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Modeling the impact of forecast-based regime switches on US inflation

Koen Bel *, Richard Paap

Erasmus School of Economics, Erasmus University Rotterdam, Burg. Oudlaan 50, 3062 PA Rotterdam, The Netherlands
Econometric Institute, Erasmus University Rotterdam, Burg. Oudlaan 50, 3062 PA Rotterdam, The Netherlands

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ABSTRACT

Forecasts of key macroeconomic variables may lead to policy changes by governments, central banks and other economic agents. Such policy changes in turn lead to structural changes in macroeconomic time series. We describe this phenomenon in US inflation by introducing a logistic smooth transition autoregressive model where the regime switches depend on the Michigan Inflation Expectation Series. Our results show that (i) forecasts lead to regime changes and have an impact on the level of inflation; (ii) the absorption time of shocks in the forecast of inflation is about four quarters; and (iii) a positive (negative) shock in the forecast results in actions which increase (decrease) the inflation rate.

1. Introduction

Lucas (1976) showed that macroeconometric models with constant parameters cannot be used for evaluating policy changes, since policy changes usually lead to behavioral changes by economic agents, which result in inconstant model parameters. It is well known that agents also react to macroeconomic forecasts. This suggests that unexpected economic forecasts may also lead to changes in the model parameters.

Several theoretical and empirical studies have indicated this effect of forecasts. Theoretically, Fellner (1976) explained that the public's expectations are prone to self-justifying skepticism about policy makers, and policy makers react to that. Empirically, Givoly and Lakonishok (1979) found that serious upward revisions in financial earnings forecasts have significant effects on stock prices. Steiner, Großand Entorf (2009) showed that asset prices demonstrate an immediate reaction to returns in macroeconomic announcements. Moreover, they find that the reactions to positive news are faster than those to negative news. Sinclair, Gamber, Stekler, and Reid (2012) showed that forecast errors have an impact on the target interest rate set by the Federal Reserve Bank.

Although the literature suggests that forecasts have an impact in various fields, this paper focuses on US inflation time series data. It is well known that the dynamic character of this series is affected by policy changes; see for example Cogley and Sargent (2002, 2005) and Primiceri (2005). Furthermore, inflation forecasts play an important role, since (i) policy makers react to forecasts due to the FED Volcker-regime inflation targeting (Clarida, Galí, & Gertler, 2000); and (ii) companies and consumers use inflation forecasts to decide upon future savings and expenditure levels. Carroll (2003) states that people update their expectations to public forecasts rather than to past inflation rates. Furthermore, economic theory also provides support for the impact of forecasts on the inflation rate. It is mainly mentioned as either the expectations trap (Christiano & Gust, 2000) or self-fulfilling expectations,

* Corresponding author at: Erasmus School of Economics, Erasmus University Rotterdam, Burg. Oudlaan 50, 3062 PA Rotterdam, The Netherlands.
E-mail address: bel@ese.eur.nl (K. Bel).

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where the public's expectations of high inflation increase the actual inflation rate. Albanesi, Chari, and Christiano (2003) stated that "expectations of high or low inflation lead the public to take defensive actions, which then make accommodating those expectations the optimal monetary policy". Both the expectations trap before 1979 (Leduc, Sill, & Stark, 2007) and inflation targeting since the 1980s suggest that inflation forecasts play a key role.

We describe the effects of forecasts by proposing a nonlinear time series model which accounts for the dynamic effects of (inflation) forecasts. The model allows for structural breaks in the parameters based on the relative size of a forecast of the underlying time series. Sims and Zha (2006) describe regime switches using an exogenous first-order Markov process, but this paper employs a smooth transition autoregressive (STAR) model (Chan & Tong, 1986; Teräsvirta & Anderson, 1992). The most accurate variable for determining the current regime is probably the value of the dependent variable itself. As it is not feasible to use this variable to describe regime changes, the transitions are often based on a lagged value of the dependent variable; see Teräsvirta (1994), among many others. In this paper, we opt for a different approach, and predict regime changes using the level of the forecast of the underlying dependent variable. The forecast may be better at indicating the direction in which the time series is heading.

The resulting model is applied to the gross domestic product (GDP) based inflation rate of the United States (US). The results show that inflation forecasts do indeed lead to regime changes. That is, positive shocks in the inflation forecast result in actions which increase the future inflation rate. Further, it takes about four quarters for such shocks to be absorbed.

The remainder of this paper is organized as follows. Section 2 introduces our model specification for describing the impact of forecasts. Parameter estimation and statistical inference are discussed in Section 3. Section 4 illustrates our modeling approach on the US inflation rate. Finally, Section 5 concludes.

2. Model specification

We put forward a nonlinear time series model for US inflation which accounts for structural changes due to forecasts of the underlying time series. As we expect reactions to both relatively low and relatively high forecasts, we include three regimes. Furthermore, we expect the size of the structural change to depend on the size of the forecast; we therefore use smooth transition models, see Van Dijk, Teräsvirta, and Franses (2002) for a survey.

