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A NON-STATIONARY PERSPECTIVE ON THE EUROPEAN AND SWEDISH BUSINESS CYCLE

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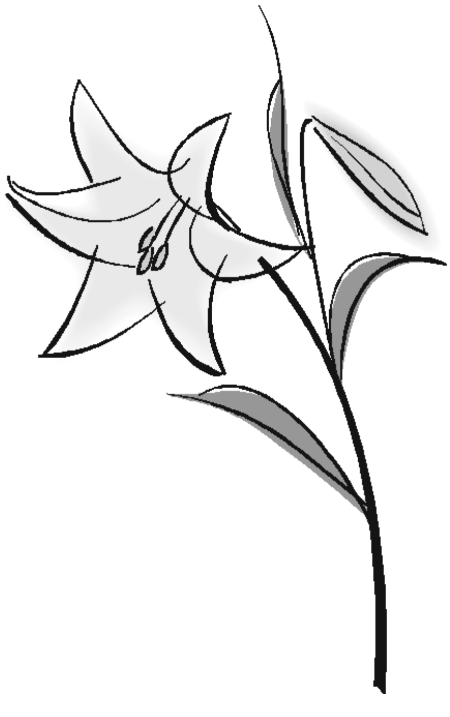
To my mother and father



Abstract

Business cycles, the ups and downs observed somewhat simultaneously in numerous macroeconomic variables in an economy and often measured using real GDP, are important and, despite much economic research, still incompletely understood. Dating the business cycle has always been of interest in macroeconomic research. The dating might help to find the causes of a recession and this understanding could help to prevent or limit the duration of recessions in the future. A non-stationary, non-parametric smoothing-technique is proposed here to make business cycles simpler to analyse and interpret. The method is applied to the Euro area and to the Swedish economy. For the Euro area the method finds two deeper and two milder recessions and one stagnation period since 1970. The dating is close to that of the CEPR. The same method is then used to date recessions in Sweden for the period 1969-2006. Four recessions were found.

One research area of interest related to the dating of business cycles is forecasting of an upcoming recession. If an upcoming recession is detected, monetary policy could respond and avoid an output gap or a fall in inflation. We use a probit model to examine the in-sample performance of various financial variables as a predictor of Swedish recessions. The results show that the slope of the yield curve appears to perform better than other variables, but also that the spread is not a reliable indicator for detecting recessions in Sweden since there are many false warnings.

Keywords: Business cycles; business cycle dating; non-parametric smoothing; non-stationarity; recession prediction; interest rate spread; binary response models.

Acknowledgement

First and foremost I would like to express my sincere gratitude and appreciation to my advisor, Professor Cătălin Stărică, for his support and guidance. He has taught me how to be a good researcher and all I have learned from him will continue to be great assets to me. I was very lucky to have him as my advisor and without his help none of this work would have been possible. I consider him to be my greatest teacher ever.

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– "Still confused, but on a higher level." Enrico Fermi (1901-1954) –

Göteborg May 2007
Louise Holm

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About this thesis

Business cycle dating refers to the ex-post dating of the start and the end of a recession in an economy. The aim of this thesis is to apply a non-stationary, non-parametric business cycle dating method and finally use these dates when the performance of some financial series are tested in a forecasting method for an upcoming recession in Sweden.

Chapter 1 presents an introduction to the dating of business cycles. In Chapter 2 some general statistics are explained and Chapter 3 contains the statistical tools for dating the business cycle. In Chapter 4 the method in the previous chapter is used to date the business cycle in the Euro area between the year 1970 and 2003. The estimated dates are here compared to the dating by CEPR Dating Committee and two previous dating results from non-parametric methods. In Chapter 5 the same method is used on Swedish data to date the business cycle in Sweden where no official dating method exists. In Chapter 6 several macroeconomic variables are tested for their ability to predict recessions in Sweden. The dates found in Chapter 5 are instrumental to performing these tests. Chapter 7 summarises.

Chapter 1

Introduction

1.1 Business cycles

Business cycles, the ups and downs observed somewhat simultaneously in numerous macroeconomic variables in an economy, are important and, despite much economic research, still incompletely understood. To call them "cycles" is misleading, as they do not usually repeat at regular intervals. Early economic theories assumed that the variations in the demand from households and firms where the only things that influenced the business cycle. These so called Keynesian models worked well in the calm macroeconomic environment after the Second World War. In the 1970s there was a substantial rise in the oil prices and lower rises in the productivity. The old models did no longer work. Kydland & Prescott [58] showed that not only variations in the demand but also disturbances in the supply were important for the business cycle. They analysed how variations in the rate of technological development can cause different phases in the business cycle.

Some of the first to discuss the business cycle and ways to date it were Arthur Burns and Wesley Mitchell in their 1946 book, Measuring Business Cycles [13]. One of their insights was the comovements of many economic series, i.e. they rise and fall together. They also noted that there is no regularity in the timing of business cycles. They suggested dating the turning point of the economic activity based on the clustering of the turning points of individual series.

In the econometric literature on the subject there are many different definitions of a business cycle. Some look at one series and others at several series or the comovement of several series. If one concentrates on the dynamic of one series (most often the GDP) there are two common definitions of a business cycle. The first definition is based on the level of the series and the turning points are selected by the absolute decline or rise of the value of the series and the second is based on the growth rate in the series. To further explain this we look at an example from Anas & Ferrara [4] of three different ways to interpret the business cycle shown in Figure 1.1. In the top graph, showing the growth rate cycle, a peak (point a) represents the maximum growth rate. On the contrary the trough (point b) indicates that the growth rate has reached its lower value and is increasing again. The negative (positive) values of the growth rate cycle represents the periods when the classical cycle is decreasing (increasing). The turning points of a classical cycle, named B for peaks and C for troughs, are shown in the middle graph in Figure 1.1. One can also define a third cycle called the growth cycle. It is found in the bottom graph and can be defined as the deviation of the reference series to the trend, though difficult to define and estimate. The trend is the underlying direction, an upward or downward tendency, in the series. The cycle separates periods of negative growth (recessions) from periods of positive growth (expansions). The turning points (named A for peaks and D for troughs) are reached when the growth rate decreases below, or increases above, the trend growth rate.

1.2 Dating the business cycle

Dating the business cycle has always been of interest in macroeconomic research. The dating is helpful in finding the causes of a recession and this understanding might help preventing or limiting the duration of recessions in the future. Previous research in business cycle dating and the modelling of individual economic series can be divided into two groups: parametric and non-parametric methods. The parametric approach assumes that the dynamic of the macroeconomic series is described by a small number of parameters. The non-parametric approach differs from parametric models in that the model structure is not specified a priori but is instead determined from data.

Beveridge & Nelson [9], Nelson & Plosser [66] and Campbell & Mankiw [15] use ARIMA and ARMA models to analyse business cycles while Harvey [49], Watson [84] and Clark [21] use linear unobserved components models. The dominant non-linear parametric approach originates from the work of Hamilton [42]. He assumes that the mean growth rate of the observed series evolves according to a two-state Markov-switching process. This means that the dynamics of expansions are qualitatively different from those of contractions. (See also Chauvet [18], Kaufmann [54] and Artis et al. [6].) Modifications of the approach of Hamilton were proposed by several authors. Krolzig [57] provides a multivariate extension of Hamilton Markov-switching regime model which produces the probability of a turning point. Filardo & Gordon [35] extends the Markov-switching model so that the information contained in leading indicator data can be used to forecast transition probabilities. Some authors use a three-state model for the business cycle (see Sichel [74], Boldin [10], Clements & Krolzig [22], Krolzig & Toro [57] and Layton & Smith [59]). The third state could either be an extra expansion phase (regular growth phase and a high growth phase) or an extra contraction phase (a slowdown phase and a recession phase).

As mentioned, the comovement of representative coincident series, i.e their common evolution along the cycle, was first used in the dating by Burns & Mitchell [13]. Geweke [40] and Sargent & Sims [73] used a parametric dynamic index model, a model that measures the comovement of many time series. More recently Quah & Sargent [71], Stock & Watson [77] and [78] used comovements of variables along the cycle to extract a common factor. Diebold & Rudebush [25] proposed a mix of dynamic factor models and regime switching (see also Chauvet [17] and Kim & Nelson [55]). Forni et al. [36] and Forni & Lippi [37] proposed a generalised dynamic factor model which allows for serial correlation within and across individual processes. Their model generalised the factor model of Geweke [40] and Sargent & Sims [73] by allowing for non-orthogonal idiosyncratic terms

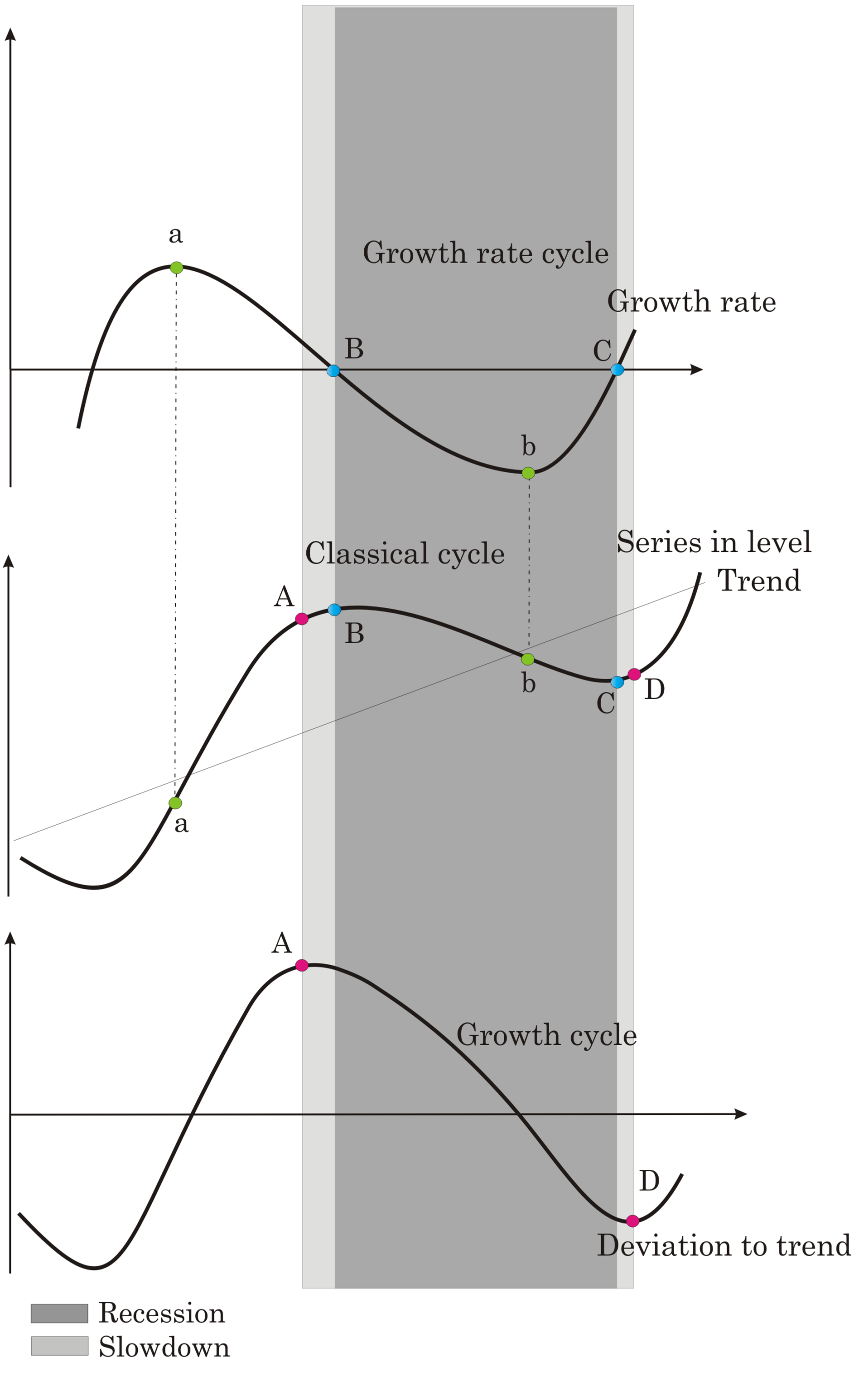

Figure 1.1: Business cycles; (top) growth rate cycle, (middle) classical cycle and (bottom) growth cycle

(see also Altissimo et al. [3] where EuroCOIN, a coincident indicator of the Euro area business cycle, is introduced). All the approaches described so far are parametric. We continue with an overview of the non-parametric methods in the literature.

The Bry & Broschan [12] procedure is a non-parametric approach which identifies points as local maxima or minima based on some censoring rules. The Burns & Mitchell procedure was, amongst many others, adopted by King & Plosser [56], Watson [83], Pedersen [68] and Harding & Pagan [44]. For comparative work on the Bry-Broschan and Hamilton cycle dating methods see Harding & Pagan [46]. They conclude that non-parametric methods are preferred[1]. The method in Chapter 3 follows a non-parametric approach and our definition of a business cycle fits the classical business cycle.

NBER - Dating the business cycle in the U.S.

The National Bureau of Economic Research (NBER) is a private non-profit non-partisan U.S. research organisation founded in 1920, dedicated to promoting a greater understanding of how the economy works. The NBER Business Cycle Dating Committee identifies the dates at which the U.S. is experiencing an economic recession and published its first business cycle dates in 1929. They define a recession as "*a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production and wholesale-retail sales*"[2]. The committee looks at measures of activity across the entire economy. The committee focuses primarily but not exclusively on (1) personal income less transfer payments, in real terms, (2) employment, (3) industrial production and (4) the volume of sales of the manufacturing and wholesale retail sectors adjusted for price changes. Recently they also look at monthly estimates of real GDP. Peaks and troughs dated since 1960 are shown in Table 1.1.

peak	**trough**
April 1960 (Q2)	February 1961 (Q1)
December 1969 (Q4)	November 1970 (Q4)
November 1973 (Q4)	March 1975 (Q1)
January 1980 (Q1)	July 1980 (Q3)
July 1981 (Q3)	November 1982 (Q4)
July 1990 (Q3)	March 1991 (Q1)
March 2001 (Q1)	November 2001 (Q4)

Table 1.1: The NBER business-cycle dates since 1960

Figure 1.2 plots quarterly GDP in the U.S. since 1960 together with the NBER recession dates. The NBER peaks and troughs are frequently used in charts and tables

[1] In the comparison of two business cycle dating methods, one non-parametric: Bry and Broschan algorithm, and one parametric: a Markov switching (MS) model, they argue that the non-parametric method is more robust than the MS model. Harding & Pagan suggest using techniques that are as non-parametric as possible.

[2] http://www.nber.org/cycles/cyclesmain.html

in private and government publications. According to Christina Romer [72], the NBER dates have been influential because they are thought to be reliable.

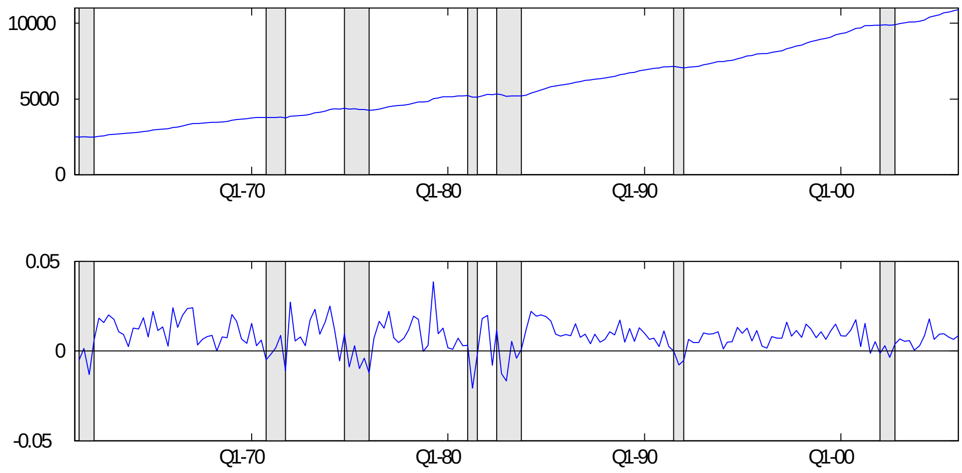

Figure 1.2: (Top) quarterly U.S. GDP since 1960 and (bottom) first difference of the logarithm of quarterly U.S. GDP, with dates of economic recessions as determined by the NBER indicated with shaded regions

Let us say that a recession rule could be two consecutive quarters of negative growth in the GDP. In the bottom graph in Figure 1.2 we can see that recession rule is hard to apply since the growth rate switch sign between one period and the next. There would be too many turning points if one used this series.

CEPR - Dating the business cycle in the Euro area

The Centre for Economic Policy Research (CEPR), has a business cycle dating committee which analyses Euro area aggregate statistics. In dating the business cycle, since the end of the 1990s the CEPR dating committee focus primarily but not exclusively on (1) quarterly GDP, (2) quarterly employment, (3) monthly industrial production, (4) quarterly business investment and (5) consumption and its main components. The CEPR Business Cycle Dating Committee uses a similar definition of a recession as the NBER. The CEPR defines a Euro area recession by "*at least two consecutive quarters of negative growth in GDP, employment and other measures of aggregate economic activity for the Euro area as a whole*"[3]. The CEPR committee, unlike the NBER, dates the business cycle in terms of quarters rather than months arguing that the most reliable and relevant European data are quarterly series. The dating committee has identified three cyclical episodes since 1970 found in Table 1.2.

Figure 1.3 plots quarterly GDP in the Euro area since 1970 together with the CEPR recession dates.

[3] http://www.cepr.org/data/Dating/info1.asp

peak	trough
1974:Q3	1975:Q1
1980:Q1	1982:Q3
1992:Q1	1993:Q3

Table 1.2: The CEPR business-cycle dates since 1970

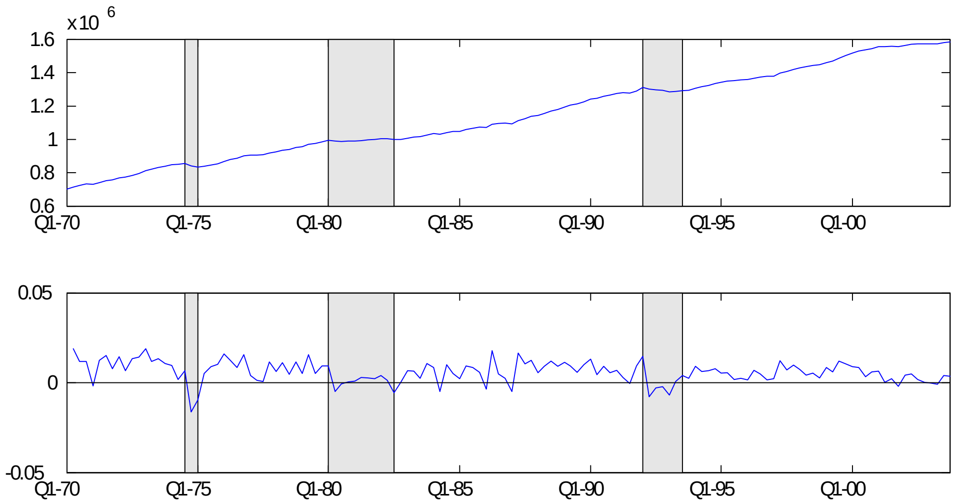

Figure 1.3: (Top) quarterly Euro area GDP since 1970 and (bottom) first difference of the logarithm of quarterly Euro area GDP, with dates of economic recessions as determined by the CEPR indicated with shaded regions

Chapter 2

Statistical methods: a bird's eye view

2.1 Non-parametric regression

By "letting the data speak for itself", a non-parametric approach can uncover structural features of the data that a parametric approach might not find. One of the most commonly used non-parametric techniques is kernel smoothing[1]. Figure 2.1 shows a comparison of establishing a relationship between two variables using first a parametric linear model and second, a non-parametric one. The second approach seems to be more truthful to the empirical relationship between the variables.

Suppose we want to find a relationship between an explanatory variable x and a response variable y. Assume that the relationship between x and y can be described with an unknown function f and residuals ε as

$$y_i = f\left(x_i\right) + \varepsilon_i, \qquad i = 1, \ldots, n, \tag{2.1}$$

where $E\left[\varepsilon_i\right] = 0$ for each i. The idea is to estimate $f\left(x_0\right)$ by averaging over the y-values corresponding to x's close to x_0.

A non-parametric estimator can be described as

$$\widehat{f}\left(x, h\right) = \sum_{i=1}^{n} W_i\left(x\right) y_i \tag{2.2}$$

where the weights $W_i(x)$ indicate the importance of the contribution of the observation y_i in the estimation of $f(x)$. Various weight schemes yield different estimations.

A common example is the Nadaraya-Watson estimator (first suggested by E.A. Nadaraya [64] and G.S. Watson [82]) with weight function

$$W_i^{NW}\left(x\right) = \frac{K\left(\frac{x-x_i}{h}\right)}{\sum_{i=1}^{n} K\left(\frac{x-x_i}{h}\right)}, \tag{2.3}$$

[1] See Härdle [51] and Wand & Jones [81] on smoothing-techniques for curve-estimation.

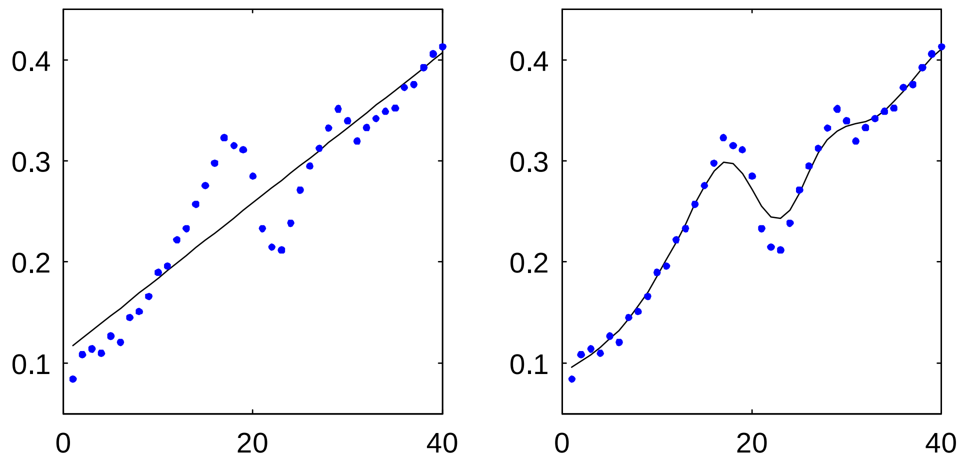

Figure 2.1: Comparing a parametric (left) with a non-parametric (right) model

where K is a kernel-function with support in the interval $[-1, 1]$, thus non-zero weights are associated only with observations y_i such that $|x_i - x| < h$, where h is the bandwidth (window-width or smoothing-parameter).

Another weight function (see Gasser & Müller [39]) is defined as

$$W_i^{GM}(x) = \frac{1}{h} \int_{s_{i-1}}^{s_i} K\left(\frac{x-u}{h}\right) du, \tag{2.4}$$

where $s_i = \frac{x_{i+1}+x_i}{2}$, $x_i = \frac{x}{n}$ and $x_i \in [0, 1]$.
Bandwidth determines how many observations should be averaged in estimating the y-value for x and how important they are in the estimation. Thus it determines the smoothness or roughness of the estimate. The kernel weighs observations closer to x more than those further away and then the contributions from each point are summed to create an overall estimate. For simplicity of presentation we will, in what follows, refer to the Nadaraya-Watson estimator. The Gasser & Müller estimator has similar properties.

One commonly used kernel-function, K, is the Epanechnikov kernel:

$$K(u) = \frac{3}{4}\left(1-u^2\right) I_{\{|u|<1\}}. \tag{2.5}$$

The Epanechnikov kernel can be found in Figure 2.2. The weight-function, which is proportionate to the distance, is

$$K\left(\frac{x-x_i}{h}\right) = \begin{cases} \frac{3}{4}\left(1-\left(\frac{x-x_i}{h}\right)^2\right) & \text{if } \mid x-x_i \mid < h \\ 0 & \text{if } \mid x-x_i \mid \geq h \end{cases}. \tag{2.6}$$

Figure 2.3 shows a smoothing obtained by the Nadaraya-Watson estimator with Epanechnikov kernel of data generated as $y = sin(x) + \varepsilon$.

Bandwidth selection

One way to measure the quality of an estimator is to calculate its mean squared error.

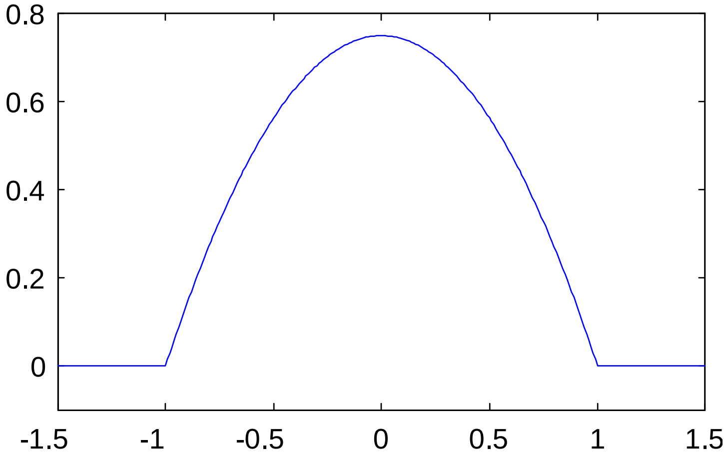

Figure 2.2: The Epanechnikov kernel

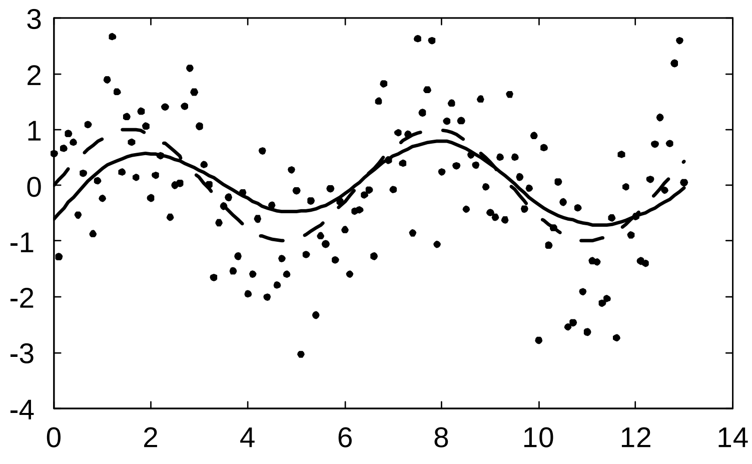

Figure 2.3: Nadaraya-Watson estimator of data points generated from $y = sin(x) + \varepsilon$ where the full line is the estimate and the dashed line is $sin(x)$

$$
\begin{aligned}
MSE(x,h) &= E\left[\hat{f}\left(x,h\right) - f\left(x\right)\right]^2 = \\
&= \left[E\left[\hat{f}\left(x,h\right)\right] - f\left(x\right)\right]^2 + E\left[\hat{f}\left(x,h\right) - E\left[\hat{f}\left(x,h\right)\right]\right]^2 = \\
&= \text{Bias}^2 + \text{Variance}
\end{aligned} \tag{2.7}
$$

Note also that

$$
\begin{aligned}
MSE(x,h) &= E\left[\hat{f}\left(x,h\right) - f\left(x\right)\right]^2 = \\
&= E\left[\hat{f}\left(x,h\right) - y\right]^2 + \sigma^2
\end{aligned} \tag{2.8}
$$

where $\sigma^2 = Var(\varepsilon)$ in Equation (2.1).

