Statistics Netherlands

Discussion Paper

Inflation dynamics in the Netherlands; a linear and non-linear analysis and the influence of economic conditions

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Summary

Insight into the nature of inflation dynamics is crucial for prediction and for understanding inflationary pressure. This study applies a whole range of linear and non-linear time series models to the rate of inflation in the Netherlands between 1970-2009 to test which one best describes inflation dynamics. It is shown that although good model fit can be achieved, inflation is relatively hard to predict. Inflation dynamics are shown to be complex, and tests indicate the presence of non-linearity. STAR-type models do achieve better fit than linear models, but even more importantly give insight into the occurrence of high-inflation periods. These are shown to be connected to boom phases in the economy, characterized by high capacity utilization and low unemployment.

Keywords

Inflation, business cycle, inflationary pressure, forecasting, time series models, non-linear models, STAR

1. Introduction

The development of the inflation rate tends to receive a lot of attention, both by professional economists and the media and general public. This is understandable, as inflation is one of the few economic quantities which affects the whole of the economy, from financial markets to business conditions and the purchasing power of households. It is also used as an important gauge for the state of the economy, with increasing inflation interpreted as potentially indicating an increase in economic activity or even as a sign of overheating. Though probably superfluous, it should be noted here that the rate of inflation is defined as the (year on year) growth rate in the consumer price index, so it does not concern the price level itself, but the changes therein.

The importance of inflation explains why there is some much interest in the dynamics of the inflation rate, i.e. the increasing and decreasing of the rate of change of the price level. This leads to the important though somewhat hazy concept of inflationary pressure, which is somewhat informally defined as developments which could result in higher future inflation rates. In order to study inflationary pressure, or directly forecast inflation, it is first necessary to arrive at a basic understanding of inflation dynamics. As this study will show, these are highly complex, more so than most economic time series.

When modelling inflation, there are roughly two basic approaches. One takes a theoretical economic model of how inflation works, and uses model variables and structure to make forecasts. Examples are models based on monetary theories and the New Keynesian Philips curve. Others are more empirical, assuming a basic, general mechanism of inflation drivers and then using time series techniques and variable selection methods to build models and construct forecasts. This study takes an even more basic approach, applying a whole range of time series models to the inflation rate itself. How the different types of models perform will give an indication of how to best predict inflation and the type of model which performs best will give insight into the nature of inflation dynamics. Knowledge of inflation dynamics is essential to analysing inflationary pressure. This study concerns itself with monthly inflation in the Netherlands, in two periods; 1970-2009 and 1990-2009. Several different linear and non-linear models are evaluated, where in the case of non-linear STAR models several exogenous economic indicators are introduced to test the influence of economic conditions.

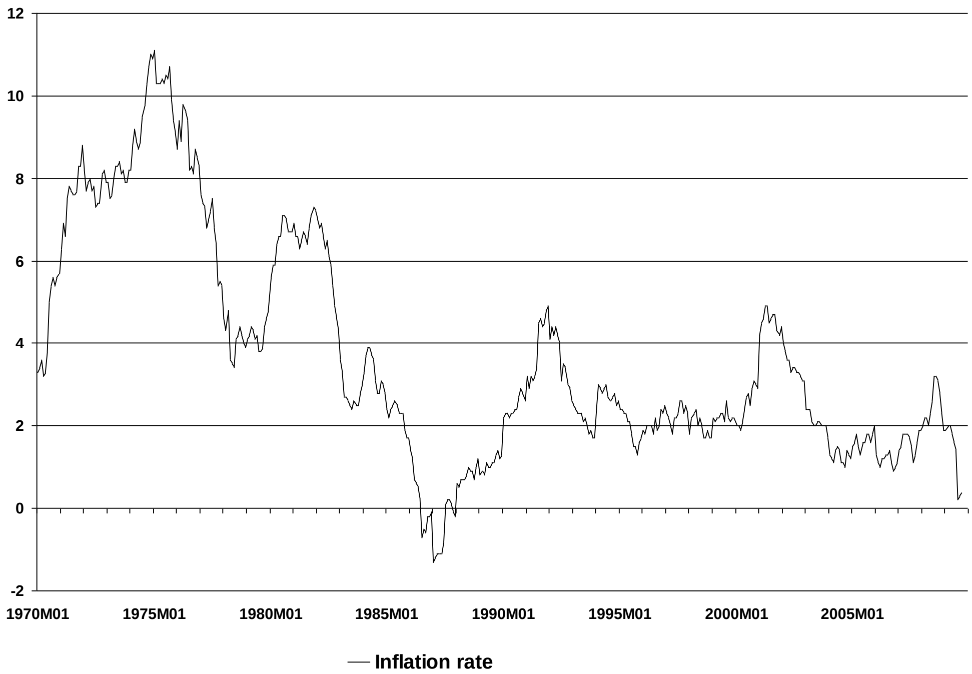
2. Linear models

In this section, the results of modelling inflation using several basic and more advanced linear univariate (autoregressive) models are reported. These will give insight into the basic dynamics of inflation. Of course an autoregressive model will never be sufficient, but these will give an indication whether a form of simple linear model could be able to satisfactorily explain developments in inflation, or if a more complex analysis is needed.

2.1 Stationarity testing

From a time series analysis point of view, the rate of inflation is a complex statistic with some peculiar properties. Looking at graph 2.1, there seem to be two distinct phases in the evolution of inflation since 1970. In the 1970’s, inflation was high but with a clear downward trend starting in the middle of the 1970’s. This downward trend ends somewhere at the end of the 1980’s, after which inflation seems to stabilise, first at a rate of around 2%-points, in the last period in the sample at a slightly lower rate. In these two periods, very different forces seem to drive the development of inflation. On top of these long-term developments, another pattern is superimposed consisting of periodic bursts of clearly higher inflation. At least five of these bursts can be seen in the sample considered here. The data generating process for the inflation series seems to be time- or situation-dependent.

Graph 2.1 ; Historical inflation rates for the Netherlands (relative year on year growth in the index of consumer prices).



Given this visual characterisation of the evolution of the inflation rate in the Netherlands, it is not surprising that the series is characterised as non-stationary. Table 2.1 shows the results of several different stationarity tests, which all either reject stationarity or accept the presence of a unit root. The analysis was performed both over the whole sample and from 1990 onwards. After 1990, the downward trend in the inflation rate seems to have ended, and therefore the series can be expected to be slightly more well-behaved. The tests nudge slightly more towards stationarity, but still clearly reject it for this time period as well.

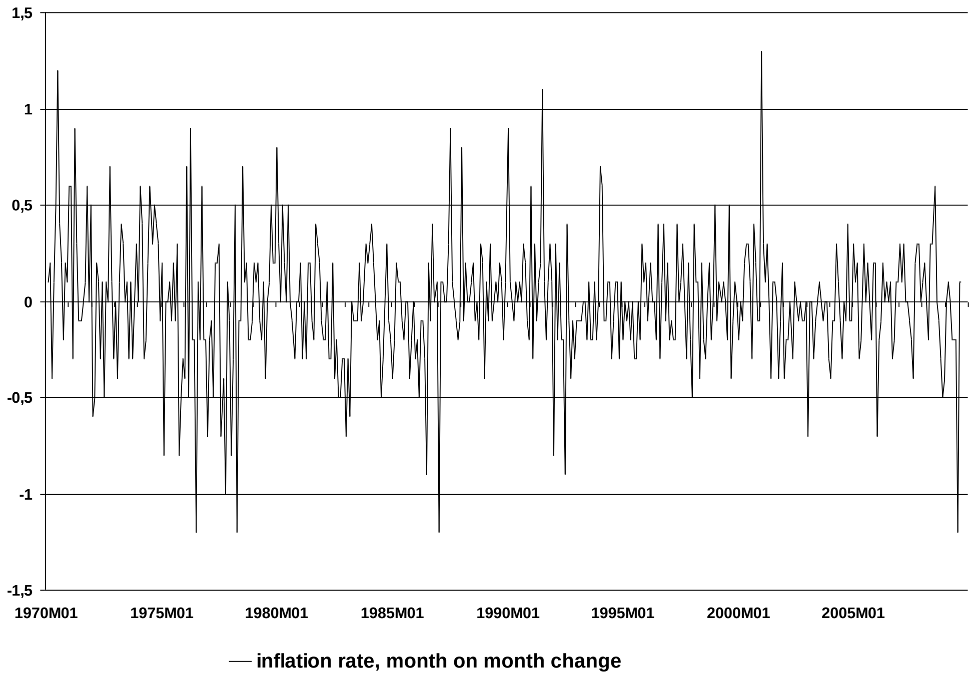
Table 2.1; results unit root tests on rate of inflation, samples 1970-2009 and 1990-2009.

	Augmented Dickey-Fuller	*Phillips-Perron*	*KPSS*	*ERS-point optimal*
H0:	Unit root	Unit root	Stationary	Unit root
Intercept	-1.556 (-2.868)	-1.358 (-2.867)	1.519 (0.463)*	5.075 (3.260)
Trend & intercept	-2.355 (-3.420)	-2.609 (-3.419)	0.304 (0.146)*	13.266 (5.620)
From 1990 - intercept	-1.966 (-2.874)	-2.306 (-2.874)	0.463 (0.463)	3.811 (3.187)
From 1990 - trend & intercept	-2.675 (-3.429)	-2.986 (-3.429)	0.096 (0.146)	11.070 (5.620)

For each test 5% critical value between parentheses. *=H0 is rejected

A transformation is needed to render the series stationary. As the inflation rate is already a transformation of the index of consumer prices, and economic time series are seldom more than I(2), a single differencing step should render the series stationary. Graph 2.2 shows the evolution of the first difference of the inflation rate, i.e. the absolute month-on-month changes.

Graph 2.2 ; Month on month ***absolute*** *changes in inflation rate.*



Tests show the transformed series to be stationary, both over the whole sample and from 1990 onwards. However, both large outliers and suggestions of patterns are visible in the series, suggesting that complex dynamics could still be present.

Table 2.2; Results unit root tests on first difference of rate of inflation, samples 1970-2009 and 1990-2009.

	Augmented Dickey-Fuller	*Phillips-Perron*	*KPSS*	*ERS-point optimal*
H0:	Unit root	Unit root	Stationary	Unit root
Intercept	-6.602 (-2.868)*	-22.079 (-2.867)*	0.052 (0.463)	3.648 (3.260)
Trend & intercept	-6.587 (-3.412)*	-22.080 (-3.419)*	0.054 (0.146)	3.302 (5.620)*
From 1990 - intercept	-14.574 (-2.874)*	-14.775 (-2.874)*	0.148 (0.463)	2.204 (3.187)*
From 1990 - trend & intercept	-14.813 (-3.429)*	-14.830 (-3.429)*	0.055 (0.146)	2.538 (5.620)*

For each test 5% critical value between parentheses. *=H0 is rejected

2.2 Basic autoregressive univariate modelling

The previous section has shown that the inflation series is non-stationary, therefore the variable actually used in the linear models is the month-on-month absolute change in the inflation rate ($inflation^{pop}{}_t$),. The models are reported in order of increasing complexity. The first model considered is the basic AR(1) model which acts as a type of benchmark, minimum performance model. For another model to be relevant, it has to beat at least the AR(1) model. Next come autoregressive models selected using the pcgive-autometrics module of the OX-suite of programs. It uses a general-to-specific approach to select the best performing set of AR-terms. All models are evaluated both on fit and on misspecification measures. Model fit is split into in-sample fit (R^2 and AIC) and out-of-sample forecasting performance. For this, a rolling regression over the period 2006:1 to 2009:9 is performed, using the model specification selected based on the sample from 1970:1 to 2005:12. All fit measures (R^2 and root mean square error (RMSE)) are transformed into measures of the fit of the inflation rate series, and therefore not the month-on-month change in inflation which in all models is the actual dependent variable. This is done to keep all results reported in this study on the same benchmark; i.e. fit compared to the rate of inflation, and because analysing inflation is the aim of this study, and therefore model performance metrics should allow for a direct evaluation compared with the inflation rate. Misspecification tests are in the form of tests on the properties of the residuals; i.e. presence of correlation, distribution tests and a GARCH test to test for stability.
For each type of model, an optimal formulation is sought both for the whole sample 1970:1-2005:12 and for the more recent period 1990:1-2005:12. This is both interesting and useful. The dynamics of inflation seem to have undergone a structural break at the end of the 1980’s, so it will be interesting to see whether different formulations will result for each sample. It is also expected that the fit over the shorter sample from 1990 onwards will be better as the dynamics seem to be more constant over that period.