Formally, let y_t be US inflation at time $t = 1, \ldots, T$. Let $p_{t|t-1}$ denote the forecast of y_t based upon all information up to and including time $t-1$. In this paper, we will take the Michigan Inflation Expectation Series for $p_{t|t-1}$. The three-regime smooth transition time series model is then given by

$$y_t = f(x_t, p_{t|t-1}; \theta) + \sigma_t \varepsilon_t, \qquad (1)$$

with $\varepsilon_t \sim nid(0, 1)$ and

$$f(x_t, p_{t|t-1}; \theta) = \phi_1' x_t + (\phi_0 - \phi_1)' x_t G_0(p_{t|t-1}; \gamma_0, \kappa_{0t}) + (\phi_2 - \phi_1)' x_t G_2(p_{t|t-1}; \gamma_2, \kappa_{2t}), \qquad (2)$$

where x_t is a k-dimensional vector containing a vector of ones, explanatory variables and lagged values of y_t; $\phi_i, i \in \{0, 1, 2\}$, are $(k \times 1)$-parameter vectors; and θ summarizes all parameters. The parameter σ_t describes the potentially time-varying standard deviation of the disturbances, which we will discuss later. The value of the variance is assumed to be independent of the forecast $p_{t|t-1}$.

The functions $G_0(\cdot)$ and $G_2(\cdot)$ take values between zero and one, depending on the level of the forecast $p_{t|t-1}$, and describe the probability as being below or above some (economically interesting) threshold value. We opt for the logistic function

$$G_i(p_{t|t-1}; \gamma_i, \kappa_{it}) = \frac{1}{1 + \exp(-\gamma_i(p_{t|t-1} - \kappa_{it}))}, \qquad (3)$$

resulting in the logistic STAR (L-STAR) model (Teräsvirta, 1994). The parameter γ_i determines the smoothness of the transition function, and κ_{it} denotes the point of inflection of the logistic curve (see Chapter 2 of Van Dijk, 1999, for a graphical representation). It is easy to see that $G_0(\cdot)$ approaches one for small forecasts under the restrictions $\kappa_{0t} < \kappa_{2t}$, $\gamma_0 < 0$ and $\gamma_2 > 0$. Hence, the relevant parameter vector is ϕ_0. For large forecasts, $G_2(\cdot)$ approaches one, meaning that ϕ_2 is the relevant parameter vector. These restrictions are not necessary for the identification of the parameters, but other restrictions may lead to different interpretations of the regime parameters.

The original STAR specification assumes the threshold parameter κ_{it} in Eq. (3) to be constant over time. However, as US inflation has been fluctuating over recent decades, it is likely that the reactions to the forecast will vary over time. For instance, a forecast that was high during the low-inflation period of the 1990s would not have been striking during the oil crises of the late 1970s. We therefore allow the threshold to be time-varying, relative to the local level of inflation. That is, agents compare the forecast to the level of the inflation series in the near past.

We consider two specifications for the time-varying κ_{it}. First, let $\kappa_{it} = \kappa_i + \bar{y}_t^{(d)}$, where $\bar{y}_t^{(d)}$ is the average of the dependent variable over the previous d periods. The larger $\bar{y}_t^{(d)}$ is, the larger $p_{t|t-1}$ has to be before agents will react. This also implies that regime 0 is more likely to occur. For the second specification of κ_{it}, imagine a large forecast in a highly volatile period. As large changes are expected, it is likely that the reactions to this forecast will be less extreme than those to the same forecast in periods with a low volatility. We therefore impose that $\kappa_{it} = \kappa_i \sigma_t + \bar{y}_t^{(d)}$. Hence, we now also account for the local level of the variance in the inflation innovations.

In summary, the specification in Eqs. (1)–(3), where $G_0(\cdot)$ and $G_2(\cdot)$ depend on the level of the forecast $p_{t|t-1}$, provides the framework for investigating the impact of forecasts on agents' decisions. We allow for time-varying threshold parameters in order to take the local level of inflation into account. The model allows us to investigate the impact of the forecasts on macroeconomic variables of interest.

3. Statistical inference

We discuss inference for our smooth transition model specification from Section 2. Section 3.1 considers parameter estimation, while Section 3.2 concerns testing for our specific form of nonlinearity.