The behaviour of $\hat{f}(x,h)$ when varying the bandwidth h can be expressed in terms of bias and variance of the estimator. From Gasser & Müller [39] we get that

$$\text{Bias}^2 \approx h^4 d_K^2 [f''(x)]^2/4 \tag{2.9}$$

while

$$\text{Variance} \approx (nh)^{-1}\sigma^2 c_K \tag{2.10}$$

where $c_K = \int K^2(u)du$ and $d_K = \int u^2 K(u)du$. We see that the bias is an increasing function of the bandwidth h and the variance is a decreasing function of h. As the bandwidth gets wider, the variance decreases, but the bias is increasing. We would like to minimise both of them but this can not be done independently since they work in different directions, there is a trade-off. This trade-off is shown in Figure 2.4. The minimum MSE is of the order $n^{-\frac{4}{5}}$.

What we need is a method to find a bandwidth that balances the bias and the variance and make the error as small as possible. One of the most popular methods is cross-validation (see Stone [79]).

Cross-validation

Non-parametric smoothing estimation faces the risk of under- or over-smoothing. A too small bandwidth will yield a too wiggly curve and a too large bandwidth will yield a too flat curve (see Figure 2.5).

The bandwidth that minimises MSE in Equation (2.7) is the optimal bandwidth. Since MSE is an unknown theoretical quantity we will need to approximate it. Towards this end we define the cross-validation function

$$CV\left(h\right) = \sum_{i=1}^{n}\left(\widehat{f}_i\left(x_i,h\right) - y_i\right)^2 \text{ where } \widehat{f}_i\left(x,h\right) = \frac{\sum_{j\neq i} K\left(\frac{x-x_j}{h}\right) y_j}{\sum_{j\neq i} K\left(\frac{x-x_j}{h}\right)}. \tag{2.11}$$

For a given h, $CV(h)$ is an estimate of the first term in Equation (2.8). The CV-method chooses the bandwidth h that minimises the function $CV(h)$.

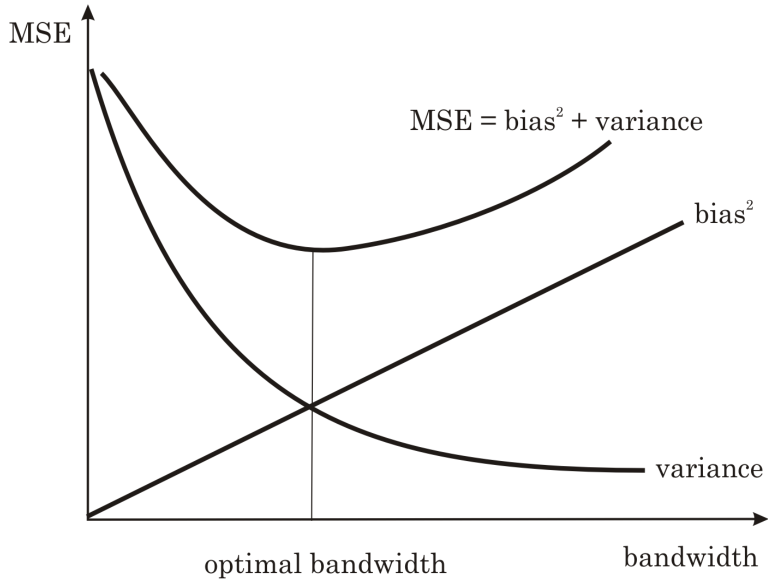

Figure 2.4: The trade-off between variance and bias

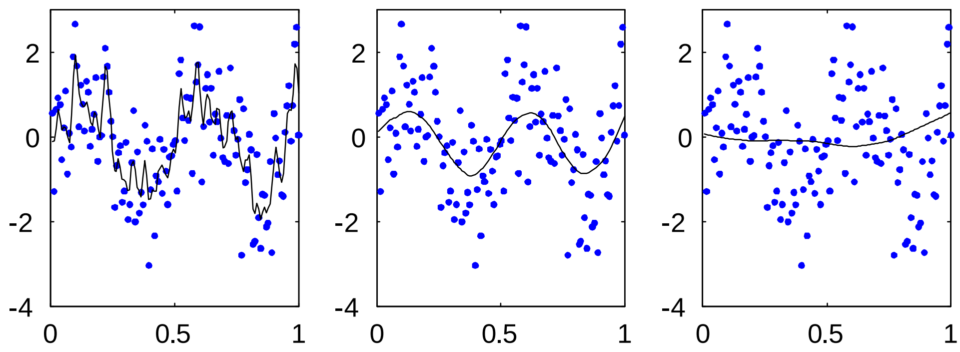

Figure 2.5: A Nadaraya-Watson estimator with (left) a very small bandwidth, (middle) an optimal bandwidth and (right) a very large bandwidth

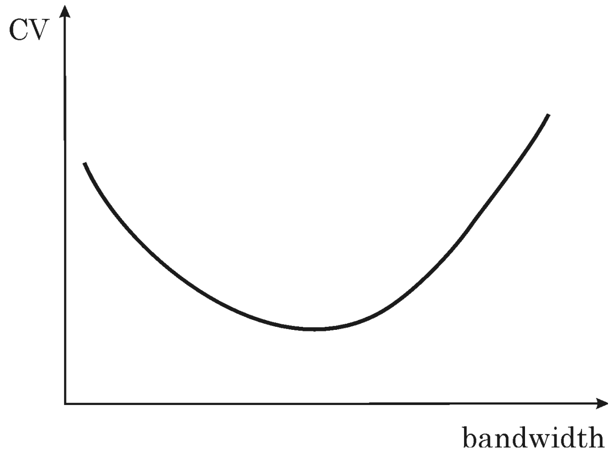

Figure 2.6: Cross-validation function

Overcoming edge-effects

Near the boundaries, the local averaging process gets asymmetric, that is, some of the weights are non-defined since we end up outside the boundary. Estimates close to the beginning and end of the study-period must be based only on data within the period and are thus likely to be biased. For the Nadaraya-Watson estimator this means that the usual optimal MSE of order $n^{-\frac{4}{5}}$ is magnified to $n^{-\frac{2}{3}}$ near the boundaries. These problems are referred to as edge effects.

Hall & Wehrly [41] suggest an easy method for overcoming edge effects by reflecting the data set around the two values of f estimated at the end points of the design interval. This generates new data (called pseudodata) and the data set becomes three times as large. An illustration is shown in Figure 2.7. The technique is applicable to both regularly spaced and randomly spaced design points. For the rest of the thesis, the x variable will be time and be regularly spaced.

The observed data-pairs (x_k, y_k), where $1 \leq k \leq n$, are first ordered such that $a < x_1 \leq ... \leq x_n < b$ and the interval $[a, b]$ is called the design interval. To estimate $\widetilde{f}(a)$ and $\widetilde{f}(b)$ at the extremes of the design interval, one uses the one-sided kernel

$$L(u) = \frac{16}{19}(8 - 15u) K(u), \qquad \text{for } 0 < u < 1, \tag{2.12}$$

where $K(u)$ is again the Epanechnikov kernel. This yield

$$\widetilde{f}(a) = \frac{\sum_{k=1}^{n} L\left(\frac{(x_k - a)}{h_a}\right) y_k}{\sum_{k=1}^{n} L\left(\frac{(x_k - a)}{h_a}\right)} \tag{2.13}$$

and

$$\widetilde{f}(b) = \frac{\sum_{k=1}^{n} L\left(\frac{(b - x_k)}{h_b}\right) y_k}{\sum_{k=1}^{n} L\left(\frac{(b - x_k)}{h_b}\right)}. \tag{2.14}$$

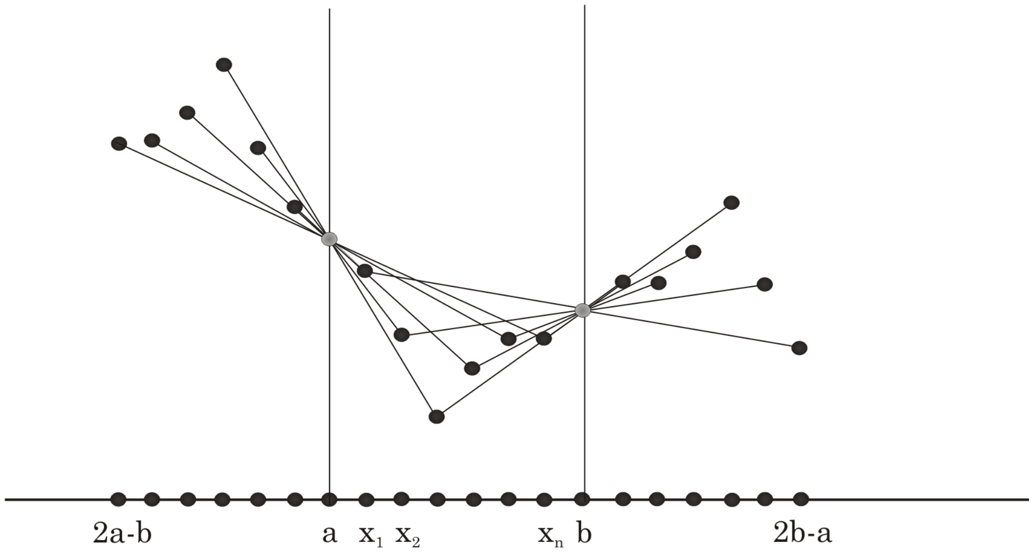

Figure 2.7: Reflection of original data in point estimates at end of interval which results in a new data set containing the original data and the pseudodata generated by the reflection suggested by Hall & Wehrly [41]

The bandwidth used here is $h_a = h_b = ch$ with $c = 1.8617$ which is given by a bandwidth selection method described in Hall & Wehrly [41]. Then the data (x_k, y_k) is reflected in the points $(a, \widetilde{f}(a))$ and $(b, \widetilde{f}(b))$ to produce pseudo-data (x_k, y_k) for the intervals $-n \leq k \leq -1$ and $n+2 \leq k \leq 2n+1$. The pseudo-data is defined by

$$
\begin{aligned}
x_{-k} &= 2a - x_k & y_{-k} &= 2\widetilde{f}(a) - y_k \\
x_{n+k+1} &= 2b - x_{n-k+1} & y_{n+k+1} &= 2\widetilde{f}(b) - y_{n-k+1} \quad (1 \leq k \leq n)
\end{aligned}
$$

Hall & Wehrly [41] state that the difference between the MSE of the estimator based on pseudodata and that of a hypothetical, but unobtainable, estimator based on data from a larger interval equals $O(h^5)$. This is negligible relative to the entire MSE, which, if h is chosen optimally, is of the size $O(h^4)$.

2.2 Probit model

Probit models extend the principles of generalised linear models. It applies in cases when the dependent variable is limited in some way. For the probit, the dependent variable is limited to be binary; either zero or one. Standard OLS can encounter some statistical problems when the dependent variable is binary, so the probit is sometimes preferred.

The dependent variable y_i can be only one or zero and the probability of y_i is estimated in

$$\Pr(y_i = 1) = \phi(x_i^T b + \varepsilon_i). \tag{2.15}$$

Here b is a parameter to be estimated, $\varepsilon \sim N(0,1)$, and ϕ is the normal cumulative standard density function.[2] The model is estimated by maximum likelihood, with the likelihood function

$$L = \prod_{[y_i=1]} F(x_i^T b) \prod_{[y_i=0]} \left[1 - F(x_i^T b)\right]. \tag{2.16}$$

Marginal effects: How does the probability of y change when x changes? In binary regression models, the marginal effect is the slope of the probability curve relating x_i to $Pr(y_i = 1|x_i)$, holding all other variables constant. Marginal effects are popular because they often provide a good approximation to the amount of change in y that will be produced by a one-unit change in x.

$$\frac{\delta\phi(x_i^T b)}{\delta x_i} \tag{2.17}$$

Measures of fit: When analysing the goodness of fit in the classical regression model we can use R^2 as a measure of the explanatory power of the regression model. The R^2 measure is however of limited use when the dependent variable is dichotomous. An alternative measure is defined as

$$\text{McFadden's } \mathrm{R}^2 = 1 - \frac{\text{L (at max)}}{\text{L (all coefficients are zero, except the constant)}}, \tag{2.18}$$

where L is the log likelihood value.

Another measure of fit is a threshold interpretation. A threshold interpretation is such that if $\phi(x_i^T b) > u$ then $y = 1$.

[2] See Aldrich & Nelson [1] for more details on probit models.

Chapter 3

Estimation procedures

In what follows we will extract the common dynamic from a number of macroeconomic series. The series have time-varying means and time-varying standard deviations and we assume that the former have a common dynamic and be such that they increase in an economic expansion and decrease in an economic contraction. The time-varying means are linear expressions of a "time-varying activity measure". We follow D'Agostino & Stărică [23] for the non-parametric setup while the common dynamic is estimated using the method of Polzehl et al. [70]. Both methods (D'Agostino & Stărică [23] and Polzehl et al. [70]) performed well on U.S. data and matched the recessions dated by the NBER.

3.1 Non-parametric kernel smoothing

We will use the heteroscedastic model of Müller & Stadtmüller [62] to describe the macroeconomic series as non-stationary independent random variables with varying unconditional means and varying standard deviations

$$y_k = \mu\left(t_k\right) + \sigma(t_k)\varepsilon_k, \qquad k = 1, \ldots, n, \tag{3.1}$$

where $t_k = \frac{k}{n}$, $t_k \in [0, 1]$ and y_k is the log of the macroeconomic variable at time t. The errors are assumed to be independent and identically distributed with zero mean and unit variance. The functions μ:$[0, 1] \to \mathbb{R}$ and σ:$[0, 1] \to \mathbb{R}_+$ are assumed to be smooth.

Estimating the mean, $\mu(t)$

Following Gasser & Müller [39], the kernel estimator used to estimate the expected levels $\mu\left(t\right)$ is

$$\hat{\mu}\left(t\right) = \sum_{k=1}^{n} W_k\left(t\right) y_k. \tag{3.2}$$

$W_k\left(t\right)$ is the kernel- or weight-function, defined as

$$W_k\left(t\right) = \frac{1}{h}\int_{s_{k-1}}^{s_k} K\left(\frac{t-u}{h}\right) du, \tag{3.3}$$

where $s_k = \frac{t_{k+1}+t_k}{2}$, $t_k = \frac{k}{n}$ and $t_k \in [0,1]$. The kernel itself (K), must be a continuous, bounded, and symmetric real function which integrates to one ($\int K(u)du = 1$).

We will use the Epanechnikov kernel here since it minimises the mean square error (MSE). The kernel satisfies the Lipschitz condition[1], the regression function, $f(t,h)$, is at least twice continuously differentiable and bandwidth (h) must satisfy $h \to 0$ and $nh \to \infty$ as $n \to \infty$.

Asymptotic properties of the estimated mean: The closeness of the estimator to its target is given in Müller & Stadtmüller [62].

Theorem 1 *Under general regularity conditions (see Müller & Stadtmüller [62]) we have that if $nh_\mu \longrightarrow \infty$ as $n \longrightarrow \infty$ and $h_\mu \longrightarrow 0$, the expected value $E\left(\hat{\mu}(t)\right)$ satisfies*

(a)

$$E\left(\hat{\mu}(t)\right) - \mu(t) = \mu''(t) \cdot h_\mu^2 \tilde{B}_2 + o\left(h_\mu^2\right) + O\left(n^{-1}\right)$$

where $\tilde{B}_2 = \int K(u)u^2du/2$.

(b) It is also true that

$$|E(\hat{\mu}(t)) - \mu(t)| \leq c(h_\mu^2 + n^{-1}),$$

where c is again an unspecified positive constant.
(c) The variance of $\hat{\mu}(t)$ satisfies

$$Var(\hat{\mu}(t)) = \frac{\sigma^2(t)}{nh_\mu} V(1 + o(1))$$

for every t where $V = \int_{-1}^{1} K(u)^2du = 0.6$ for the Epanechnikov kernel.

Estimating the standard deviation, $\sigma(t)$

Local variances are assumed to be smooth and to be Lipschitz continuous of order γ i.e., $\sigma^2(t) \in Lip_\gamma([0,1])$ where $\gamma \in (0,1]$. In Equation (3.1), estimation of the standard deviation is done in two steps. First, one removes the mean from Equation (3.1). A new series with mean zero and variance $\sigma\left(t_k\right)^2$ is produced

$$\widetilde{\sigma}^2\left(t_k\right) = \left(\sum_{j=-m_1}^{m_2} w_j y_{k+j}\right)^2, \tag{3.4}$$

where w_j are weights that satisfy $\sum_{j=-m_1}^{m_2} w_j = 0$ and $\sum_{j=-m_1}^{m_2} w_j^2 = 1$ for some fixed $m_1, m_2 \geq 0$. In this case $m_1 = 1$ and $m_2 = 0$, so the weights are $w_{-1} = -\frac{1}{\sqrt{2}}$ and $w_0 = \frac{1}{\sqrt{2}}$. Second, the variance is estimated noting that

$$\widetilde{\sigma}^2\left(t_k\right) = \sigma^2\left(t_k\right) + \widetilde{\varepsilon}_k, \qquad 1 \leq k \leq n, \tag{3.5}$$

[1] Lipschitz continuity, named after Rudolf Lipschitz, is a smoothness condition for functions which is stronger than regular continuity.

where the errors $\widetilde{\varepsilon}_k$ form an $m_1 + m_2$-dependent sequence and $E\left[\widetilde{\varepsilon}_k\right] = 0$. Since Equation (3.5) has the form of Equation (3.1) the variance can be estimated as

$$\widehat{\sigma}^2\left(t, h_{\sigma^2}\right) = \sum_{k=1}^{n} W_k\left(t\right) \widetilde{\sigma}^2\left(t_k\right), \tag{3.6}$$

where $W_k\left(t\right)$ is given by Equation (3.3).

The estimated errors $\left(\varepsilon_k\right)$ are defined as

$$\hat{\varepsilon}_k = \frac{y_k - \hat{\mu}(t)}{\hat{\sigma}^i(t)}. \tag{3.7}$$

Asymptotic properties of the estimated variance: The closeness of the estimator to its target is given in Müller & Stadtmüller [62].

Theorem 2 *Under general regularity conditions (see Müller & Stadtmüller [62]) we have*

(a)

$$\sup_{t \in I} |\hat{\sigma}^2(t) - \sigma^2(t)| = O\left(\left(\frac{\log n}{n}\right)^{(k+\zeta)/(2(k+\zeta)+1)}\right),$$

for any compact interval $I \subset (0, 1)$.
The function found in Equation (3.4) is twice differentiable with a continuous second derivative, $k = 2$, and ζ is chosen to be zero.

(b) Then the estimated variance satisfies

$$|\hat{\sigma}^2(t) - \sigma^2(t)| \leq c\left(\left(\frac{\log n}{n}\right)^{(2/5)}\right),$$

where c is an unspecified positive constant and bandwidth is chosen to be $h_{\sigma^2} \sim [\log n/n]^{1/5}$.

(c) The expected value of the variance satisfies

$$|E(\hat{\sigma}^2(t)) - \sigma^2(t)| \leq c\left(h_{\sigma^2}^2 + n^{-1}\right),$$

where c is again an unspecified positive constant.

Confidence-bands

The 95% confidence bands for the mean $\mu(t)$, will be calculated using the asymptotic formula of the variance in Theorem 1,

$$\hat{\mu}(t) \pm 1.96\hat{\sigma}(t)\sqrt{V/nh} \tag{3.8}$$

where $V = \int_{-1}^{1} K(u)^2 du = 0.6$ for the Epanechnikov kernel and $\hat{\sigma}(t)$ is the standard deviation in Equation (3.1).

3.2 Modelling and estimating the common dynamic

In the sequel we will assume that the time-varying means of the macroeconomic series have a common dynamic: $\mu^{(i)}(t_k) = m^{(i)} + \alpha^{(i)} f(t_k)$. Let $y_t^{(i)}$, $(i = 1, ..., p)$, be the log of macroeconomic variable i at time t. Then the hypothesis of a common dynamic yield the following model

$$y_k^{(i)} = m^{(i)} + \alpha^{(i)} f(t_k) + \sigma^{(i)}(t_k)\varepsilon_k^{(i)}, \quad k = 1, \ldots, n, \quad i = 1, \ldots, p, \tag{3.9}$$

where $t_k = \frac{k}{n}$, $t_k \in [0, 1]$, m and α are positive coefficients, the function $f(t_k)$ (the time-varying unconditional mean) is the state of the economy and $\sigma(t_k)$ is the varying standard deviation.

First the coefficients $m^{(i)}$ and $\alpha^{(i)}$ must be estimated. They are only identifiable up to a shift and scaling factor, so one of the m's can arbitrarily be set to zero, and the α set to unity. The least noisy series will be taken as reference and be denoted i_0. Hence, $m^{i_0} = 0$ and $\alpha^{i_0} = 1$. Note that for $i \neq i_0$ Equation (3.9) can be rewritten as:

$$y_s^{(i)} = m^{(i)} + \alpha^{(i)} y_s^{(i_0)} + \delta_s^{(i)} \tag{3.10}$$

where the errors, $\delta^{(i)}$, are independent with zero mean and finite variance. The coefficients, m and α, can be estimated by OLS

$$\left(\widehat{m}^{(i)}, \widehat{\alpha}^{(i)}\right) = argmin_{(m,\alpha)} \sum_{t=1}^{n} \left(y_k^{(i)} - m^{(i)} - \alpha^{(i)} y_k^{(i_0)}\right)^2 \tag{3.11}$$

where m and α minimise the sum of locally-weighted squared-errors.
If m and α are allowed to be time-dependent the expression in Equation (3.11) is modified to read

$$\begin{aligned} \left(\widehat{m}^{(i)}\left(t\right), \widehat{\alpha}^{(i)}\left(t\right)\right) &= \\ &= arginf_{(m,\alpha)} \sum_{s=1}^{n} \left(y_s^{(i)} - m^{(i)} - \alpha^{(i)} y_s^{(i_0)}\right)^2 W_s\left(t\right) \end{aligned} \tag{3.12}$$

where $W_s\left(t\right)$ are weights defined in Equation (3.3) that localise the estimation of m and α. In matrix notation this is

$$\left(\begin{array}{c} \widehat{m}^{(i)}\left(t\right) \\ \widehat{\alpha}^{(i)}\left(t\right) \end{array}\right) =$$
$$\left(\begin{array}{cc} \sum_s W_s\left(t\right) & \sum_s y_s^{(i_o)} W_s\left(t\right) \\ \sum_s y_s^{(i_o)} W_s\left(t\right) & \sum_s \mid y_s^{(i_o)} \mid^2 W_s\left(t\right) \end{array}\right)^{-1} \left(\begin{array}{c} \sum_s y_s^{(i)} W_s\left(t\right) \\ \sum_s y_s^{(i)} y_s^{(i_o)} W_s\left(t\right) \end{array}\right).$$

Next, the y_t's are standardised by scaling them with the estimated m and α to produce

$$z_k^{(i)} = \frac{y_k^{(i)} - m^{(i)}\left(t_k\right)}{\alpha^{(i)}\left(t_k\right)} = f\left(t_k\right) + \frac{\sigma^{(i)}\left(t_k\right)}{\alpha^{(i)}\left(t_k\right)} \varepsilon_k^{(i)}. \tag{3.13}$$

The z's have mean $f(t_k)$ and variance $\left(\frac{\sigma^{(i)}(t_k)}{\alpha^{(i)}(t_k)}\right)^2$. Next, we construct the linear combination, series $X(t)$, that has the smallest variance

$$X(t) = \beta(t)^T z_k \tag{3.14}$$

where

$$\begin{aligned} \beta(t) &= \arg\min_{\beta\in\beta+} Var(\beta^T z_k) = \\ &= \arg\min_{\beta\in\beta+} \beta^T Var(z_k)\beta = \\ &= \arg\min_{\beta\in\beta+} \beta^T A^{-1}(t)\Sigma^{-1}A^{-1}(t)\beta \end{aligned} \tag{3.15}$$

and $\boldsymbol{\beta}$ must satisfy $\sum_{i=1}^{p}\beta^{(i)} = 1$, $\beta^{(i)} \geq 0$. $\Sigma(t)$ is the covariance matrix of the innovations in Equation (3.9) and $A(t)$ is the α's from Equation (3.9) organised as the diagonal matrix $A(t) = diag(\alpha^{(1)}(t), ..., \alpha^{(p)}(t))$. Solving the minimisation in Equation (3.15) one gets:

$$\beta(t) = \frac{1}{\mathbf{1}^T A(t)\Sigma^{-1}A(t)\mathbf{1}} A(t)\Sigma^{-1}A(t)\mathbf{1}. \tag{3.16}$$

The β's represent the contribution to $X(t)$ of each of the macroeconomic series. Note that $X(t)$ has the expectation $f(t_k)$.

The series $X(t)$ has a time-varying mean and the noise added to it has the smallest variance possible. When estimating the mean of the first difference of the $X(t)$ series (that we denote $\Delta X(t)$) we use Equation (3.1) with $y_k = \Delta X(t)$.

$$\Delta X(t) = g\left(t_k\right) + \sigma_{\Delta X}(t_k)\eta_k, \qquad k = 1, \ldots, n \tag{3.17}$$

where $g(t_k)$ is the mean and the errors η_k are assumed to be independent and identically distributed with zero mean and unit variance.

We estimate $g(t_k)$ using

$$g\left(t_k\right) = \sum_{k=1}^{n} W_k\left(t\right)\Delta X(t). \tag{3.18}$$

A positive mean, $g(t_k) > 0$, will be interpreted as an expansion period and a negative mean, $g(t_k) < 0$, as a recession. Furthermore, a recession period must be at least two quarters and if a recession is followed by a period with a mean very close to zero (a stagnation), that period is also part of the recession.

Chapter 4

Dating the business cycle in the Euro area

Activity in industrialised economies alternates between periods of economic growth and economic contraction, the so-called business cycle. Since introduction of the Euro in the Euro currency area, the interest in and need for a reliable indicator of a European business cycle has increased. Dating the business cycle is the first step in creating models to predict the business cycle.

Dating the business cycle is an arduous enterprise. A first reason is that there is no unique way to define a business cycle. It could be about movements in a single macroeconomic variable such as the GDP or the industrial production, or it could be the comovement of several macroeconomic series.