Reference AR(1) model

1. sample 1970-2005

$$\textbf{inflation}^{pop}_t = -0.0030 + 0.0800*ar(1)$$
$$(0.8502) \quad (0.0997)$$

Table 2.3; Goodness of fit measures AR(1) model, sample 1970-2005

R^2	*AIC*	R^2 *vs. inflation*[1] *in sample*	R^2 *vs. inflation*[1] *forecast*[2]	*RMSE forecast (%-points)*
0.006	0.605	0.9861	0.8091	0.30

[1]These are a kind of pseudo-R^2 measures, computed by converting the estimated period-on-period changes to inflation rates, and then computing the fraction of variance explained by the estimates. [2] period 2006m1-2009m9

Table 2.4 ; Residual diagnostics (p-values).

Q-stat (12 lags)	*Jarque-Berra*	*LM-Test*	*ARCH-test F(12, 394)*	*ARCH-test Chi-square(12)*
0.0000	94.5 (0.0000)	0.0000	0.0000	0.0000

2. sample 1990-2005

$$\textbf{inflation}^{pop}_t = 0.0037 - 0.0262*ar(1)$$
$$(0.8525) \quad (0.7188)$$

Table 2.5 ; Goodness of fit measures AR(1) model, sample 1990-2005

R^2	*AIC*	R^2 *vs. inflation*[1] *in sample*	R^2 *vs. inflation*[1] *forecast*[2]	*RMSE forecast (%-points)*
0.0007	0.283	0.9182	0.7979	0.30

[1]These are a kind of pseudo-R^2 measures, computed by converting the estimated period-on-period changes to inflation rates, and then computing the fraction of variance explained by the estimates. [2] period 2006m1-2009m9

Table 2.6; Residual diagnostics (p-values).

Q-stat (12 lags)	*Jarque-Berra*	*LM-Test*	*ARCH-test F(12, 167)*	*ARCH-test Chi-square (12)*
0.0030	145.6 (0.0000)	0.0001	0.2126	0.2118

The surprising fact about the AR(1) models is that despite the poor fit of the period on period models themselves ($R^2<0.01$), the fit with the inflation rate is actually quite good, with an in-sample R^2 of more than 0.9. This is due to the high degree of short-term persistence in the rate of inflation (lag 1 autocorrelation is 0.991), which means that the realisation at t-1 is by itself already a very good predictor of the rate of inflation at t. Residual diagnostics show the AR(1) models to be poorly specified, though somewhat surprisingly there is no evidence of GARCH for the sample 1990-2009. The models for the whole sample and for the 1990 onwards sample do differ greatly, with the sign of the AR(1) coefficient being reversed. This is an indication of changing dynamics.

AR models (PC-give)

3. sample 1970-2005

inflation$^{pop}_{t}$ = -0.012 + 0.066*ar(1)+ 0.066*ar(2) + 0.119*ar(4)
(0.5574) (0.1627) (0.1539) (0.0117)
+0.160*ar(6) +0.118*ar(8) -0.322*ar(12) +0.0823*ar(13)
(0.0006) (0.0101) (0.0000) (0.0748)

Table 2.7; Goodness of fit measures AR-mode PC-give, sample 1970-2005

R^2	*AIC*	*R^2 vs. inflation[1] in sample*	*R^2 vs. inflation[1] forecast[2]*	*RMSE forecast (%-points)*
0.155	0.434	0.988	0.849	0.26

[1]These are a kind of pseudo-R^2 measures, computed by converting the estimated period-on-period changes to inflation rates, and then computing the fraction of variance explained by the estimates. [2]These forecasts result from a rolling regression exercise over the period 2006m1-2009m9

Table 2.8 ; Residual diagnostics (p-values).

Q-stat (12 lags)	*Jarque-Berra*	*LM-Test*	*ARCH-test F(12, 394)*	*ARCH-test Chi-square(12)*
0.812	113.8 (0.0000)	0.606	0.0001	0.0002

4. sample 1990-2005

inflation$^{pop}_{t}$ = 0.0003 + 0.1804*ar(4) -0.3114*ar(12)
(0.8763) (0.0087) (0.0000)

Table 2.9; Goodness of fit measures AR-modelPC-give, sample 1990-2005

R^2	*AIC*	*R^2 vs. inflation[1] in sample*	*R^2 vs. inflation[1] forecast[2]*	*RMSE forecast (%-points)*
0.127	0.159	0.927	0.842	0.27

[1]These are a kind of pseudo-R^2 measures, computed by converting the estimated period-on-period changes to inflation rates, and then computing the fraction of variance explained by the estimates. [2]These forecasts result from a rolling regression exercise over the period 2006m1-2009m9

Table 2.10; Residual diagnostics (p-values).

Q-stat (12 lags, p)	*Jarque-Berra*	*LM-Test*	*ARCH-test F(12, 167)*	*ARCH-test Chi-square(12)*
0.591	137.4 (0.0000)	0.305	0.463	0.452

The autoregressive models selected by the autometrics module of PC-Give perform distinctly better than the AR(1) benchmark models. Fit is increased and forecast errors reduced. Also, residual diagnostics are far more satisfactory, with no significant autocorrelation in residuals. The residuals are still not normally distributed though, as indicated by the Jarque-Berra statistics. Large outliers remain. And again, the model specification for the period 1990-2005 is markedly different from the one for 1970-2005.

2.3 Advanced autoregressive univariate models

After these basic linear models, now the results of ARMA modelling will be considered. The final type of linear model tested in this study is the GARCH-extension of ARMA models, which can cope with time-varying volatility and should therefore be able to better handle the changing inflation dynamics.

ARMA models

1. sample 1970-2005

$$\textbf{inflation}^{pop}_t = -0.015 + 0.069*ar(4) + 0.273*ar(6) + 0.052*ar(8)$$
(0.0104) (0.0852) (0.0000) (0.1892)

$$+0.353*ar(12) - 0.0974*ma(6) - 0.861*ma(12)$$
(0.0000) (0.0028) (0.0000)

Table 2.11 ; Goodness of fit measures ARMA-model, sample 1970-2005

R^2	*AIC*	*R^2 vs. inflation[1] in sample*	*R^2 vs. inflation[1] forecast[2]*	*RMSE forecast (%-points)*
0.240	0.330	0.989	0.836	0.27

[1]These are a kind of pseudo-R^2 measures, computed by converting the estimated period-on-period changes to inflation rates, and then computing the fraction of variance explained by the estimates. [2]These forecasts result from a rolling regression exercise over the period 2006m1-2009m9

Table 2.12 ; Residual diagnostics (p-values).

Q-stat (12 lags)	*Jarque-Berra*	*LM-Test*	*ARCH-test F(12, 394)*	*ARCH-test Chi-square(12)*
0.036	191.7 (0.0000)	0.1260	0.000	0.000

2. sample 1990-2005

$$\textbf{inflation}^{pop}_t = -0.005 + 0.129*ar(4) + 0.128*ar(11) + 0.265*ar(12) - 0.936*ma(12)$$
(0.5229) (0.0707) (0.0707) (0.0002) (0.0000)

Table 2.13; Goodness of fit measures ARMA-model, sample 1990-2005

R^2	*AIC*	*R^2 vs. inflation[1] in sample*	*R^2 vs. inflation[1] forecast[2]*	*RMSE forecast (%-points)*
0.333	-0.094	0.944	0.820	0.28

[1]These are a kind of pseudo-R^2 measures, computed by converting the estimated period-on-period changes to inflation rates, and then computing the fraction of variance explained by the estimates. [2]These forecasts result from a rolling regression exercise over the period 2006m1-2009m9

Table 2.14; Residual diagnostics (p-values).

Q-stat (12 lags)	*Jarque-Berra*	*LM-Test*	*ARCH-test F(12, 394)*	*ARCH-test Chi-square(12)*
0.636	235.9 (0.0000)	0.721	0.9902	0.9984

The fit of the ARMA models is comparable to those of the AR-models, both for in sample and forecast performance. Residuals are somewhat less satisfactory, with especially for the sample 1970-2005 more autocorrelation. Again, the model for the shorter sample 1990-2005 is simpler (less elements) than the one for the whole sample.

GARCH model:

3. sample 1970-2005

$inflation^{pop}_t$ = -0.016 + 0.086*ar(4)+ 0.254*ar(6) + 0.086*ar(9)
(0.0358) (0.0785) (0.0000) (0.0266)
+0.370*ar(12) -0.0997*ma(6) - 0.863*ma(12)
(0.0000) (0.0005) (0.0000) GARCH = 0.009
+0.050*RESID(-1)^2 + 0.831*GARCH(-1)

Table 2.15; Goodness of fit measures model, sample 1970-2005

R^2	*AIC*	*R^2 vs. inflation[1] in sample*	*R^2 vs. inflation[1] forecast[2]*	*RMSE forecast (%-points)*
0.238	0.313	0.990	0.830	0.28

[1]These are a kind of pseudo-R^2 measures, computed by converting the estimated period-on-period changes to inflation rates, and then computing the fraction of variance explained by the estimates. [2]These forecasts result from a rolling regression exercise over the period 2006m1-2009m9

Table 2.16; Residual diagnostics (p-values).

