by the government by a lower corporate tax rate, higher inflation will lead to higher real equity prices (Lächler, 1983).

5. This ordering implies that current innovations in real output affect the other three variables contemporaneously, while current innovations in goods prices affect only themselves.

6. Using quarterly data for 1953/1 - 1998/9, tests indicate that causality runs from *CPI* to *MCI* at the 5% level, and from both *CPI* and *MCI* to returns, the former relation being statistically insignificant. Based on monthly data, *CPI* causes both returns and *M1*, returns cause *M1* and interest rates and *M1* causes *CPI*.

7. In 1986 the price of oil was reduced, income taxes were reduced by 9%, the terms of trade improved by 10% and the interest rate dropped. The forecasts for 1987 GDP growth were 1.5% but the result was 4%. The rate of growth in the money supply jumped 13.5% in 1987 and 23.6% in 1988 following the large increase in the demand for money. At this point the Bank of Finland tried to prevent the economy from overheating, but the revaluation in 1988 was too late.

8. Since testing the statistical significance of several states is problematic most authors of applied papers use a model with several states on purely theoretical grounds.

9. Ergodic probabilities = unconditional estimates that the process will fall into each regime at an arbitrary date.

10. Details and the way of constructing M1 for 1868 - 1980 can be found in Autio (1996).

11. For the construction of this series see BOF5 (Bank of Finland) & Tarkka (1993).

12. At its highest the proportion of Soviet trade was over a quarter of Finland's exports.

13. The dummies we have used are the following: as the Finnish *markka* was devalued on several occasions at least the largest devaluations against the US dollar and/or German *mark* need to be accounted for. *D1* includes the following devaluations: *{1957/9}* by 39.1% due to the general strike and international slump, *{1967/10}* by 31.3% following the Vietnam War upturn, *{1982/10}* by 4% due to second oil crisis and *{1992/9}* by 4% when the currency was allowed to float. *U1 = {1960/1 - 1967/9}* and *U2= {1967/10 - 1973/2}* are needed to describe the behavior of e_{USD} at the beginning of the sample period. Other irregularities can be seen in short-term interest rates. *I1* identifies a rise in *{1975/10}* following the slump brought on by the first oil crisis. The need to defend the *markka* from devaluing shows as a rise in the long- and short run interest rates in *{1986/8}*. The long-term Government bond rate in August was as high as 24.17% because of currency speculation, which made the Central Bank raise the prime rate temporarily up to 40%. *I2* identifies the results of the *{1977/4, 1977/9}* devaluations. The dummy *M1* captures the increase in *M1* just after joining the currency basket in *{1973/12}* as well as some exceptional events during the first oil crisis *{1974/1, 1975/12}*. The drop in industrial production in *{1974/12, 1991/1}* is captured by *Y1*.

In addition, we want to add the following more general dummies: stock returns were exceptionally high in *{1968/3 - 1968/4, 1972/1, 1973/1}* under a de facto floating currency, in *{1992/1, 1992/10}* following the switch to a floating exchange rate regime, and low in *{1987/10}* or "black November," in *{1990/9}* and *{1992/8}*. Inflation was lower than average during *P1 = {1954/11, 1967/12, 1968/1}*. Some peaks in industrial production were in 1980, 1989 and 1996, and falls in 1952, 1958, 1977, 1982 and 1992 (Pohjola, 1996). The variable measuring the availability of loans identifies the credit boom in *C1 = {1988/12, 1990/1, 1992/9}* followed by a huge drop due to a recession continuing until *{1993/12}*. In the case of quarterly data the corresponding quarter inherits its properties from the monthly data, and quarterly dummies are set accordingly.

14. Deregulation may have affected the number of stochastic trends in the model. The Finnish economy was highly regulated until 1980 and Germany deregulated as a result of German Unification in the 1990s.

15. The test statistic is $\chi^2(k)$ distributed, where k is the number of restrictions implied by a homoskedastic model.

16. There may be asymmetry in the persistence: in the case of two regimes, upward moves could be short but sharp ($\mu_1(s_t)$ is large and positive, p_{11} is small), whereas downward moves could be

gradual and drawn out ($\mu_2(s_t)$ is negative and small in absolute value, p_{22} is large). Changes in the series could also be completely independent of the state that prevailed last period, as in a random walk, if $p_{11} = 1 - p_{22}$. The long swing hypothesis holds if $\mu_1(s_t)$ and $\mu_2(s_t)$ are opposite in signs, and values for p_{11} and p_{22} are large.

17. Krolzig's MS-VAR procedure for Ox reports variances in different regimes as a byproduct.

18. Trend is restricted to zero in all cointegration vectors.

19. Conover et al. (1999) tested the links between local country stock returns (inflation adjusted) against local and US monetary policy environment dummy variables for 1956/1 - 1995/12. Using monthly OECD Main Economic Indicators data from 16 countries, they classify the period following a decrease in the discount rate as an expansive monetary policy regime. Likewise, restrictive monetary environments begin when the discount rate first increases and end when the discount rate is decreased. As increased inflation is usually accompanied by contractionary policies, and stock returns are usually negatively related to inflation, they also use real returns in their regressions. This does not change the results greatly. They find that foreign stock returns are generally higher in the expansive US and local monetary environments than they are in restrictive environments. Several of the stock markets are more strongly related to the US monetary environment than to local monetary conditions. Their study includes Finland, where they find 8 expansive and 7 restrictive periods with a mean duration of 32 months. The correlation between Finnish stock returns and US returns is positive but less than 20%. They conclude that since an expansive monetary policy is frequently initiated by a Central Bank when there is increased concern about an economic downturn, a shift in higher required returns is a reasonable expectation. Thus it is not inconsistent with the EMH.