Previous research on business cycle dating in Europe can be grouped into parametric and non-parametric methods. The dating can be done on growth cycles or classical cycles, using one or several series. Artis et al. [5] used a parametric method, a univariate Markov-switching method, introduced by Hamilton [42], for individual countries in Europe. Krolzig [57] proposed a multivariate extension of the Hamilton Markov-switching regime model which produced the probability of a turning point. Bengoecha & Quirós [7] investigates the identification and dating of the European business cycle using a Markov-switching method on an industrial confidence indicator and an industrial production index. Altissimo et al. [3] used a dynamic factor model and constructed the EuroCOIN, a coincident indicator for the Euro area produced monthly by the Centre for Economic Policy Research (CEPR) Dating Committee[1]. Altavilla [2] analyses different approaches for dating the business cycles of a set of European monetary union (EMU) member countries. Valle e Azevedo et al. [80] uses a dynamic factor model to produce a growth coincident indicator for the business cycle and compare it to the EuroCOIN constructed by Altissimo et al. [3].

Artis et al. [6] used an algorithm which implements a non-parametric method following Harding & Pagan [43] and [45] and dated the Euro area business cycle defined as the growth cycle and as the classical cycle. Their results match those found by Harding & Pagan [43]. Mönch & Uhlig [63] used a non-parametric method developed by Bry & Broschan [12] to date the business cycle from industrial production in the Euro area on

[1] www.cepr.org

a monthly basis. Anas & Ferrara [4] compare parametric and non-parametric methods on their dating of the Euro Zone economy. They find that a non-parametric method is recommended for dating and a parametric method is recommended for detecting the business cycle (prediction of a turning point).

We will follow the National Bureau of Economic Research (NBER) definition of arecession. Our approach fits in the non-parametric line of business dating literature and we adopted the classical definition of the business cycle.

This chapter is organised as follows. The next section describes the data set. Section 2 then presents the results from the estimations, and the Euro area business cycle is discussed. Section 3 summarises and draws conclusions.

4.1 Previous non-parametric dating

In this section we discuss the committee of the Centre for Economic Policy Research (CEPR), which dates Euro-area recessions first for the eleven original Euro countries from 1970 to 1998, then for the Euro area as a whole. The Committee has adopted a definition similar to the one used by the NBER. The CEPR defines a recession "as a significant decline in the level of economic activity, spread across the economy of the Euro area, usually visible in two or more consecutive quarters of negative growth in GDP, employment and other measures of aggregate economic activity for the Euro area as a whole, and reflecting similar developments in most countries". The challenge, not existing for the U.S. economy, is how to combine data from the separate economies of the Euro area. Despite a common monetary policy since 1999, they still have heterogeneous institutions and fiscal policies. European statistics are also of uneven quality. Hence, long time series are not available and data-definitions differ across countries and sources. The CEPR Committee analyses Euro area aggregate statistics, but it also monitors country statistics to verify that expansions or recessions are widespread. Besides GDP, it also looks at quarterly employment, monthly industrial production, quarterly business investment and consumption and its main components. There is no fixed rule by which country information is weighted. The CEPR uses quarterly rather than monthly data for greater liability. Since 1970 the CEPR Committee dated the following recessions

CEPR	
peak	trough
1974:Q3	1975:Q1
1980:Q1	1982:Q3
1992:Q1	1993:Q3

Table 4.1: CEPR business-cycle dates

We will also compare our results to the dates found by Mönch & Uhlig [63] and Harding & Pagan [43].

4.2 The data

The empirical analysis in this chapter is based on seven quarterly time series: industrial production (IP)[2], GDP (YER), total demand (FDD), imports of goods and services (MTR), private consumption (PCR), household's disposable income (PYR) and exports of goods and services (XTR). The data runs from 1970:Q1 to 2002:Q3, with seasonally adjusted real level data, in logarithms. All series except industrial production are from the database constructed by Fagan et al. [34]. The area-wide structural macroeconomic model (AWM)[3] developed for the European Central Bank (ECB), supplies aggregated Euro area series and among them series with similar dynamic were chosen. The similar dynamic in the series is necessary for the method to work. We have chosen series from AWM that fitted the CEPR definition of a recession and had the same dynamic. Figure 4.1 plots the data together with the recessions dated by the CEPR. First differences are plotted in Figure 4.2. We will follow the recession definition of NBER and also assume that if a recession is followed by stagnation it will be part of the recession period.

4.3 Results

The individual series and goodness of fit: The sample autocorrelation of the growth rate for our seven series, displayed in Figure 4.3, shows that there is some autocorrelation in the series. Figure 4.4 displays the cross-validation functions obtained by Equation (2.11). Bandwidth $h_{IP} = 4$, $h_{YER} = 4$, $h_{FDD} = 4$, $h_{MTR} = 4$, $h_{PCR} = 6$, $h_{PYR} = 5$ and $h_{XTR} = 5$ were used when estimating the means of the individual series and bandwidth $h = 10$ when estimating the standard deviations in Equation (3.1). The standard deviations are shown in the top graph in Figure 4.8.

In Figure 4.5, which plots the first difference of the estimated means, it is easy to see that all series have a negative growth rate or a growth rate close to zero in the first recession dated by the CEPR. In the second recession several series are very close to zero and IP, MTR and PYR are below zero. Between the first two recessions there was an expansion period and looking at the smoothed growth rates in Figure 4.5 they were all positive here. The last recession period also contain several negative growth rates. In the year 2001 IP and MTR were negative, suggesting it might have been a recession here as well. Since each series has unique characteristics, as well as features in common with the others, no single series can thus explain the cyclical fluctuation in overall activity over time.

In the top graph in Figure 4.8 we can see that XTR, MTR and IP have the largest standard deviations. In Figure 4.2 it is obvious that those three series are noisier than the other four. Figure 4.6 displays autocorrelations of the estimated residuals and of their absolute values, with lags 1 to 15 and 95% confidence-bands. Under the assumption

[2] Constructed by Mönch & Uhlig [63] for the Euro area from country time-series except Ireland, since data was unavailable.

[3] This area-wide structural macroeconomic model developed for the European Central Bank (ECB), is a relatively standard model for the Euro area, treating the Euro area as a single economy and producing area wide variables (www.ecb.int). The notations; YER, FDD, MTR and so on, are the notations of the Area-Wide Model, AWM.

of the model (3.1), the residuals are independent and identically distributed. Hence a good fit should yield uncorrelated estimated residuals. The first lag of the autocorrelation decreased compared to Figure 4.3. Note that the left column tells us how well the mean is estimated. Variance seems well estimated since the absolute values show no autocorrelation. Thus the hypothesis of identically distributed residuals seems correct.

The common dynamic: In what follows we assume that the common dynamic of the individual series are specified by Equation (3.9).

Household's disposable income, PYR, was used as the i_0-series since it had one of the smallest standard deviations. The rest of the $\hat{m}(t)$ and $\hat{\alpha}(t)$ coefficients were estimated using Equation (3.12). A bandwidth of fifteen years ($h = 30$) was used. The choice of such a large bandwidth is motivated by the need to not interfere with the dynamic of the business cycle (which has a frequency between two to ten years). We also run tests using bandwidths of $h = 10$, 20, 25 and 35 and the final results did not change much. The choice reflects our assumption that m and α change slower than the means.

In the next step we produce the standardised series $\mathbf{z}$. Figure 4.7 shows (a) the logarithmic series minus their first values in 1970:Q1 and (b) the standardised series $\hat{z}_k$ i.e., the logarithmic series scaled with estimates $\hat{m}(t)$ and $\hat{\alpha}(t)$, (3.13). This graph indicates that the method of finding their common dynamic works since the standardised series are very much alike. Figure 4.7 also shows (c) the coefficients $\hat{m}(t)$ and (d) $\hat{\alpha}(t)$. Both change over time, but slowly. The bottom graph in Figure 4.8 shows the estimated coefficients $\hat{\beta}(t)$, obtained from Equation (3.16), which tell us how much each series contribute to building $X(t)$. We note that the contribution of the series change through time. GDP contributes 10-20% during the whole period. From 1980 onwards, imports contributed between 20-30% and since 1990 exports contributed between 25-30%. Industrial production contributed the least, followed by household's disposable income. An $\hat{\alpha}(t)$ lower than 1 will give the standardised series a larger variance than the estimated variance from Equation (3.1). We can see in Figure 4.7 that all series except industrial production, IP, has $\hat{\alpha}$ values greater than 1. The middle graph in Figure 4.8 shows that $\hat{X}(t)$ has a small variance compared to the other series.

The estimated business cycle: As mentioned, IP contributed the least to $\hat{X}(t)$ and the estimated business cycle shown in Figure 4.10 would not change much if we just used the other six series. From Figure 4.7 (b) we can see that IP does not follow the other series in some periods. The middle graph in Figure 4.10 shows the first difference, $\Delta\hat{X}(t)$, indicating that $\Delta\hat{X}(t)$ is negative in the CEPR-dated recessions, so the method corresponds to that extent and it is also negative in 2001. Figure 4.9 shows the autocorrelation of the residuals and their absolute values from estimating the mean and variance of $\Delta\hat{X}(t)$ with Equation (3.17). They show no evidence of autocorrelation and support the assumption of independent and identically distributed residuals. The bottom graph in Figure 4.10 displays the series $\hat{g}(t)$, estimated for the Euro area from Equation (3.18) with bandwidth $h = 5$ since that minimised $CV(h)$ (see Figure 4.4). If we look at the middle and the bottom graph in Figure 4.10 we can see that the latter is much easier to analyse and interpret. The comparison shows the effect of our smoothing technique. We can interpret the numbers on the y-axis as the growth rate in the economy. In 1972 it was 5.5% and in

1992 it was -0.04%. Table 4.2 compares the peaks and troughs from our estimation with the dates found by Harding & Pagan [43] and Mönch & Uhlig [63].

Our dates		**M&U**		**H&P**	
peak	**trough**	**peak**	**trough**	**peak**	**trough**
1974:Q3	1974:Q4	1974:Q3	1975:Q2	1974:Q3	1975:Q1
1980:Q3	1980:Q4	1980:Q1	1980:Q3	1980:Q1	1981:Q1
1982:Q2	1982:Q3	1982:Q2	1982:Q3	1982:Q3	1982:Q4
1992:Q3	1993:Q2	1992:Q1	1993:Q1	1992:Q1	1993:Q1

Table 4.2: Our estimated business-cycle dates together with dates found by Mönch & Uhlig (2004) and Harding & Pagan (2001)

The first and last of our four recessions estimated here match closely those dated by the CEPR (compare Table 4.1 and Table 4.2). The first peaks (in 1974) are the same and the trough (in 1975) is one quarter earlier in our estimation. The estimated mean also suggests that the last recession (1992-1993) started two quarters later and ended one quarter earlier. The CEPR also identified a recession in 1980-82, milder but longer than the others[4]. Our estimated mean is negative in 1980 and in 1982. Mönch & Uhlig [63] used the Bry-Broschan dating-procedure and also found two shorter recessions in that period where the former is a little bit longer than ours and the latter is exactly the same. GDP did not decline sharply, but rather stagnated for almost three years. The CEPR dated the recession mostly based on investment and employment which, unlike GDP, declined sharply. It is clear that something happens in the beginning of the 1980s, but if it qualifies as a recession or a stagnation period is hard to tell. We define stagnation as a period of little or no economic growth. According to our definition, the period 1980:Q3-1982:Q3 is a long period of stagnation. However, qualifying a period as a recession or a stagnation is a matter of convention. From the dates found by Harding & Pagan we see that they too suggest that there were two recessions in this period.

The mean in the bottom graph in Figure 4.10 is also very close to zero in 2001 during Q2 and Q3. The CEPR says that the Euro area economy has stagnated since 2001:Q1. The GDP slowed, but their judgment is that the Euro area has been experiencing a prolonged pause in growth rather than a recession. They also acknowledge that the picture may change as revised GDP figures become available. Finally, looking at Table 4.2, we conclude that the other non-parametric methods find similar results.

We finish with a discussion on the sensitivity of our analysis to the set of macroeconomic indicators used in dating. We tested different combinations of our seven series. We extracted the common dynamic from various subsets of the larger set of seven variables. The results are presented in Table 4.3. Using only GDP (YER) the method found two recessions (see top graph in Figure 4.5), one in 1974 and one in 1992-1993. Both of them exactly match the first and last found using all seven series. If we use GDP and some of its component (exports, imports and private consumption) we get four recessions. One in 1974 which starts one quarter earlier and end one quarter later and one in 1992-1993 which exactly match the one found by using only GDP and using all seven series. It also

[4]see http://www.cepr.org/EEP/2004/April/buscycle.asp

finds a recession in the beginning of the 80s and one in 2001-2002. These two could be thought of as stagnation periods when using all seven series. Our final combination tries to mimic the combination of series used by the NBER (GDP, real income, employment, industrial production and wholesale-retail sales). Using GDP, industrial production and household's disposable income we found the dates in the third column in Table 4.3. These dates also have its similarities with using all seven series. It finds four recessions, one in 1974, 1992-1993 and two milder, shorter ones in the beginning of the 80s.

YER		YER+MTR+PCR+XTR		IP+YER+PYR	
peak	trough	peak	trough	peak	trough
1974:Q3	1974:Q4	1974:Q2	1975:Q1	1974:Q4	1974:Q4
		1980:Q3	1981:Q1	1980:Q3	1981:Q1
				1982:Q1	1982:Q4
1992:Q3	1993:Q2	1992:Q3	1993:Q2	1992:Q2	1993:Q3
		2001:Q3	2002:Q1		

Table 4.3: Business-cycle dates using different combinations of the series

This discussion shows how important the choice of the set of macroeconomic variables is for the results of the dating.

4.4 Conclusions

A non-stationary, non-parametric method was used to estimate the business cycle in the Euro area from seven coincident macroeconomic time series. The business cycle was constructed by finding the common dynamic of industrial production, GDP, total demand, imports of goods and services, private consumption, household's disposable income and exports of goods and services. The estimated business cycle did of course depend on the macroeconomic series chosen.

We analysed the series individually, looking at the mean and the standard deviations and found negative growth in the series in the middle of the 70s and the beginning of the 90s. Some series showed mild negative growth in the beginning of the 1980s.

The estimated business cycle dates were compared to those of CEPR and two other non-parametric methods. The estimated recession in the mid 70s matched the CEPR dates but ended one quarter earlier, and the one in the beginning of the 1990s was estimated here as shorter than the period dated by the CEPR. Our estimation suggests that there was two shorter and not so severe recession periods in the beginning of the 1980s. We argue that since the mean in this period was so close to zero, this might have been a stagnation period (1980:Q3-1982:Q3), i.e. a period with very low economic growth where there are no drastic changes in prices and the economy is moving forward with a very low or no growth rate. Also in 2001 the mean was very close to zero, suggesting that the economy stagnated in this year. Our dates had many similarities to the previous dates found by the two other non-parametric methods.

The study was done with quarterly data. Monthly data, if and when it becomes available, might provide better and more accurate dating.

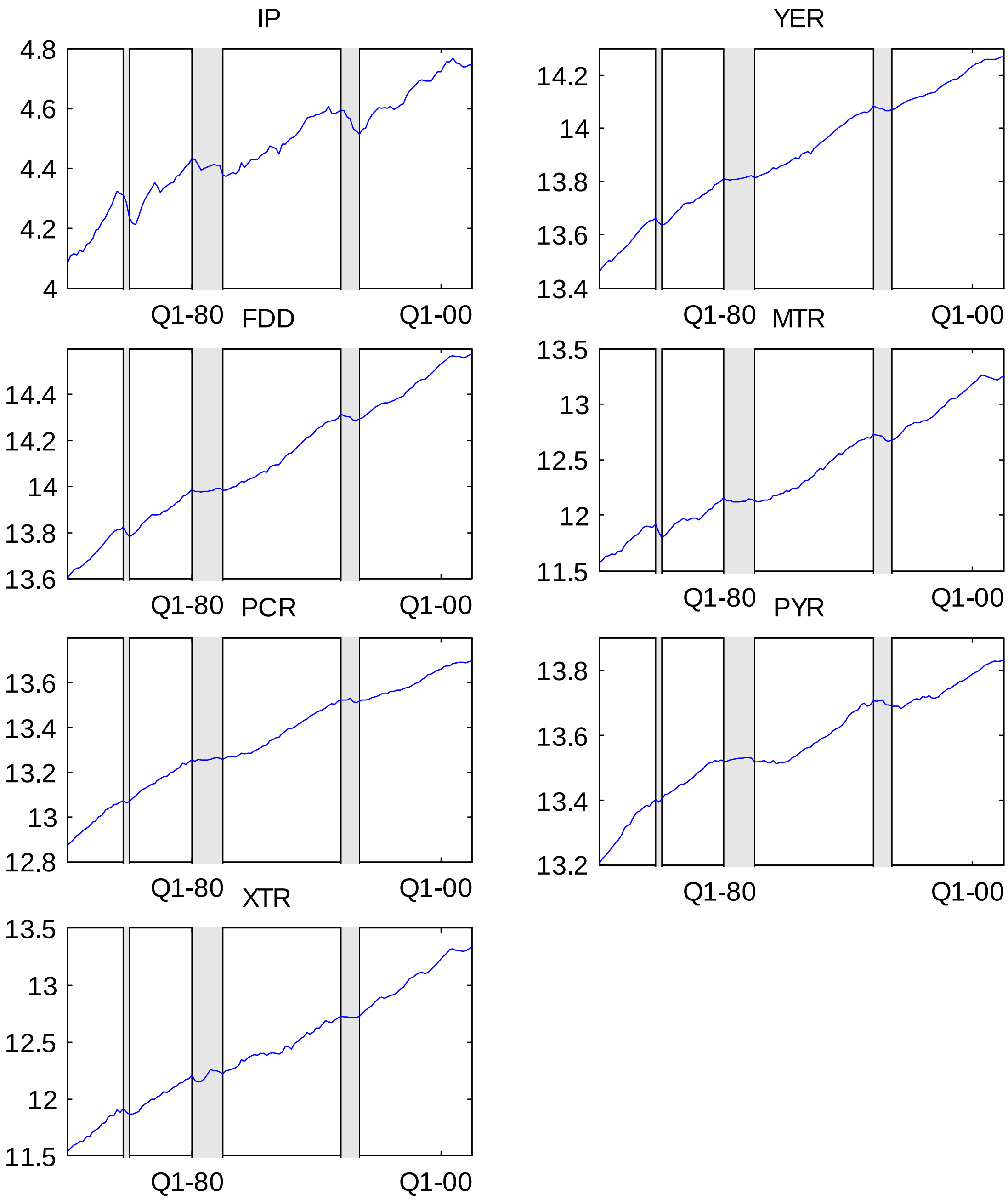

Figure 4.1: The logarithm of the macroeconomic aggregated series for the Euro area (the shaded areas indicate recession periods dated by the CEPR)

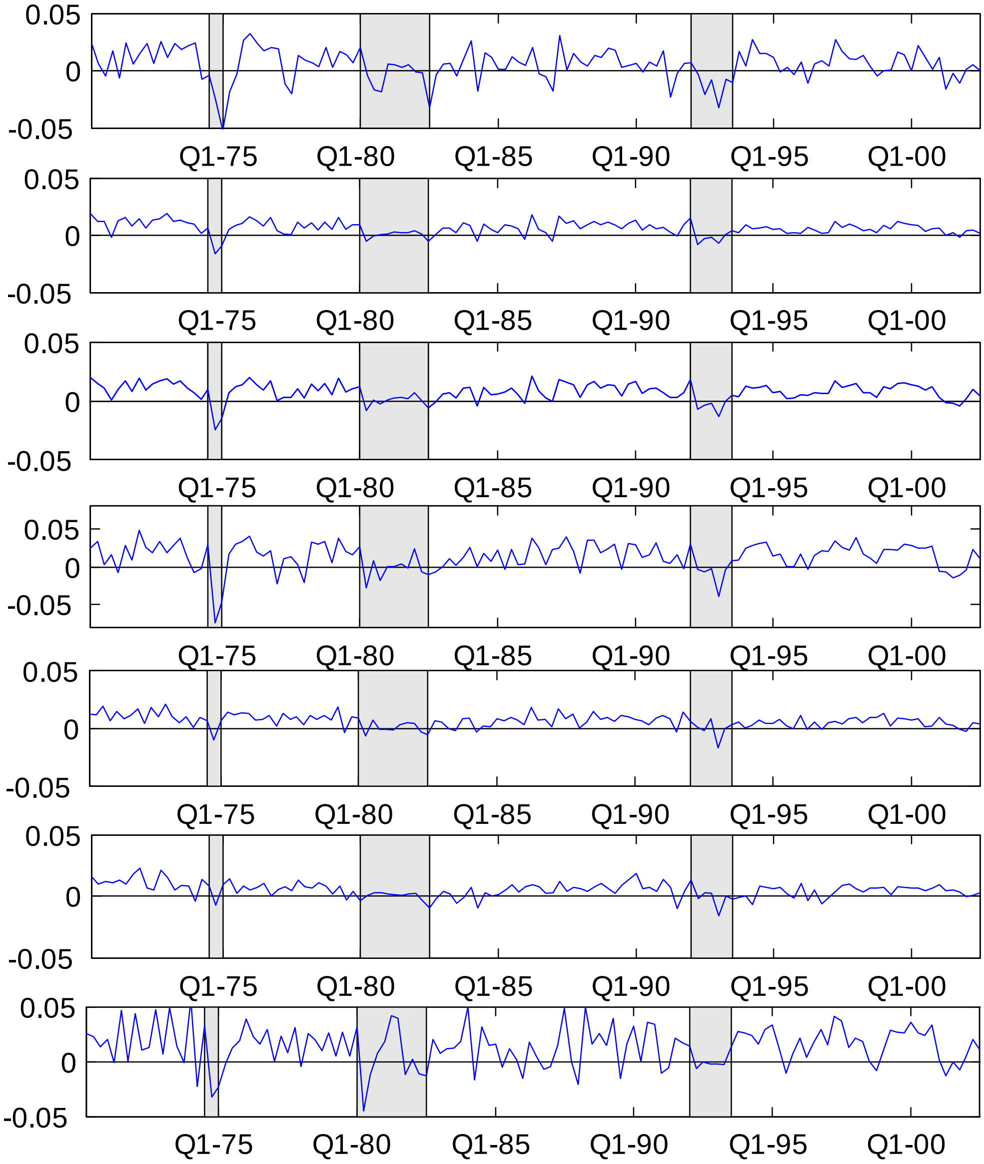

Figure 4.2: Growth rates of the logarithm of the series: IP, YER, FDD, MTR, PCR, PYR, and XTR (the shaded areas indicate recession periods dated by the CEPR)

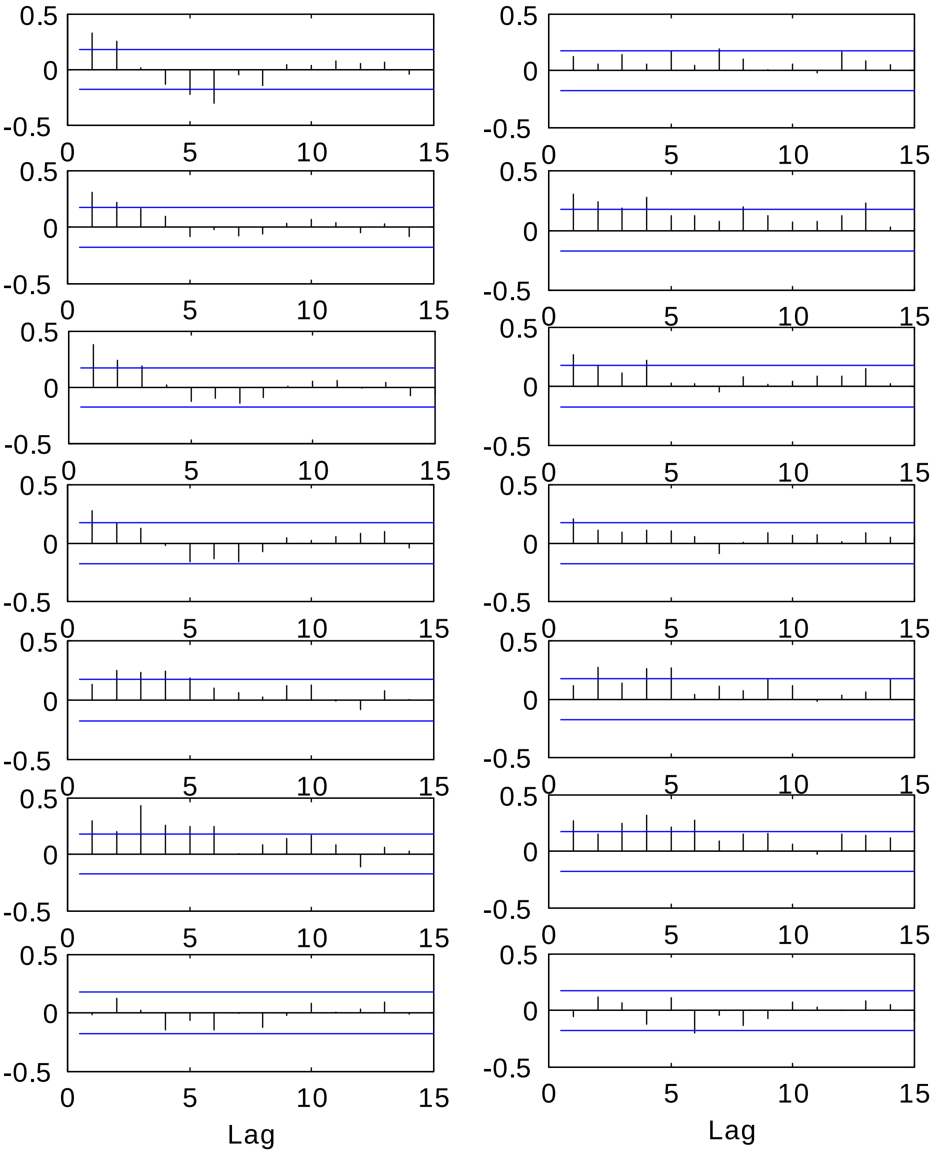

Figure 4.3: (Left) the autocorrelation of the growth rates and (right) their absolute values: IP, YER, FDD, MTR, PCR, PYR, and XTR