Q-stat (24 lags)	*Jarque-Berra*	*LM-Test*	*ARCH-LM test F(12, 394)*	*ARCH-LM test Chi-square(12)*
0.369	148 (0.0000)		0.0035	0.0041

4. sample 1990-2005

$inflation^{pop}_t$ = 0.0001 +0.101*ar(4) +0.149*ar(11) +0.242*ar(12)
(0.9987) (0.2483) (0.0355) (0.0002)
-0.956*ma(12)
(0.0000) GARCH
= 0.004 -0.007*RESID(-1)^2 +0.895*GARCH(-1)

Table 2.17; Goodness of fit measures model, sample 1990-2005

R^2	*AIC*	R^2 *vs. inflation*[1] *in sample*	R^2 *vs. inflation*[1] *forecast*[2]	*RMSE forecast (%-points)*
0.324	-0.172	0.993	0.833	0.28

[1]These are a kind of pseudo-R^2 measures, computed by converting the estimated period-on-period changes to inflation rates, and then computing the fraction of variance explained by the estimates. [2]These forecasts result from a rolling regression exercise over the period 2006m1-2009m9

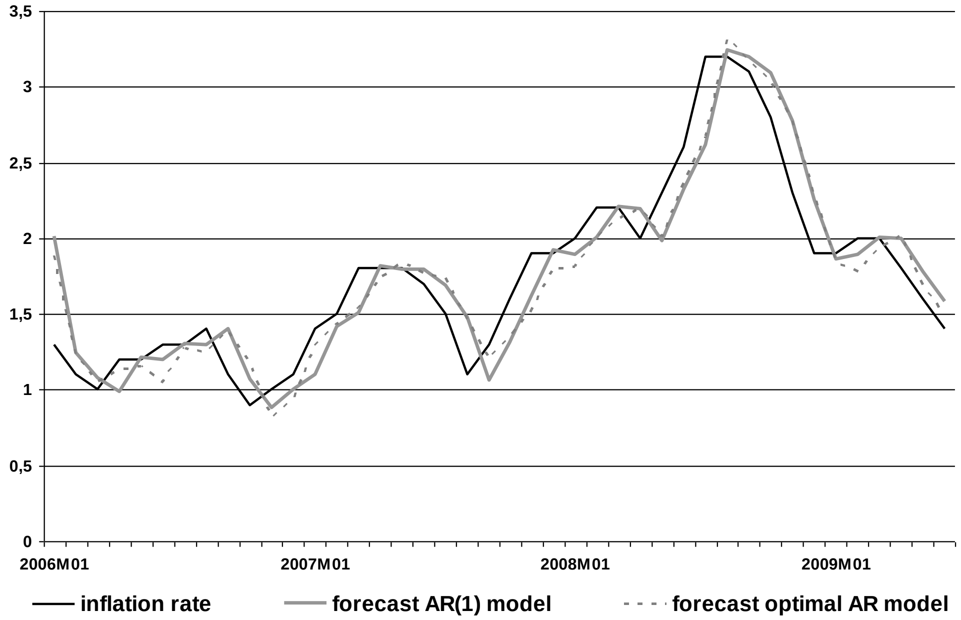
Table 2.18; Residual diagnostics (p-values).

Q-stat (24 lags)	*Jarque-Berra*	*LM-Test*	*ARCH-LM test F(12, 155)*	*ARCH-LM test Chi-square(12)*
0.605	206.9 (0.0000)		0.9914	0.9898

The GARCH-models were estimated to test whether they would be able to handle the non-constant dynamics of the inflation series better than the non-time varying models shown above. This is somewhat the case, ARCH-effects are reduced by the GARCH(1,1) formulation which was found to be optimal for both samples. But in the 1970-2009 sample, ARCH is not eliminated. In-sample fit is improved, especially for the 1990-2005 period, but forecast performance is comparable to that of the AR and ARMA models. As residuals still contain large outliers for the GARCH-models, it is questionable whether adding GARCH effects improves the specification much.

It might even be said that the more advanced models hardly improve upon the basic AR(1) model. Even though most diagnostics are far better for the PC-give optimal AR model, the model with the lowest out-of-sample forecast RMS, its forecasts are not much more useful than those of the AR(1) model, see graph 2.3. Both forecast series suffer from the typical problem associated with forecasts from linear AR-models in that they are behind the curve. So even though the optimal-AR model forecasts are superior in a RMSE-sense, they are not more useful as early warnings of the future evolution of the rate of inflation.

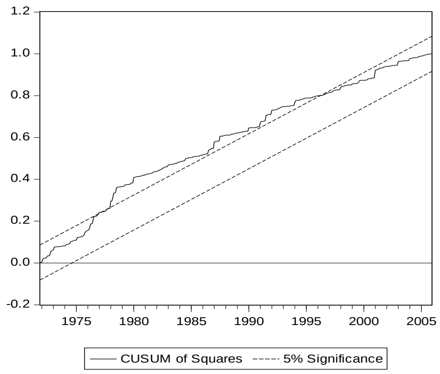
Graph 2.3 ; Inflation rate compared to forecasts (out of sample rolling regressions) from basic AR(1) model and optimal AR-model.

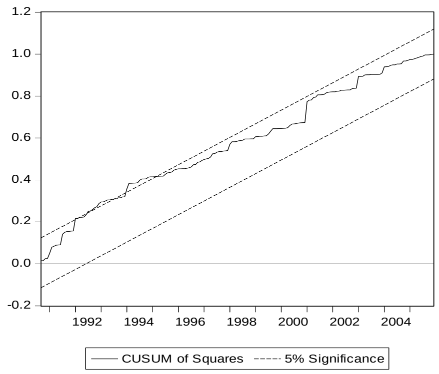


3. Non-linear analysis

The evolution of the inflation rate seems to contain distinct bursts of higher inflation. In these volcano-shaped periods of strongly waxing and waning inflation, the dynamics of the series seem to be distinctly different from the far more steady evolution in “normal” times, this is clearly visible in graph 2.1. This suggests the presence of some type non-linearity, possibly a two-phase or regime data generation process, with a “normal” phase and a high-inflation phase. One way to test for the presence of processes like these is to consider the cumulative sum of squared residuals of a linear model. If this is well-specified, the cumulative sum of squared residuals should grow proportional to the number of observations. The Brown, Durbin and Evans [1975] CUSUM of squares test is a general misspecification test, which also has power for non-linearity. This test was available for OLS estimates only, and was therefore applied to the residuals of the two PC-give AR-models, one for the full sample and one for the model for the 1990-2005 sample. Graphs 3.1a and 3.1b show the results.

Graph 3.1a and 3.1b; Cumulative sum of squared residuals tests for pc-give AR-models 1970-2005 and 1990-2005. Straight lines give 5% confidence intervals for parameter or variance instability.

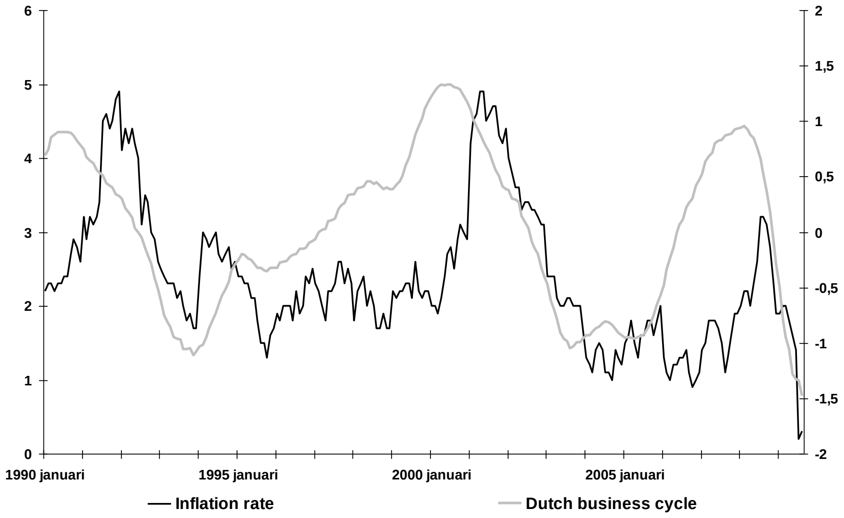




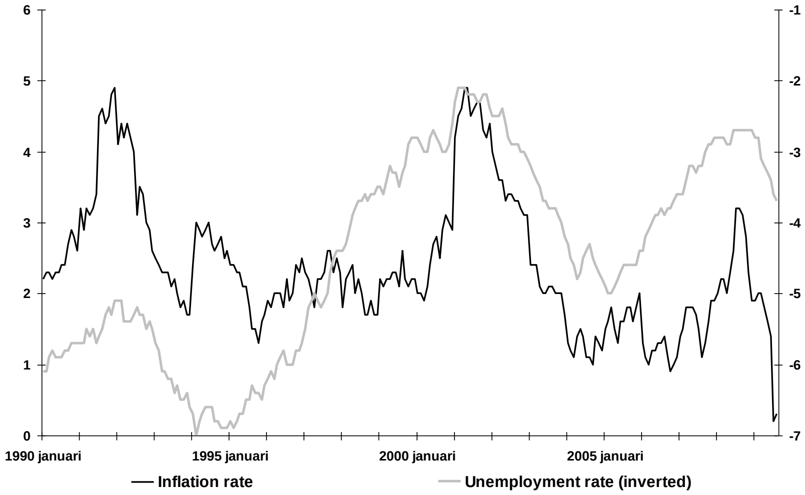
Especially for the full sample 1970-2005 the CUSUM of squared residuals is out of the 5%-tolerance limits for a large fraction of the sample. This indicates parameter or variance instability, and suggests misspecification issues. The residuals of the model for the 1990-2005 sample are much better behaved, but the CUSUM is beyond or close to the 5% tolerance limits for quite a large fraction of the observations, and there are several clear outliers in the residuals as represented by “step changes” in the cumulative sum of squares. This suggests that a non-linear model might achieve a better fit.

It is interesting and relevant for further modelling steps to consider the source of the non-linearity. Standard theory states that inflation dynamics are influenced by input (raw materials) price developments, inflation expectations and the amount of slack in the economy. The influence of each of these potential inflation drivers will be studied in this study via non-linear modelling. But is interesting to do a quick qualitative analysis of the influence of one of these factors, the amount of slack in the economy, or how far output is below or above potential. Thus, it is linked to the business cycle. Graphs 3.2 and 3.3 compare the development of the rate of inflation in the Netherlands with respectively the business cycle and the unemployment rate (a measure of labour market tension).

Graph 3.2; Inflation rate vs. Dutch business cycle as represented by the Statistics Netherlands business cycle tracer.



Graph 3.3; Inflation rate vs. Dutch unemployment rate.



This comparison shows that the periods of high inflation in the period 1990-2009 coincide with periods of relatively low slack in the economy, where the economy develops above potential and with relatively low unemployment.

3.1 Smooth transition autoregressive approach

The smooth transition autoregressive (STAR) model is a non-linear model which is based on the concept that the data generating process of the series possesses different regimes, each with their own dynamics. The dynamics of the series in any one regime are linear, the non-linearity arises from the possibility of transitions from one regime to the other[Van Dijk et al. (2000]. In a STAR model, the transition from one regime to another is governed, or described, by a transition function G(t). The general model specification is [Teräsvirta and Anderson (1992)]:

$$y_t = \left(\phi_{1,0} + \phi_{1,1} y_{t-1} + \ldots + \phi_{1,p} y_{t-p}\right)\left(1 - G\left(s_t;\gamma,c\right)\right) + \left(\phi_{2,0} + \phi_{2,1} y_{t-1} + \ldots + \phi_{2,p} y_{t-p}\right)\left(G\left(s_t;\gamma,c\right)\right) + \varepsilon_t \qquad (1)$$

The switching behaviour is governed by the transition function $G(s_t;\gamma,c)$, which can take several forms, and by the transition or transition variable s_t. The transition variable can either be a lagged value of the series y_t itself, in which case the model is a self-exciting –TAR or SETAR, or a lagged exogenous variable. In both cases the lag parameter d of the transition variable needs to be determined. The transition function is bounded between 0 (regime 1) and 1 (regime 2) and needs to exhibit a smooth evolution. Important examples are:

The logistic function (LSTAR):

$$G\left(s_t;\gamma,c\right) = \frac{1}{1 + \exp\left\{-\gamma\left(s_t - c\right)\right\}} \qquad (2)$$

This choice of transition function results in the logistic STAR or LSTAR model [Van Dijk (2000]. In this formulation, the transition function $G(s_t;\gamma,c)$, increases monotonically from 0 to 1 as s_t increases. There are two possible interpretations for this model; a 2-regime switching model associated with the two extreme values of the transition function, or a continuum of regimes along s_t. Van Dijk et al (2000) chose the former interpretation, and this will be followed in this paper. This formulation can for example be used to describe different behaviour of economic variables over the business cycle, see for example [Öcal and Osborn (2000)], who find different dynamics in recession and expansion phases, and Teräsvirta and Anderson[1992], who find that non-linearity arises from the asymmetry introduced by large negative shocks to the economy. The constant γ determines the smoothness of the transition, the larger the value of γ, the more abrupt the transition will be. In the case of $\gamma \rightarrow \infty$, the model becomes a transition autoregression (TAR) model, which changes instantly from one regime to the other as s_t=c. In that case, c acts as a pure transition variable.