20. Since there were problems in solving the MSMH- and MSIH-VAR models they are not reported.

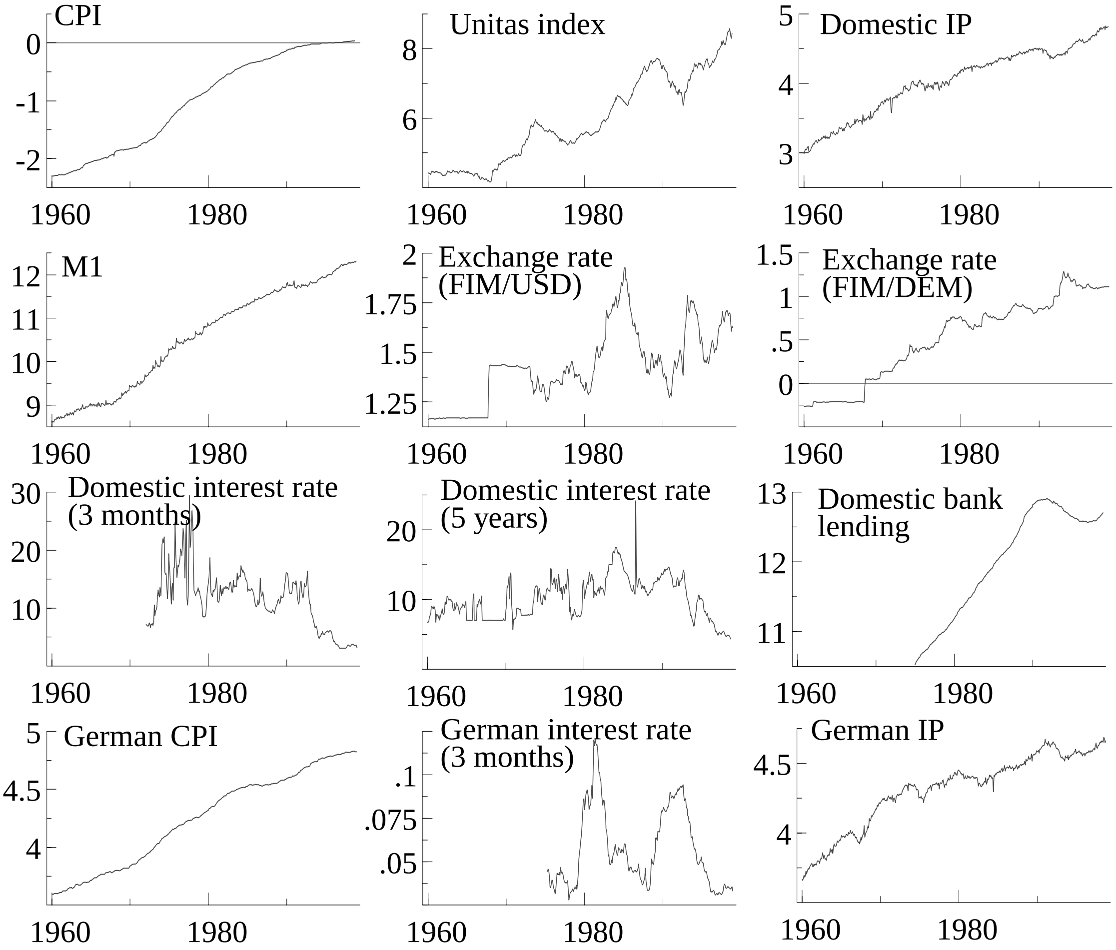
21. For further details of the generalized impulse response function, see Koop et al. (1996).

22.When we calculate regime-dependent IRFs, the variables are orthogonalized.

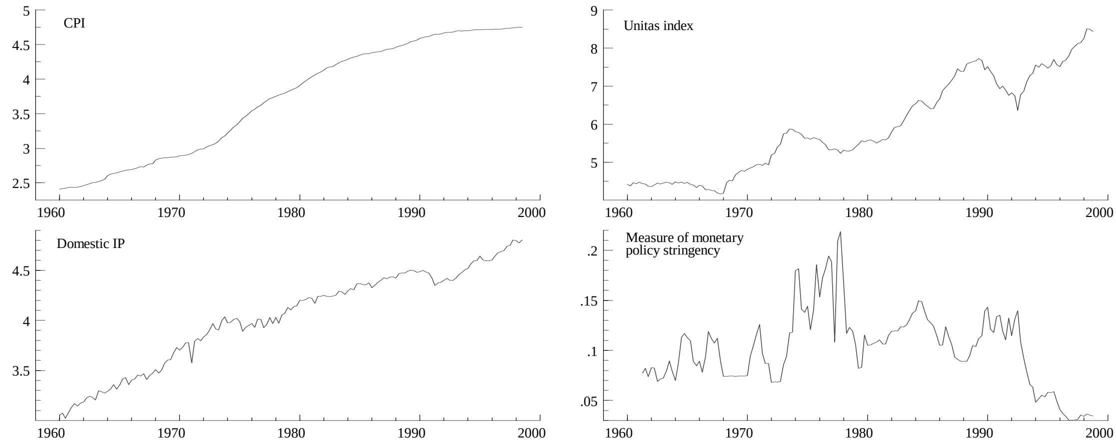
23.We are especially interested in the contemporaneous correlation between inflation and stock returns, but here the main focus is on the effects of monetary and real shocks.

24. Not all of the IRFs from the alternative models with the same elements as in the *MCI* are reported, as the available Ox procedures first need to be modified to allow for more than four variables in a VAR.

Appendix 3.1: The data for 1960/1 - 1998/3.