3.1. Estimation procedure

We estimate the parameters in Eqs. (1)–(3) using weighted nonlinear least squares (wNLS); see for example Davidson and MacKinnon (2004, Chapter 6), where the weights follow from the time-varying variance σ_t^2. Many macroeconomic time series display a drop in volatility in the 1980s (Great Moderation; GM), see Kahn, McConnell, and Perez-Quiros (2002) and Summers (2005). Lately, there has been evidence that the ending of the Great Moderation was due to the 2008–2009 financial crisis (Clarida, 2010). We capture the Great Moderation period in our STAR model in Eq. (1) by allowing for two breaks in the variance σ_t^2 and considering

$$\sigma_t^2 = \sigma_1^2 + (\sigma_2^2 - \sigma_1^2)(GM_{in}(t; \gamma_{gm:in}, \kappa_{gm:in}) - GM_{out}(t; \gamma_{gm:out}, \kappa_{gm:out})) + \eta_t. \quad (4)$$

Hence, we add a transition function for the transitions into and out of the Great Moderation stage. Since there are not yet enough data available to permit the estimation of a variance parameter after the Great Moderation, we assume that the variance has returned to the same level as before the Great Moderation. In contrast to Sensier and van Dijk (2004), we allow for the possibility of smooth transitions between the variance regimes using

$$GM(t; \gamma_{gm}, \kappa_{gm}) = \frac{1}{1 + \exp(-\gamma_{gm}(t - \kappa_{gm}))}, \quad (5)$$

which is again the logistic function. Hence, for $\gamma_{gm} > 0$, the variance is σ_1^2 for the first part of the sample, σ_2^2 for the second part, and σ_1^2 again after the Great Moderation. The transition is halfway at $t = \kappa_{gm}$, and γ_{gm} reflects the smoothness of this transition.

The wNLS procedure for estimating the model parameters θ can be summarized by the following five steps:

1. minimize $\sum_{t=1}^{T}(y_t - f(x_t; \theta))^2$ with respect to θ, resulting in $\hat{\theta}_0$;
2. compute the residuals $\hat{\varepsilon}_t = y_t - f(x_t; \hat{\theta}_0)$;
3. use NLS on Eq. (4), replacing σ_t^2 with $\hat{\varepsilon}_t^2$;
4. compute the fitted values of σ_t^2 using Eq. (4), resulting in $\hat{\sigma}_t^2$;
5. minimize $\sum_{t=1}^{T}(\frac{1}{\hat{\sigma}_t}(y_t - f(x_t; \theta)))^2$ with respect to θ, resulting in $\hat{\theta}$.

The estimator is asymptotically normally distributed. The covariance matrix of the estimator can be computed using

$$\hat{\sigma}_\varepsilon^2 \left(\sum_{t=1}^{T} \frac{1}{\hat{\sigma}_t^2} \left(\frac{\partial f(x_t; \theta)}{\partial \theta} \bigg|_{\theta=\hat{\theta}} \right) \left(\frac{\partial f(x_t; \theta)}{\partial \theta} \bigg|_{\theta=\hat{\theta}} \right)' \right)^{-1}. \quad (6)$$

Diagnostic tests on the residuals (such as heteroskedasticity and serial correlation tests) can be done in a manner similar to that for linear time series models. Since there are unidentified nuisance parameters under the null hypothesis of linearity, we cannot use standard tests to compare our model to a linear specification. The next section introduces the nonlinearity test of Luukkonen, Saikkonen and Teräsvirta (1988) for testing for our specific type of nonlinearity.

3.2. Nonlinearity test

The first step in the modeling process is to test for the presence of our proposed type of nonlinearity. Comparing our model specification in Eq. (1) with a linear model specification leads to the problem of unidentified parameters under the null hypothesis. That is, there is no structural change under the null, and hence, γ and κ are not identified. Hence, standard tests do not apply. Instead, we use the test of Luukkonen et al. (1988), which is based on the first-order Taylor expansion around $\gamma_i = 0$ of the logistic function $G_i(\cdot)$ in Eq. (3).

A first-order Taylor expansion of the restricted model in Eq. (1) results in

$$y_t = \phi_1' x_t + \tilde{\beta}_0 x_t + \tilde{\beta}_1 x_t p_{t|t-1} + \sigma_t \varepsilon_t, \quad (7)$$

where

$$\tilde{\beta}_0 = (0.5 - 0.25\gamma_0\kappa_0)(\phi_0 - \phi_1) \quad (8)$$

$$\tilde{\beta}_1 = 0.25\gamma_0(\phi_0 - \phi_1). \quad (9)$$

It is easy to see that the additional regime is not present in the specification if $\gamma_0 = 0$ or $\phi_0 = \phi_1$. Hence, the nonlinearity test boils down to testing $\tilde{\beta}_1 = 0$ using a standard Wald or t-test with a standard distribution. For testing for an additional third regime, we use the approach of Van Dijk and Franses (1999) with a small adjustment, as we do not fix the smoothness and location parameters of the first transition function in the test procedure. That is, we allow the second regime to be located differently when a third regime is added to the specification. These nonlinearity tests are used in the next section to test for STAR-type nonlinearity in US inflation data.

4. Application

We apply the model discussed in Section 2 to the seasonally adjusted quarterly gross domestic product deflator based US inflation rate (called US inflation henceforth) over the period 1960.Q1–2014.Q3.[1] There are many (potentially influential) forecasts available for this inflation series (Fama & Gibbons, 1984). This application uses the University of Michigan Inflation Expectation Series (henceforth called Michigan Series), which is a widely-accepted example of an inflation forecast series created by a large number of consumers (Curtin, 1982).