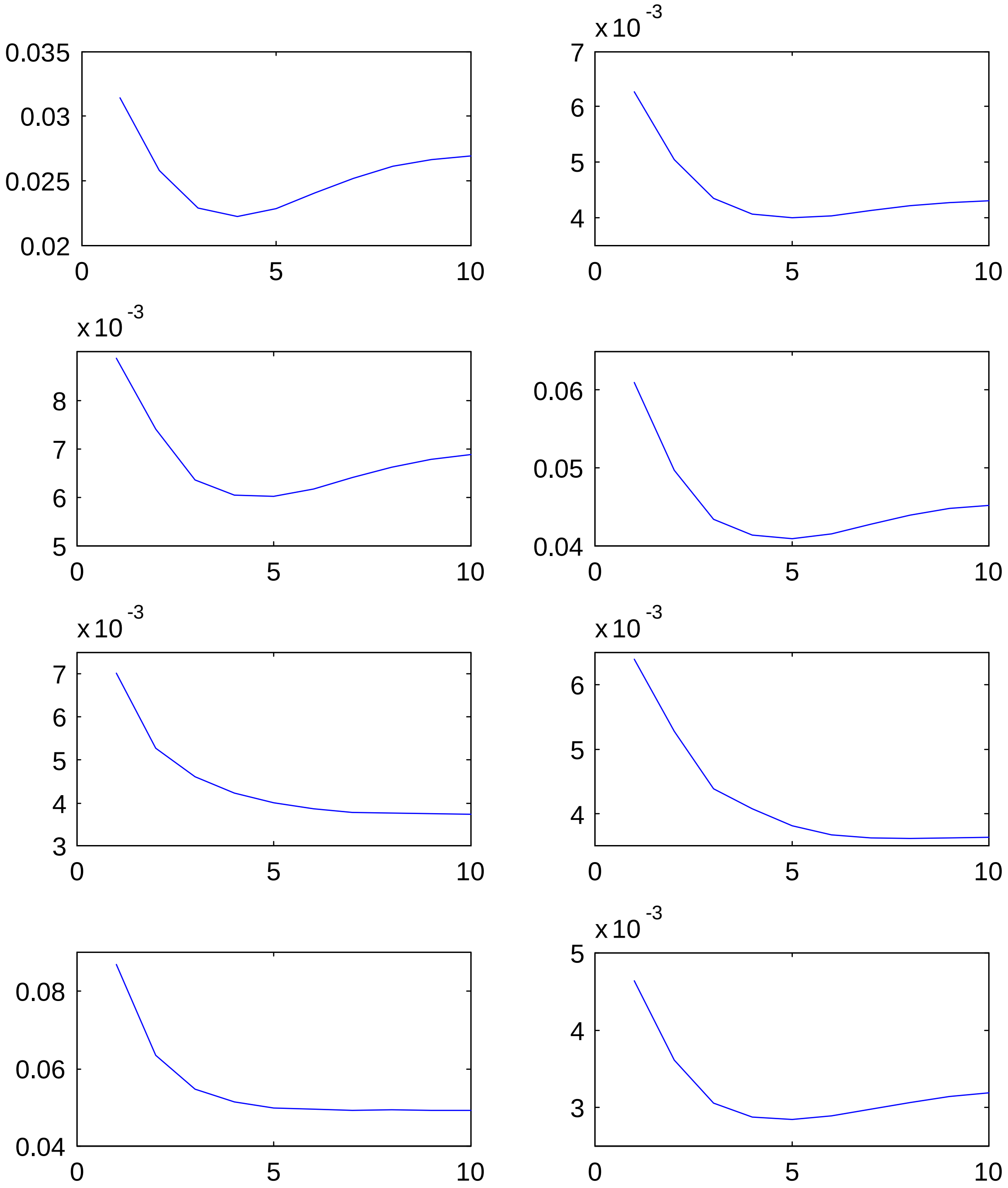

Figure 4.4: The cross-validation function of the seven series and $X(t)$; (top) IP and YER, followed by FDD and MTR, PCR and PYR and (bottom) XTR and CV-function for $X(t)$ when estimating Equation (3.18)

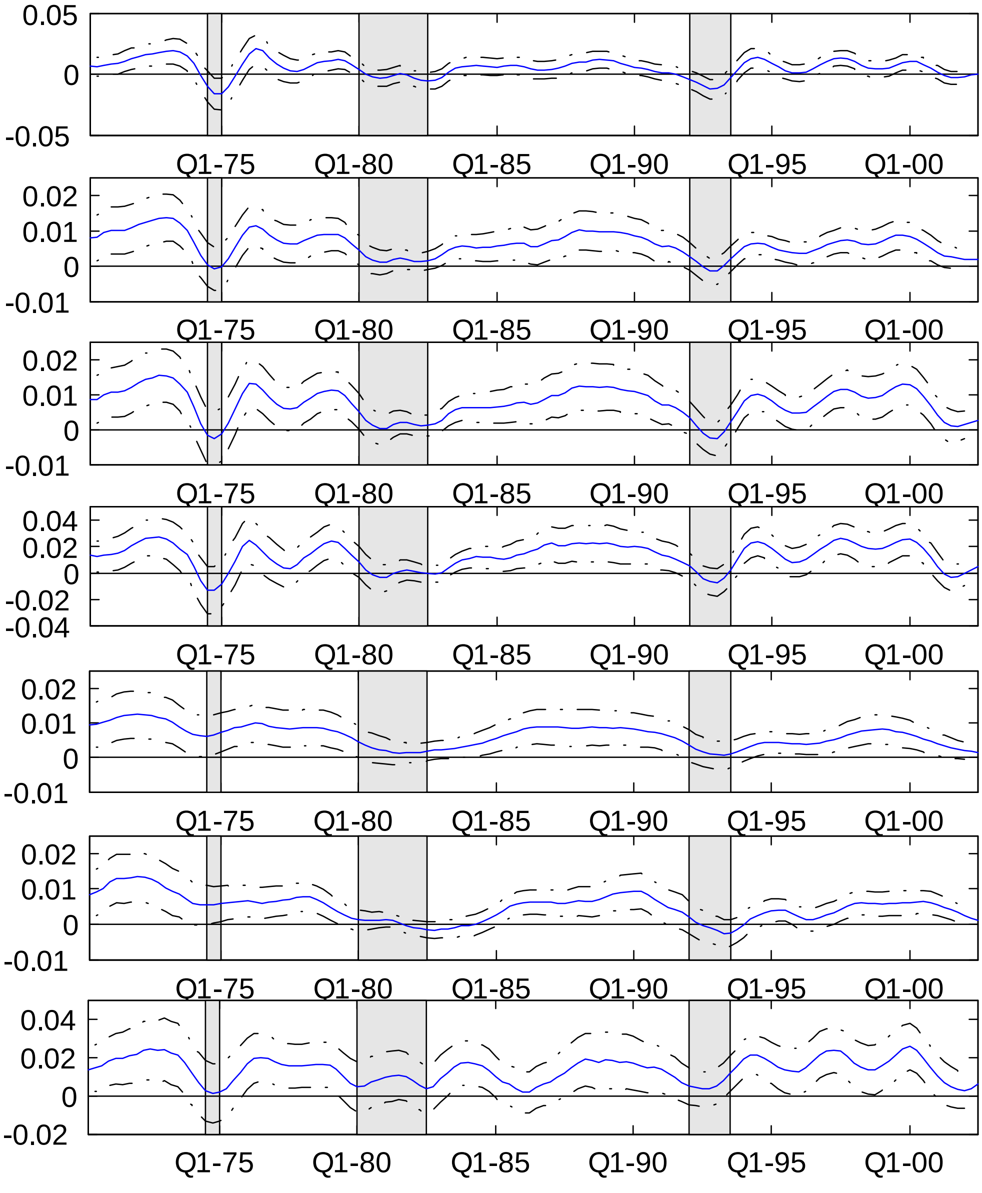

Figure 4.5: The first difference of the estimated means using Equation (3.1): IP, YER, FDD, MTR, PCR, PYR, and XTR

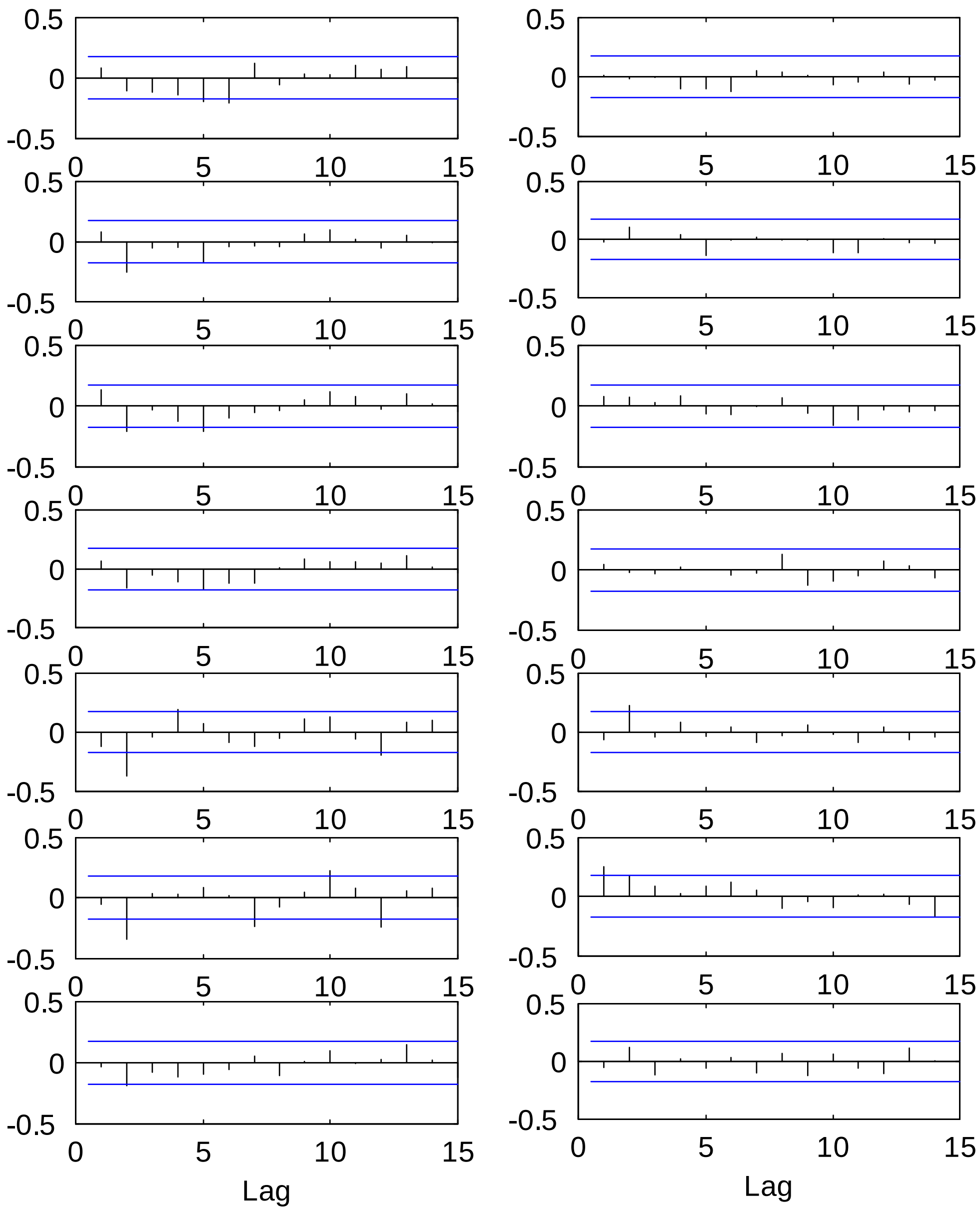

Figure 4.6: (Left) autocorrelations of the residuals ($\hat{\varepsilon}_k$), from estimating the series with Equation (3.1) and (right) autocorrelations of the absolute values of the residuals: IP, YER, FDD, MTR, PCR, PYR, and XTR

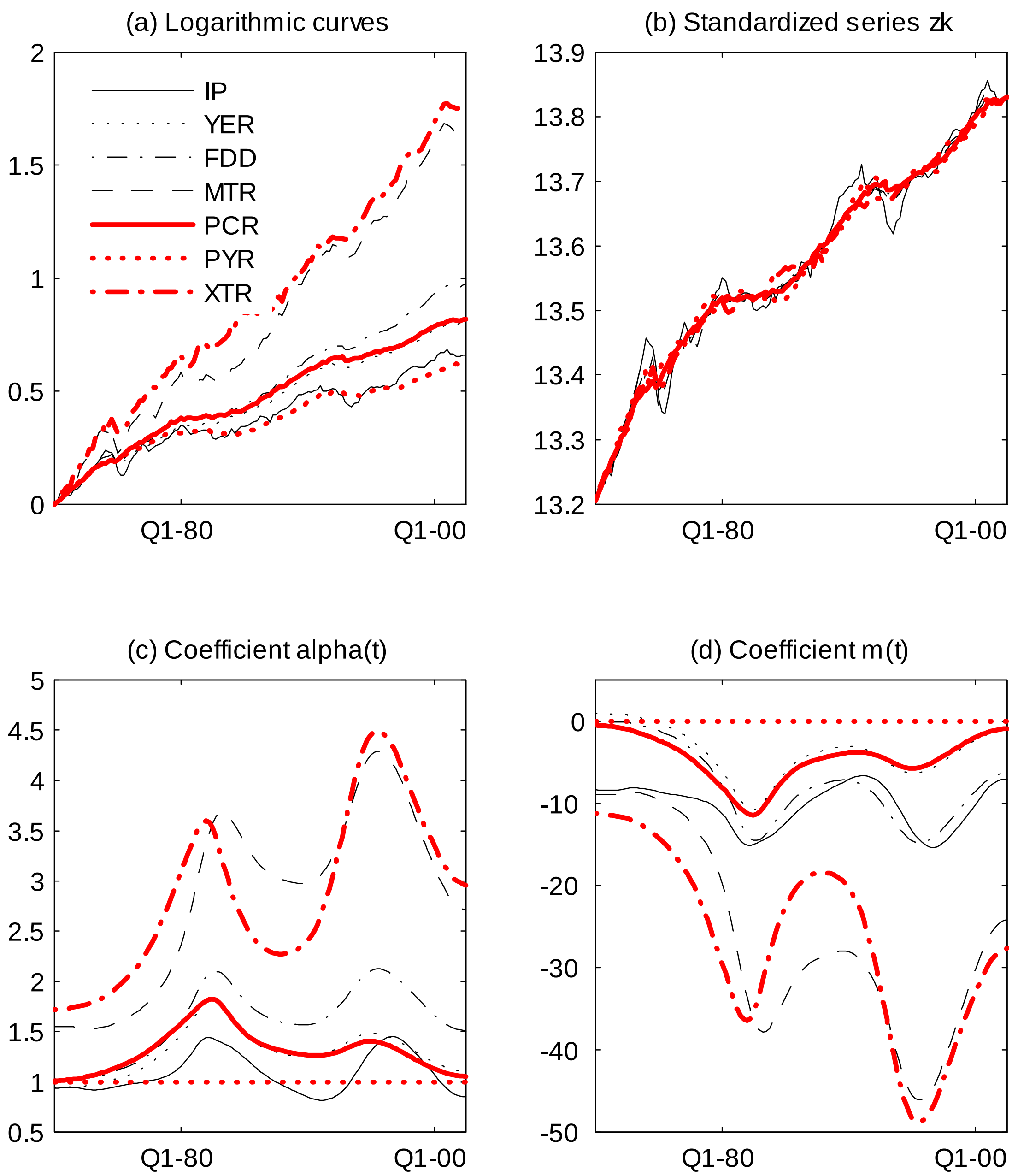

Figure 4.7: (a) the logarithmic series minus their first value; (b) the standardised series $\hat{z}_k$ calculated from Equation (3.13); (c) and (d) the coefficients $\hat{\alpha}(t)$ and $\hat{m}(t)$

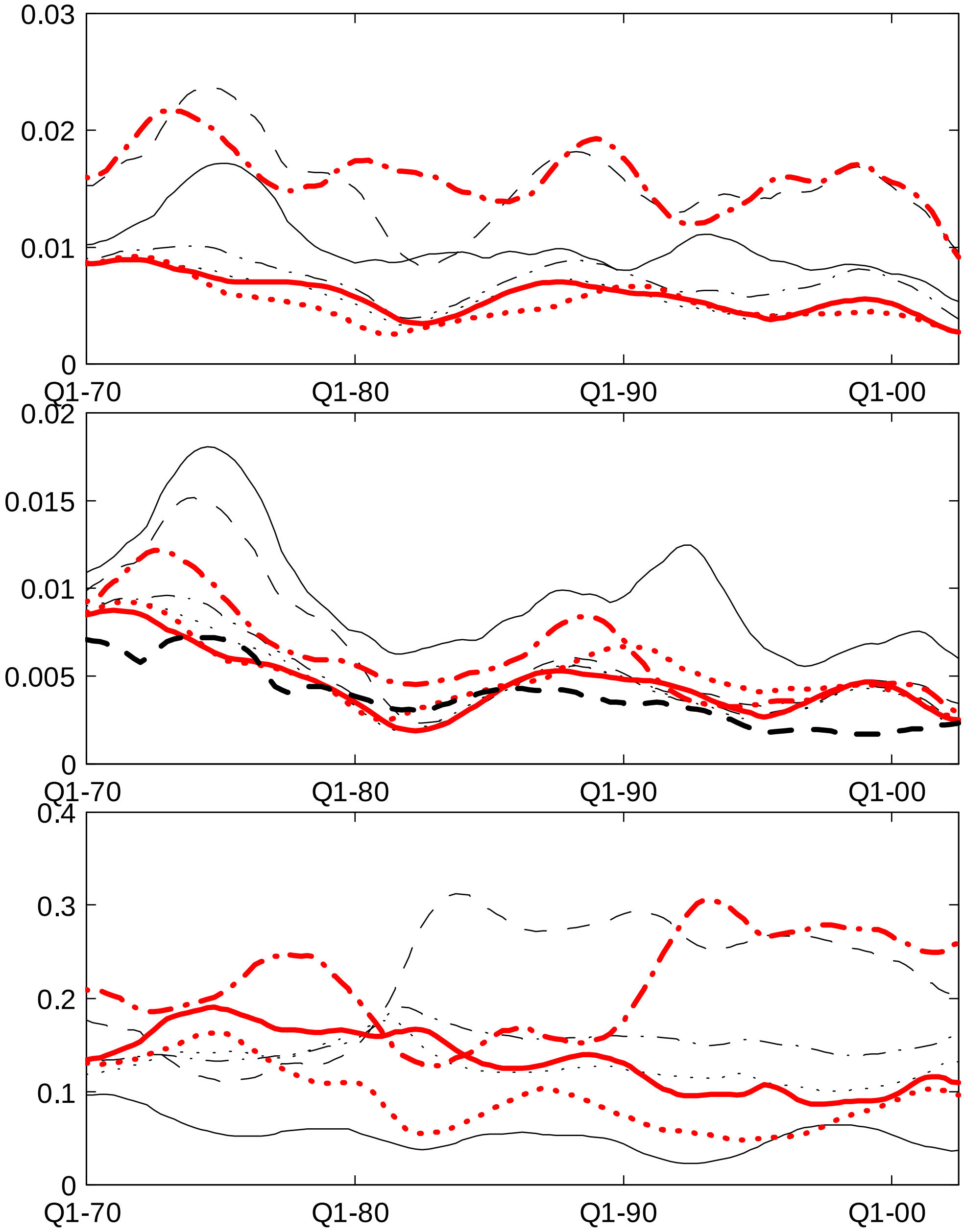

Figure 4.8: (Top) estimated standard deviations ($\hat{\sigma}(t)$), of the seven macroeconomic series modelled according to Equation (3.1); (middle) standardised standard deviations ($\hat{\sigma}(t)/\hat{\alpha}(t)$) for IP, YER, FDD, MTR, PCR, PYR and XTR together with the standard deviation of $\hat{X}(t)$ (thick dashed line); (bottom) coefficients $\hat{\beta}(t)$ calculated with Equation (3.16) (IP, PCR, and PYR contribute the least to $\hat{X}(t)$ and the result would not change much if only YER, FDD, MTR, and XTR were used)

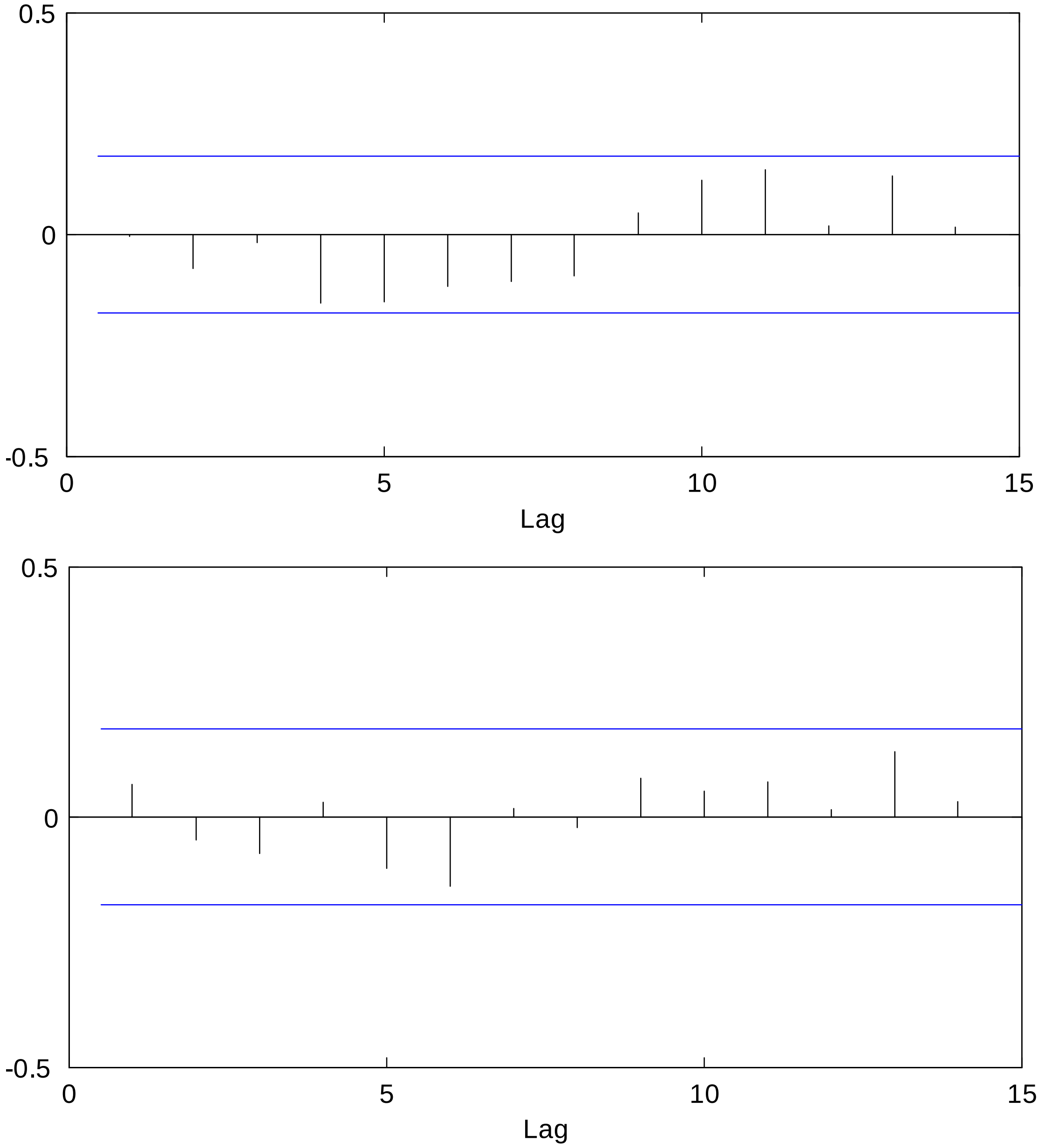

Figure 4.9: Autocorrelation of the residuals $\hat{\eta}_k$ from estimating Equation (3.17) (top) and their absolute values (bottom)

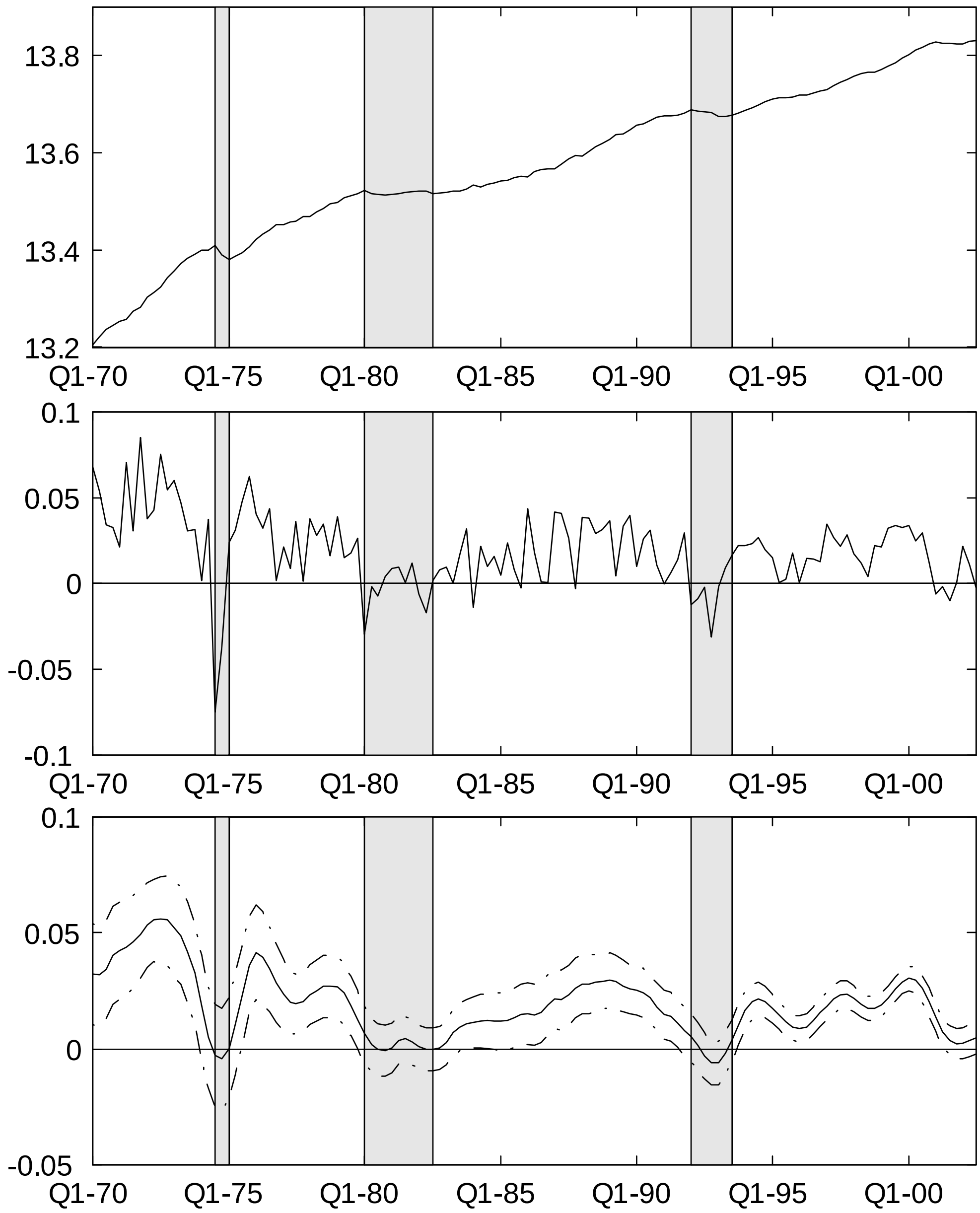

Figure 4.10: (Top) the $\hat{X}(t)$ series calculated with Equation (3.14); (middle) the first difference of the $\hat{X}(t)$ series; (bottom) the estimated business cycle for the Euro area with 95% confidence-bands (the shaded areas represent recessions dated by the CEPR)

Chapter 5

The Swedish business cycle, 1969-2006

The literature on the dating of the business cycle for Nordic countries is not too rich. Among earlier research Christoffersen [20] dates economic peaks (beginning points of recessions) and troughs (ending points of recessions) for the Nordic countries by applying the Bry & Broschan [12] algorithms. Jonung et al. [53] investigated the boom-bust cycle in Finland and Sweden 1984-1995. They use a non-parametric method initially proposed by Harding & Pagan [45].