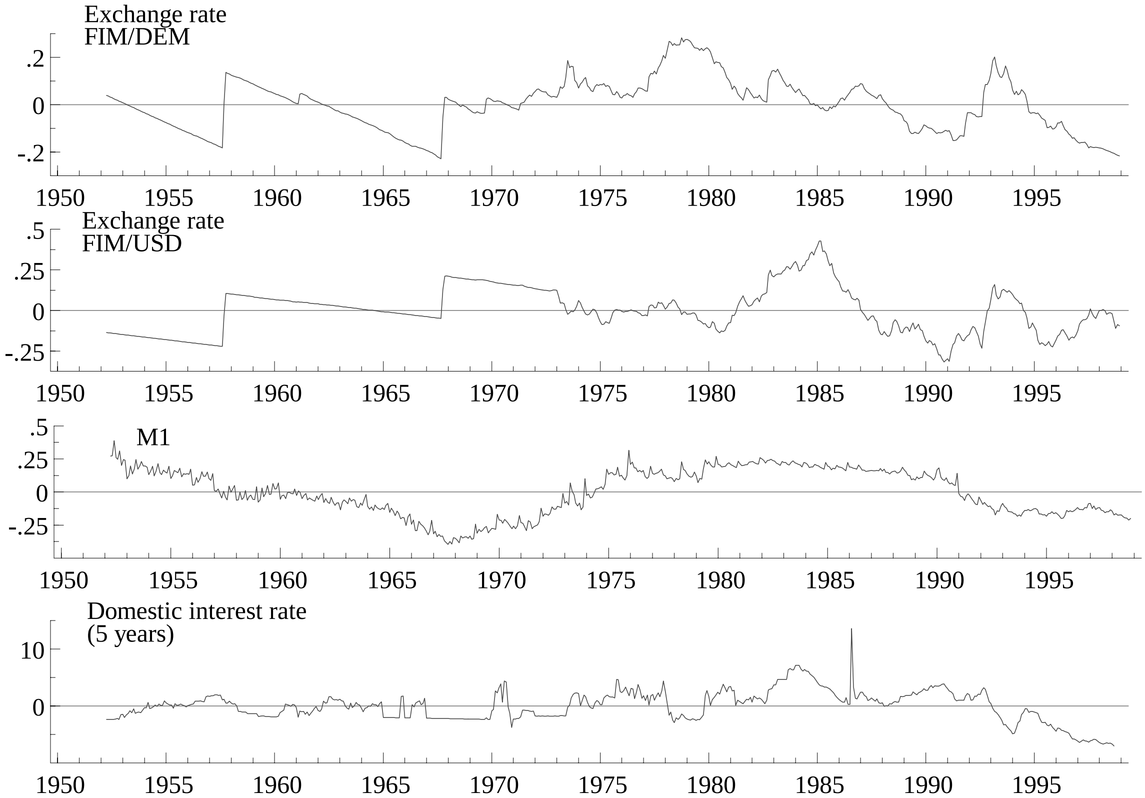


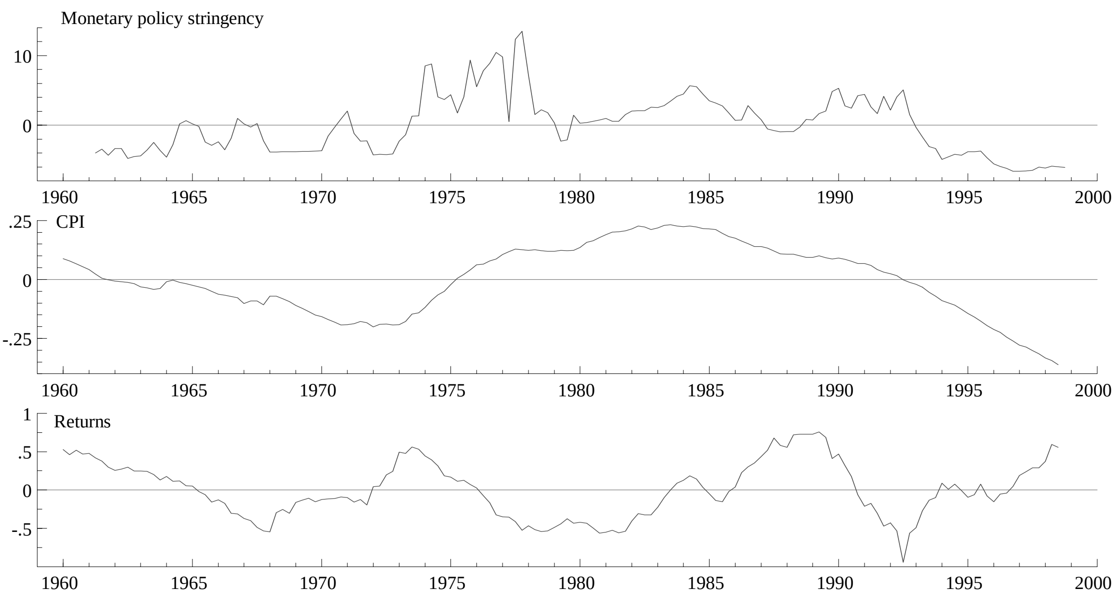
Monthly data (logarithm)



Quarterly data (logarithm)

Appendix 3.2: Deviations from a constant and a trend, monthly data (upper fiqures) and quarterly data (lower figures).



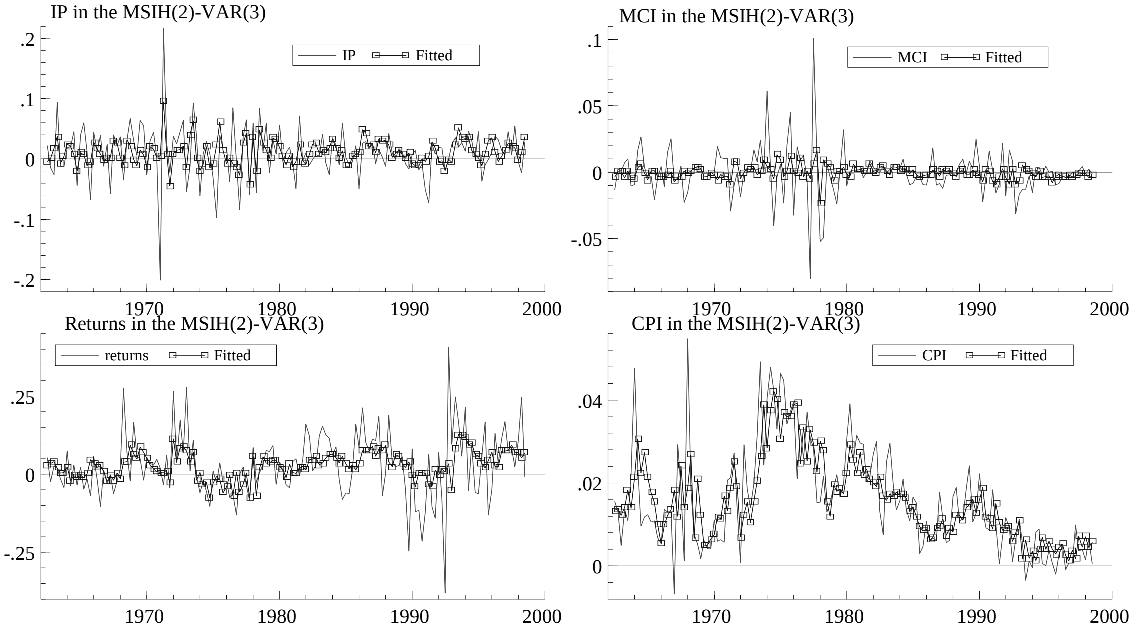


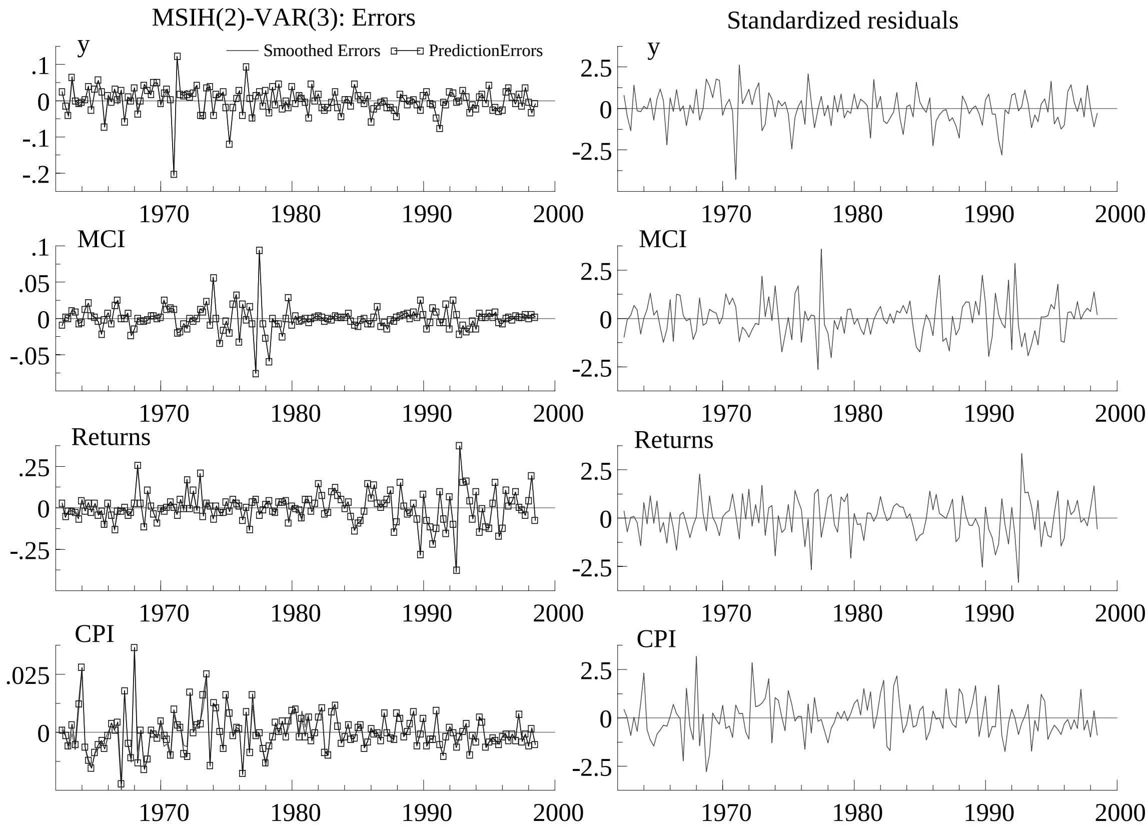
Appendix 3.3: Estimation results from the quarterly MS-AR models for 1962/3 - 1998/3 for monetary policy stringency (*MCI*), inflation and returns individually and the MS(*M*)-VAR(*p*) models for 1962/4 - 1998/3, where *z* = [*CPI MCI r*]′ (last four columns).