Indicator-type transition function (TAR) :

$G(s_t;\gamma,c)=1$ for $s_t>c$

$G(s_t;\gamma,c)=0$ for $s_t<c$ (3)

Another important variant is the exponential STAR (ESTAR). In this case, regime switching is symmetrical around the threshold; i.e. if the transition variable is “in the neighbourhood” of the threshold c, the system is in regime 1, and if the deviation becomes “large enough”, a transition to regime 2 starts to take place. This is achieved by using a squared deviation in the transition function:

The exponential function (ESTAR):

$$G\left(s_t;\gamma,c\right) = 1 - \exp\left\{-\gamma\left(s_t - c\right)^2\right\} \qquad (4)$$

Thus, this type of non-linear specification is relevant for systems where the dynamics change if a certain deviation or difference becomes large enough [Van Dijk 2000]. Examples are cointergration relationships where there are barriers (costs) present to adjustment [Balke and Fomby (1992)], and arbitrage situations where arbitrage only becomes profitable when deviations from fair price are large enough [Martens et all.(1998)]. Other extension of the STAR framework include time-varying properties, introducing multiple regimes and multivariate formulations [Van Dijk et al. (2000)]. Of these options, only multiple regime analysis will be tested in this study. Extending STAR models to include multiple regimes is actually rather straightforward, the formulation for a three-regime STAR is as follows:

$$\begin{aligned} y_t &= \left(\phi_{1,0} + \phi_{1,1} y_{t-1} + \ldots + \phi_{1,p} y_{t-p}\right)\left(1 - G_1\left(s_t;\gamma,c\right)\right) \\ &+ \left(\phi_{2,0} + \phi_{2,1} y_{t-1} + \ldots + \phi_{2,p} y_{t-p}\right)\left(1 - G_2\left(s_t;\gamma,c\right)\right) + \\ &\left(\phi_{3,0} + \phi_{3,1} y_{t-1} + \ldots + \phi_{3,p} y_{t-p}\right)\left(G_3\left(s_t;\gamma,c\right)\right) + \varepsilon_t \end{aligned} \quad (5)$$

So all it takes is introducing a second transferfunction G_2 which will add a third regime to the model. Estimation is executed along the same lines as for the two regime model.

Testing for transition autoregression

Before beginning model estimation, it is important to actually test for the presence of non-linearity. Not only to prevent misspecification or unnecessarily complex model formulations, but also because when basing model evaluation on standard fit parameters, linear AR models tend to do as well as or outperform non-linear specifications even when the data generating process is non-linear. This is especially the case in small-samples, though evaluating using out-of-sample point forecast errors might have discriminating power [Clements et all (2003)]. Other studies state though that the (relative) forecasting performance of STAR-models is disappointing [Van Dijk et all. (2000), Teräsvirta et all. (2005)] Testing for STAR-type non-linearity is performed using LM-type statistics. The basic idea is to first estimate a linear AR-model of order p, and then a Taylor-expansion of the STAR model of the same order p. The LM-type statistic is then computed from the sums of squared residuals from these equations [Teräsvirta (1994)]. A problem is which autoregressive lag p and lag d of the transition variable to use. The standard solution is to test a range of values for these parameters, compare the fit on some measure, and use the optimal values to perform the desired test. The overall testing procedure is as follows [Van Dijk (2000), Van Dijk et al. (2000)]:

- Determine the optimal lag length p of the linear autoregressive model using lag-length criteria (AIC, as BIC might be too restrictive)
- Estimate the linear AR model, and use the residuals to compute the sum of squared residuals SSR^{lin}
- Estimate the Taylor expansion of the non-linear model using the optimal lag length p determined earlier. Use the residuals to compute the sum of squared residuals SSR^{nonlin}
- Compute the LM-type test statistic, either in the χ^2 or F-version, where the latter has better small-sample properties.
- Given the autoregressive lag p, Do this for a range of values for the lag d of the transition variable. Use the lag d with the smallest p-value in the final tests for non-linearity.

χ^2-version: $$LM = \frac{T\left(SSR^{lin} - SSR^{nonlin}\right)}{SSR^{lin}}$$

F-version: $$LM = \frac{\left(SSR^{lin} - SSR^{nonlin}\right)/3(p+1)}{SSR^{nonlin}/\left(T - 4(p+1)\right)}$$

Where p=number of autoregressive lags in equation and T is number of observations

The specific form of the non-linear equation depends on the type of non-linearity tested and the Taylor expansion used. Here, the following test equations were used.

Test against LSTAR:
A first-order Taylor expansion results in the auxiliary regression:

$$y_t = \beta_0 x_t + \beta_1 x_t s_t + e_t \tag{6}$$

Where y_t is the series to be modelled, x_t a vector of explanatory variables, containing a constant and the autoregressive lags, $x_t=(1,y_{t-1},\ldots,y_{t-p})$, and s_t is the transition variable, in the self-exiting (SETAR) case $s_t=y_{t-d}$. The residuals of this equation can be used to perform a χ^2-test with p+1 degrees of freedom and a H_0 of no non-linearity, which can also be formulated for this model as H^0:$\beta_1=0$. A more comprehensive variant of this test, which also has power if only the constant of the model varies across regimes is based on a third-order Taylor expansion [Luukkonen et all. (1998)]:

$$y_t = \beta_0 x_t + \beta_1 x_t s_t + \beta_2 x_t s_t^2 + \beta_3 x_t s_t^3 + e_t \tag{7}$$

The residuals of this equation can be used to perform a χ^2-test with 3(p+1) degrees of freedom, or a F-test with (3(p+1),T-4(p+1)) degrees of freedom, both with a H_0 of no non-linearity. Adjustments have to be made to the auxiliary regressions if the transition variable s_t is a lagged endogenous variable y_{t-d} where the threshold lag d is larger than the autoregressive lag p, and also if s_t is an exogenous variable [Van Dijk (2000)]. The adjustments are fairly straightforward and consist of introducing additional terms $\beta_i s^j_t$ for each term $\beta_j x_t s^j_t$ present in the original equation. For example equation 7 becomes:

$$y_t = \beta_0 x_t + \beta_1 x_t s_t + \beta_2 s_t + \beta_3 x_t s_t^2 + \beta_4 s_t^2 + \beta_5 x_t s_t^3 + \beta_6 s_t^3 + e_t \tag{8}$$

Test against ESTAR:
In the case of testing for ESTAR versus linearity, a second order Taylor expansion is required [Saikonnen and Luukkonen (1988)], resulting in the following auxiliary regression:

$$y_t = \beta_0 x_t + \beta_1 x_t s_t + \beta_2 x_t s_t^2 + e_t \tag{9}$$

The resulting LM statistic can be tested using a χ^2-test with 2(p+1) degrees of freedom against a H^0 of no non-linearity. [Escribano and Jordá (1999)] state that a 2^{th} order Taylor expansion is required to capture all the characteristics of the ESTAR transition function, resulting in the auxiliary regression:

$$y_t = \beta_0 x_t + \beta_1 x_t s_t + \beta_2 x_t s_t^2 + \beta_3 x_t s_t^3 + \beta_4 x_t s_t^4 + e_t \qquad (10)$$

The null hypothesis is now $\beta_1=\beta_2=\beta_3=\beta_4=0$, which is the linear case. The LM statistic is then χ^2 distributed with 4(p+1) degrees of freedom. If the tests indicate the presence of non-linearity, the choice between LSTAR and ESTAR is made by selecting the formulation with the lowest p-value.

3.2 Estimation of smooth transition autoregressive models

In principal, estimating a basic STAR model, see equation 1, is relatively straightforward. Given a lag length p for the autoregressive process of y_t and a lag d for the transition variable, equation 1 can be estimated using non-linear least squares. However, the specification is a complex one, and convergence can be difficult to achieve. The most difficult aspects of the estimation are determining the sensitivity parameter γ and the value of the transition threshold c. Therefore, a robust estimation strategy was followed here, based on the approach of Teräsvirta (1994) and Tsay (1998). The core of this approach is to use a grid search to test all plausible values for the transition lag d and threshold value c. Given a test value for d and c, the coefficients and γ can be estimated using conditional least squares. This means that the sample is divided in the two regimes which result from the chosen threshold values. The advice is to chose the range of test values for c in such a manner that each regime contains at least 15% of the available observations. For each regime i, the autoregressive coefficients $\phi_{i,j}$ of y_t are estimated, using OLS. These coefficient values are then retained and entered in the full model 1 for a final modelling step in which γ is estimated. The model with the highest log-likelihood gives the optimal values for c and d. The lag length p of the autoregressive process of y_t is conventionally determined by applying lag length tests to the full sample before the STAR modelling stage. Here, the lag length p was included in the grid search as the thesis is that the high-inflation regime has a fundamentally different nature from the "normal" inflation regime. It is therefore plausible that the difference in dynamics also manifests itself in a different lag length for the autoregressive process. Given the presence of non-linearity, the lag length determined from the full-sample using linear tests is bound to be suboptimal. Therefore, the grid search for the transition variable parameters was incorporated in two larger loops, performing a grid search for the optimal lag lengths p_1 and p_2 for the different regimes. Maximum log-likelihood remained the selection criterion.

Results testing for STAR-type non-linearity

The tests for STAR-type non-linearity vs. linearity described above were performed both on the rate of inflation (year on year change in CPI) and the absolute month on month change in the rate of inflation (inflation^{pop}). The rate of inflation is the actual target variable in this study, and the non-linearity seems to be most pronounced in this variable. The inflation rate however is non-stationary, and first differencing is required to remove the unit root. As the techniques for statistical inference related to STAR were developed assuming stationarity, the tests are performed on the transformed variable as well. To start with, tests were performed assuming SETAR-behaviour, i.e. the transition variable was the appropriate inflation variable itself. A strict interpretation is that this assumes that the regime change is caused by a change in the internal dynamics of the variable modelled. Further tests were performed using other, potentially relevant transition variables. The variables considered were the following. From the manufacturing survey: capacity utilisation, capacity assessment, production constraints staffing, and production constraints capacity. Furthermore the stance of the Dutch business cycle as represented by the Statistics Netherlands Business Cycle Tracer Indicator, which represents the output gap, and the change in registered unemployment. Also tested were the inflation expectations from the Dutch consumer survey, the change in hourly earnings in manufacturing and in the IMF-price index of industrial inputs. The first six indicators are related to the output gap and input constraints, which can spark inflation. The others more reflect potential causes of pure price dynamics. Together, they represent important influences on prices, and they might therefore be responsible for changes in inflation dynamics.