[1] This dataset is available publicly at http://ww.phil.frb.org/research-and-data/; we use the revised data series.

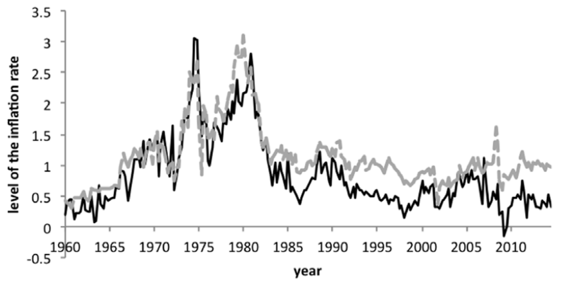


Fig. 1. Seasonally adjusted quarterly GDP US inflation rate (black) and the Michigan Inflation Expectation Series (dashed), 1960.Q1–2013.Q4.

This series is available over the whole sample period, and shows a correlation of 0.88 with US inflation.

Section 4.1 discusses several specifications of the STAR model in Eq. (1) to the description of US inflation. Section 4.2 discusses the selection of the appropriate model. Section 4.3 deals with parameter interpretation. As the model is nonlinear, marginal effects (Section 4.3.1) and impulse responses (Section 4.3.2) are used.

4.1. Model specification

Fig. 1 displays a plot of the US inflation series. It is clear from the figure that inflation peaked in the 1970s and 1980s because of the oil crises (Byrne & Davis, 2004), and became less volatile in the second half of the 1980s (the Great Moderation, see Rossi & Sekhposyan, 2010). The inflation rate is almost never negative in this period: deflation is only found in 2009 during the latest financial crisis.

When modeling this US inflation series, we first consider a simple linear ARX model, where we include an intercept and the Michigan Series. There are many potential predictors of inflation (Groen, Paap, & Ravazzolo, 2013; Stock & Watson, 2007), but this simple structure allows us to focus fully on regime changes in the inflation series due to inflation forecasts. According to the Schwarz (1978) information criterion, the appropriate lag order is 2. LM-tests indicate that there is no serial correlation in the residuals.

Next, we consider several STAR specifications (Eqs. (1)–(3)), where we include the Michigan Series both in the switching function and as a regressor. We begin by assuming constant κ threshold parameters, but it is clear from Fig. 1 that a constant threshold parameter results in a fitted model with the two oil crises in regime 2, where inflation, and hence forecasts of inflation, are high. However, a large forecast in this high inflation period is different from a large forecast in the 1990s. We therefore also consider time-varying threshold parameters, as discussed in Section 2. A grid search over $d = 1, \ldots, 20$ in $\bar{y}_t^{(d)}$ shows that $d = 8$ generally yields the best fit in terms of root mean squared errors. This suggests that agents compare the level of the forecast to the level of US inflation over the previous two years. Finally, for reasons of comparison, we also add to our analysis a regular STAR model with y_{t-1} as the switching variable.

4.2. Model selection

Before we can adopt the model specification in Eqs. (1)–(3), we test for our specific form of nonlinearity. Panel (a) of Table 1 displays the results for the nonlinearity test described in Section 3.2. The starting point for these tests is the ARX(2) specification. The first row shows that the hypothesis of linearity is rejected in favor of an additional regime. Further, a third regime is a significant improvement in the specifications with $\kappa_{it} = \kappa_i + \bar{y}_t^{(d)}$. Hence, these results are in favor of our three-regime model specification.

Panel (b) of Table 1 shows that there is no indication of severe misspecification in the nonlinear models. Ramsey (1969) RESET-tests indicate that there is no neglected nonlinearity in the series. LM-tests for first- and first-to-second-order serial correlation in the residuals (Breusch, 1978; Godfrey, 1978) do not indicate misspecification. Likewise, tests for first- and first-to-second-order ARCH effects (Engle, 1982) do not find heteroskedasticity in the residuals. In summary, these test results provide a justification for using the model as explained in Section 2.

For model selection purposes, we compare the fits of the model specifications, that is, the regular STAR model and the influential forecast model, for all threshold specifications. However, standard likelihood ratio tests cannot be used because these models are non-nested. We therefore opt for the test of Vuong (1989), based on the assumption of normality of the disturbances. Furthermore, we use a nonparametric sign test on the absolute value of the residuals (Dixon & Mood, 1946). Table 2 displays the test statistics.

The test of Vuong (1989) does not favor the nonlinear specifications over the linear ARX(2)-model, because of the large number of additional parameters. However, the nonlinearity test in Table 1, which is especially designed for comparing linear AR models with STAR models, indicated that adding nonlinearity improves the model. The nonparametric sign test shows more support for this claim concerning the ARX(2)-specification. The Vuong (1989) and sign tests do not result in one nonlinear specification that is obviously favored, although the RMSEs of the residuals are smallest for the STAR model that uses the Michigan Series to describe the regime switches and includes a time-varying threshold parameter $\kappa_t = \kappa + \bar{y}_t^{(d)}$, see the first row of the second panel of Table 2.