Variable	**returns**	***CPI***	***MCI***		***z* = [*CPI MCI r*]′**			
Model	MSM(2)-AR(4)	MSMH(2)-AR(4)	MSM(2)-AR(4)		MSI(2)-VAR(2)	MSIH(2)-VAR(2)	MSM(2)-VAR(2)	MSMH(2) - VAR(2)
Mean μ_L	-0.018	0.009	-0.372		0.031*	0.046**	-0.032	0.040*
Mean μ_T	0.11**	0.023**	0.266		0.137**	0.024*	0.060*	0.001
ϕ_{t-1}	-0.138	0.476**	-0.127	ϕ_{t-1}	-0.596	-0.356	-1.049	-0.654
ϕ_{t-2}	0.058	-0.112	-0.287**	ϕ_{t-2}	-3.158**	-0.824	-1.221	-0.136
ϕ_{t-3}	0.197**	0.269**	0.030	ζ_{t-1}	0.001	-0.237	-0.202	-0.169
ϕ_{t-4}	0.172*	0.244**	0.029	ζ_{t-2}	0.248	0.251	-0.232	0.166
				η_{t-1}	-0.022	0.053	-0.026	0.079
				η_{t-2}	0.114	0.248**	0.100	0.242**
p_{LL}	0.922	0.966	0.707		0.894	0.940	0.863	0.944
p_{TT}	0.874	0.910	0.744		0.899	0.880	0.939	0.888
prob. L	0.618	0.726	0.466		0.488	0.665	0.308	0.666
prob. T	0.382	0.274	0.534		0.512	0.335	0.692	0.334
Duration L	13.	30.	3.		9.	17.	7.	18.
Duration T	8.	11.	4.		1.	8.	16.	9.
Obs.	145	145	145		144	144	144	144
LogL.	134.194	507.932	-304.753		999.101	1059.918	987.949	1056.573
LR test	7.548	51.221	0.026		18.22	139.854	-4.083	133.165
corr Regime 1					-0.135	0.104	-0.092	0.147*
Regime 2						0.152*		0.178*

The estimation uses logarithmic differences of the data. Mean μ_L and μ_T are mean/intercept terms of returns in regimes L and T. ϕ_{t-p}, $p = 1,...,4$ are the AR coefficients. In the last four columns ϕ_{t-p}, $\zeta_{t-p.}$ and η_{t-p}, $p = 1, 2$ are coefficients for lagged CPI, MCI and lagged returns in the equation for returns. p_{LL} (p_{TT}) is the probability of staying in regime L after being in regime L for the previous period, where L(T) refers to estimated regimes. Also of interest are the unconditional probabilities (prob. L./T.) that the process is in each of the regimes L/T, that is, P($s_t = L$) or P($s_t = T$) (Hamilton, 1994). Duration L/T is the time the process stays in regime L/T. Obs. is the number of observations and LogL. the value of the log-likelihood function. LR test is the value of the test against a linear model. Finally, contemporaneous correlation between inflation and stock returns is given in Regime 1 and Regime 2 under corr Regime 1/2. Statistically significant coefficients and correlations are marked with an asterisk: * at the 5% level or ** at the 1% level.

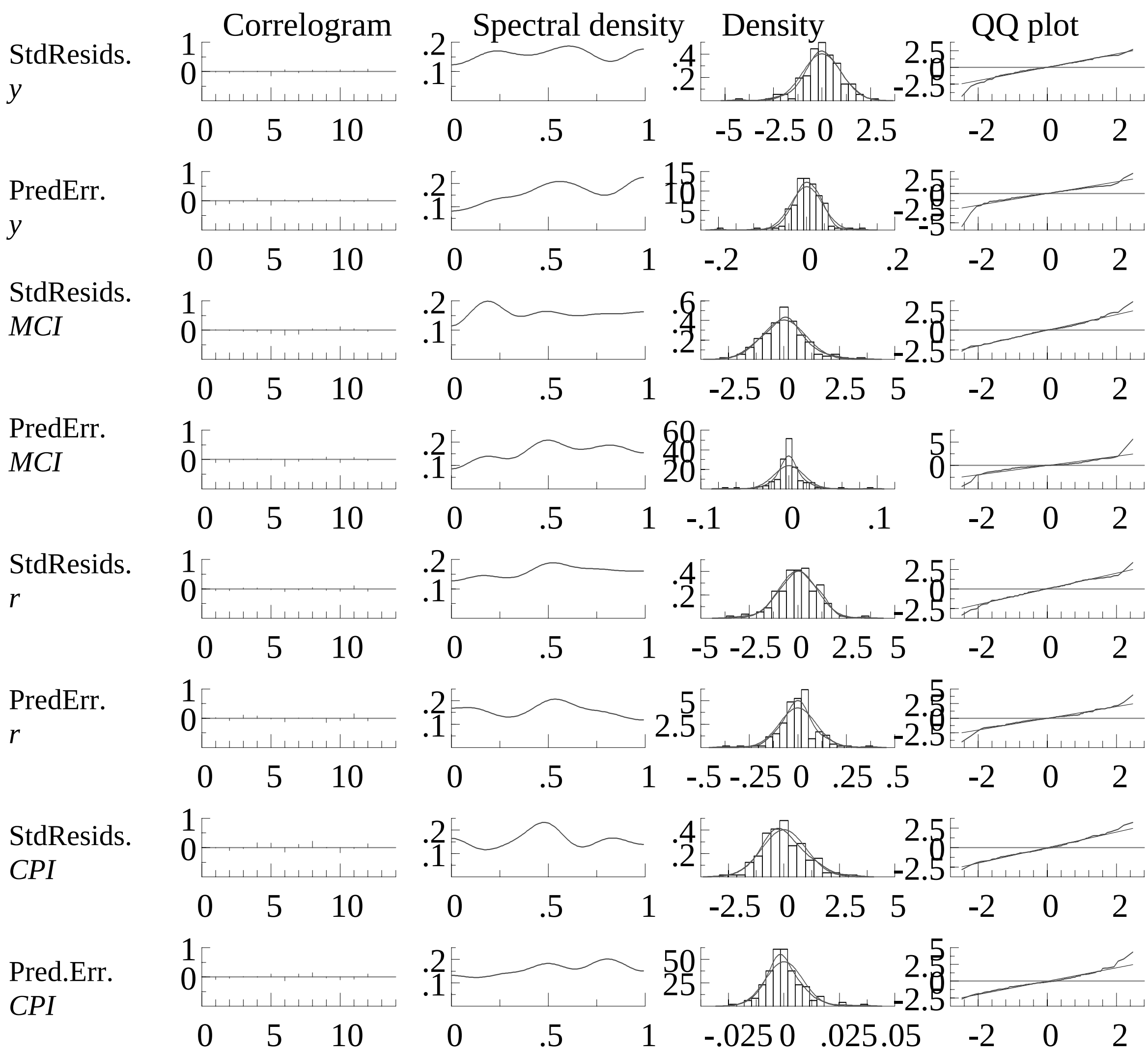
Appendix 3.4: Model diagnostics for the quarterly MSIH(2)-VAR(3) model, where *z* = [*y MCI r CPI*]′.