When the data allowed it, the tests were performed both for the period 1970-2010 and 1990-2010. The second period is the most relevant, as it will be the basis for further modelling in this paper, and it excludes the change in inflation dynamics visible at the end of the 1980's. Tests were performed both for linearity vs. LSTAR-non linearity and for linearity vs. ESTAR-non linearity. The parameters and test statistics can be found in appendix A, the results will be summarized here. When using a SETAR-specification, the evidence for STAR-non linearity is relatively weak. For the untransformed inflation rate evidence was found only for LSTAR (p-value 0.033) and even then only for the 1970-2010 sample, but not after 1990. For the transformed series inflation^{pop}, there is also evidence for LSTAR after 1990, with a p-value of 0.037. The picture changes somewhat dramatically when other indicators are used as transition variable. Strong evidence is found for the presence of STAR-type non-linearity both for the inflation rate itself and in the inflation^{pop} series. Non-linearity is now also identified in the 1990-2010 sample, though somewhat less pronounced than in the full sample. On the whole, the evidence is somewhat stronger for the presence of LSTAR. The presence LSTAR is also more logical than ESTAR in this case, as it seems logical to assume a division in a "normal"- and high-inflation regime. ESTAR would mean that very low and very high inflation behave the same, whilst "middle" inflation would have different dynamics. The strongest evidence for the presence of STAR is when output gap/production constraints indicators are used as transition variables, though using inflation expectations and hourly earnings in manufacturing also results in very low p-values, substantiating the presence of STAR. The strong evidence the use of these indicators yields for the existence of two different inflation regimes, makes it plausible that the origin of the transition in inflation dynamics can be found in the phenomena these indicators represent, and not in inflation itself. Something on the origin of bursts of higher inflation can be learned when considering the nature of the indicators which yielded the strongest evidence for the presence of STAR-type non linearity. These were the rate of capacity utilisation, production impediments caused by shortage of capacity or staff, the SN business cycle indicator and hourly earnings in manufacturing. These are all connected to the business cycle, and more over to periods when the economy is nearing or at full capacity. Even the growth in wages has a strong business cycle component. The next stage is to take these potential transition indicators and use these to estimate and test LSTAR-models.

Two regime STAR models

Based on the results above, several LSTAR-type models were estimated. SETAR models will not be considered in this study, as the inflation rate itself did not seem to have much power in identifying different STAR regimes. Instead, a selection of indicators which proved relevant in the previous section and which are traditionally associated with inflationary pressure were tested as transition variables. For each model the optimum lags of the dependent variable (i.e.

the inflation rate) in both regimes, the optimal lag of the transition variable and the threshold value c were determined. The sample considered was 1990-2010m06, where the period 2006-2010m06 was used for an out-of-sample forecast test. The exercise was performed both for the inflation rate itself and the month on month change in the inflation rate $inflation^{pop}$. It is more correct to use the latter transformation, as it is stationary, but as the inflation rate is the target variable in this study, a direct estimation is attempted as well. In table 3.1 a summary of the outcomes for different LSTAR formulations for the inflation rate are presented.

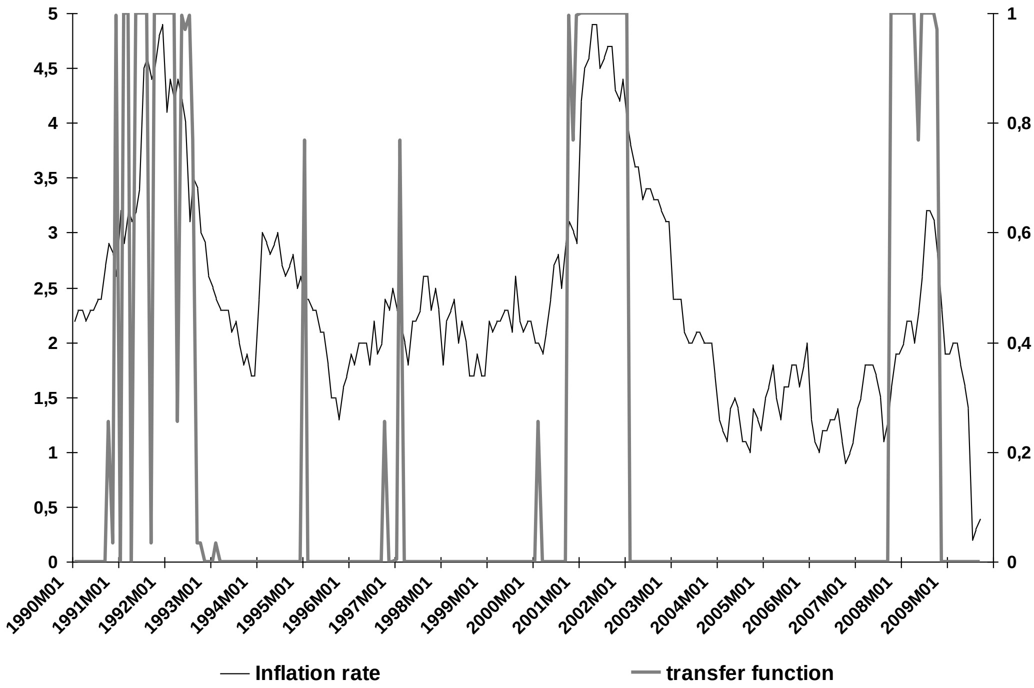
Table 3.1; Summary of results of smooth transition autoregression models for the monthly rate of inflation using exogenous variables as transition variables. Sample 1990:01-2010:06. Forecast sample 2006:01-2010:6, based on rolling regression. STAR parameters were not re-estimated.

Transition variable	*Capacity utilisation* (yoy)*	*Capacity assessment**	*Production constraints; capacity**	*Production constraints; staffing**	*Inflation expectations†*	*Hourly earnings manufacturing (yoy)*	*IMF prices industrial inputs (yoy)*	*SN Business cycle indicator*
Lags regime 1	13	13	12	13	13	13	13	13
Lags regime 2	3	13	13	13	13	13	13	2
Lag threshold	12	3	11	8	1	8	11	5
Critical value	1.69	6.4	3.3	6.1	71.5	11.1	17.4	1.32
γ	3.30	5.77	5.83	2.43	0.81	6.75	1.42	0.96
Jarque-Berra residuals	719 (0.0000)	827 (0.0000)	120 (0.0000)	31 (0.0000)	68 (0.0000)	1004 (0.0000)	971 (0.0000)	629 (0.0000)
P-value Q-stat (12 lags) residuals	0.987	0.645	0.427	0.524	0.702	0.598	0.948	0.995
R^2 1990-2009[1]	0.938	0.925	0.933	0.940	0.943	0.938	0.928	0.930
Forecast RMSE (%-points)	0.22	0.21	0.19	0.22	0.25	0.22	0.23	0.23

*from manufacturing industry survey, † from consumer survey, yoy= year on year growth rate,
[1]based on error sum of squares model vs. total sum of squares inflation rate

The R^2 of the LSTAR-models are comparable to those of the benchmark univariate models tested in the previous section. Contrary to the in-sample fit, the forecast performance of the LSTAR models is superior. This indicates that LSTAR-type models are better able to capture the dynamics of the inflation series than linear models. Supporting this is that the Jarque-Berra statistic tends to be better for the LSTAR models, even though the residuals are still not normally distributed due to the presence of large outliers. Given the fact that in general the lag length differs little or not at all between the regimes, the superior performance is probably due to a more efficient coefficient estimation. The fit and diagnostic statistics are in this particular case not the only properties on which the models are scored. STAR models yield an additional outcome apart from the model estimate itself, namely the transfer function which shows which regime is prevailing at any given time.

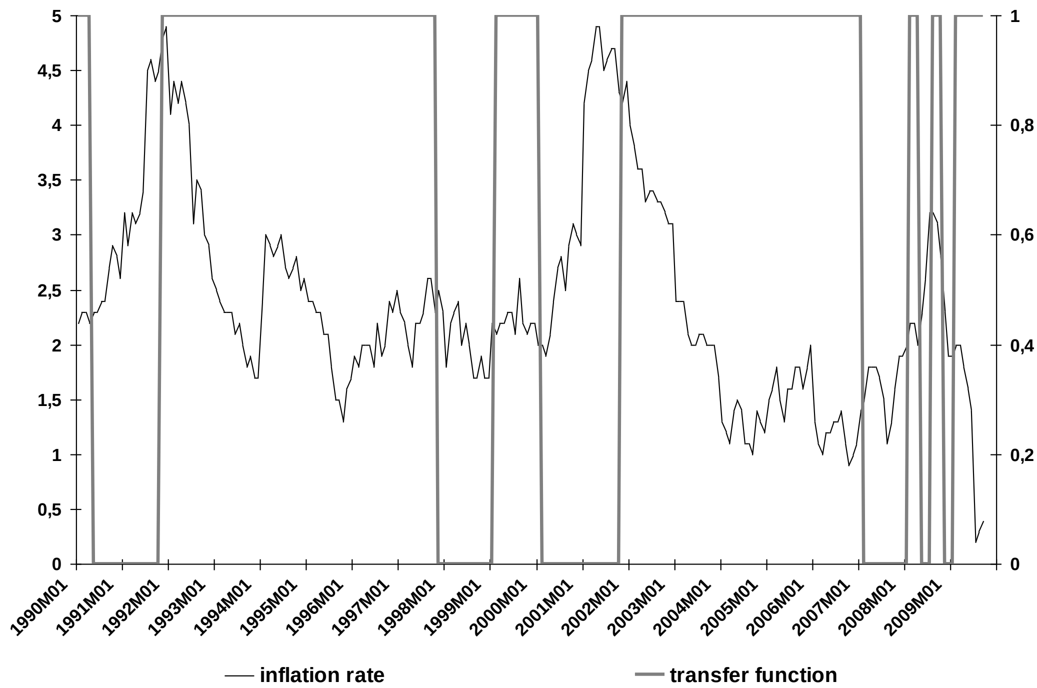
Graph 3.4; Inflation rate (left axis) compared to 2-regime transfer function (right axis) from STAR of inflation rate with consumer survey inflation expectations as transition variable.



The thesis here is that the non-linearity is connected to the observed bursts of higher inflation, therefore the regimes identified by the model should in one way or the other be connected to these periods of different dynamics. Both the timing should be right and the interpretation consistent. Of the indicators tested in modelling the inflation rate, the inflation expectations from the consumer survey and the capacity assessment from the manufacturing survey performed best in this respect. A closer look at their transition functions will illustrate the point. Graph 3.4 shows the transfer function from the model containing the inflation expectations, compared to the rate of inflation. The STAR model is wholly in regime 1 if the transfer function is 0 and wholly in regime 2 if it has value 1. It is clearly visible that the model is in regime 2 in three distinct periods, all contemporaneous with bursts of higher inflation. Importantly, there are few “false signals”, where the transfer function indicates higher inflation when there is none.

The chronology of the capacity assessment indicator fits the inflation chronology less neatly, but the measure of identification is still impressive. Here, regime 1 and 2 have been exchanged compared to the inflation expectations estimates, but the model is indifferent to the assignment of the different regimes. Regime 1 is now the high-inflation regime, and compared to the inflation expectations chronology it seems to be more connected to periods of *increasing* inflation, so a small difference of analysis and identification here. The only blemish is a false signal in 1998.