We also consider an out-of-sample forecasting exercise where we split the sample into two parts. The first part runs from 1960.Q1 to 1989.Q4 (approximately half of the sample, at a convenient cut-off point), and is used to estimate the model parameters. The second part starts at 1990.Q1, and is used to evaluate the models' forecasting performances, for one-step-ahead forecasts. As the limited estimation sample does not allow us to estimate the ending of the Great Moderation, we base the estimate of the variance on the whole sample. The second panel of Table 2 displays the root mean squared prediction errors (RMSPEs) for all model specifications. Again, the smallest average forecast error is found for the model that uses the Michigan Series to describe the regime changes and includes a time-varying threshold parameter $\kappa_t = \kappa + \bar{y}_t^{(d)}$. The forecasts

Table 1
Nonlinearity and misspecification tests (p-values) for the six model specifications.

		$\kappa_t = \kappa$		$\kappa_t = \kappa + \bar{y}_t^{(d)}$		$\kappa_t = \kappa\sigma_t + \bar{y}_t^{(d)}$	
		STAR	MS	STAR	MS	STAR	MS
Panel (a): Luukkonen et al. (1988) tests							
Nonlinearity	Second regime	0.070	0.147	0.035	0.029	0.061	0.043
	Third regime	0.030	0.045	0.036	0.050	0.110	0.195
Panel (b): Misspecification tests							
RESET test		0.857	0.754	0.938	0.555	0.843	0.546
Serial correlation	First order	0.960	0.964	0.668	0.956	0.347	0.951
	First-to-second order	0.962	0.965	0.761	0.945	0.424	0.967
ARCH effects	First order	0.669	0.535	0.109	0.642	0.602	0.042
	First-to-second order	0.909	0.799	0.272	0.884	0.166	0.043

Notes: The tests are the adjusted nonlinearity test by Luukkonen et al. (1988), the RESET test of Ramsey (1969), the serial correlation test by Breusch (1978) and Godfrey (1978), and the ARCH LM-test for heteroskedasticity by Engle (1982).

Table 2
Vuong (1989) and sign tests for comparing the six different specifications and an ARX(2)-model (p-values in parentheses).

		ARX(2)	$\kappa_t = \kappa$		$\kappa_t = \kappa + \bar{y}_t^{(d)}$		$\kappa_t = \kappa\sigma_t + \bar{y}_t^{(d)}$	
			STAR	MS	STAR	MS	STAR	MS
ARX(2)			1.857	2.966	4.168	1.079	3.146	0.639
			(0.063)	(0.003)	(0.000)	(0.281)	(0.002)	(0.523)
$\kappa_t = \kappa$	STAR	0.417		0.779	0.701	−0.457	0.900	−0.317
		(0.007)		(0.436)	(0.483)	(0.648)	(0.368)	(0.751)
	MS	0.422	0.555		−0.030	−1.382	0.181	−1.175
		(0.011)	(0.052)		(0.976)	(0.167)	(0.856)	(0.240)
$\kappa_t = \kappa + \bar{y}_{t-1\|t-d}$	STAR	0.431	0.550	0.518		−1.070	0.193	−0.930
		(0.021)	(0.068)	(0.294)		(0.284)	(0.847)	(0.352)
	MS	0.440	0.532	0.514	0.477		1.392	0.060
		(0.039)	(0.172)	(0.343)	(0.250)		(0.164)	(0.952)
$\kappa_t = \kappa\hat{\sigma}_t + \bar{y}_{t-1\|t-d}$	STAR	0.413	0.537	0.500	0.505	0.532		−1.044
		(0.005)	(0.140)	(0.500)	(0.446)	(0.172)		(0.296)
	MS	0.385	0.468	0.436	0.431	0.472	0.454	
		(0.000)	(0.172)	(0.029)	(0.021)	(0.209)	(0.088)	
RMSE		1	0.896	0.915	0.908	0.847	0.922	0.859
RMSPE		1	0.974	1.034	1.097	0.966	1.077	0.994

Notes: The upper-triangular matrix in the table shows the results for the Vuong (1989) test. A positive test value indicates that the model presented in the row is better than that in the column. The lower-triangular matrix displays the sign test results. A test value smaller than 0.5 indicates that the model presented in the row is better. 'STAR' stands for the regular STAR model and 'MS' stands for the model with the Michigan Series as influential forecasts. The root mean squared (prediction) error (RMS(P)E) for the ARX(2) specification is normalized to 1.

of this specification are better than the same regular STAR model in 63 cases out of 99. The specification outperforms a simple ARX(2) specification in 57 cases.

4.3. Parameter interpretation

Tables 3 and 4 display the parameter estimates of the model specifications. We focus the interpretation of the estimation results on the specification selected in Section 4.2, which is shown in Panel (b) of Table 4. We can see at first glance that the estimates of γ_i are relatively large, indicating fast transitions between regimes.