The actual and fitted values for the equations for output *y (or IP)*, monetary condition index *MCI*, returns *r* and inflation *CPI* are drawn first. The errors associated with the estimated MS-VAR are plotted next. Smoothed errors are corrected for the effects of regime shifts in the MS(M)-VAR(p) models in the following way: $\sum_{m=1}^{M}\{(\Delta z_t - E_t[\Delta z_t|s_t = m,\Omega_{t-1}])Pr(s_t = m|\Omega_T)\}$. Prediction errors are the one-step prediction errors $\Delta z_t - E_t(\Delta z_t|\Omega_{t-1})$ using the information set $\Omega_{t-1} = \{z_{t-1},z_{t-2},\ldots,z_0\}$. We also draw standardized residuals from the corresponding equation in the system.

This is followed by MSVAR Graphics by DrawErrors. Standardized residuals and 1-step prediction errors are drawn. Correlogram refers to error autocorrelation. The spectral density is a smoothed function of the model autocorrelations. Peaks indicate regular cyclical or seasonal behavior in the time series (GIVEWIN-manual Section 4.1.4 and 7.3). Density and QQ plot (cross probability plots) $P_x(X > x)$ can be used to test the normality of the model standardized residuals and prediction errors. Standard normal distribution is used as a comparison.



Appendix 3.5: The quarterly MS(*M*)-VARX(*p*) models for 1962/4 (1963/2) - 1998/3, where $z = [y\ MCI\ r\ CPI]'$, with cointegration vectors $CI_1 = [1\ b_{12}\ b_{13}\ \text{-}1]'$ and $CI_2 = [b_{21}\ b_{22}\ 1\ \text{-}1]'$.

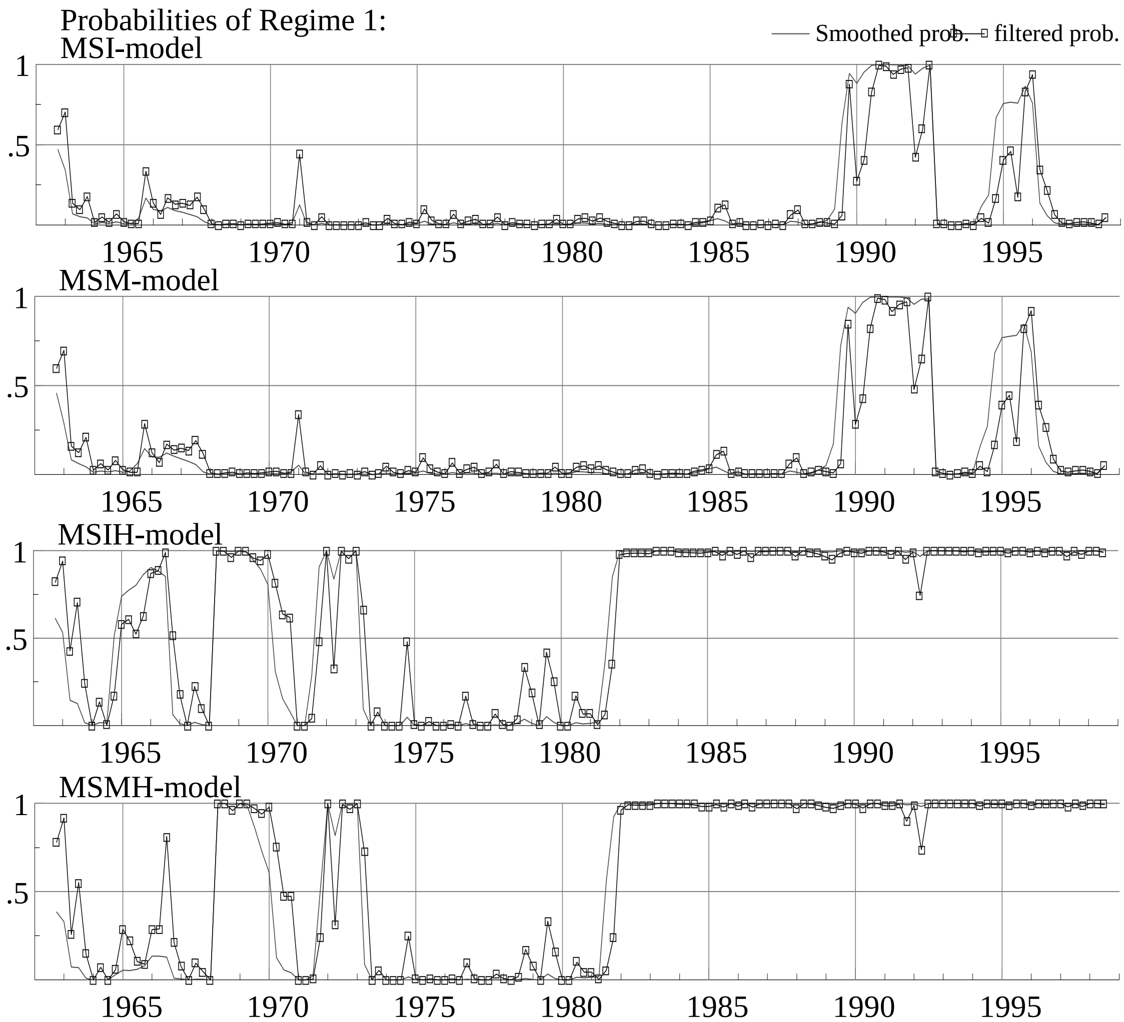
First column under the same model: nominal output and returns,
second column: real output and real returns.