*Graph 3.5 ; Inflation rate (left axis) compared to 2-regime transfer function (right axis) from STAR of **period on period** change in inflation rate with manufacturing survey capacity assessment as transition variable.*



The need to produce a logical and consistent match between the inflation chronology and that of the transfer function was the reason for the rejection of the staffing production impediments indicator. It produced an illogical outcome for the 2008-2009 peak. This is probably due to long-term developments in the Dutch labour market, where there is a trend towards an ever more structural labour shortage in certain sectors. Other indicators can be rejected for reasons of timeliness and reliability. On both counts, sentiment indicators are far superior to the other types of indicators considered here. The Statistics Netherlands business cycle tracer indicator is as timely as the sentiment indicators, but it falls short on the reliability front. As all measures of the output gap, it suffers from strong revisions. Both the inflation expectations and the capacity assessment indicator performed well for the LSTAR-modelling of the inflation^{pop} series as well, see table 3.2. The results for the transformed series are broadly in agreement with those for the inflation rate itself. In-sample fit values are comparable with those of the basic univariate models tested earlier, but forecast performance is superior. The Jarque-Berra statistic indicates that the distribution of the residuals is much less distorted. This is more support for the thesis that STAR models are better able to capture the dynamics of the series.

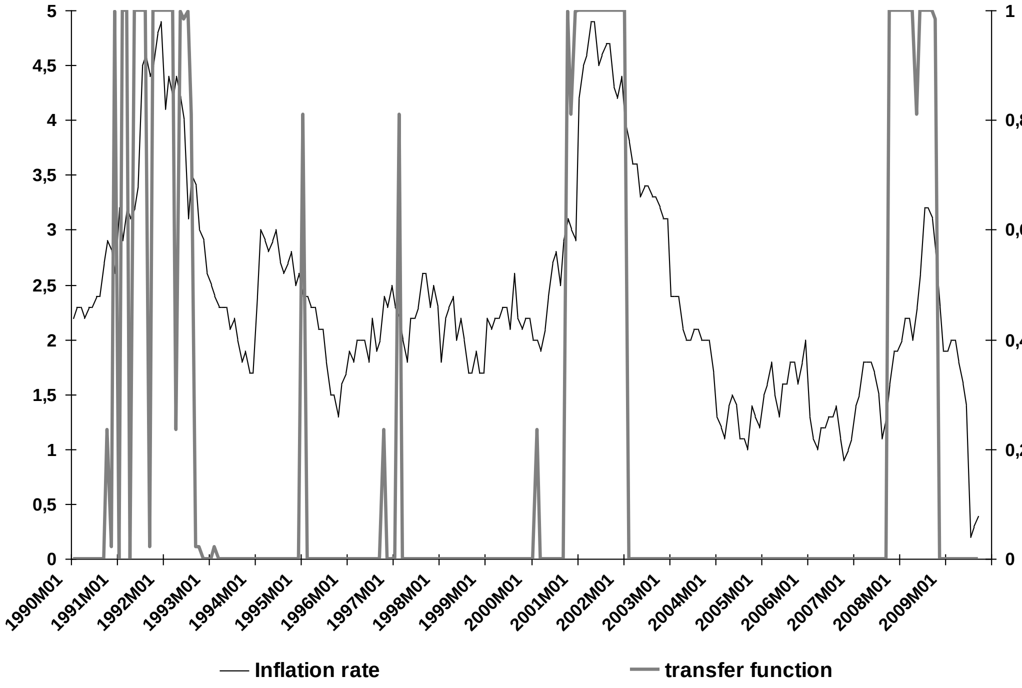
*Table 3.2 ; Summary of results of smooth transition autoregression models for **period on period** change in monthly rate of inflation using exogenous variables as transition variables. Sample 1990:01-2010:06. Forecast sample 2006:01-2010:6, based on rolling regression. STAR parameters were not re-estimated.*

Transition variable	*Capacity utilisation* (yoy)*	*Capacity assessment**	*Production constraints; capacity**	*Production constraints; staffing**	*Inflation expectations†*	*Hourly earnings manufacturing (yoy)*	*IMF prices industrial inputs (yoy)*	*SN Business cycle indicator*
Lags regime 1	**13**	**13**	**13**	**13**	**13**	**13**	**13**	**13**
Lags regime 2	**13**	**13**	**12**	**13**	**13**	**13**	**13**	**13**
Lag transition	**9**	**4**	**11**	**8**	**1**	**8**	**7**	**7**
Critical value	**-1.09**	**1.1**	**3.7**	**6.0**	**71.4**	**2.4**	**-2.5**	**0.77**
γ	**9.95**	**0.95**	**1.07**	**3.69**	**1.02**	**4.25**	**8.36**	**5.96**
Jarque-Berra residuals	**40.8 (0.0000)**	**16.7 (0.0002)**	**112 (0.0000)**	**16.7 (0.0002)**	**20.8 (0.0000)**	**80.1 (0.0000)**	**68.8 (0.0000)**	**21.5 (0.0000)**
P-value Q-stat (12 lags) residuals	**1.000**	**1.000**	**0.995**	**0.975**	**0.973**	**1.000**	**0.983**	**0.965**
R^2 1990-2009[1]	**0.946**	**0.944**	**0.939**	**0.944**	**0.947**	**0.948**	**0.944**	**0.945**
Forecast RMSE (%-points)	**0.23**	**0.20**	**0.19**	**0.21**	**0.21**	**0.18**	**0.21**	**0.21**

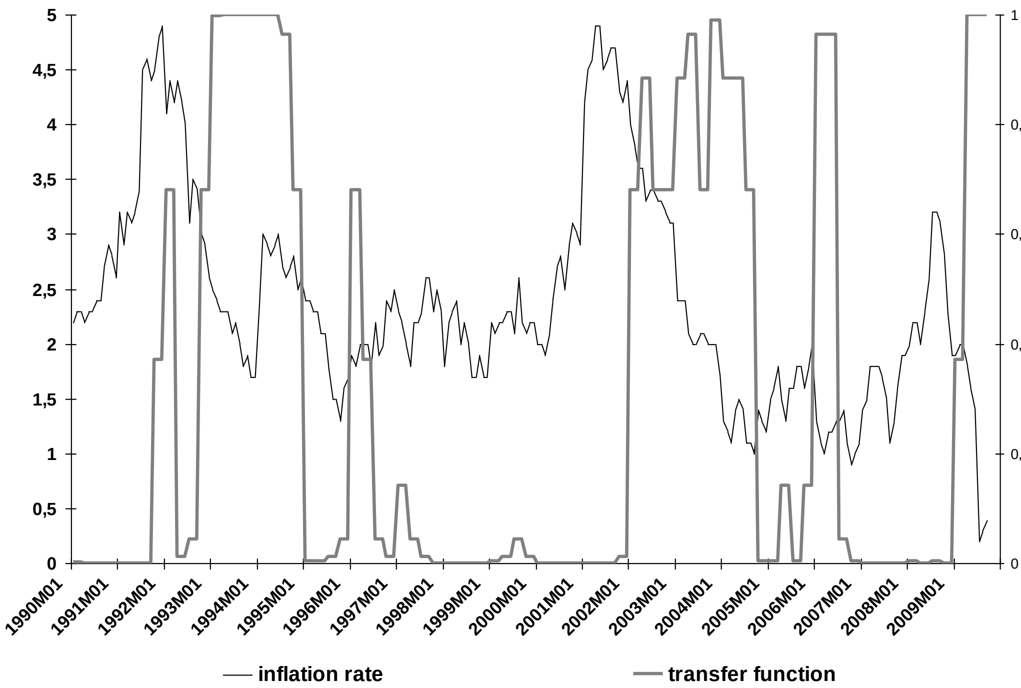
*from manufacturing industry survey, † from consumer survey, yoy= year on year growth rate, [1]based on error sum of squares model vs. total sum of squares inflation rate

The good performance of inflation expectations and capacity assessment for both types of dependent variable gives further support for choosing one of these two indicators for further use as the transition variable. This is confirmed when one considers the transfer functions which these two transition variables yield for the inflation^{pop} series. Graph 3.6 shows that the inflation expectations yield practically the same regime chronology for the inflation^{pop} as for the inflation rate itself.

Graph 3.6 ; Inflation rate (left axis) compared to 2-regime transfer function (right axis) from STAR of ***period on period*** *change in inflation rate with consumer survey inflation expectations as transition variable.*



Graph 3.7 ; Inflation rate (left axis) compared to 2-regime transfer function (right axis) from STAR of inflation rate with manufacturing survey capacity assessment as transition variable.

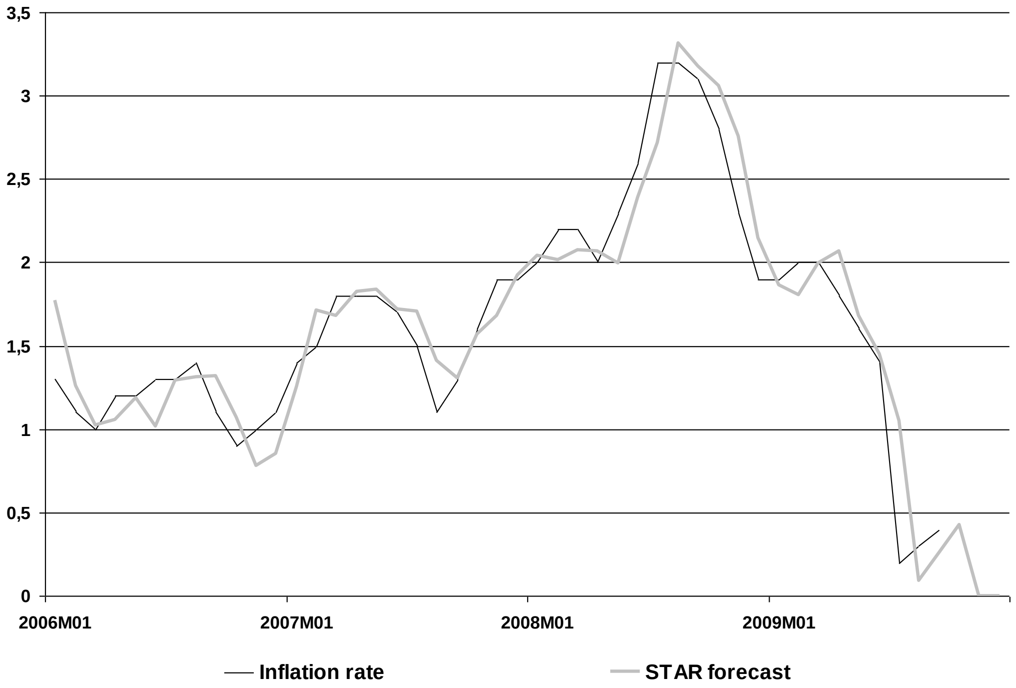


The transfer function resulting from using the capacity assessment to model the inflation^{pop} series is an interesting one. At first sight it might seem to do a relatively poor job in identifying high-inflation periods. But then this was not the goal per se. It is about a consistent and logical relationship with the periods of higher inflation. And in this case, the second regime identified by the LSTAR model can be seen to be connected with periods of (strongly) decreasing inflation, as mostly seen after the peak of a high-inflation episode. Thus these regimes are relevant and credible as well.