Interpreting individual parameter estimates directly is difficult, because the structure of the model is highly nonlinear. We therefore consider several graphs in our investigation of the features of US inflation and the impacts of forecasts. Fig. 2 plots the values of the transition functions over time. The spikes in the transition function for regime 2 during the oil crises show that the model can distinguish between high and moderate forecasts during these crises. Since $\bar{y}_t^{(d)}$ is relatively large just after these crises, the low forecast regime dominates. Inflation targeting led

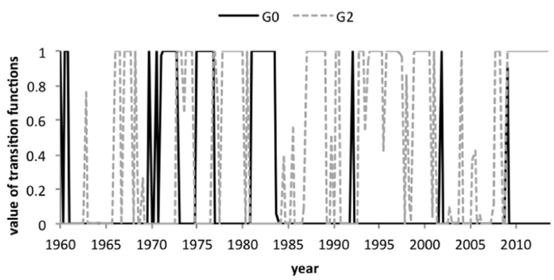


Fig. 2. Transition functions for the preferred model specification.

to a steady US inflation rate in the 1990s. Since the Michigan Series overestimates inflation in this period, regime 2 is the steady regime in this Great Moderation era.

The parameter estimates of the time-varying variance are shown in Table 4. These imply that a decrease in variance took place in the fourth quarter of 1985, which fits with the existing literature (Kahn et al., 2002). The transition to this Great Moderation era is relatively fast. The variance of the error term is about 60% smaller in this

Table 3
WNLS parameter estimates of the three model specifications with y_{t-1} as the transition variable (standard errors in parentheses).

	Regime 0		Regime 1		Regime 2	
Panel (a): $\kappa_t = \kappa$						
κ	0.602	(0.013)			1.224	(0.898)
γ	−181.272	–			399.271	–
c	0.255	(0.165)	−0.167	(0.117)	0.131	(0.188)
y_{t-1}	0.357	(0.263)	0.095	(0.134)	0.362	(0.185)
y_{t-2}	−0.114	(0.171)	0.250	(0.100)	−0.261	(0.149)
MS_{t-1}	−0.485	(0.189)	0.623	(0.117)	−0.097	(0.142)
$\kappa_{gm:in}$			1985.Q2	(4.287)		
$\gamma_{gm:in}$			5.888	–		
$\kappa_{gm:out}$			2006.Q3	(2.411)		
$\gamma_{gm:out}$			5.889	–		
σ_1^2			0.057	(0.006)		
$\sigma_2^2 - \sigma_1^2$			−0.039	(0.007)		
Panel (b): $\kappa_t = \kappa + \bar{y}_t^{(d)}$						
κ	−0.366	(8.895)			0.340	(0.024)
γ	−589.077	–			589.926	–
c	0.128	(0.430)	−0.125	(0.041)	−0.491	(0.242)
y_{t-1}	−0.219	(0.295)	0.482	(0.090)	−0.130	(0.372)
y_{t-2}	−0.176	(0.277)	0.128	(0.078)	0.156	(0.320)
MS_{t-1}	0.347	(0.531)	0.384	(0.061)	0.302	(0.167)
$\kappa_{gm:in}$			1985.Q3	(1.909)		
$\gamma_{gm:in}$			5.888	–		
$\kappa_{gm:out}$			2006.Q3	(3.122)		
$\gamma_{gm:out}$			5.879	–		
σ_1^2			0.058	(0.008)		
$\sigma_2^2 - \sigma_1^2$			−0.040	(0.008)		
Panel (c): $\kappa_t = \kappa\sigma_t + \bar{y}_t^{(d)}$						
κ	−0.172	(0.030)			0.319	(0.135)
γ	−589.928	–			589.927	–
c	−0.101	(0.150)	−0.121	(0.042)	−0.247	(0.128)
y_{t-1}	−0.090	(0.197)	0.454	(0.100)	−0.360	(0.415)
y_{t-2}	−0.089	(0.159)	0.180	(0.083)	0.196	(0.344)
MS_{t-1}	0.266	(0.185)	0.355	(0.065)	0.427	(0.206)
$\kappa_{gm:in}$			1985.Q3	(2.255)		
$\gamma_{gm:in}$			5.878	–		
$\kappa_{gm:out}$			2006.Q3	(3.188)		
$\gamma_{gm:out}$			5.884	–		
σ_1^2			0.058	(0.007)		
$\sigma_2^2 - \sigma_1^2$			−0.040	(0.008)		

Note: The parameters of regimes 0 and 2 are different from those in regime 1.

period. The results indicate that Great Moderation seems to end in 2006.Q3.[2]

We shed more light on the effect of forecasts by decomposing the change in US inflation into three parts. The first part concerns the effect of changes in explanatory variables when holding the regime constant (average absolute effect of 0.11). The second part is the error term (average absolute effect of 0.15). The third part describes the effect of the forecast-based regime switches (average absolute effect of 0.16). Panel (a) of Fig. 3 displays the decomposition over time in percentage points. The effects of the forecast-based regime switches are largest about 41% of the time.