Model	**MSI(2)-VARX(1)**		**MSM(2)-VARX(1)**		**MSIH(2)-VARX(1)**		**MSMH(2)-VARX(1)**	
Mean μ_L	-0.072*	-0.051**	-0.064*	-0.042**	0.056**	0.048**	0.046**	0.032*
Mean μ_T	0.057**	0.078**	0.046**	0.062**	0.026*	-0.006	0.002	-0.022
ϕ_{t-1}	-0.207	-0.148	-0.177	-0.130	-0.124	-0.300*	-0.159	-0.322
ζ_{t-1}	0.343	0.931*	0.326	0.869*	0.057	0.143	0.096	0.166*
η_{t-1}	-0.082	-0.160	-0.069	-0.134	-0.004	-0.015	-0.002	-0.013
δ_{t-1}	-0.302	-0.118	-0.246	-0.156	-0.968*	-0.997	-0.999*	-1.031
CI_{t-1}	-0.047**	-0.017**	-0.046**	-0.016**	-0.030**	-0.003	-0.030**	-0.003
CI_{t-2}	0.012	-0.001**	0.010	-0.001**	0.027**	-0.001**	0.029**	-0.001*
p_{LL}	0.826	0.942	0.833	0.938	0.951	0.970	0.953	0.972
p_{TT}	0.974	0.947	0.975	0.945	0.911	0.937	0.930	0.936
prob. L	0.132	0.475	0.130	0.473	0.644	0.681	0.596	0.698
prob. T	0.868	0.525	0.870	0.527	0.356	0.319	0.404	0.302
Duration L	6.	17.	6.	16.	20.	34.	21.	36.
Duration T	38.	19.	4.	18.	11.	16.	14.	16.
Obs.	144	142	144	142	144	142	144	142
LogL.	1266.477	1250.654	1266.129	1249.846	1346.68	1318.489	1346.992	1318.397
LR test	10.682	18.281	9.986	16.665	171.087	153.950	171.712	153.768
corr Reg.1	0.004	0.051	0.008	0.057	0.097	0.041	0.091	-0.003
Reg. 2					0.143*	-0.040	0.167*	-0.00001

The estimation uses differences of logarithmic data. In testing for cointegration dummies, *R1* and *Y1* are entered in the cointegration space unrestricted and a trend is entered restricted. Mean μ_L and μ_T are mean/intercept terms of returns in regimes L and T. $\phi_{t\ -1}$ = coefficients for lagged *y*, $\zeta_{t\ -\ 1} = M1$, $\eta_{t\ -\ 1} = r$ and $\delta_{t\ -1} = CPI$ in the equation for returns. The $CI_{1,t\ -1}$ and $CI_{2,t\ -1}$ are the coefficients of the cointegration vectors. p_{LL} (p_{TT}) is the probability of staying in regime L after being in regime L for the previous period, where L(T) refers to the estimated regimes. Also of interest are the unconditional probabilities (prob. L./T.) that the process is in each of the regimes L/T, that is, $P(s_t = L)$ or $P(s_t = T)$ (Hamilton, 1994). Duration L/T is the time the process stays in regime L/T. Obs. is the number of observations and LogL. is the value of the log-likelihood function. LR test is the value of the test against a linear model. Finally, contemporaneous correlation between inflation and stock returns is given in Regime 1 and Regime 2 under corr Reg.1 and Reg.2. Statistically significant coefficients and correlations are marked with an asterisk: * at the 5% level or ** at the 1% level.

Appendix 3.6: Smoothed and filtered probabilities from the quarterly MS-VARX models for 1962/4 - 1998/3, where $z = [y\ MCI\ r\ CPI]'$ with the cointegration vectors $CI_1 = [1\ b_{12}\ b_{13}\ -1]'$ and $CI_2 = [1\ b_{22}\ 1\ b_{24}]'$.

The filtered probabilities represent an optimal inference using only the current information up to time *t*. The smoothed probabilities of being in state one or two are based on the full information of the sample.



Appendix 3.7: The monthly MS(M)-VAR(p) models for 1953/3 - 1998/11 with $z = [y\ M1\ r\ CPI]'$ and the cointegration vectors $CI_1 = [1\ b_{12}\ b_{13}\ -1]'$ and $CI_2 = [b_{11}\ b_{12}\ 1\ -1]'$. The last four columns employ real output and real returns: $z = [y_r\ M1\ r_r\ CPI]'$.

Model	MSI(2)-VARX(2)	MSM(2)-VARX(2)	MSI(2)-VARX(2)	MSM(2)-VARX(2)	MSM(2)-VAR(3)	MSI(2)-VAR(3)	MSMH(2)-VAR(3)	MSIH(2)-VAR(3)
coint.	CI_1	CI_1	CI_2	CI_2	-	-	-	-
Mean μ_L	-0.016**	-0.011*	-0.017**	-0.009	0.007	0.019	0.019**	0.006**
Mean μ_T	0.018**	0.023**	0.015*	0.028	-0.001	0.002	0.002	0.003
ϕ_{t-1}	-0.010	-0.011	0.003	0.0005	0.038	0.036	0.040	0.036
ϕ_{t-2}	-0.022	-0.020	-0.013	-0.014	0.031	0.026	0.033	0.020
ϕ_{t-3}	-	-	-	-	0.074	0.069	0.073	0.076
ζ_{t-1}	0.095	0.079	0.105*	0.077	0.128*	0.120*	0.098	0.109
ζ_{t-2}	0.018	0.014	0.028	0.018	0.061	0.056	0.049	0.044
ζ_{t-3}	-	-	-	-	0.120*	0.110*	0.104*	0.111*
η_{t-1}	0.109*	0.118**	0.117**	0.094	0.189**	0.188**	0.185**	0.181**
η_{t-2}	-0.037	-0.027	-0.030	-0.044	0.026	0.025	0.031	0.021
η_{t-3}	-	-	-	-	0.091*	0.091*	0.099*	0.089*
δ_{t-1}	0.352	0.077	0.424	0.055	0.219	0.110	-0.009	-0.072
δ_{t-2}	0.559*	0.484	0.630*	0.537*	0.014	-0.049	0.218	-0.119
δ_{t-3}	-	-	-	-	-0.337	-0.408	-0.567*	-0.336*
CI_{t-1}	-0.001	-0.0004	-0.004	-0.003	-	-	-	-
p_{LL}	0.964	0.966	0.963	0.961	0.987	0.191	0.565	0.636
p_{TT}	0.973	0.977	0.977	0.959	0.967	0.986	0.880	0.888
prob. L	0.421	0.405	0.387	0.515	0.712	0.018	0.217	0.236
prob. T	0.579	0.595	0.613	0.485	0.288	0.982	0.783	0.764
Duration L	27.	29.	27.	26.	75.	1.	2.	3.
Duration T	38.	43.	43.	24.	30.	69.	8.	9.
Obs.	549	549	549	549	548	548	548	548
LogL.	5005.53	5002.84	5005.77	5001.36	4989.13	5026.03	5250.37	5269.04
LR test	34.44	29.058	33.681	24.862	30.975	104.792	553.466	590.806
corr Reg.1	0.021	0.013	0.03	0.023	-0.165**	-0.169**	-0.0003	-0.350**
Reg.2							-0.00001	-0.084*

The estimation uses first differences of logarithmic data. When we are testing for cointegration (coint.), constant plus dummies *R1* and *Y1* are entered in the cointegration space unrestricted but a trend is entered restricted. Mean μ_L and μ_T are mean/intercept terms of returns in regimes L and T. ϕ_{t-p} = coefficients for lagged output, ζ_{t-p} = M1, η_{t-p} = returns and $\delta_{t-p} = CPI$ in the equation for returns, $p = 1, 2, 3$. The CI_{t-1} is the coefficient of the cointegration vector. p_{LL} (p_{TT}) is the probability of staying in regime L after being in regime L for the previous period. Also of interest are the unconditional probabilities (prob. L./T.) that the process is in each of the regimes L/T, that is, $P(s_t = L)$ or $P(s_t = T)$ (Hamilton, 1994). Duration L/T is the time the process stays in regime L/T. Obs. is the number of observations and LogL. is the value of the log-likelihood function. LR test is the value of the test against a linear model. Finally, contemporaneous correlation between inflation and stock returns is given in Regime 1 and Regime 2 under corr Reg.1/Reg.2. Statistically significant coefficients and correlations are marked with an asterisk: * at the 5% significance level or with ** at the 1% level.