However, dividing inflation dynamics in one regime of decreasing inflation, and another consisting of both stable and increasing inflation is not entirely satisfactory. The regime chronology resulting from the STAR model with inflation expectations is much clearer, filtering out high-inflation episodes. An alternative might be a three regime analysis, which could result in a low/normal/high inflation division. Nevertheless, these results show that information on manufacturing capacity and inflation expectations can be used to assess the probability of inflation increasing or decreasing. A clear link is shown to the level of slack in the economy and the rate of inflation.

Also, it might seem that given these results that LSTAR models are a good basis for measuring inflationary pressure. But as the example in graph 3.8 shows, the forecast from the LSTAR models are behind the curve, just as the standard univariate models. The lower forecast-rmse's do not translate into more relevant forecasts.

Graph 3.8 ; Inflation rate and one month ahead forecast from rolling regression real-time simulation of STAR of period on period change in rate of inflation with manufacturing survey capacity assessment as transition variable (frmse=0.20 %-points).



Multi-regime STAR models

The STAR models using manufacturing capacity-related indicators described in the previous section, though exhibiting a good fit, did not yield a satisfactory regime classification. In this section, the results for a three-regime STAR analysis are presented. This might yield better results, as a two-regime division is somewhat restrictive given the complexity of inflation dynamics. Only inflation expectations and manufacturing capacity related indicators were used here as threshold variables, as these performed best in the two-regime analysis and are also of clear economic interest. The focus here lies on extracting a credible and relevant regime chronology from the transfer functions, as that is of considerable analytical interest.
The models using capacity assessment from the manufacturing survey and all the models with $inflation^{pop}$ as dependent did not yield useful regime chronologies. Models based on the rate of inflation itself with either the level of capacity utilization in manufacturing or inflation expectations as transition variable did. For the sake of conciseness, only the results of those models are reported here. As table 3.3 shows, model performance is not impressive compared to the alternatives studied here, with poorer fit and higher forecast errors. This might be partly due to the fact that here the maximum AR lag had to be restricted to three, as otherwise too few observations were available to estimate a three regime model. For the same reason, the lag of the transition variable was restricted to be identical in both transition functions.

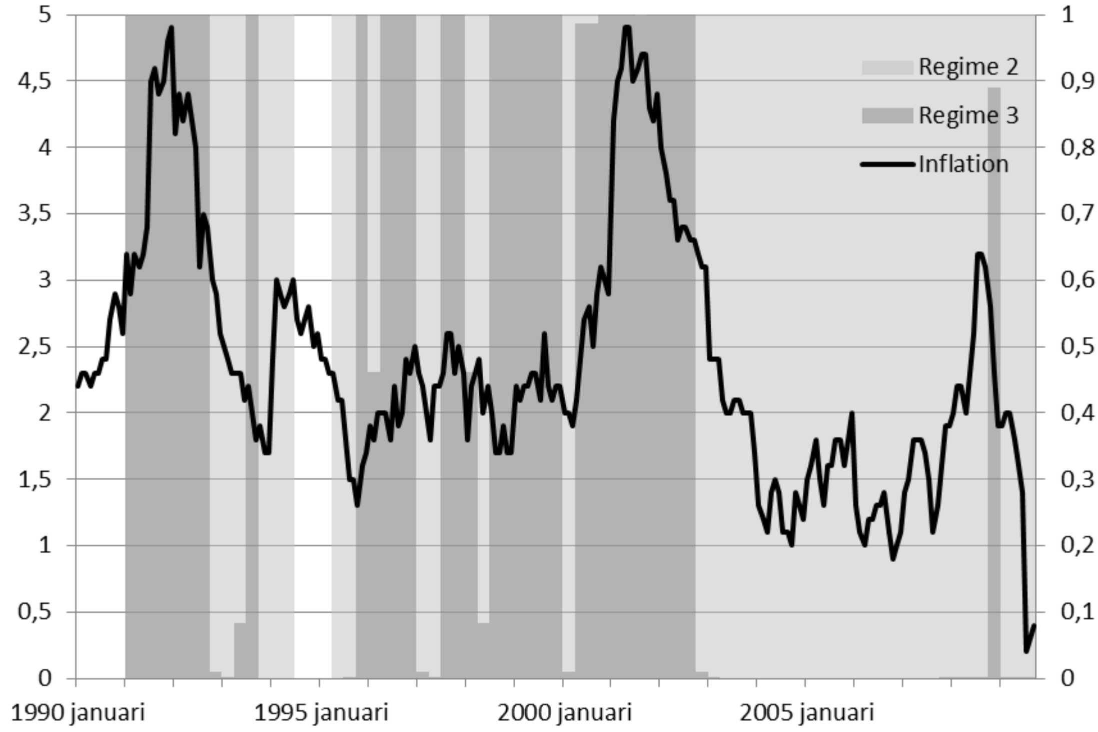
Table 3.3 ; Summary of results of 3-regime STAR models for monthly rate of inflation using exogenous variables as transition variables. Sample 1990:01-2010:06. Forecast sample 2006:01-2010:6, based on rolling regression. STAR parameters were not re-estimated.

Transition variable	Lags regime 1	Lags regime 2	Lags regime 3	Lag thresholds	Critical value 1	Critical value 2	γ 1	γ 2	R^2 1990-2009[1]	Forecast RMSE (%-points)
Capacity utilisation[*]	3	3	3	11	81.0	83.9	8.0	2.0	0.924	0.31
Inflation expectations[†]	3	3	3	12	52.1	69.3	2.1	7.4	0.925	0.31

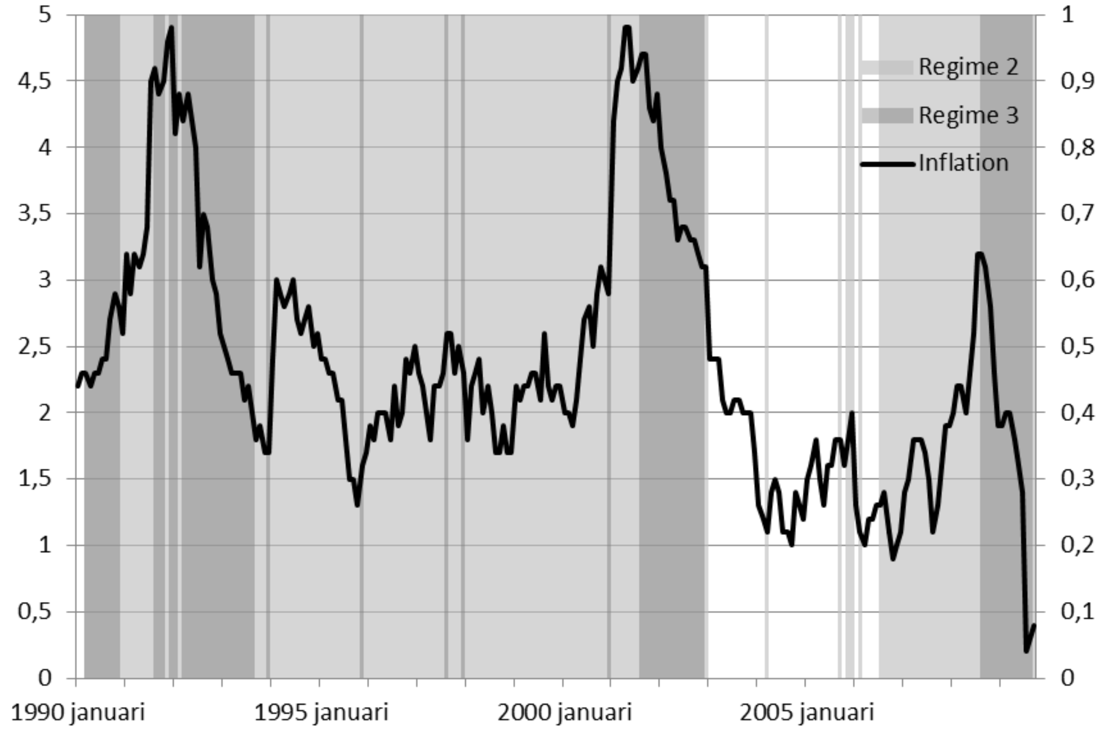
[*] from manufacturing industry survey, [†] from consumer survey, [1] based on error sum of squares model vs. total sum of squares inflation rate

However, these models did yield informative and consistent regime chronologies, see graphs 3.9 and 3.10. The STAR Model using manufacturing capacity utilization as transition variable shows one regime generally associated with inflation peaks, one with lower inflation, and one for a few “unclear” periods. The switch to three regimes resulted here in a much clearer and useful regime chronology, showing how the degree of capacity utilisation can be used to assess the likelihood of inflation increasing. This again shows the connection between the amount of slack left in the economy and inflationary pressure. The results for inflation expectations are a somewhat less useful here, as these seem to lag inflation somewhat, though again periods of high inflation are clearly singled out by the third regime.

Graph 3.9 ; Inflation rate (left axis) compared to 3-regime transfer function (right axis) from STAR of inflation rate with manufacturing survey capacity assessment as transition variable.



Graph 3.10; Inflation rate (left axis) compared to 3-regime transfer function (right axis) from STAR of inflation rate with consumer survey inflation expectations as transition variable.



4. Conclusions

This study applied a range of time series models to the rate of inflation in the Netherlands, in an attempt to gain an understanding of the dynamics of inflation. This would be a step towards analysing inflationary pressure, i.e. finding what determines future inflation. It is shown here that inflation dynamics are rather complex, even though inflation is already a differentiated series. It is of course defined as the year on year growth rate in the index of consumer prices. Predicting one month ahead inflation, a standard measure of how well one has captured the dynamics of a series, is both rather simple and quite difficult. This needs some explanation. The mean error rate of most models, even very basic ones, is quite low, around 0.2%-points. But if one compares graphs of forecasts and actual data, it becomes clearly visible that the forecasts actually lag inflation. The good performance in the root-mean-square error sense is actually do to the fact that inflation is a high-persistence series, i.e. month-on-month volatility is rather low. This means that a simple AR1-model will be a quite good predictor, whilst of course missing all the interesting turning points. It will also be relatively hard to beat.

A crucial result here is that inflation dynamics are shown to be non-linear. Periods of high and increasing inflation alternate with periods of more subdued and stable inflation. Tests confirm the presence of different regimes of inflation dynamics. This means that normal, linear time series models will perform relatively poorly in capturing inflation dynamics. A tentative analysis indicates that the change in Dutch inflation dynamics in the period considered in this study is connected to business cycle developments. More precisely, the peaks in the inflation rate seem to coincide with the boom phase of the business cycle.

One method to study non-linear time series dynamics like these is to use smooth threshold regression models. These divide the dynamics of the series modelled into different regimes, each with different parameters and therefore dynamics. A threshold function models the transition between the different regimes. Both autoregression and exogenous transition models were studied here. In the first case, the transition to a different (i.e. high inflation) regime is caused/signalled by inflation itself crossing a certain critical value, an alternative is to use another economic variable as threshold variable. The last option connects the transition to another inflation regime to some change in economic conditions, making possible a deeper analysis of the nature of changes in inflation dynamics.

Both autoregressive and exogenous based smooth transition models were able to successfully model inflation. As exogenous regime indicators, both variables related to the business cycle and to input prices were tested. Sentiment variables related to capacity utilisation in manufacturing and to consumer inflation expectations resulted in the most credible smooth transition models, clearly identifying regimes of high inflation when certain thresholds were crossed. Goodness of fit measures and forecast performance were superior to those of the linear models. Unfortunately, predicted dynamics still lagged actual realisations. The non-linear models were therefore not that much more useful in predicting inflation, but on the other hand yield valuable analytical insight. They give an indication of when periods of higher and less stable inflation are likely, and what might cause the change. This is useful information for economic and monetary policy, and gives some insight into the nature of inflationary processes.