To compare these results with a standard STAR, Fig. 3(b) shows the same graph for a transition variable of y_{t-1}. Regime switches for a regular STAR have the largest effect 40% of the time, which corresponds to our forecast-based specification. However, there are clear differences over time. The greatest difference is found in the 1990s, where shocks have a greater impact on inflation in the standard STAR specification, while our new specification captures part of these shocks as regime switches. In general, the forecast-based regime specification seems to be especially valuable in economically stable periods, while the specifications are largely comparable in other periods. Hence, lagged inflation seems to contain similar information about regime switches as inflation forecasts in non-stable periods, whereas forecasts are better at signaling regime changes in stable periods.

4.3.1. *Marginal effects*

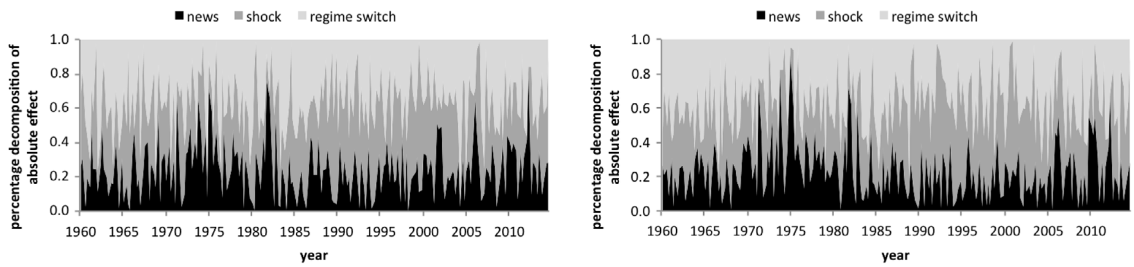
We analyze the differences in dynamic patterns across the three regimes by considering marginal effects. Marginal effects are defined as the change in y caused by a one standard deviation increase in x, where x denotes lagged values of US inflation or the Michigan Series. Note that the

[2] There is some evidence that the Great Recession did not imply the end of the Great Moderation, see Gadea-Rivas, Gomez-Loscos, and Perez-Quiros (2014), among others. Unreported results show that a model specification without the ending of the Great Moderation yields results similar to those reported below.

Table 4
WNLS parameter estimates of the three model specifications with the Michigan Series as the transition variable (standard errors in parentheses).

	Regime 0		Regime 1		Regime 2	
Panel (a): $\kappa_t = \kappa$						
κ	0.612	(0.741)			1.262	(0.546)
γ	−454.839	–			454.855	. –
c	0.896	(1.198)	−0.046	(0.089)	−0.041	(0.128)
y_{t-1}	−0.717	(1.245)	0.335	(0.086)	0.226	(0.142)
y_{t-2}	−0.520	(0.602)	0.236	(0.082)	−0.239	(0.130)
MS_{t-1}	−1.042	(1.864)	0.311	(0.105)	0.131	(0.137)
$\kappa_{gm:in}$			1985.Q3	(3.927)		
$\gamma_{gm:in}$			5.888	. –		
$\kappa_{gm:out}$			2006.Q3	(2.935)		
$\gamma_{gm:out}$			5.889	-.-		
σ_1^2			0.058	(0.006)		
$\sigma_2^2 - \sigma_1^2$			−0.040	(0.007)		
Panel (b): $\kappa_t = \kappa + \bar{y}_t^{(d)}$						
κ	0.063	(0.034)			0.362	(0.014)
γ	−497.681	–			125.679	. –
c	0.150	(0.140)	−0.195	(0.094)	0.067	(0.119)
y_{t-1}	0.290	(0.161)	0.095	(0.119)	0.596	(0.174)
y_{t-2}	−0.338	(0.151)	0.291	(0.108)	−0.118	(0.176)
MS_{t-1}	0.001	(0.230)	0.642	(0.185)	−0.421	(0.222)
$\kappa_{gm:in}$			1985.Q4	(30.316)		
$\gamma_{gm:in}$			2.989	. –		
$\kappa_{gm:out}$			2006.Q3	(2.432)		
$\gamma_{gm:out}$			5.342	. –		
σ_1^2			0.053	(0.006)		
$\sigma_2^2 - \sigma_1^2$			−0.035	(0.007)		
Panel (c): $\kappa_t = \kappa\sigma_t + \bar{y}_t^{(d)}$						
κ	0.263	(0.024)			0.362	(0.058)
γ	−497.701	–			496.890	. –
c	0.000	(0.181)	−0.166	(0.163)	0.098	(0.172)
y_{t-1}	−0.069	(0.202)	0.364	(0.179)	0.250	(0.211)
y_{t-2}	−0.104	(0.210)	0.182	(0.190)	0.139	(0.228)
MS_{t-1}	0.265	(0.310)	0.411	(0.278)	−0.266	(0.294)
$\kappa_{gm:in}$			1985.Q3	(6.912)		
$\gamma_{gm:in}$			5.882	. –		
$\kappa_{gm:out}$			2006.Q3	(2.196)		
$\gamma_{gm:out}$			5.889	. –		
σ_1^2			0.053	(0.006)		
$\sigma_2^2 - \sigma_1^2$			−0.035	(0.007)		

Note: The parameters of regimes 0 and 2 are different from those in regime 1.