In Sweden the National Institute of Economic Research (NIER, known as Konjunkturinstitutet), an independent government agency, is responsible for analysis and forecast of business cycles. They interview 7000 companies every month about their position, results and expectations, based on which they publish a monthly and quarterly "business cycle barometer" using the growth-cycle definition of a business cycle. NIER does not date the turning points of the business cycle.

We will use the non-stationary, non-parametric method developed in Chapter 3 using four macroeconomic series to date the Swedish business cycle ex-post. We will use the classical definition of the business cycle.

Section 1 describes the dataset and Section 2 discusses the business cycle in Sweden generally since the 1970s. Section 3 then presents the results and Section 4 concludes.

5.1 The data

In our dating we will use four of the five series used by the NBER: retail trade[1], industrial production[2], household's disposable income and GDP. All series were seasonally-adjusted real quarterly data in logarithms, taken from Datastream and the NIER for the period 1969:Q1 to 2006:Q1. Employment is also used by the NBER but it was not included in the estimation here due to the different dynamic compared to the other series. This is to some extent explained by the change in the measurement procedure during that time and

[1] Retail trade includes all merchandise sold for personal or household consumption and incidental services.

[2] Industrial production includes total output from factories and mines.

perhaps due to a heavily regulated labour market.

Figure 5.1 plots the data minus their first values and first-order differences are plotted in Figure 5.2.

5.2 Recessions and expansions in Sweden 1970 - 2006

According to Edvinsson [29] Sweden experienced 12 recessions during 1850-2000 and nearly half of those were depressions. A depression, a severe economic crisis, is defined as an event when GDP in one year is beneath the level of GDP two years earlier. Most business cycles since World War II lasted 4-5 years, but that changed during the 1980s. The expansion in the 80s was very long. The deregulations of the financial markets during the latter half of the 1980s created a situation of overheating in the economy, which especially led to a real estate bubble. The burst of the bubble together with the bankruptcy of several big financial companies opened the stage for a depression in the early 1990s. This depression was particularly severe and it was the only time since the Napoleonic war during 1806-1809 when GDP fell for three consecutive years.

Christoffersen [20] found the following recessions in Sweden during the study period for the Nordic countries by applying the Bry & Broschan [12] algorithms to industrial production.

peak	**trough**
1971:1	1972:1
1974:6	1978:7
1979:12	1982:11
1985:8	1986:5
1989:1	1993:1

Table 5.1: Peaks and troughs in Sweden during 1970-2000 according to Christoffersen (2000)

5.3 Results

The macroeconomic series: We computed the autocorrelation of the growth rates to investigate the relationship between the observations within the series. The autocorrelations are shown in Figure 5.3 and we can see that we have some autocorrelation in the first series, the GDP, and since the plot shows high values at fixed intervals we probably have some seasonality left in the series. Figure 5.4 displays the cross-validation function of the four series. Bandwidths $h_1 = 6$, $h_2 = 3$, $h_3 = 2$ and $h_4 = 3$ were used when estimating the means of the individual series and bandwidth $h = 10$ when estimating standard deviations (shown in the top graph in Figure 5.8). Figure 5.5 shows the first difference of the estimated means for the series together with 95% confidence bands. From this we see that some series show negative values in the late 1970s and the beginning of the 1980s. Furthermore, all series have a negative growth rate in the beginning of the 1990s.

Figure 5.6 shows autocorrelations of the estimated residuals and of their absolute values from the estimation using Equation (3.1) with 15 lags and 95% confidence bands. The first lag autocorrelation for the series are quite small (compared to the autocorrelation of the first lags in Figure 5.3), indicating that Equation (3.1) seems to fit well, representing valid assumptions.

The common dynamic: Retail trade was designated i_0 but the final results are practically the same if we choose any of the other series. The rest of the $\hat{m}(t)$ and $\hat{\alpha}(t)$ coefficients were estimated with Equation (3.12), using a bandwidth of fifteen years, $h = 30$. A bandwidth of 20 or 35 did not make a major difference in the results. The standardised series z_k, obtained using Equation (3.13), i.e., the logarithmic series scaled with estimates $\hat{m}(t)$ and $\hat{\alpha}(t)$ are shown in (a) in Figure 5.7, (b) shows the estimated coefficients $\hat{\beta}(t)$, which indicate how much each series was contributing when building $\hat{X}(t)$, (c) coefficients $\hat{m}(t)$ and (d) coefficients $\hat{\alpha}(t)$. The method used here for finding the common dynamic of the four series clearly works, as indicated by the $\hat{z}$'s and the $\hat{m}$'s and $\hat{\alpha}$'s which changed over time, but slowly. (Compare Figure (5.1) with Figure (5.7(a).)

The estimated coefficients $\hat{\beta}(t)$, from Equation (3.16), indicate that the contributions of each series varied over the study period. In the beginning of the period, all series follow each other. In this period the $\hat{\beta}$-value for all series is around 0.25. At the end of 1970 $\hat{\beta}(t)$ is small for industrial production and the other three series will alone contribute to building $\hat{X}(t)$. During this period industrial production does not follow the other series. This is easily spotted in Figure 5.7(a). The middle graph in Figure 5.8 shows standardised standard deviations of the four series together with the standard deviation of $\hat{X}(t)$. From this we can see that the standard deviation is small for $\hat{X}(t)$.

Looking at the series in Figure 5.1 or Figure 5.2, it is hard to see any common dynamic, but after the standardisation it is simpler to see that they move up and down together in some periods. When $\hat{\alpha}(t)$ is lower than 1, the standardised series has a larger variance than the estimated variance from Equation (3.1). We can see that this is the case for all series in different periods. The $\hat{\alpha}$ for industrial production is below 1 in different periods indicating that it does not follow the other series in these periods.

The business cycle: Figure 5.9 shows the autocorrelation of the residuals and their absolute values when estimating Equation (3.17). We find no evidence of autocorrelation. The $\hat{X}(t)$ series and the first difference, $\Delta\hat{X}(t)$, are shown in the top and middle graph in Figure 5.10. A positive slope of the common dynamic indicates an upswing in the economic activity, negative a downturn. The bottom graph in Figure 5.10 shows the estimated business cycle, $\hat{g}(t)$, from Equation (3.17), with 95% confidence-bands, using bandwidth $h = 6$. It indicates four recessions between 1969:Q1 and 2006:Q1. If we compare the middle graph in Figure 5.10 with the bottom graph in the same figure it is easy to see the effect of our smoothing technique, it reduces irregularities and provides a clearer view. The recession in the beginning of the 70s is very small and could be referred to as a stagnation period instead.

If we used GDP to date the business cycle, we would get only two recessions as shown in the second graph in Figure 5.5. The similarities and differences between the business cycle using all four series and using only the GDP is presented in Table 5.2.

Estimated business cycle using all four series		Estimated business cycle using only GDP	
peak	**trough**	**peak**	**trough**
1971:Q1	1971:Q2		
1976:Q4	1977:Q4	1976:Q2	1977:Q2
1979:Q4	1982:Q2		
1991:Q2	1993:Q2	1990:Q2	1992:Q3

Table 5.2: The peaks and troughs identified by the procedure here with all four series (left) and with only GDP (right)

Using only GDP one could also say that since the confidence bands are so wide, it all looks like stagnation.

If we compare the dates in Table 5.2 to the dates found by Christoffersen in Table 5.1 we see that he also found recessions in 1971, mid 70s, 1979 and the beginning of 1990. Unlike us, Christoffersen found a recession in 1985-1986. He used a different definition and looked at industrial production. It is shown in Figure 5.2 that the growth rate of IP in this period is negative and the smoothed IP in Figure 5.5 is near zero which can explain his results.

In the bottom graph in Figure 5.8, the standard deviation of ΔGDP is shown together with the standard deviation of $\Delta X(t)$. We can see that it is larger for ΔGDP than for $\Delta\hat{X}(t)$. This is why the confidence bands are wider for GDP in Figure 5.5 than in Figure 5.10 and why the GDP alone, using this method, is not a good indicator for the business cycle.

The numbers on the y-axis in the bottom graph in Figure 5.10 could be thought of as the growth rate in the economy. For instance, according to the definition of our estimated business cycle, the growth rate in 1985 was 3.4% while the growth rate in 1992 was -3%.

Statistics Sweden (SCB)[3], does not date peaks and troughs in the Swedish business cycle but they declare that there was a peak in the economy in the following years: 1969-79, 1974-75, 1979-80, 1984-85, 1989-1990, 1994-1995, 1999-2000. These peaks represent the highest value on the business cycle defined as the deviation to the trend in different time series. Our estimated business cycle is plotted together with these dates in Figure 5.11. They seem to coincide quite well except from 1969-79 and 1974-75 where our peaks are just before (in 1973:Q4 and in 1978:Q4). Our peaks in Figure 5.11 represents the time when the growth rate in the economy peaked.

5.4 Conclusions

A non-stationary, non-parametric method was used to estimate the Swedish business cycle from 1969:Q1 to 2006:Q1, from the common dynamic of four macroeconomic time series: GDP, industrial production, household's disposable income and retail trade.

[3] Statistiska CentralByrån, SCB, www.scb.se

From the estimated business cycle four recessions were found. If GDP alone was used in this approach one would only have found two recessions. The 1980-1982-recession would not have been found. Or one could say that using only the GDP we would get the impression that the economy has stagnated during the whole study period since the confidence bands are so wide.

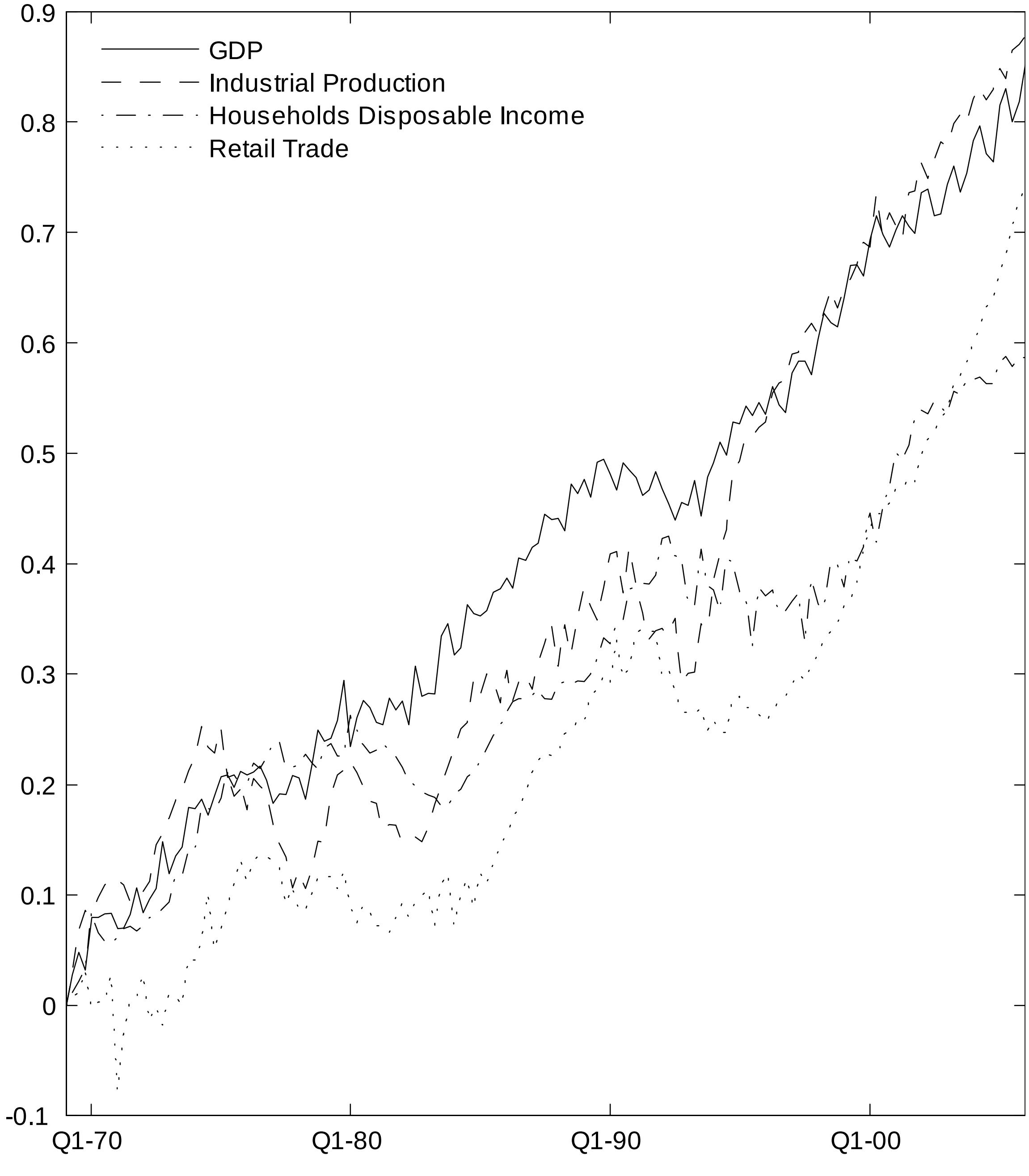

Figure 5.1: The four logarithmic series minus their first values, Q1 in 1969

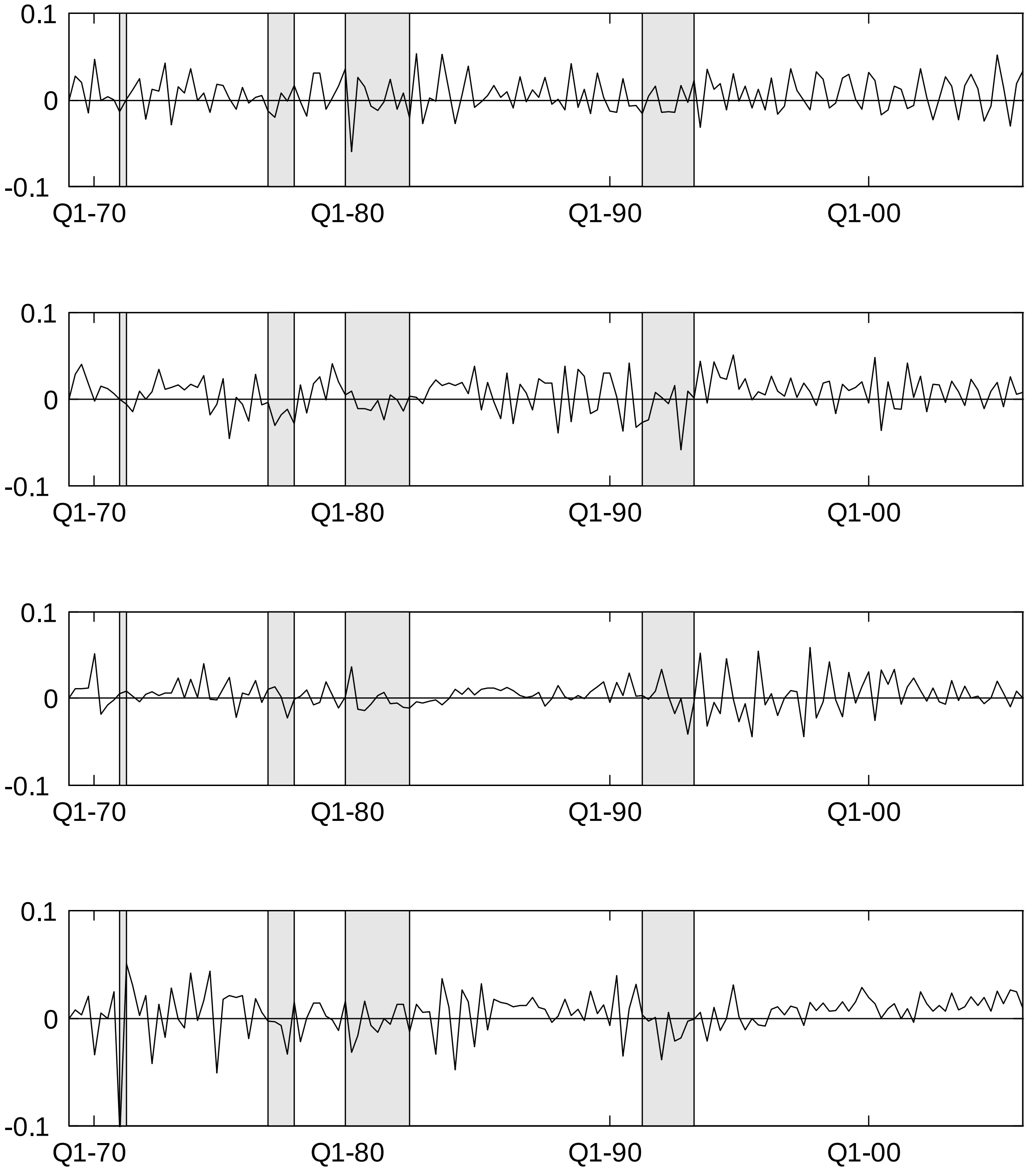

Figure 5.2: Growth rates of the logarithmic series: GDP, industrial production, household's disposable income and retail trade together with the recession periods found by our method

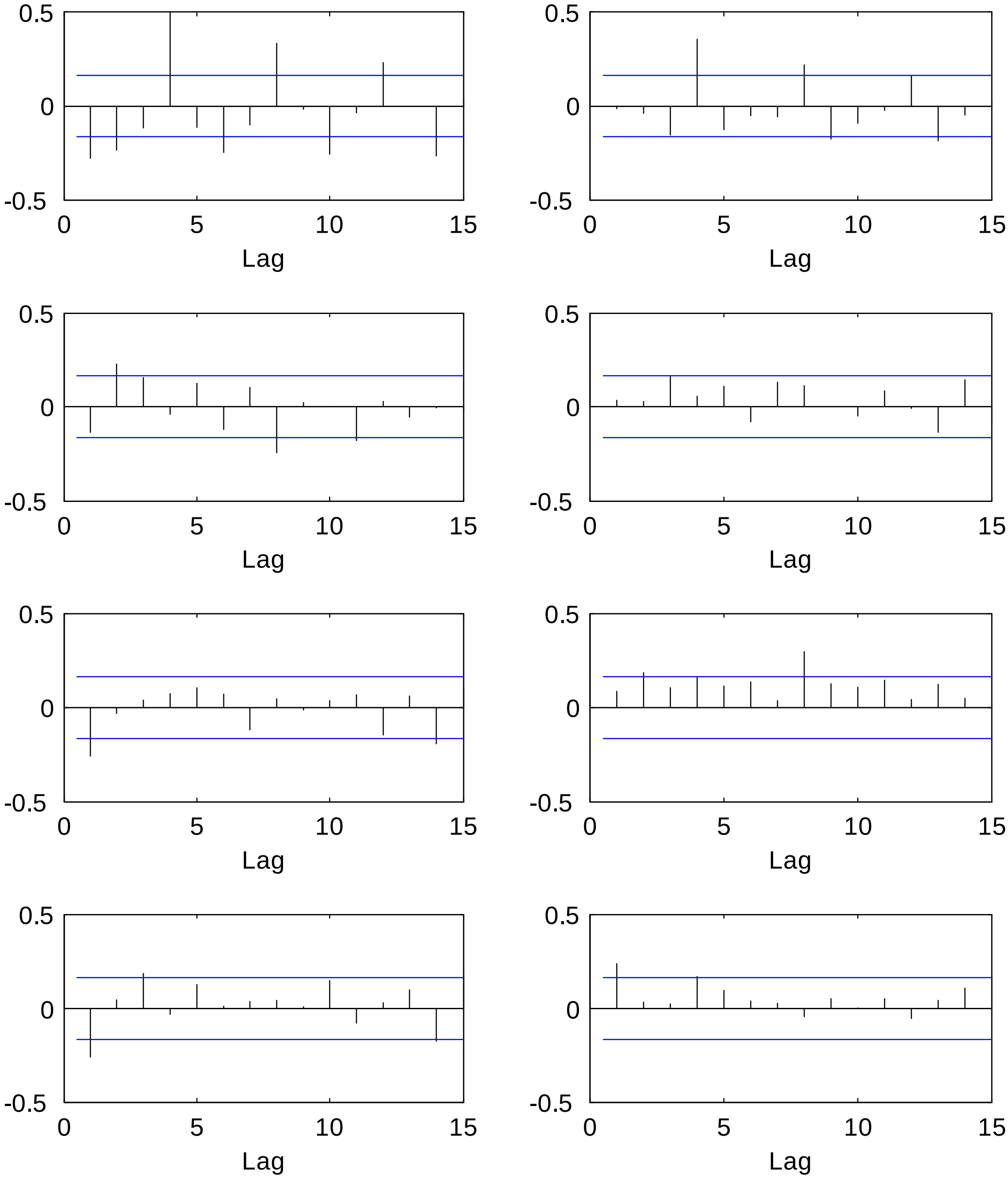

Figure 5.3: (Left) the autocorrelation of the growth rates and (right) their absolute values: GDP, industrial production, household's disposable income and retail trade

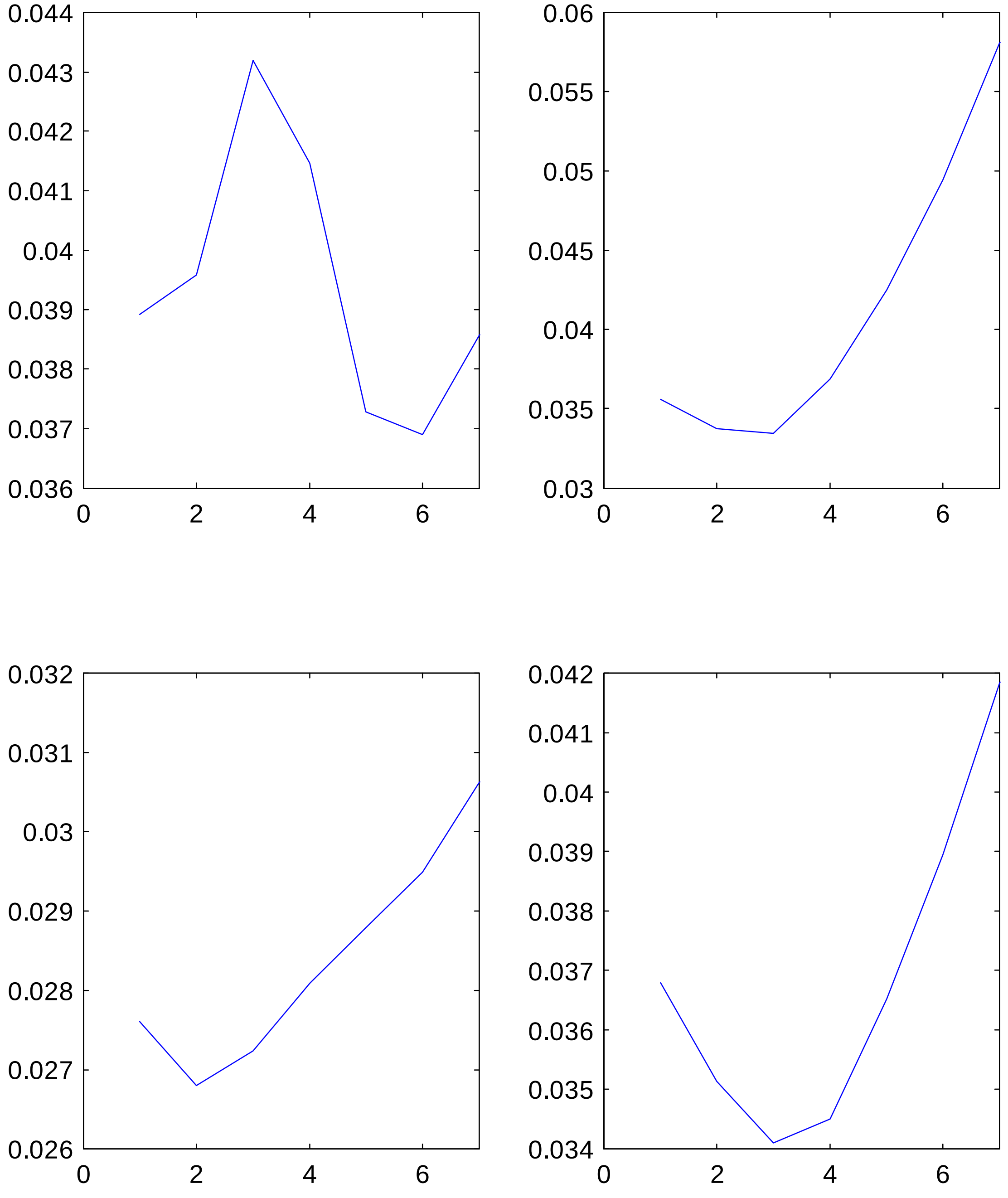

Figure 5.4: The cross-validation functions for the four series: (top) GDP and industrial production; (bottom) household's disposable income and retail trade

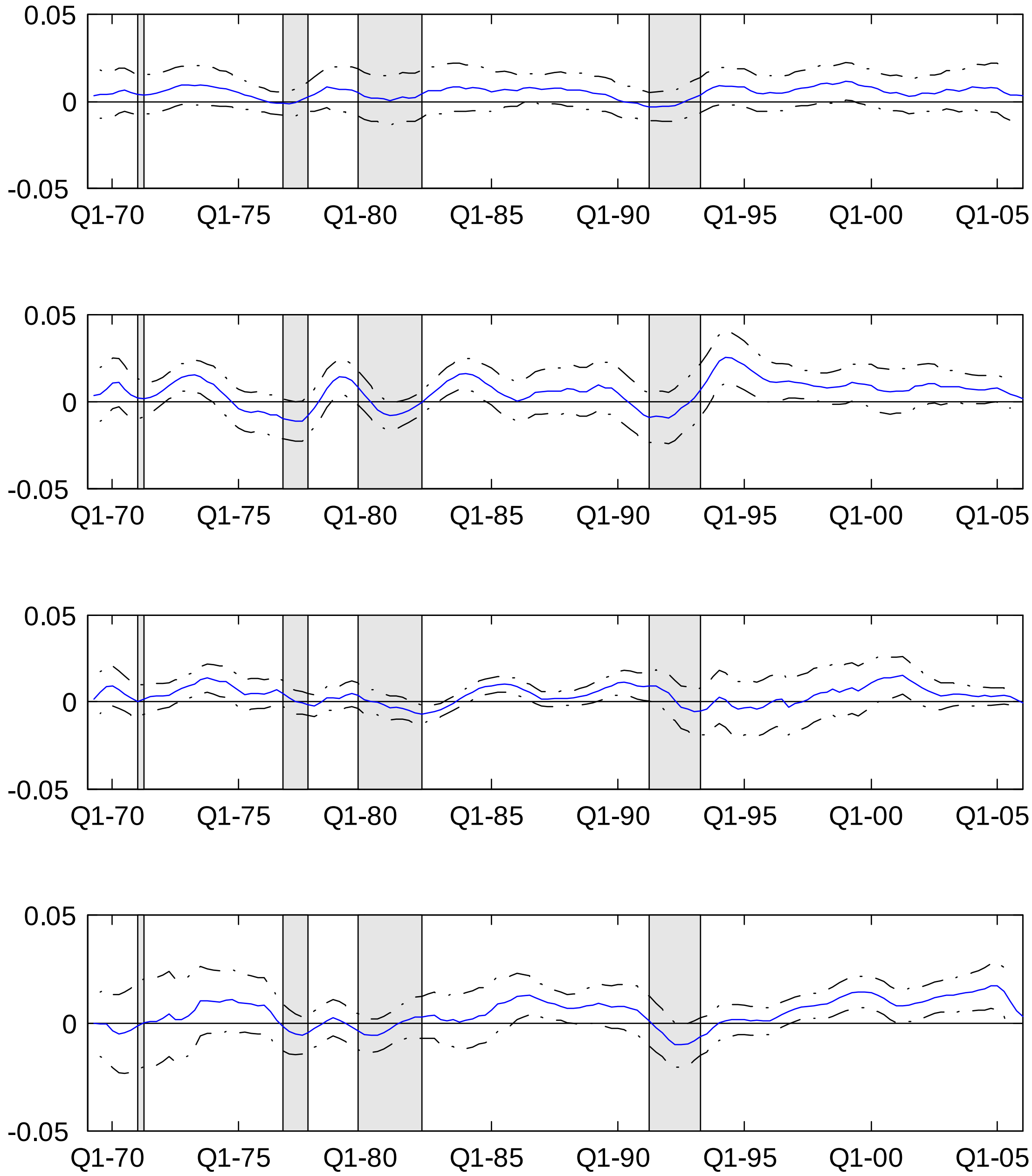

Figure 5.5: The first difference of the mean $\hat{\mu}(t)$ estimated using Equation (3.1): GDP, industrial production, household's disposable income and retail trade