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5. Appendix. Results tests for STAR-type non-linearity

Table A.1 ; Results Lagrange multiplier (LM) tests for presence of LSTAR and ESTAR-type non-linearity. χ^2 distribution p-values in brackets. Inflation rate=monthly year on year growth rates in CPI, Inflation^{pop}=month on month absolute changes in the inflation rate.

Transition variable:SETAR	*Inflation rate sample 1970-2009*	*Inflation rate sample 1990-2009*	*Inflation^{pop} sample 1970-2009*	*Inflation^{pop} sample 1990-2009*
Autoregressive lag p (months)	**13**	**13**	**13**	**13**
Lag transition variable d (months)	**12**	**12**	**12**	**12**
LSTAR test 1st order (χ^2, p+1 dof)	**13.01 (0.525)**	**7.74 (0.902)**	**35.32 (0.001)**	**22.37 (0.071)**
LSTAR test 3rd order (χ^2, 3(p+1) dof)	**60.04 (0.033)**	**43.36 (0.413)**	**98.90 (0.000)**	**59.69 (0.037)**
ESTAR test 2nd order (χ^2, 2(p+1) dof)	**39.92 (0.067)**	**28.52 (0.437)**	**73.59 (0.000)**	**40.15 (0.064)**
ESTAR test 4th order (χ^2, 4(p+1) dof)	**73.08 (0.062)**	**51.97 (0.628)**	**111.8 (0.000)**	**72.32 (0.070)**

Table A.2 ; Results Lagrange multiplier (LM) tests for presence of LSTAR and ESTAR-type non-linearity. χ^2 distribution p-values in brackets. Transition variable = Statistics Netherlands coincident business cycle indicator.

Transition variable:SN business cycle indicator	*Inflation rate sample 1970-2009*	*Inflation rate sample 1990-2009*	*Inflation^{pop} sample 1970-2009*	*Inflation^{pop} sample 1990-2009*
Autoregressive lag p (months)		**13**		**13**
Lag transition variable d (months)		**13**		**13**
LSTAR test 1st order (χ^2, p+1 dof)		**36.06 (0.001)**		**32.84 (0.003)**
LSTAR test 3rd order (χ^2, 3(p+1) dof)		**64.31 (0.015)**		**60.60 (0.032)**
ESTAR test 2nd order (χ^2, 2(p+1) dof)		**49.5 (0.007)**		**45.37 (0.020)**
ESTAR test 4th order (χ^2, 4(p+1) dof)		**88.13 (0.004)**		**80.20 (0.019)**

Table A.3 ; Results Lagrange multiplier (LM) tests for presence of LSTAR and ESTAR-type non-linearity. χ^2 distribution p-values in brackets. Transition variable = business survey manufacturing; personnel constraints.

Transition variable: manufacturing; personnel constraints	*Inflation rate sample 1970-2009*	*Inflation rate sample 1990-2009*	*Inflation^{pop} sample 1970-2009*	*Inflation^{pop} sample 1990-2009*
Autoregressive lag p (months)		**13**		**13**
Lag transition variable d (months)		**10**		**10**
LSTAR test 1st order (χ^2, p+1 dof)		**25.16 (0.033)**		**21.62 (0.087)**
LSTAR test 3rd order (χ^2, 3(p+1) dof)		**71.36 (0.003)**		**63.65 (0.017)**
ESTAR test 2nd order (χ^2, 2(p+1) dof)		**37.61 (0.106)**		**41.65 (0.047)**
ESTAR test 4th order (χ^2, 4(p+1) dof)		**82.11 (0.013)**		**80.47 (0.018)**

Table A.4; Results Lagrange multiplier (LM) tests for presence of LSTAR and ESTAR-type non-linearity. χ^2 distribution p-values in brackets. Transition variable = registered unemployment(year on year change.

Transition variable: unemployment	*Inflation rate sample 1970-2009*	*Inflation rate sample 1990-2009*	*Inflation^{pop} sample 1970-2009*	*Inflation^{pop} sample 1990-2009*
Autoregressive lag p (months)	**13**	**13**	**13**	**13**
Lag transition variable d (months)	**8**	**7**	**8**	**8**
LSTAR test 1st order (χ^2, p+1 dof)	**21.0 (0.102)**	**10.82 (0.700)**	**22.0 (0.079)**	**9.121 (0.823)**
LSTAR test 3rd order (χ^2, 3(p+1) dof)	**60.57 (0.032)**	**43.32 (0.419)**	**61.08 (0.029)**	**40.17 (0.552)**
ESTAR test 2nd order (χ^2, 2(p+1) dof)	**35.51 (0.156)**	**28.91 (0.417)**	**36.33 (0.134)**	**27.79 (0.476)**
ESTAR test 4th order (χ^2, 4(p+1) dof)	**75.87 (0.040)**	**54.58 (0.528)**	**78.25 (0.026)**	**51.61 (0.642)**

Table A.5 ; Results Lagrange multiplier (LM) tests for presence of LSTAR and ESTAR-type non-linearity. χ^2 distribution p-values in brackets. Transition variable = business survey manufacturing; rate of capacity utilization (year on year change).

Transition variable: capacity utilization	*Inflation rate sample 1970-2009*	*Inflation rate sample 1990-2009*	*Inflation^{pop} sample 1970-2009*	*Inflation^{pop} sample 1990-2009*
Autoregressive lag p (months)		**13**		**13**
Lag transition variable d (months)		**13**		**13**
LSTAR test 1st order (χ^2, p+1 dof)		**68.37 (0.000)**		**16.29 (0.234)**
LSTAR test 3rd order (χ^2, 3(p+1) dof)		**90.56 (0.000)**		**54.81 (0.048)**
ESTAR test 2nd order (χ^2, 2(p+1) dof)		**75.20 (0.000)**		**30.06 (0.266)**
ESTAR test 4th order (χ^2, 4(p+1) dof)		**101.1 (0.000)**		**63.19 (0.137)**

Table A.6; Results Lagrange multiplier (LM) tests for presence of LSTAR and ESTAR-type non-linearity. χ^2 distribution p-values in brackets. Transition variable = consumer survey; inflation expectations.

Transition variable: inflation expectations	*Inflation rate sample 1970-2009*	*Inflation rate sample 1990-2009*	*Inflation^{pop} sample 1970-2009*	*Inflation^{pop} sample 1990-2009*
Autoregressive lag p (months)		**13**		**13**
Lag transition variable d (months)		**2**		**2**
LSTAR test 1st order (χ^2, p+1 dof)		**70.02 (0.000)**		**14.30 (0.353)**
LSTAR test 3rd order (χ^2, 3(p+1) dof)		**89.27 (0.000)**		**47.73 (0.159)**
ESTAR test 2nd order (χ^2, 2(p+1) dof)		**78.19 (0.000)**		**19.11 (0.831)**
ESTAR test 4th order (χ^2, 4(p+1) dof)		**99.23 (0.000)**		**63.49 (0.053)**

Table A.7 ; Results Lagrange multiplier (LM) tests for presence of LSTAR and ESTAR-type non-linearity. χ^2 distribution p-values in brackets. Transition variable = business survey manufacturing; capacity constraints.

Transition variable: capacity constraints	*Inflation rate sample 1970-2009*	*Inflation rate sample 1990-2009*	*Inflation^{pop} sample 1970-2009*	*Inflation^{pop} sample 1990-2009*
Autoregressive lag p (months)		**13**		**13**
Lag transition variable d (months)		**13**		**12**
LSTAR test 1st order (χ^2, p+1 dof)		**62.31 (0.000)**		**25.28 (0.021)**
LSTAR test 3rd order (χ^2, 3(p+1) dof)		**94.46 (0.000)**		**54.30 (0.053)**
ESTAR test 2nd order (χ^2, 2(p+1) dof)		**78.00 (0.000)**		**41.63 (0.027)**
ESTAR test 4th order (χ^2, 4(p+1) dof)		**105.8 (0.000)**		**63.91 (0.124)**

Table A.8; Results Lagrange multiplier (LM) tests for presence of LSTAR and ESTAR-type non-linearity. χ^2 distribution p-values in brackets. Transition variable = IMF price index of industrial inputs(year on year change.

Transition variable: prices industrial inputs	*Inflation rate sample **1980**-2009*	*Inflation rate sample 1990-2009*	*Inflation^{pop} sample 1970-2009*	*Inflation^{pop} sample 1990-2009*
Autoregressive lag p (months)	**13**	**13**	**13**	**13**
Lag transition variable d (months)	**8**	**1**	**8**	**4**
LSTAR test 1st order (χ^2, p+1 dof)	**49.38(0.000)**	**23.28 (0.056)**	**45.55(0.000)**	**17.08 (0.252)**
LSTAR test 3rd order (χ^2, 3(p+1) dof)	**89.74(0.000)**	**55.16 (0.084)**	**78.68(0.000)**	**47.96 (0.244)**
ESTAR test 2nd order (χ^2, 2(p+1) dof)	**75.55(0.000)**	**42.54 (0.038)**	**63.87(0.000)**	**33.86 (0.206)**
ESTAR test 4th order (χ^2, 4(p+1) dof)	**95.46(0.000)**	**69.39 (0.108)**	**84.59(0.008)**	**60.35 (0.322)**

Table A.9 ; Results Lagrange multiplier (LM) tests for presence of LSTAR and ESTAR-type non-linearity. χ^2 distribution p-values in brackets. Transition variable =hourly earnings in manufacturing (year on year change).

Transition variable: hourly earnings manufacturing	*Inflation rate sample 1970-2009*	*Inflation rate sample 1990-2009*	*Inflation^{pop} sample 1970-2009*	*Inflation^{pop} sample 1990-2009*
Autoregressive lag p (months)	**13**	**13**	**13**	**13**
Lag transition variable d (months)	**13**	**10**	**7**	**8**
LSTAR test 1st order (χ^2, p+1 dof)	**55.32 (0.000)**	**87.46 (0.000)**	**54.63 (0.000)**	**47.86 (0.000)**
LSTAR test 3rd order (χ^2, 3(p+1) dof)	**93.16 (0.000)**	**109.8 (0.000)**	**94.89 (0.000)**	**76.36 (0.000)**
ESTAR test 2nd order (χ^2, 2(p+1) dof)	**76.69 (0.000)**	**101.60 (0.000)**	**83.31 (0.000)**	**66.30 (0.000)**
ESTAR test 4th order (χ^2, 4(p+1) dof)	**113.2 (0.000)**	**116.2 (0.000)**	**105.5 (0.000)**	**84.92 (0.003)**

Explanation of symbols

.	Data not available
*	Provisional figure
**	Revised provisional figure (but not definite)
x	Publication prohibited (confidential figure)
–	Nil
–	(Between two figures) inclusive
0 (0.0)	Less than half of unit concerned
empty cell	Not applicable
2013–2014	2013 to 2014 inclusive
2013/2014	Average for 2013 to 2014 inclusive
2013/’14	Crop year, financial year, school year, etc., beginning in 2013 and ending in 2014
2011/’12–2013/’14	Crop year, financial year, etc., 2011/’12 to 2013/’14 inclusive

Due to rounding, some totals may not correspond to the sum of the separate figures.

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