Appendix 3.8: The monthly MS(M)-VARX(p) models for 1987/2 - 1996/12, where z = [y $M1$ i CPI e_{USD} r]′, with the cointegration vector $CI_1 = [b_{11}\ b_{12}\ b_{13}\ -1\ 1\ b_{16}]'$.

Model	**MSI(2)- VARX(2)**	**MSM(2)-VARX(2)**	**MSIH(2)-VARX(2)**	**MSMH(2)-VARX(2)**
Mean μ_L	-0.057**	-0.046**	-0.044**	-0.045**
Mean μ_T	0.015*	0.030**	-0.006	0.028**
ϕ_{t-1}	-0.687*	-0.149	-0.236	-0.299
ϕ_{t-2}	-0.416	-0.301	-0.597*	-0.151
ζ_{t-1}	-0.085	0.152	0.230	0.192
ζ_{t-2}	-0.363*	-0.414*	-0.255	-0.174
η_{t-1}	-1.476	1.913*	1.023	-0.622
η_{t-2}	0.780	0.496	-0.046	0.750
δ_{t-1}	5.111**	5.598**	3.332**	3.092*
δ_{t-2}	3.293**	1.281	4.747**	-0.096
λ_{t-1}	0.253	0.471**	0.035	0.504**
λ_{t-2}	-0.040	0.274	0.381**	0.206
ρ_{t-1}	-0.014	0.335**	0.067	0.164*
ρ_{t-2}	-0.206**	-0.161*	-0.091	-0.199**
CI_{t-1}	0.047**	0.034**	0.031**	0.029**
p_{LL}	0.572	0.521	0.533	0.612
p_{TT}	0.777	0.769	0.898	0.875
prob. L	0.343	0.326	0.180	0.243
prob. T	0.657	0.674	0.820	0.757
Duration L	2.	2.	2.	3.
Duration T	4.	4.	1.	8.
Obs.	119	119	119	119
LogL.	2046.661	2045.593	2132.6	2098.137
LR test	14.814	12.677	186.686	117.766
corr Reg.1	-0.003	-0.178*	-0.099	-0.086
Reg.2			0.032	-0.009

The estimation uses first differences of logarithmic data. Mean μ_L and μ_T are mean/intercept terms of returns in regimes L and T. ϕ_{t-p} = coefficients for lagged output, $\zeta_{t-p} = M1$, η_{t-p} = interest rate, $\delta_{t-p} = CPI$, $\lambda_{t-p} = e_{USD}$, ρ_{t-p} = r in the equation for returns, $p = 1,2$, CI_{t-1} is the coefficient for the cointegration vector. p_{LL} (p_{TT}) is the probability of staying in regime L after being in regime L for the previous period, where L(T) refer to estimated regimes. Also of interest are the unconditional probabilities (prob. L./T.) that the process is in each of the regimes L/T, that is, $P(s_t = L)$ or $P(s_t = T)$ (Hamilton, 1994). Duration L/T is the time the process stays in regime L/T. Obs. is the number of observations and LogL. is the value of the log-likelihood function. LR test is the value of the test against a linear model. Finally, contemporaneous correlation between inflation and stock returns is given in Regime 1 and Regime 2 under corr Reg.1/Reg.2. Statistically significant coefficients and correlations are marked with an asterisk: * at the 5% level and ** at the 1% level.

Appendix 3.9: The monthly MS(M)-VAR(p) models for 1976/5 - 1998/11, where z = [y CPI M1 r i* e_{DEM}]′ or z = [y CPI i r e_{DEM} y* CPI* i*]′ (last four columns).

Model	**MSI(2)-VAR(2)**	**MSMH(2)-VAR(2)**	**MSIH(2)-VAR(2)**		**MSM(2)-VAR(1)**	**MSI(2)-VAR(1)**	**MSMH(2)-VAR(1)**	**MSIH(2)-VAR(1)**
Mean μ_L	-0.049**	0.015	0.005		0.014	0.009	0.007	0.005
Mean μ_T	0.024**	0.006	-0.007		0.008	0.004	0.016	0.015
ϕ_{t-1}	-0.249	0.019	-0.032	ϕ_{t-1}	-0.057	-0.057	-0.076	-0.055
ϕ_{t-2}	-0.081	0.094	0.092	ζ_{t-1}	0.337	0.349	0.058	-0.364
ζ_{t-1}	-0.713	0.434	0.167	η_{t-1}	0.040	0.040	0.057	-0.0003
ζ_{t-2}	0.090	0.769	1.141*	δ_{t-1}	0.208*	0.208*	0.233*	0.228*
η_{t-1}	0.060	0.144	0.244*	λ_{t-1}	0.563*	0.562*	0.623*	0.494*
η_{t-2}	-0.101	0.016	0.002	ρ_{t-1}	0.088	0.089	0.115	0.135
δ_{t-1}	0.038	0.173*	0.168*	κ_{t-1}	-0.370	-0.373	0.104	-0.324
δ_{t-2}	-0.021	0.053	0.050	ν_{t-1}	-1.868	-1.865	-1.510	-1.731
λ_{t-1}	-1.177	-0.200	-1.441					
λ_{t-2}	-1.992*	-0.101	-1.090					
ρ_{t-1}	0.417*	0.340	0.415*					
ρ_{t-2}	0.140	0.160	-0.046					
p_{LL}	0.799	0.881	0.840		1.000	1.000	0.877	0.862
p_{TT}	0.969	0.807	0.793		0.994	0.994	0.770	0.748
prob. L	0.135	0.619	0.564		0.9996	0.9992	0.652	0.647
prob. T	0.865	0.381	0.436		0.0004	0.0008	0.348	0.353
Duration L	5.	8.	6.		460770.	215050.	8.	7.
Duration T	32.	5.	5.		179.	179.	4.	4.
Obs.	271	271	271		270	270	270	270
LogL.	4768.97	4880.937	4911.09		6851.40	6851.57	7125.08	7125.90
LR test	29.064	253.000	313.302		46.703	47.048	594.072	595.719
corr Reg.1	-0.117*	-0.097*	-0.140**		-0.02	-0.021	-0.132*	-0.115*
Reg.2		-0.001	0.045				0.061	-0.010