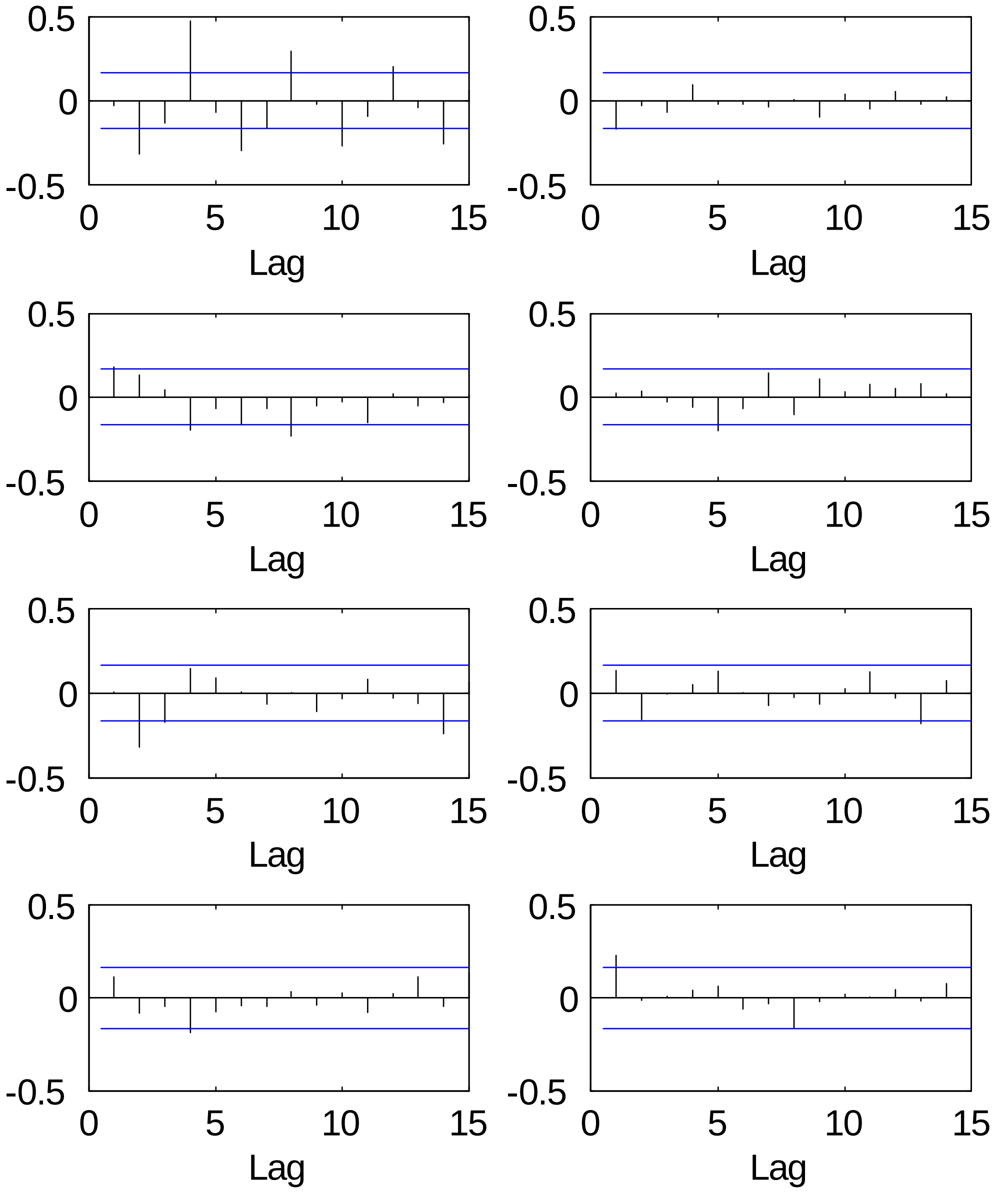

Figure 5.6: (Left) autocorrelation of estimated residuals ($\hat{\varepsilon}_k$) of the four series in Equation (3.1); (right) autocorrelation of the absolute values of the estimated residuals: GDP, industrial production, household's disposable income and retail trade

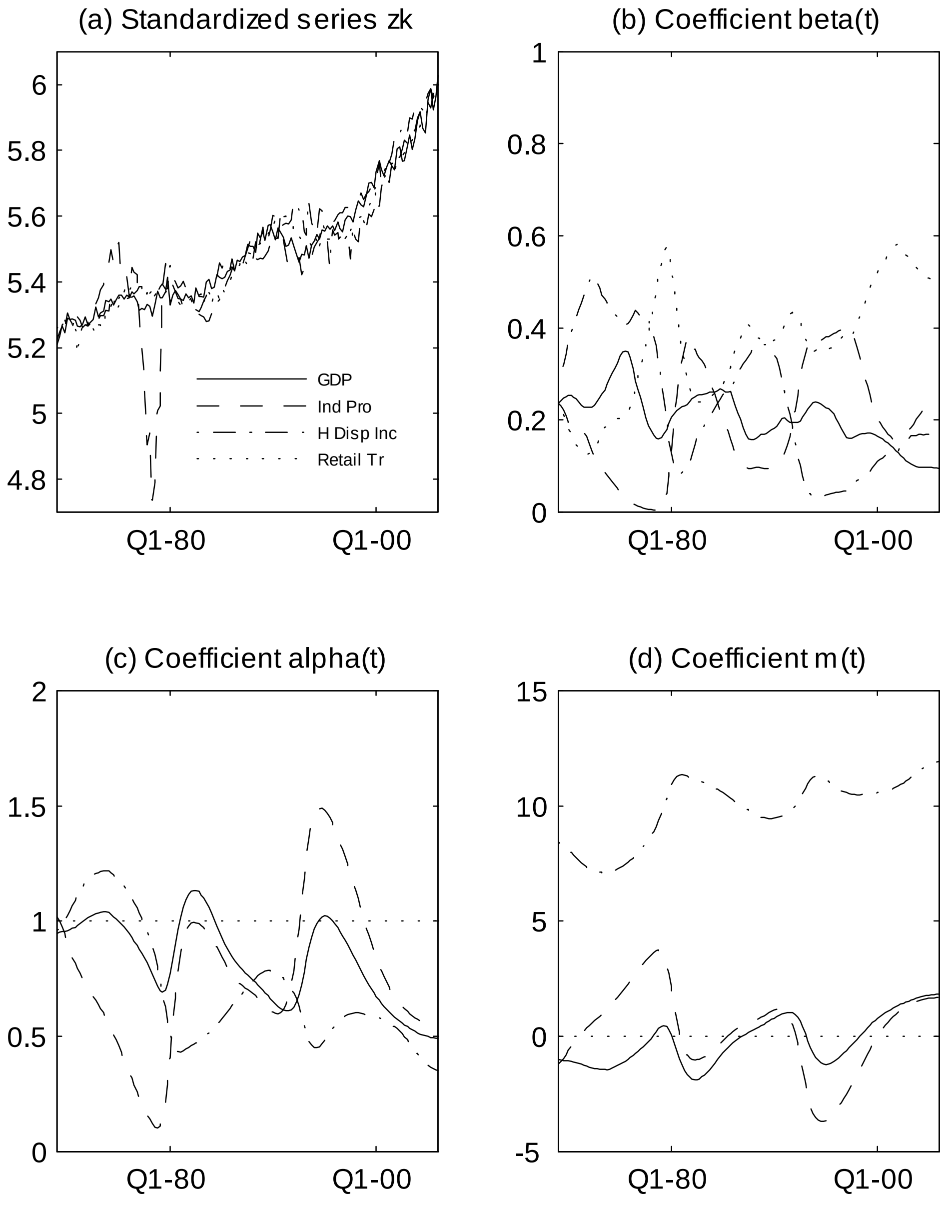

Figure 5.7: (a) the standardised series $\hat{z}_k$ calculated from Equation (3.13); (b) the time-varying coefficient $\hat{\beta}(t)$; (c) the time-varying coefficient $\hat{\alpha}(t)$; (d) the time-varying coefficient $\hat{m}(t)$

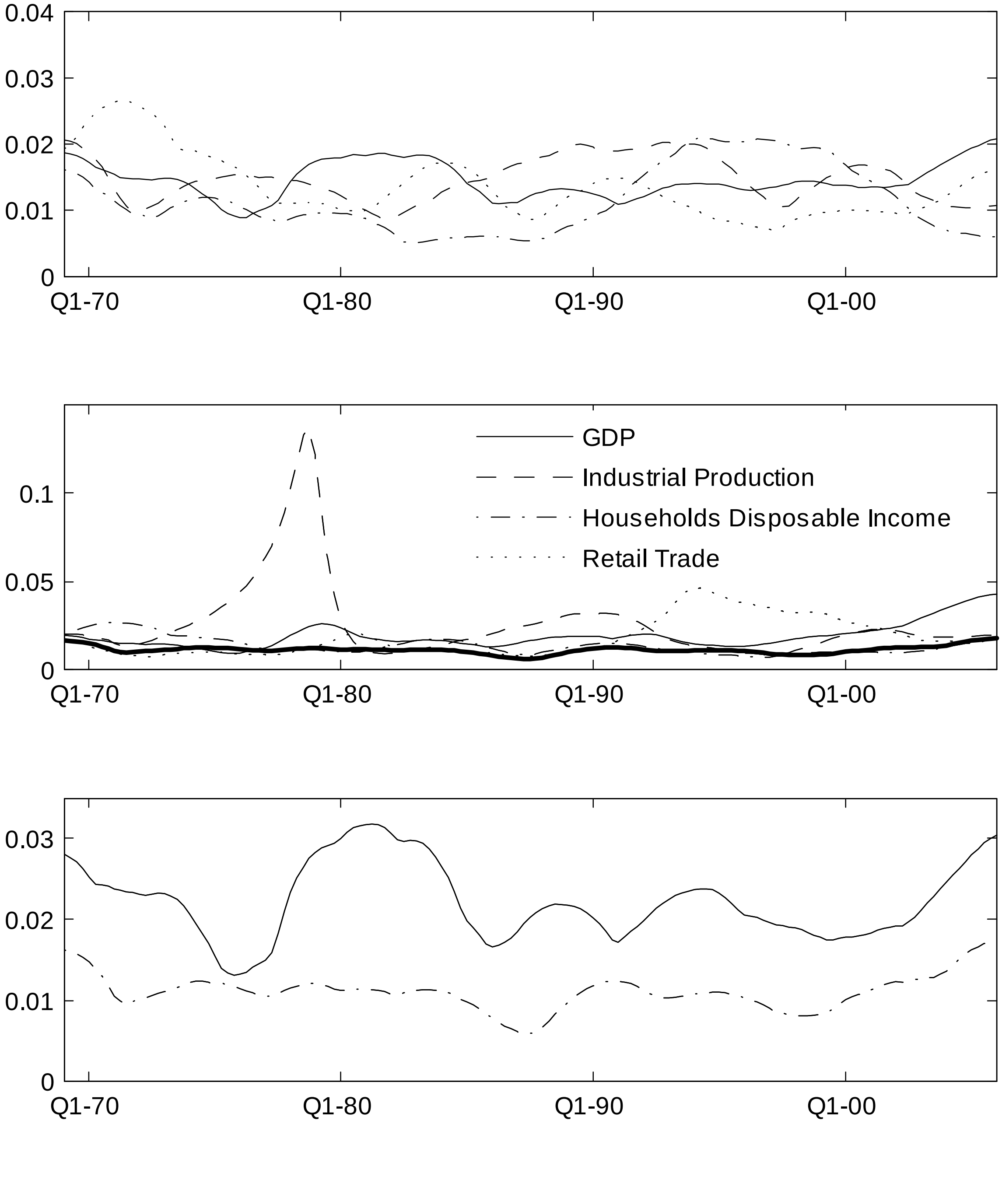

Figure 5.8: (Top) estimated standard deviations ($\hat{\sigma}(t)$) of the four series in Equation (3.1); (middle) standardised standard deviations ($\hat{\sigma}(t)/\hat{\alpha}(t)$) for GDP, industrial production, household's disposable income and retail trade together with the standard deviation of $\hat{X}(t)$ (thick line); (bottom) the standard deviations, $\hat{\sigma}(t)$ from estimating Equation (3.1) for ΔGDP (full line) and Equation (3.17) $\Delta\hat{X}(t)$ (dashed line)

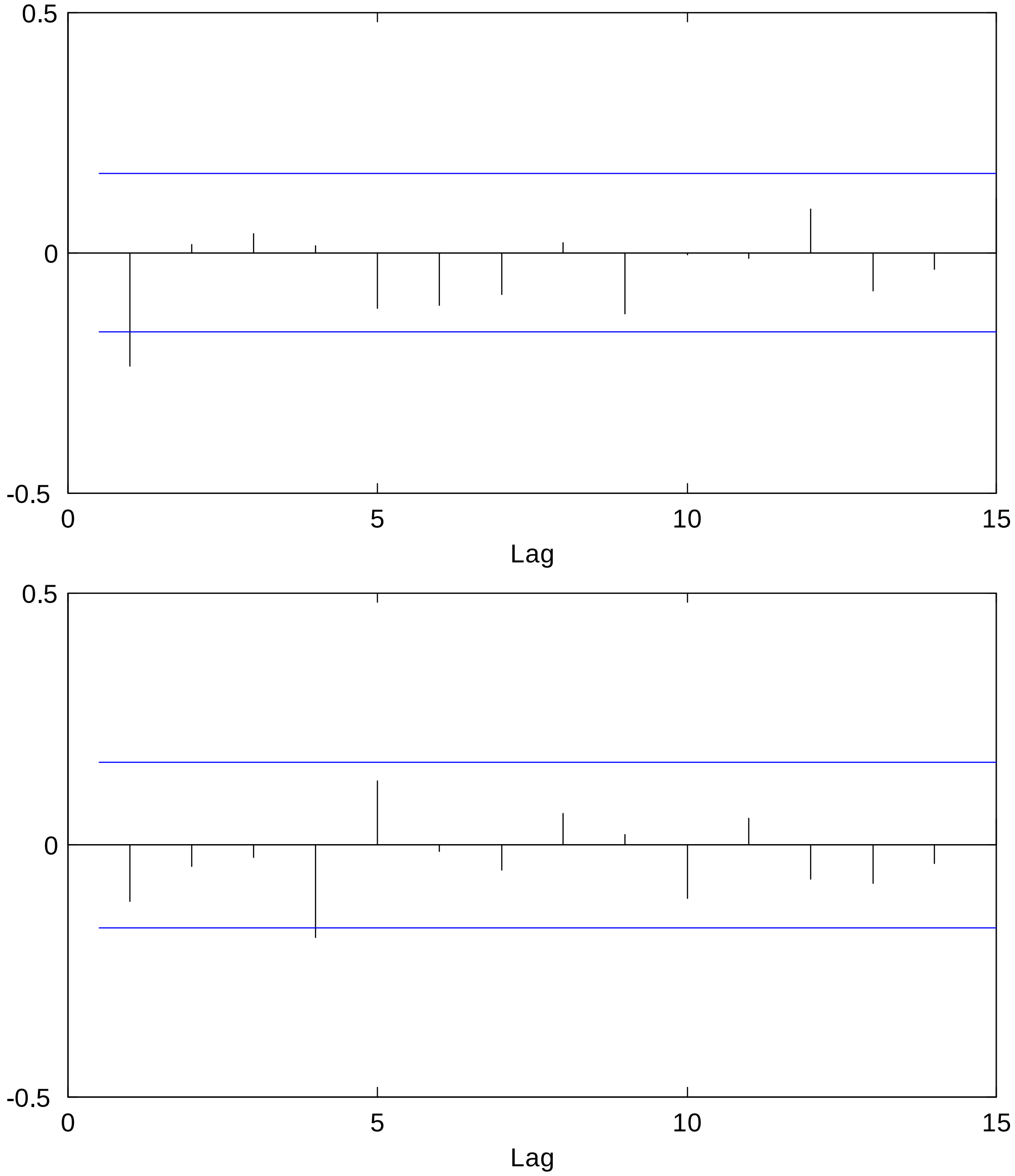

Figure 5.9: Autocorrelation of the residuals $\hat{\eta}_k$ from estimating Equation (3.17) (top) and of their absolute values (bottom)

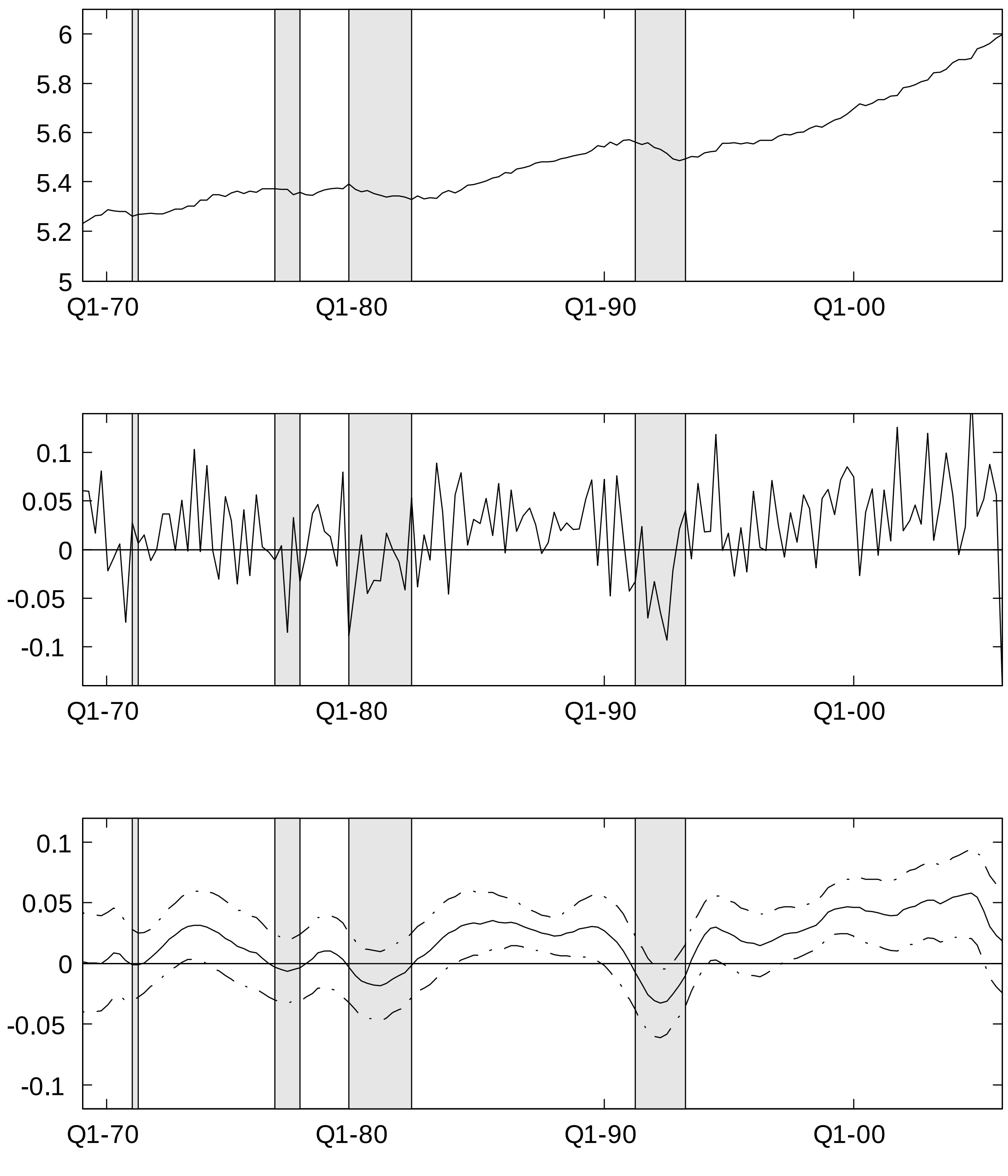

Figure 5.10: (Top) the $\hat{X}(t)$ series calculated with Equation (3.14); (middle) the first difference of the $\hat{X}(t)$ series; (bottom) the estimated business cycle for Sweden during 1969:Q1-2005:Q4 with 95% confidence-bands using all four series

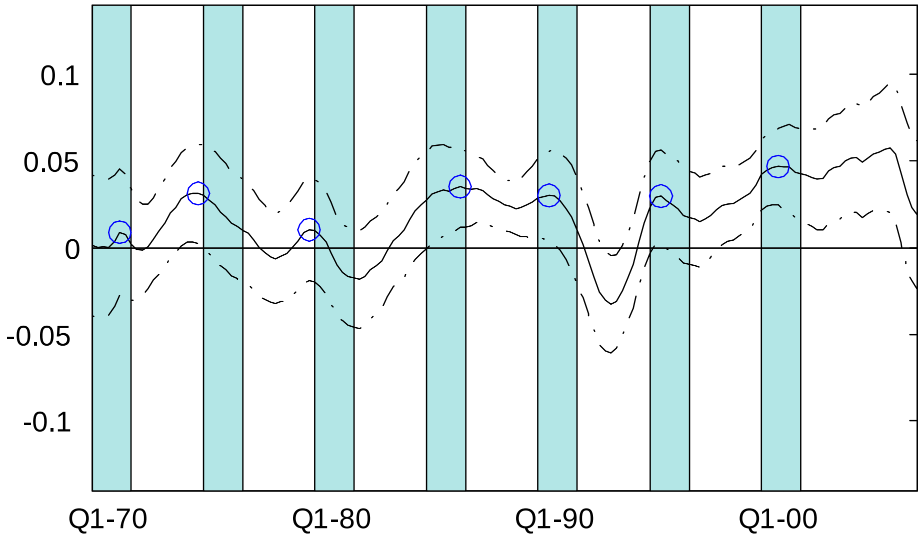

Figure 5.11: The estimated business cycle with peaks in the growth rate (circles) for Sweden during 1969:Q1-2005:Q4 with 95% confidence-bands where the shaded areas represent the peak period dated by Statistics Sweden

Chapter 6

Evaluation of variables for forecasting recessions in Sweden using a probit model

To know in advance the future movements in the economic activity could be very important from a policy perspective. If recessions can be predicted, monetary policy could respond and avoid an output gap or a fall in inflation. There are both theoretical and empirical evidences supporting the ability of the yield curve, defined as the difference between long and short-term interest rates, to forecast future recessions in an economy. A large empirical literature (starting with Harvey [50] and Estrella & Hardouvelis [31]) has documented the excellent leading indicator properties of the slope of the yield curve for future economic activity. Recent examples are Bernard & Gerlach [8], Estrella & Mishkin [32], [33], Dueker [26], Haubrich & Dombrosky [48], Hu [52], Plosser & Rouwenhorst [69] and Stock & Watson [76]. Estrella & Mishkin [33] found that the slope of the yield curve outperforms other financial indicators as a predictor of real economic activity.

The aim of this chapter is to test if simple financial variables are useful predictors of future recessions in Sweden. Following Estrella & Mishkin [33], we will examine variables such as interest rates, a stock price index, monetary aggregates and macroeconomic variables. In particular we want to test if the yield curve performs better than the other variables in predicting an upcoming recession. We follow previous research and use a probit approach. Judged on the in-sample fit by the fraction of correctly predicted months a modified probit model which includes the autoregressive series of the state of the economy (suggested by Dueker [26]) will also be estimated.

This chapter is organised as follows. Section 1 explains the macroeconomic relationship between yield curve and recessions. In Section 2 we summarise some previously related work done in the area. Section 3 describes recession periods in Sweden since 1970. Section 4 and 5 discusses the data and the models. In Section 6 the results are presented. Section 7 concludes the chapter.

6.1 Relationship between yield curve and recessions

The yield curve[1] plots the interest rates, at a set point in time, of bonds having equal credit quality, but differing maturity dates. The most frequently reported yield curve compares the three-month, two-year, five-year and 30-year treasury debt. This yield curve is used as a benchmark for other debt in the market, such as mortgage rates or bank lending rates. The curve is also used to predict changes in economic output and growth. The shape of the yield curve is closely scrutinised because it helps to give an idea of future interest rate change and economic activity. There are three main types of yield curve shapes: normal, inverted and flat. A normal yield curve is one in which longer maturity bonds have a higher yield compared to shorter-term bonds due to the risks associated with time. An inverted yield curve is one in which the shorter-term yields are higher than the longer-term yields, possibly signalling an upcoming recession. A flat yield curve is one in which the shorter- and longer-term yields are very close to each other. Historically, an inverted yield curve has been viewed as an indicator of a pending economic recession. When short-term interest rates exceed long-term rates, market sentiment suggests that the long-term outlook is poor and that the yields offered by long-term fixed income will continue to fall.

For example, in a recession the central bank uses a monetary policy and adjusts its key interest rate. The key interest rate is one of the most important instruments for stabilising the economy, i.e. for ensuring that economic fluctuations do not become too aggressive. The agents of the market are aware that the inflation will increase during the expansion part of the defined cycle and the longer-term yields will be higher. The yield curve will then have a positive slope. When the economy is expanding, the central bank will use restrictive monetary policy to maintain price stability and to avoid high inflation. The slope of the yield curve will decrease but remain positive. When the business cycle reaches a peak the central bank will raise the key interest rate to avoid an overheating economy. The market expects lower inflation in the future and the longer-term yield will be lower than the shorter-term yields, hence the slope of the yield curve will be negative.

6.2 Related work

Estrella & Mishkin [33] established that the slope of the yield curve outperforms other indicators in predicting recessions in an economy on horizons over one quarter. They also found that the spread performs better by itself than in conjunction with other variables. They used a probit model for their estimation on U.S. data. Dueker [26] suggests a modified probit model which includes the autoregressive series of the state of the economy. This is also done on U.S. data. According to new research from Harding & Pagan [47] one should be careful with constructed binary series when used in econometric work. Using constructed data rarely yields independently distributed variables and therefore the results might be misleading. Harding & Pagan present an alternative non-parametric method that allows for dependence when using the yield spread to predict recessions.

Since the work by Estrella & Mishkin [33] many studies have been made on the subject

[1] See more details on the yield curve in Campbell [14].

in different countries. Bernard & Gerlach [8] examined the ability of the term structure to predict recessions in eight countries (Belgium, Canada, France, Germany, Japan, the Nederlands, the United Kingdom and the United States) between 1972:Q1-1993:Q4. They found that the yield curve provides information about the likelihood of the future recessions eight quarters ahead. Chauvet & Potter [19] performed a comparison of four different specifications of the probit model. They found strong evidence in favour of their more sophisticated specification, which allows for autocorrelation and multiple breakpoints across business cycles.

There has also been research investigating whether the spread between long and short-term interest rates is as good a cyclical indicator as previously been stated. Boulier & Stekler [11] estimated a probit regression for the U.S. economy during 1960-1997. The performance of the term spread varied over time but there were an extremely large number of false predictions. They concluded that the term spread alone, is not a reliable predictor of economic activity. Fritsche [38] explored the leading indicator properties of different time series for the German business cycle and tested for the ability of different indicator series to forecast recessions by using a probit approach as proposed by Estrella & Mishkin [32]. He found no clear evidence that any of the indicators can be solely used for the purpose of identifying turning points.

6.3 Recessions and expansions in Sweden since 1970

Starting in the mid 1970s, growth fell in Sweden as it did in many Western European countries. One problem was the tougher competition from other regions of the world. The Swedish krona was forced to several devaluations during the 1970s and 1980s. In the mid 80s the economic growth rose again. The deregulation of the credit market contributed to a very rapid increase in lending, mainly focusing on the real estate sector. Because of this Sweden developed a banking and financial services bubble. The bubble burst in the early 1990s and marked the beginning of the deepest crisis for Sweden since the 1930s. This crisis led to a number of structural reforms. The economic conditions became better and a very quick growth in the information technology (IT) sector took place. After 1993 Sweden was in line with the average for countries belonging to the Organisation for Economic Cooperation and Development, OECD. However, the growth in the IT sector led to unrealistic valuations of shares and causing a new bubble that burst in the early 21st century. There was a slowdown in the IT sector but compared to the downturn a decade earlier this was very mild. Since then the economic growth has been pointing upwards.

For the probit model estimation we need ex-post dating of the business cycle in Sweden. There are several ways to define the business cycle in an economy. The business cycle could be defined as the movements in one series or the comovement of a number of series. Two common ways to define a business cycle found in the literature are classical cycles and growth cycles. The classical cycle examines the level of a relevant series like the GDP, industrial production and such, while the growth cycle looks at the level of the series less a permanent component. One problem with the growth cycle is that it is quite hard to identify a trend line in the economic activity. The National Institute of

Economic Research (NIER, known as Konjunkturinstitutet), in Sweden uses the output gap to date recessions. The output gap is defined as the difference between the potential output and the actual output in the economy. The approach used by the NIER differs from the definition of the National Bureau of Economic Research NBER, in the U.S., or the Centre of Economic Policy Research CEPR, in the Euro Area since both of them uses the classical cycle.

The method described in Chapter 3 adopts the definition of the NBER and defines a recession as a significant decline in the level of economic activity in Sweden visible in GDP, industrial production, household's disposable income and retail trade. The method uses the comovements in the four series and produces a new series that can be thought of as driving "the economy". A positive first derivative of the new series indicates an expansion period and a negative a recession. Table 6.1 shows the four recessions found in Chapter 5.

peak	**trough**
1971:Q1	1971:Q2
1976:Q4	1977:Q4
1979:Q4	1982:Q2
1991:Q2	1993:Q2

Table 6.1: Peaks and troughs according the Swedish dating between 1969:Q1 and 2006:Q1 in Chapter 5

6.4 The data

Estrella & Mishkin [33] used five different kinds of series: interest rates and spread, stock prices, monetary aggregates, individual macro indicators, and indexes and leading indicators. We will use series with the same properties. The series are found in Table 6.2. Some of the series are available on a monthly basis and some on a quarterly.[2] Estrella & Mishkin [33] tested both monthly and quarterly frequencies on some series and found no difference in the results.

The spread is calculated by two maturities on interest rates series in Sweden since 1969:M1: three-month and 10-year series. We will use average monthly data and define the spread as the difference between the two rates

$$\text{spread} = S_t = r_t^l - r_t^s \tag{6.1}$$

where r_t^l is the long-term rate and r_t^s is the short-term rate.

[2] Data sources: 10-year treasury bond rate and three-month treasury bill were obtained from the database Ecowin. The rest of the series were obtained from Datastream.

Series	**Description**	**Frequency**
Interest rates and spread		
SPREAD	10-year - three-months treasury spread	M
BILL	Three-month T bill	M
BOND	10-year T bond	M
Stock prices		
OMX	OMX Stockholm	M
Monetary aggregates		
M0	Monetary Base, seasonally adjusted	M
M3	M3, seasonally adjusted	M
Individual macro indicators		
RETR	Retail trade, seasonally adjusted	Q
INPR	Industrial production, seasonally adjusted	Q
HDI	Household's disposable income, seasonally adjusted	Q
GDP	Real GDP, seasonally adjusted	Q
EMP	Employment, seasonally adjusted	Q
Indexes and leading indicators		
FPI	Factor price index	M
COML	Composite leading indicator	M
MANP	Survey shortage of manpower	Q

Table 6.2: Indicator series

The financial market in Sweden was strongly regulated before 1985. The regulations were used as monetary policy instruments in the form of interest rates regulations, upper limit for loans, placing duty and minimum reserve requirements for example. Then in May 1985 interest rate controls were scrapped. On November 21, the central bank decided to give up all lending constraints for the banking system. Currently the key interest rate is the means of control and their main task is to facilitate the stability and effectivity in the financial system. Due to the regulated market before 1986, we will perform our analysis based on the spread and the interest rates on two sub samples, 1969:M1 to 1985:M12 and 1986:M1 to 2006:M3, where the latter corresponds to the period when the market was unregulated. The other variables will be used on the entire sample.

Figure 6.1 shows the spread where the gray areas corresponds to the recessions dated in Chapter 5. Our first subset of monthly data, 1969:M1-1985:M12, contains 204 observations of which 54 (26.47%) were recessions. The last subset contains 243 observations where 27 (11.11%) of them were recessions. For the sake of comparison, Estrella & Mishkin [33] had 15%, Dueker [26] had 16.67% for the U.S. and for Europe, Moneta [61] had 17%.

6.5 Estimation procedures

Following Estrella & Mishkin [33], we use the dates from Chapter 5 and construct a binary time series where the value stands for whether the economy is in a recession or not.

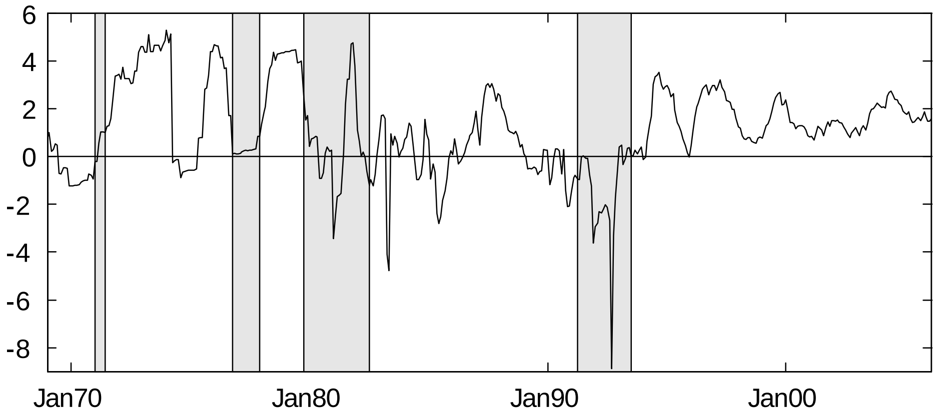

Figure 6.1: Interest rate spread since 1969:M1 in Sweden together with recessions dated in Chapter 5

6.5.1 The standard probit model

Estrella & Mishkin [33] used a standard probit model for the recessions. A probit model is a binary econometric model in which the dependent variable R_t can be only one or zero, and the continuous independent variable X_t are estimated in

$$\Pr(R_{t+k} = 1) = \phi(b_0 + b_1 X_t + \varepsilon_t) \qquad t = 1, ..., T \tag{6.2}$$

where b_0 and b_1 are parameters to be estimated, $\varepsilon \sim N(0,1)$ and ϕ is the cumulative normal probability distribution. Equation (6.2) is a regression model with forecast horizon k in time t. R_t is the dependent variable, where $R_t = 1$ means that the economy is in a recession and $R_t = 0$ otherwise. The model is estimated by maximum likelihood, with the likelihood function

$$L = \prod_{[R_{t+k}=1]} \phi(\mathbf{X}_t^T \mathbf{b}) \prod_{[R_{t+k}=0]} \left[1 - \phi(\mathbf{X}_t^T \mathbf{b})\right] \tag{6.3}$$

where $\mathbf{b}$ is the coefficient vector and $\mathbf{X}_t$ a matrix containing the variables. To account for potential autocorrelation in the residuals, we compute robust standard errors.

6.5.2 The modified probit model

An assumption in the standard probit model is that the errors are independent, identically distributed random variables. This is most likely not the case for the problem at hand. This is pointed out in Harding & Pagan [47] where they explain that an adjustment is needed to be made for the serial correlation in the series. They clarify that the constructed binary series is following a Markov process and suggests some methods to deal with this. A possible remedy for the problem is proposed by Dueker [26] and consists in adding a lagged dependent variable. He argues that if the economy already is in a recession that must be controlled for. Adding a lag of R_t the model becomes

$$\Pr(R_{t+k} = 1) = \phi(b_0 + b_1 X_t + b_2 R_t + \varepsilon_t) \qquad t = 1, ..., T. \tag{6.4}$$

6.5.3 Ordinary least square

Apart from these probit models we will also do a simple OLS estimation as

$$R_{t+k} = b_0 + b_1 X_t + \varepsilon_t, \qquad \text{where the errors are i.i.d.} \tag{6.5}$$

and with the lagged dependent variable as

$$R_{t+k} = b_0 + b_1 X_t + b_2 R_t + \varepsilon_t, \qquad \text{where the errors are i.i.d.} \tag{6.6}$$

to see if the estimations could have been done with a simple OLS instead.

We want to point out that comparing the standard model (6.2 and 6.5) with the modified (6.4 and 6.6), is not really fair. The reason is that R_t, our recession information from Chapter 5, has been obtained using information after the moment of the recession. This is because the estimation of the recession dates were done using the non-parametric approach with bandwidths that reaches both backwards and forward in time from the estimation point.

6.5.4 Measures of fit

When analysing the goodness of fit in the classical regression model we use R^2 as a measure of the explanatory power of the regression model. The R^2 measure is however of limited use when the dependent variable is dichotomous. To test how well the model estimates the recessions we will calculate a version of McFadden's pseudo-R^2 proposed by Estrella [30].[3] In this measure of fit for probit models, Estrella proposed a pseudo-R^2 in which the log-likelihood of a model, L_u, is compared with the log-likelihood of a nested model[4], L_c, that by construction must have a lower likelihood value. L_u denotes the likelihood of the estimated model and L_c is the likelihood of a model with only a constant as a regressor.

$$\text{Pseudo-R}^2 = 1 - \left[\frac{L_u}{L_c}\right]^{-\left(\frac{2}{n}\right)L_c} \tag{6.7}$$

n is the number of observations and just like R^2, pseudo-R^2 will lie between 0 and 1. In order to find the best predictor of recessions, different horizons will be tested.

The pseudo-R^2 for the modified model is calculated in the same manner as explained above with the exception that now the unrestricted model yields L_u. The restricted model with $b_1 = 0$ yields L_c. This test will give us information which goes beyond that information already contained in the autoregressive structure of the binary time series at the moment when the indicator gave a signal.

[3] The original McFaddens R^2 is defined as $1 - L_u/L_c$ (see McFadden [60]).

[4] In the nested model b_1 is zero.

Another measure of fit that is easy to understand is "fraction correctly predicted" which uses the following rule: If $R_t = 1$ and the predicted probability exceeds a threshold of 50% (or 25%), or if $R_t = 0$ and the predicted probability is less than 50% (or 25%), then R_t is said to be correctly predicted. Otherwise, R_t is said to be incorrectly predicted. The "fraction correctly predicted" is simply the fraction of the n observations $R_1, ..., R_n$ that are correctly predicted.

6.6 Results

6.6.1 Results from the series

Both the probit and OLS models were estimated using the series alone and in conjunction with the spread. The horizons with all significant coefficients are presented in Table 6.9. Among the quarterly series, employment, industrial production and retail trade work well on very short horizons while GDP, household's disposable income and manpower seem to contain no useful information. The performance of the monthly series is almost just as poor. The composite leading indicator however had significant coefficients for several of the horizons.

Composite leading indicator: Because of this we estimated the standard probit model, Equation (6.2), and the modified probit model, Equation (6.4), on the composite leading indicator during the whole period (1969:M1-2006:M3). We also estimated the OLS models (6.5) and (6.6). The results are presented in Table 6.10 and we see that the composite leading indicator had significant coefficients for all horizons and all models. We calculated the pseudo-R^2's for the standard and the modified model and they are shown in Figure 6.2. The pseudo-R^2's are very small. The left graph shows how much the model improves if we add the composite leading indicator to the model instead of using just a constant. The right graph shows how the model improves with the composite leading indicator added to the lagged dependent variable and a constant. They both give the highest pseudo-R^2 for eight horizons.

Figure 6.3 plots the predicted probabilities for a recession using the composite leading indicator eight months back. The estimated coefficients and statistics are shown in Table 6.3. In non-linear regression models, such as the probit model, coefficients can not be interpreted as marginal effects. The marginal effects report the change in predicted probability for a unit change in the predictor. For example, in the standard model, the variable composite leading indicator has a marginal effect of -0.2482. This means that an increment of one to the variable composite leading indicator leads to a decrease in the probability of having a recession with 0.2482, or 24.82 percentage points. For the modified model the marginal effect is 19.36 percentage points. The estimated recession probabilities from (6.2) and (6.4) can be seen in the top left graph in Figure 6.5 and Table 6.4. The thin line in Figure 6.5 corresponds to the standard model in Equation (6.2) and the thick to the modified model in Equation (6.4).

We also computed the predicted and actual monthly recessions using thresholds of 0.25 and 0.5. The results from the standard model are shown in Table 6.11 and for the

R_t	dF/dx	Coef	Robust Std.Err.	z	P>|z|
b_1	-0.2482	-1.0291	0.1601	-6.43	0.000
b_0		-0.8346	0.0733	-11.39	0.000

R_t	dF/dx	Coef	Robust Std.Err.	z	P>|z|
b_2		1.6599	0.1764	9.41	0.000
b_1	-0.1936	-0.9568	0.1591	-6.01	0.000
b_0		-1.3142	0.1006	-13.06	0.000

Table 6.3: Standard (top) and modified (bottom) probit model using the composite leading indicator with $k = 8$, 1969:M1-2006:M3

Value of COMP	Standard model Recession Probability	Modified model Recession Probability
-4	99.95	99.76
-3	98.79	96.87
-2	88.95	81.74
-1	57.71	47.96
0	20.20	15.67
-1	3.12	2.47
-2	0.19	0.17

Table 6.4: Estimated recession probabilities for the probit models using the composite leading indicator 8 months back

modified model in Table 6.12. Using a threshold of 0.25, the standard model is not a good predictor of an upcoming recession since 66% of the warnings are incorrect. It also fails to predict a recession in 13.5% of the cases. The fraction correctly predicted is 0.738. If we use a threshold of 0.5 the model fails to predict a recession in 75% of the cases and only two of the 81 recession months were predicted which gives us a fraction of correctly predicted months of 0.806. For the modified model 42.8% are false warnings for threshold 0.25 and 31.8% for 0.5. However, the number of failures to predict a recession is only 8.3% and 9.7%. The fractions correctly predicted are 0.845 and 0.870. In the bottom graph in Figure 6.3 we can see that the probability of a recession makes a large jump as soon as the economy is in a recession. As we pointed out earlier, the marginal effect of the spread is larger for the standard model than for the modified model. It is clear that the lagged dependent variable makes a big difference. This could be explained by the fact that we use information that was not available at the time of the estimation. As a conclusion, if we are in a recession period the probability that the next period is a recession is very much higher than if we are not in a recession in the time of the estimation. We can see that the probability drops again eight months after the end of a recession. So, if we compare the standard model to the modified model, the latter makes fewer false warnings and misses fewer recessions but the warnings are always late and last longer than the actual recession.

Combinations of series: We also tested different combinations of the financial variables but none of them gave good results. The majority of the combinations did not get significant coefficients. Figure 6.4 shows the predicted probabilities for the first period using (top) industrial production and retail trade with a horizon of one quarter and (bottom) the spread and employment with the horizon of seven quarters. These combinations and horizons were two of the few that gave significant coefficients and it is easy to see from the figure that they will both generate several false warnings.

6.6.2 A closer look at the spread

Figure 6.2 shows that the explanatory power varies with the forecast horizon. We can see that the explanatory power rises from $k = 1$, peaks after eight months for the composite leading indicator and after six months for the spread (displayed in the two bottom graphs), and then falls gradually as increasingly higher k's are considered. The largest pseudo-R^2 for the spread in the last period is found for the sixth month in both of the models (0.362 and 0.610 respectively). Bernard & Gerlach [8] found large differences between countries in the predictive power of the spread. The predictive power, as measured by the pseudo-R^2, was highest in Germany, followed by Canada and the United States, and lowest in Japan. Estrella & Mishkin [33] had the largest pseudo-R^2 for four quarters (0.296) and Dueker [26] for nine months using his modified model (0.284) and 0.305 for the standard model. In Europe, Moneta [61] had 0.212 for the standard model and 0.242 for the modified model, both four quarters ahead.

Regulated period: 1969:M1-1985:M12 For the first period[5] one month horizon had the largest pseudo-R^2. For the modified model the coefficients were not significant so coefficients and the pseudo-R^2 will not be presented. The result from the standard probit estimation using a three month horizon is presented in the bottom graph in Figure 6.5. We chose to present the probabilities using a horizon of three months since one month is not long enough to affect the economy and the results using one or three months was not that different.

To determine whether the term spread is able to forecast turning points without making too many false predictions we calculated the number of warnings using a threshold of 0.25 and 0.5. The results are found in Table 6.13. From the bottom graph in Figure 6.5 we can see that the model does not seem to work. With a threshold of 0.50 we do not get any warnings at all. With a threshold of 0.25 we get 127, but 87 (68.5%) of them are false warnings. The fractions of correctly predicted are 0.498 and 0.721.

If the economy is currently in a recession then the probability of future recession or recovery may be influenced by the fact that the economy is in a recession. However, with the addition of the lagged dependent variable in the modified probit model, Equation (6.4), coefficient b_1 is not significant at any horizon.

[5] Pseudo-R^2 for one month horizon: 0.040, two: 0.038 and three: 0.032.

R_t	dF/dx	Coef	Robust Std.Err.	z	P>|z|
b_1	-0.0315	-0.0965	0.0423	-2.28	0.022
b_0		-0.5090	0.1074	-4.74	0.000

Table 6.5: Standard probit model using the spread with $k = 3$, 1969:M1-1985:M12

Unregulated period: 1986:M1-2006:M3 From the result of the pseudo-R^2 for the unregulated period we estimated the standard model found in Equation (6.2) at a six month forecast horizon. The marginal effect for the standard model is 0.51 percentage points and even smaller for the modified model. The estimated probabilities for a recession for different values of the spread could be found in the top right graph in Figure 6.5 and in Table 6.7. The estimated probabilities in each month are presented in Figure 6.6. The statistics are found in Table 6.6. The summary of the distributions of forecasts and outcomes using thresholds of 0.25 and 0.50 for the second period could be found in Table 6.14 and in Table 6.15. Here we can see that 32.4% of the warnings for the standard model are false for a threshold of 0.25, but only two out of 23 when the threshold is 0.5. The fractions correctly predicted are 0.937 and 0.966. For the modified model the performance changes. When the threshold is 0.50 we get three false warnings and four missed warnings. The fractions correctly predicted are 0.979 (threshold 0.25) and 0.970 (threshold 0.50). Hence, the modified model is preferred here.

R_t	dF/dx	Coef	Robust Std.Err.	z	P>|z|
b_1	-0.0051	-1.7944	0.2720	-6.60	0.000
b_0		-1.3735	0.2386	-5.76	0.000

R_t	dF/dx	Coef	Robust Std.Err.	z	P>|z|
b_2		3.2627	0.9392	3.47	0.001
b_1	$-1.21e^{-8}$	-3.1574	0.7261	-4.35	0.000
b_0		-3.3319	0.6721	-4.96	0.000

Table 6.6: Standard (top) and modified (bottom) probit model using the spread with $k = 6$, 1986:M1-2006:M3

6.6.3 Comparison of statistics

Probit estimation yield coefficients that are interpreted as changes in probabilities. The marginal effects from the probit model are comparable to the coefficients of the OLS estimation. We repeated the estimation of the standard model and the modified model using OLS since they are easier to interpret than probit results. The results of comparing OLS with probit models are mixed. The coefficients from the OLS estimations are found in Table 6.8. We can see that the results in the first and the third row show that the OLS

Value of Spread	Standard model Recession Probability	Modified model Recession Probability
-3	100	100
-2	98.66	99.96
-1	66.31	57.82
0	8.48	0.15
1	0.08	0
2	0	0

Table 6.7: Estimated recession probabilities for probit model using the spread 6 months back, 1986:M1-2006:M3

coefficients and the marginal effects from the probit are similar. The estimated probabilities of a recession are hard to tell apart. However, when we are using the spread for the unregulated period, they do not show similar outcomes and their estimated probabilities differ a lot more.

variables in the model	OLS b_1	dF/dx from PROBIT
COML_{t-8}	-0.2337	-0.2482
COML_{t-8} and R_{t-8}	-0.1596	-0.1936
SPREAD_{t-3}	-0.0299	-0.0315
SPREAD_{t-6}	-0.1407	-0.0051
SPREAD_{t-6} and R_{t-6}	-0.0745	$-1.21e^{-8}$

Table 6.8: Coefficients from OLS estimations and marginal effects from the probit estimations; (first and second row) the composite leading indicator with and without lagged dependent variable; (third row) spread in the regulated period and (fourth and fifth row) spread in the unregulated period with and without lagged dependent variable

6.7 Conclusions

In this paper the usefulness of the term spread as predictor of recessions is among other financial indicators tested in Sweden. We used a probit model which is a non-linear regression model that translates the information contained in the independent variable into a probability of recession at a particular time horizon. The dating procedure refers to the study done in Chapter 5 and Figure 6.1 plots the Swedish interest rate spread together with the recessions.

When we estimated the models using the spread or variables together with the spread we divided the data into two samples. We had one sample during the time when the financial market was regulated (1969:M1-1985:M12) and one sample when it was unregulated (1986:M1-2006:M3). We estimated the standard models using all the variables with the standard probit model, following Estrella & Mishkin [33], by themselves and together with the spread. A majority of the series did not give significant coefficients at the 95% level for several horizons. However, the composite leading indicator seemed to contain some information. We also tested if different combinations of the variables could give extra information of an upcoming recession and found nothing that performed better than the spread.

For a closer look at the predicting qualities of the spread and the composite leading indicator we estimated the standard probit model and a modified probit model proposed by Dueker [26] which includes the autoregressive series of the state of the economy. We let the forecast horizon vary from one to 12 months.

In sample the spread was the best predictor of an upcoming recession. The best forecast horizon for both the simple and the modified probit model in the unregulated period was six months. The result from the first period was not satisfactory. It was clear that neither the spread nor the composite leading indicator would have helped to forecast an upcoming recession.

While earlier work has shown that such models predicts U.S. recessions well up to four quarters horizons, the results are not very satisfactory for the Swedish economy. It is hard to judge whether a probit model based on the yield spread is a good instrument to determine the likelihood of a recession in Sweden. The reason is that the unregulated period is too short and we need more history of recessions. Before 1986, the Swedish term spread does not contain information useful for predicting recessions. Even though the research suffers from few observations of recession periods, our conclusion is that the term spread is not a good forecasting indicator for Sweden. The hints found for an upcoming recessions is available only two quarters ahead. However, among the variables, models and periods tested here, the standard model suggested by Estrella & Mishkin [33] had the best performance during 1986:M1-2006:M3 with few wrongly predicted months. As time goes by and more observations of the spread will be available, an out of sample analysis and the implementation of the method suggested by Harding & Pagan [47] would be needed before the spread is ruled out as a useful predictor of an upcoming recession in Sweden.