The estimation uses first differences of logarithmic data. Mean μ_L and μ_T are mean/intercept terms of returns in regimes L and T. ϕ_{t-p}, ζ_{t-p}, η_{t-p}, δ_{t-p}, λ_{t-p} & ρ_{t-p} for $p = 1, 2$, and κ_{t-p} & ν_{t-p} for $p = 1$ are coefficients for lagged output, *CPI*, interest rate (3 months), *r*, e_{DEM}, foreign output, foreign inflation and foreign interest rate in the equation for returns. p_{LL} (p_{TT}) is the probability of staying in regime L after being in regime L for the previous period, where L(T) refers to estimated regimes. Also of interest are the unconditional probabilities (prob.L./T.) that the process is in each of the regimes L/T, that is, P($s_t = L$) or P($s_t = T$) (Hamilton, 1994). Duration L/T is the time the process stays in regime L/T. Obs. is the number of observations and LogL. is the value of the log-likelihood function. LR test is the value of the test against a linear model. Finally, contemporaneous correlation between inflation and returns is given in Regime 1 and Regime 2 under corr Reg.1/Reg.2. Statistically significant coefficients and correlations are marked with an asterisk: * at the 5% level and ** at the 1% level. Using the first set of explanatory variables the estimated MSM-model was worse than a linear system, and is therefore not reported.

Appendix 3.10: The monthly MS(M)-VAR(p) models for 1953/2 - 1998/9, where z = [$y\ c_i\ r\ CPI$]′ and z = [$y\ c_i\ r\ CPI\ e_{USD}$]′ (last four columns).

Model	**MSM(2)-VAR(2)**	**MSI(2)-VAR(2)**	**MSH(2)-VAR(2)**	**MSIH(2)-VAR(2)**	**MSM(2)-VAR(2)**	**MSI(2)-VAR(2)**	**MSH(2)-VAR(2)**	**MSIH(2)-VAR(2)**
Mean μ_L	-0.008	-0.017*	0.008*	0.010*	0.010**	-0.018**	0.007*	0.008**
Mean μ_T	0.026*	0.030*	-	0.002	0.007	0.026**	-	0.007
ϕ_{t-1}	-0.004	-0.026	0.028	0.017	0.009	-0.014	0.019	0.016
ϕ_{t-2}	-0.014	-0.034	-0.035	-0.015	-0.004	-0.025	-0.007	0.002
ζ_{t-1}	-0.113	-0.221	0.072	0.027	0.028	-0.179	0.036	0.050
ζ_{t-2}	0.038	-0.106	0.251	0.172	0.109	-0.063	0.161	0.163
η_{t-1}	0.104*	0.042	0.174*	0.173*	0.192*	0.052	0.190**	0.194**
η_{t-2}	-0.022	-0.076	0.068	0.068	0.052	-0.074	0.062	0.058
δ_{t-1}	0.226	0.234	-0.293	-0.313	-0.094	0.291	-0.217	-0.219
δ_{t-2}	0.602*	0.505	-0.010	0.020	0.149	0.553*	0.061	0.050
λ_{t-1}	-	-	-	-	0.022	0.104	-0.018	-0.005
λ_{t-2}	-	-	-	-	0.026	0.086	0.033	0.027
p_{LL}	0.969	0.948	0.903	0.904	0.984	0.955	0.883	0.856
p_{TT}	0.968	0.944	0.518	0.645	0.962	0.958	0.234	0.311
prob. L	0.515	0.517	0.833	0.788	0.707	0.486	0.868	0.827
prob. T	0.485	0.483	0.167	0.212	0.293	0.514	0.132	0.173
Duration L	33.	19.	10.	10.	64.	22.	9.	7.
Duration T	31.	18.	2.	3.	26.	24.	1.	1.
Obs.	548	548	548	548	548	548	548	548
LogL.	5712.19	5719.85	6127.30	6130.35	7087.115	7088.75	7548.513	7561.673
LR test	20.324	35.641	850.539	856.635	37.591	40.861	960.386	986.705
corr Reg.1	0.04	0.022	-0.079*	-0.041	-0.032	0.032	-0.065	-0.066
Reg.2			0.013	-0.005			-0.004	-0.011

The estimation uses first differences of logarithmic data. Mean μ_L and μ_T are mean/intercept terms in regimes L and T. ϕ_{t-p} = coefficients for lagged output, ζ_{t-p} = total credits to the public or *M1*, $\eta_{t-p} = r$, $\delta_{t-p} = CPI$ and $\lambda_{t-p} = e_{USD}$ in the equation for returns, $p = 1, 2$. p_{LL} (p_{TT}) is the probability of staying in regime L after being in regime L for the previous period, where L(T) refers to estimated regimes. Also of interest are the unconditional probabilities (prob. L./T.) that the process is in each of the regimes L/T, that is, $P(s_t = L)$ or $P(s_t = T)$ (Hamilton, 1994). Duration L/T is the time the process stays in regime L/T. Obs. is the number of observations and LogL. is the value of the log-likelihood function. LR test is the value of the test against a linear model. Finally, contemporaneous correlation between inflation and returns is given in Regime 1 and Regime 2 under corr Reg.1/Reg.2. Statistically significant coefficients and correlations are marked with an asterisk: * at the 5% level and ** at the 1% level. Note that as the MSMH model did not solve, a MSH model was estimated instead.

Appendix 3.11: The effect on equity prices of monetary policy announcements.

Study	**Instrument**	**Period**	**Effect of looser monetary policy**		
			Actual	**Expected**	**Unexpected**
Waud (1970)	discount rate	1952 - 67	pos		
Berkman (1978)	money supply (*M1*)	1975 - 77	neg		neg
Lynge (1981)	money supply (*M1*,*M2*)	1976 - 79	neg		
Pearce & Roley (1983)	money supply (*M1*)	1977 - 79 1979 - 80 1980 - 81			neg neg neg
Cornell (1983)	money supply (*M1*)	1978 - 79 1979 - 81		none	neg neg
Smirlock & Yawitz (1985)	discount rate	1975 - 79 1979 - 82	none pos		
Pearce & Roley (1985)	money supply (*M1*)	1977 - 79			neg/neg
	discount rate	1979 - 82	pos/pos		
Hafer (1986)	money supply (*M1*)	1977 - 79 1979 - 82 1982 - 84		none	neg neg neg
	discount rate		neg/pos/ neg		
Hardouvelis (1987)	money supply (*M1*)	1979 - 82			neg/neg
	discount rate	1982 - 84	pos/none		
Jensen & Johnson (1983)	discount rate	1962 - 79 1979 - 82 1982 - 90	pos pos pos		
Thorbecke & Alami (1994)	fed funds rate target	1974 - 86	pos		
Jensen & Johnson (1995)	discount rate	1962 - 79 1979 - 91	pos pos		
Tarhan (1995)	open market operations	1979 - 84			none
Thorbecke (1997)	fed funds rate target	1974 - 94	pos		
Sellin (1997)	repo rate	1992 - 97	pos		

Source: Sellin (1998). See references therein. Pos = positive effect, neg = negative effect and none = no effect.

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