Period	Model	EMP	GDP	INPR	HDI	RETR	MANP
1969:Q1-2006:Q1	$R_t = b_0 + b_1 X_{t-1}$	1-3	1	1-4	-	1,3	-
	$Pr(R_t = 1) = \phi(b_0 + b_1 X_{t-1})$	1-3	1	1-4	-	1,3	-
1969:Q1-1985:Q4	$R_t = b_0 + b_1 X_{t-1}$	-	-	1	-	-	-
	$R_t = b_0 + b_1 X_{t-1} + b_2 S_{t-1}$	-	-	-	-	-	-
	$Pr(R_t = 1) = \phi(b_0 + b_1 X_{t-1})$	7-8	-	1	-	1	6
	$Pr(R_t = 1) = \phi(b_0 + b_1 X_{t-1} + b_2 S_{t-1})$	-	-	-	-	-	-
1986:Q1-2006:Q1	$R_t = b_0 + b_1 X_{t-1}$	1-5	-	1-4	-	1-3	-
	$R_t = b_0 + b_1 X_{t-1} + b_2 S_{t-1}$	1-3,8	-	1	-	1-7	-
	$Pr(R_t = 1) = \phi(b_0 + b_1 X_{t-1})$	1-5	-	1	-	1	-
	$Pr(R_t = 1) = \phi(b_0 + b_1 X_{t-1} + b_2 S_{t-1})$	1-2,8	-	1-2	1	-	-

Period	Model	OMX	M0	M3	COML	FPI	BILL	BOND
1969:M1-2006:M3	$R_t = b_0 + b_1 X_{t-1}$	-	-	-	1-12	1	9	-
	$Pr(R_t = 1) = \phi(b_0 + b_1 X_{t-1})$	8-9	-	-	1-12	-	-	-
1969:M1-1985:M12	$R_t = b_0 + b_1 X_{t-1}$	-	-	-	1-12	-	-	10
	$R_t = b_0 + b_1 X_{t-1} + b_2 S_{t-1}$	-	-	1	8-12	-	-	-
	$Pr(R_t = 1) = \phi(b_0 + b_1 X_{t-1})$	-	-	-	1-12	-		7-8,10-12
	$Pr(R_t = 1) = \phi(b_0 + b_1 X_{t-1} + b_2 S_{t-1})$	-	-	1	8-12	10-11		
1986:M1-2006:M3	$R_t = b_0 + b_1 X_{t-1}$	-	-	-	5-12	1-5	9	-
	$R_t = b_0 + b_1 X_{t-1} + b_2 S_{t-1}$	-			1-5	1-5	1-7,12	-
	$Pr(R_t = 1) = \phi(b_0 + b_1 X_{t-1})$	8-9			5-12	1-2	-	-
	$Pr(R_t = 1) = \phi(b_0 + b_1 X_{t-1} + b_2 S_{t-1})$	8-9	6	4-5	1-4	1-2	1-6	-

Table 6.9: (Top) horizons with significant coefficients for employment, GDP, industrial production, household's disposable income, retail trade and survey shortage of manpower, quarterly data; (bottom) horizons with significant coefficients for OMX, monetary aggregates M0 and M3, composite leading indicator, factor price index, three-month T bill and 10-year T bill, monthly data

Period	Model	SPREAD	COML
1969:M1-2006:M3	$R_t = b_0 + b_1 X_{t-1}$	NE	1-12
	$R_t = b_0 + b_1 X_{t-1} + b_2 R_{t-1}$	NE	1-12
	$Pr(R_t = 1) = \phi(b_0 + b_1 X_{t-1})$	NE	1-12
	$Pr(R_t = 1) = \phi(b_0 + b_1 X_{t-1} + b_2 R_{t-1})$	NE	1-12
1969:M1-1985:M12	$R_t = b_0 + b_1 X_{t-1}$	1-3	NE
	$R_t = b_0 + b_1 X_{t-1} + b_2 R_{t-1}$	-	NE
	$Pr(R_t = 1) = \phi(b_0 + b_1 X_{t-1})$	1-3	NE
	$Pr(R_t = 1) = \phi(b_0 + b_1 X_{t-1} + b_2 R_{t-1})$	-	NE
1986:M1-2006:M3	$R_t = b_0 + b_1 X_{t-1}$	1-12	NE
	$R_t = b_0 + b_1 X_{t-1} + b_2 R_{t-1}$	1-12	NE
	$Pr(R_t = 1) = \phi(b_0 + b_1 X_{t-1})$	1-12	NE
	$Pr(R_t = 1) = \phi(b_0 + b_1 X_{t-1} + b_2 R_{t-1})$	1-9	NE

Table 6.10: Horizons with significant coefficients for the spread and the composite leading indicator, monthly data (NE=not estimated), where X is the variable described in each column and R is the state of the economy

25% Threshold probability			
	Actual recession outcome		
Recession prediction	Yes	No	Total
Yes	36 (8.20)	70 (15.95)	106 (21.55)
No	45 (10.25)	288 (65.60)	333 (75.85)
Total	81 (18.45)	358 (81.55)	439 (100)
50% Threshold probability			
	Actual recession outcome		
Recession prediction	Yes	No	Total
Yes	2 (0.46)	6 (1.37)	8 (1.82)
No	79 (18.00)	352 (80.18)	431 (98.18)
Total	81 (18.45)	358 (81.55)	439 (100)

Table 6.11: Predicted and actual monthly recession outcomes by threshold probability, using the compositing leading indicator eight months back, 1969:M9-2006:M3

25% Threshold probability			
	Actual recession outcome		
Recession prediction	Yes	No	Total
Yes	52 (11.85)	39 (8.88)	91 (20.73)
No	29 (6.61)	319 (72.67)	348 (79.27)
Total	81 (18.45)	358 (81.55)	439 (100)
50% Threshold probability			
	Actual recession outcome		
Recession prediction	Yes	No	Total
Yes	45 (10.25)	21 (4.78)	66 (15.03)
No	36 (8.20)	337 (76.77)	373 (84.97)
Total	81 (18.45	358 (81.55)	439 (100)

Table 6.12: Predicted and actual monthly recession outcomes by threshold probability, using the compositing leading indicator and the recession status eight months back, 1969:M9-2006:M3

25% Threshold probability			
	Actual recession outcome		
Recession prediction	Yes	No	Total
Yes	40 (19.90)	87 (43.28)	127 (63.18)
No	14 (6.97)	60 (29.85)	74 (36.82)
Total	54 (26.87)	147 (73.13)	201 (100)
50% Threshold probability			
	Actual recession outcome		
Recession prediction	Yes	No	Total
Yes	0 (0.00)	0 (0.00)	0 (0.00)
No	54 (26.87)	147 (73.13)	201 (100)
Total	54 (26.87)	147 (73.13)	201 (100)

Table 6.13: Predicted and actual monthly recession outcomes by threshold probability, using the spread three months back, 1969:M4-1985:M12

25% Threshold probability			
	Actual recession outcome		
Recession prediction	Yes	No	Total
Yes	23 (9.70)	11 (4.65)	34 (14.35)
No	4 (1.69)	199 (83.97)	203 (85.65)
Total	27 (11.40)	210 (88.61)	237 (100)
50% Threshold probability			
	Actual recession outcome		
Recession prediction	Yes	No	Total
Yes	21 (8.86)	2 (0.84)	23 (9.70)
No	6 (2.53)	208 (87.76)	214 (90.30)
Total	27 (11.39)	210 (88.60)	237 (100)

Table 6.14: Predicted and actual monthly recession outcomes by threshold probability, using the spread six months back, 1986:M9-2006:M3

25% Threshold probability			
	Actual recession outcome		
Recession prediction	Yes	No	Total
Yes	26 (10.97)	4 (1.69)	30 (12.66)
No	1 (0.42)	206 (86.92)	207 (87.34)
Total	27 (11.39)	210 (88.61)	237 (100)
50% Threshold probability			
	Actual recession outcome		
Recession prediction	Yes	No	Total
Yes	23 (9.70)	3 (1.27)	26 (10.97)
No	4 (1.69)	207 (87.34)	211 (89.03)
Total	27 (11.39)	210 (88.61)	237 (100)

Table 6.15: Predicted and actual monthly recession outcomes by threshold probability, using the spread and the recession status six months back, 1986:M7-2006:M3

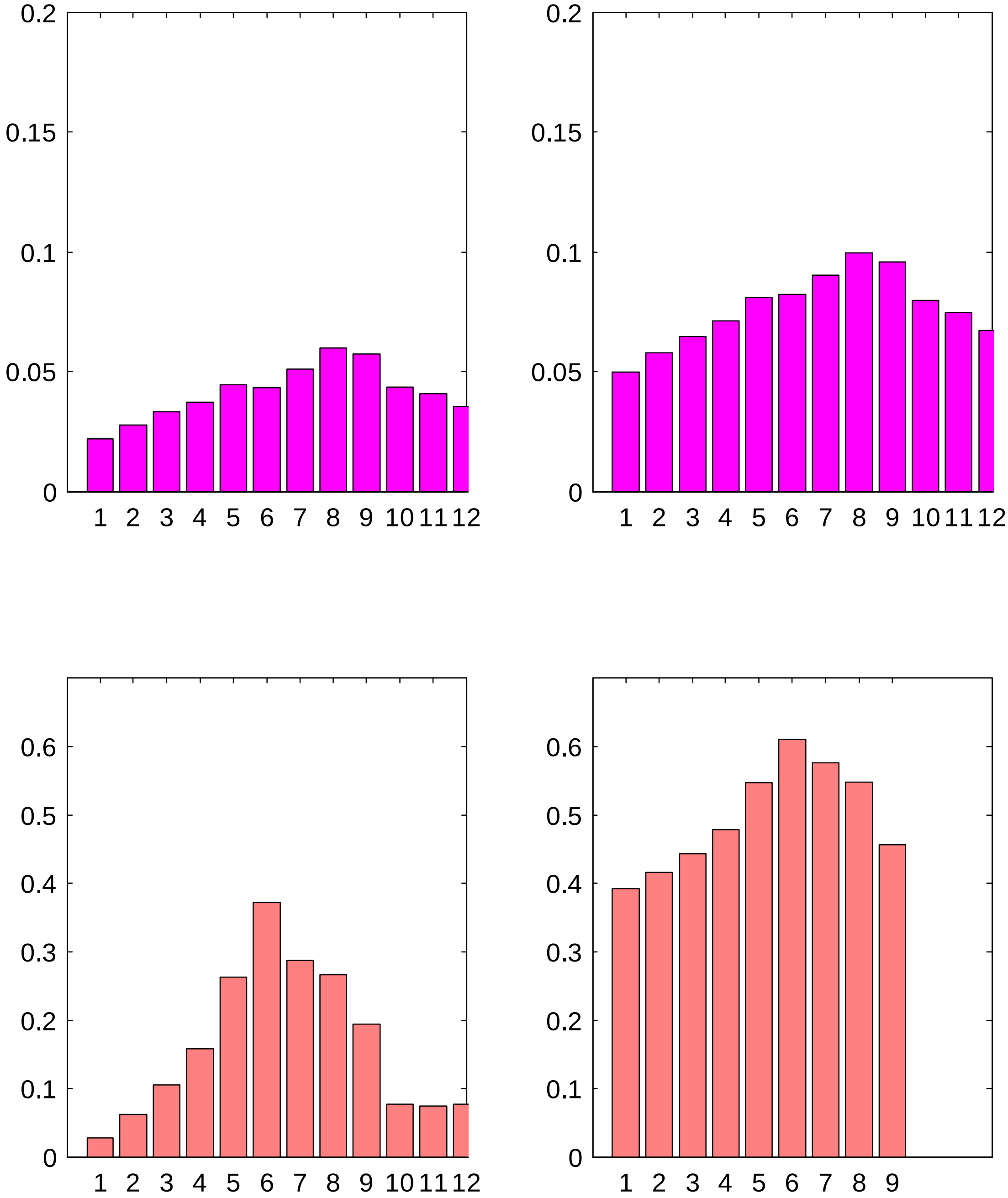

Figure 6.2: (Top) pseudo-R^2 for the standard probit model (left) and the modified model (right) using the composite leading indicator, 1969:M1-2006:M3; (bottom) pseudo-R^2 for the standard probit model (left) and the modified model (right) using the spread, 1986:M1-2006:M3

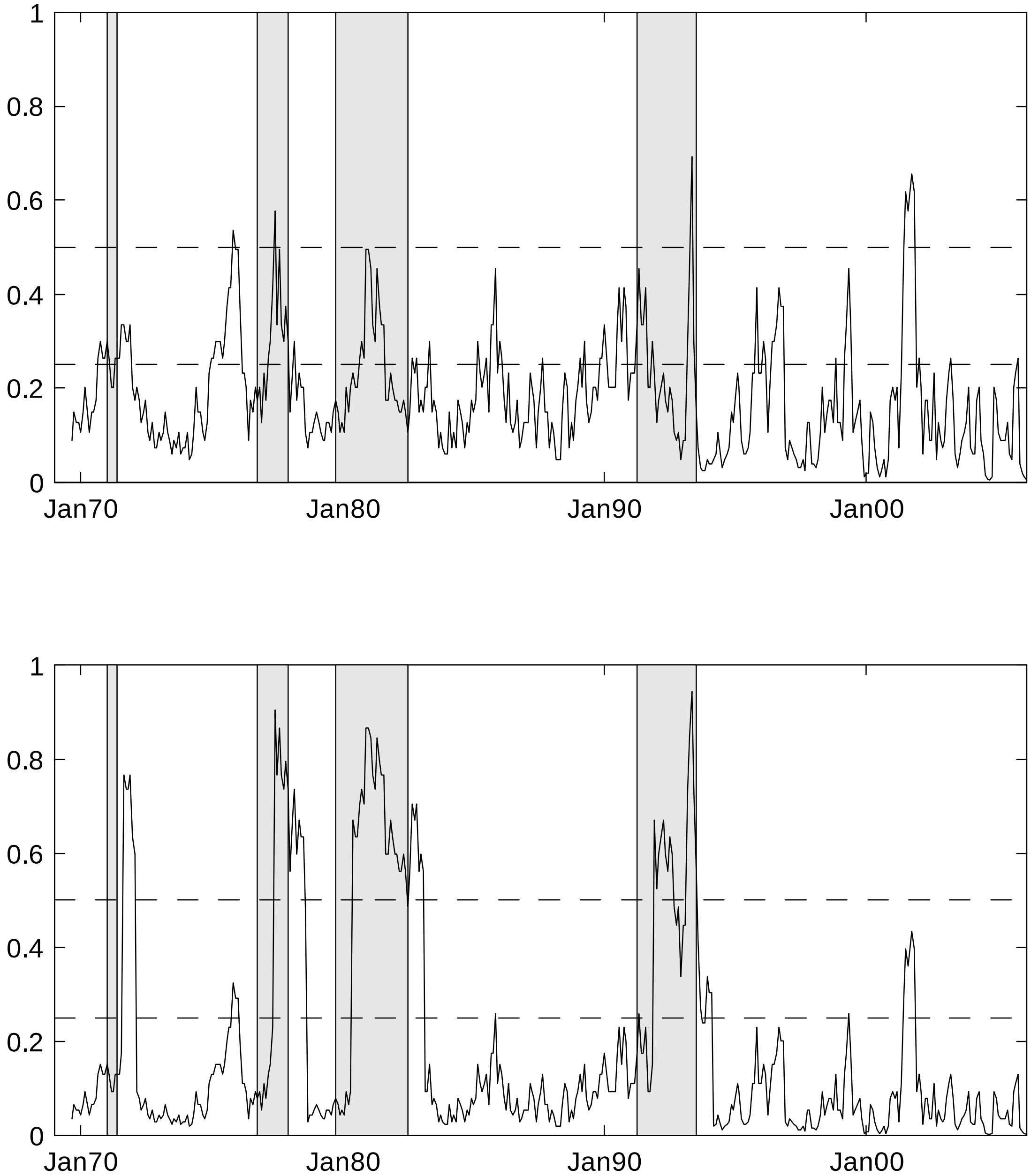

Figure 6.3: The predicted probabilities for a recession; standard model (top) and modified model (bottom) with thresholds 0.25 and 0.50 for the period 1969:M9-2006:M3 using the composite leading indicator (the shaded areas represent the recessions dated in Chapter 5)

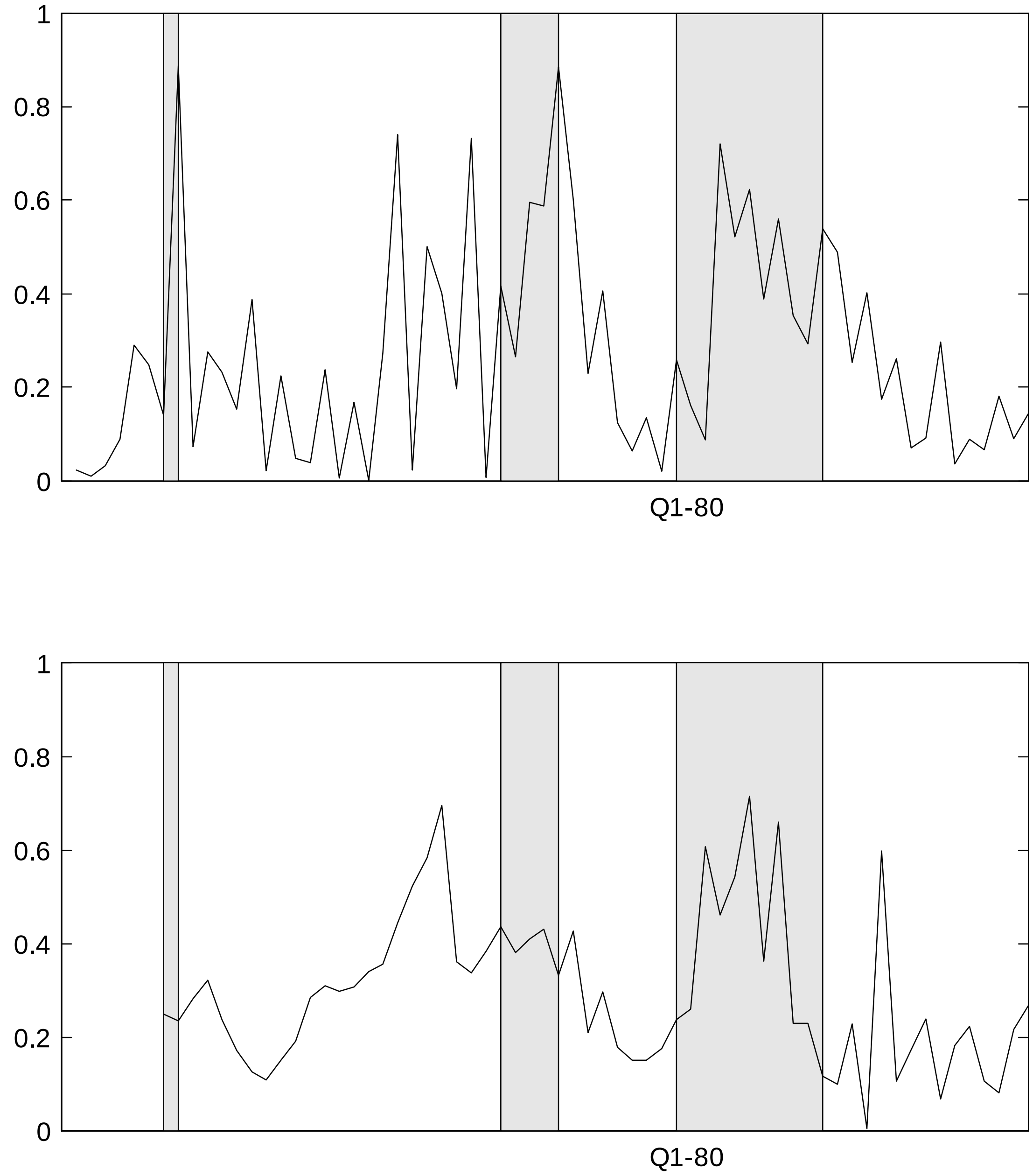

Figure 6.4: The predicted probabilities of a recession 1969:Q1-1985:Q4; (top) industrial production, household's disposable income and retail trade with a horizon of one quarter, (bottom) the spread and employment with a horizon of seven quarters (shaded areas represent the recessions dated in Chapter 5)

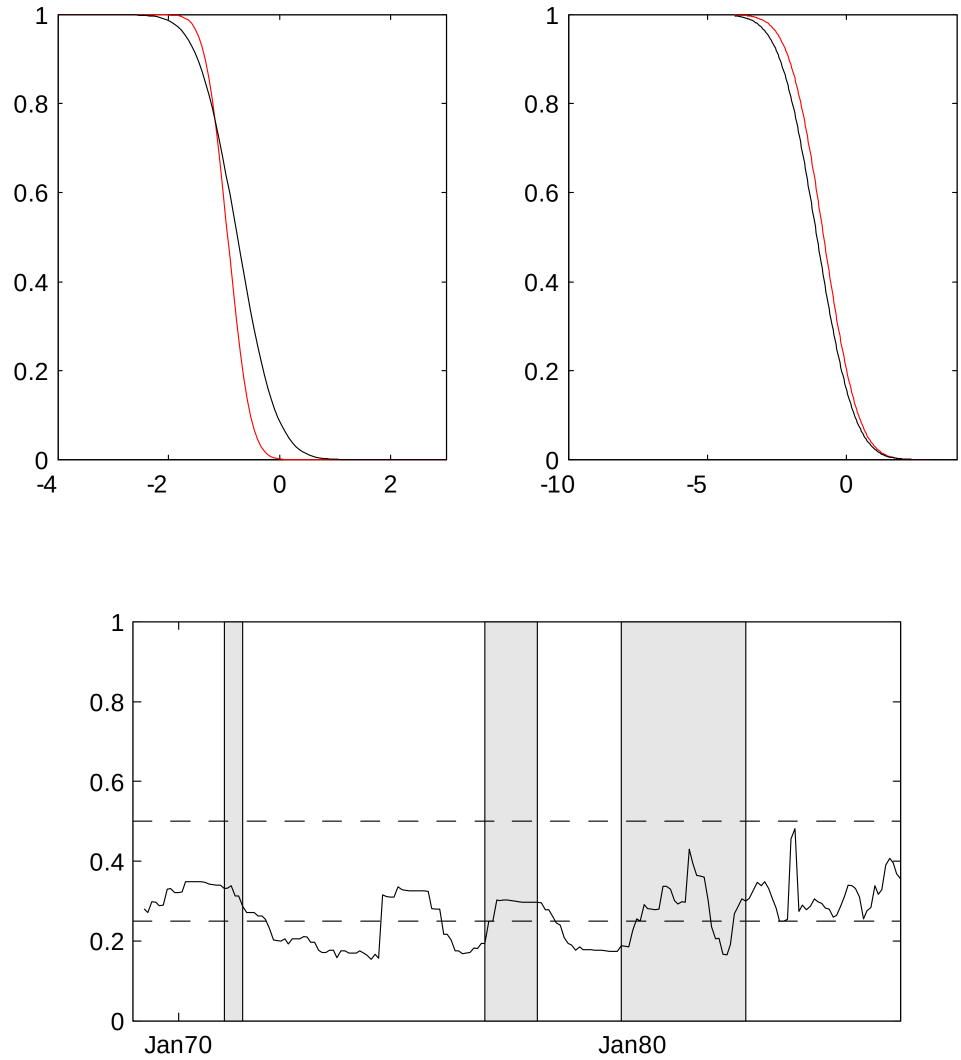

Figure 6.5: (Top left) estimated recession probabilities for the standard model using the compositing leading indicator eight months back (thin) and the modified model using the compositing leading indicator and the recession status eight months back (thick) for the period 1969:M9-2006:M3, where the value of the composite leading indicator is measured on the x-axis and the probability is measured on the y-axis; (top right) probability of a recession six months ahead as a function of the current spread for standard probit model (thin) and the modified probit model using the spread and the recession status 6 months back (thick) for the period 1986:M1-2006:M3, where the value of the spread is measured on the x-axis and the probability is measured on the y-axis; (bottom) predicted recession probabilities using the spread three months back (standard model for the period 1969:M4-1985:M12) with thresholds 0.25 and 0.50 and where the shaded areas represent recessions dated in Chapter 5

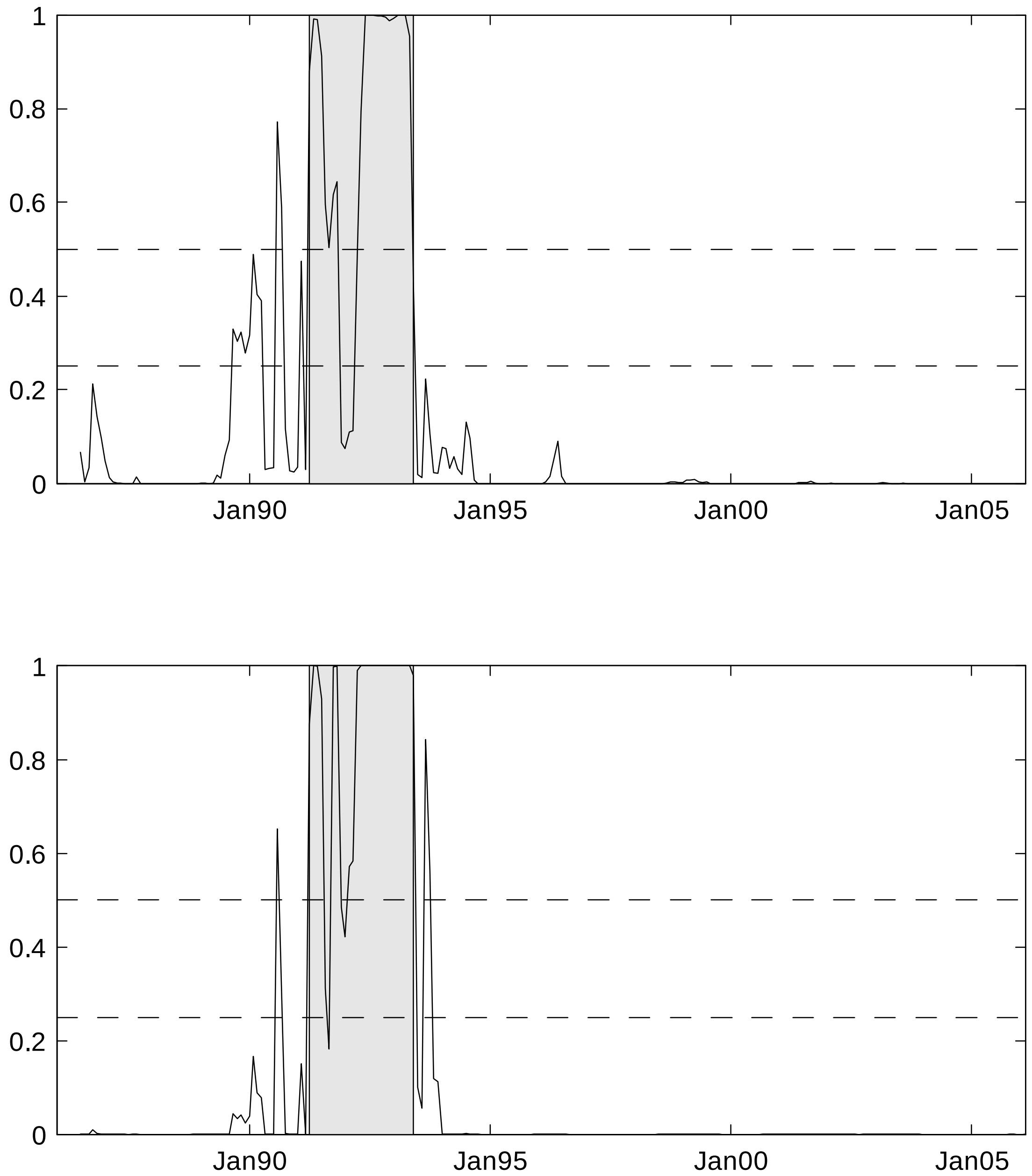

Figure 6.6: Predicted recession probabilities using the spread six months back; standard model (top) and modified model (bottom) for the period 1986:M7-2006:M3, with thresholds 0.25 and 0.50 and where the shaded areas represent recessions dated in Chapter 5

Chapter 7

Summary

There are so many different ways to define a business cycle, thus different methods to date them are needed. Among previous research there are several parametric methods but not so many non-parametric methods. Anas & Ferrara [4] suggests using non-parametric methods for dating and parametric methods for detecting. Harding & Pagan [46] suggests using methods that are as non-parametric as possible for dating.

In Chapter 4 a non-stationary, non-parametric smoothing-technique, described in Chapter 3, was tested on the Euro area and recession dates between the year 1970 and 2003 were found. The estimated dates were then compared to the dates dated by CEPR Dating Committee and to two previous research results using non-parametric dating methods. The method found two deeper and two milder recessions and one stagnation period since 1970. The two milder recessions could be thought of as a stagnation period. Since the method worked satisfactorily the same method was used on Swedish data to date the business cycle in Sweden where no institution dates the recessions ex-post. The method found four recession periods. In Chapter 6 the usefulness of several macroeconomic variables were evaluated for forecasting recessions in Sweden. In order to perform this test we needed recession dates in Sweden, thus the dates found in Chapter 5 were used here. The slope of the yield curve appeared to perform better than the other variables even though the results were not impressive.

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