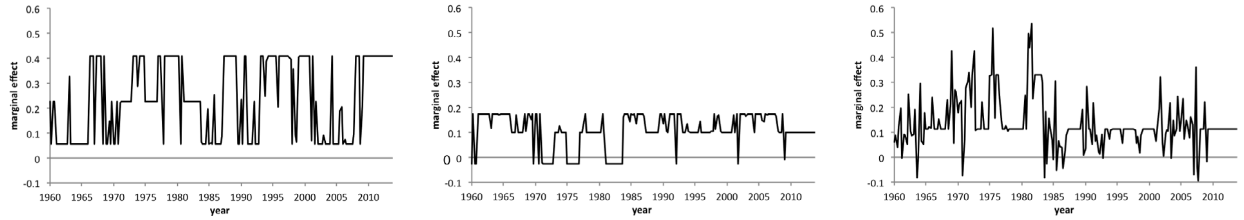
(a) Transition variable: Michigan Series. (b) Transition variable: y_{t-1}.

Fig. 3. Percentage decomposition of the absolute effect of changes over time ($y_t - y_{t-1}$) in US inflation for the preferred model specification.

change in x can also cause regime switches to occur. Thus, marginal effects differ over time, as is plotted in Fig. 4. Furthermore, Table 5 displays the average marginal effects weighted with the regimes.

Table 5 shows that, on average, the first lag of inflation has a larger impact in the outer regimes. This indicates that agents rely more on the near past in periods with relatively large or small forecasts. On the other hand, the second lag of inflation has a smaller absolute impact in these outer regimes. Thus, the distant past is less important to agents in economically uncertain periods.

The last panel of Fig. 4 shows the marginal effect of a positive change in $p_{t|t-1}$. On average, this effect is positive for all regimes. That is, an increase in the (influential) Michigan Series forecast adjusts the inflation rate upward. Thus, the behavior of agents is such that the inflation rate follows the influential forecast, which is in line with the expectations trap literature (Christiano & Gust, 2000).



(a) Marginal effect of y_{t-1}. (b) Marginal effect of y_{t-2}. (c) Marginal effect of $p_{t|t-1}$.

Fig. 4. Marginal effects of a one standard deviation increase in the explanatory variables and $p_{t|t-1}$ for the preferred model specification.

Table 5
Descriptive statistics of the marginal effects, as displayed in Fig. 4.

	y_{t-1}			y_{t-2}			$p_{t\|t-1}$		
	5%	Average	95%	5%	Average	95%	5%	Average	95%
	0.056	0.242	0.408	−0.028	0.109	0.172	−0.011	0.135	0.330
Regime 0	0.224	0.227	0.228	−0.028	−0.027	−0.023	−0.014	0.259	0.513
Regime 1	0.056	0.070	0.192	0.145	0.169	0.172	−0.055	0.111	0.286
Regime 2	0.295	0.396	0.408	0.102	0.104	0.125	0.095	0.112	0.113

Notes: The first row shows the equally weighted marginal effects. The second to fourth rows show the weighted marginal effect where the weights are based on the probability of being in the specific regime. 5% stands for the 5% percentile, while 95% stands for the 95% percentile.

4.3.2. Impulse response analysis

We interpret the dynamic properties of the model using generalized impulse response functions (GIRF; Koop, Pesaran, & Potter, 1996). We examine the impact of a shock δ for different information sets Ω_t in a similar way as Van Dijk (1999). The GIRF is defined as

$$GIRF_y(h, \delta, \Omega_\tau) = E[y_{\tau+h}|\varepsilon_\tau = \varepsilon_\tau + \delta, \Omega_\tau] - E[y_{\tau+h}|\Omega_\tau], \quad (10)$$

where τ denotes the timing of the shock, h is the horizon, and Ω_τ is the information set at time τ. Hence, the impulse response function denotes the dynamic effect of a shock δ at time τ on future values of y_t. We average over all possible information sets Ω_τ, and split the results depending on the regime at time τ. Note that a shock may also affect future regimes, and thus, the analysis takes full advantage of the nonlinearity of the model specification. Furthermore, we define the π-absorption time of the shock as the number of time periods before π% of the shock is absorbed (Van Dijk, Franses, & Boswijk, 2007); that is

$$A_y(\pi, \delta, \Omega_t) = \sum_{m=0}^{\infty}\left(1 - \prod_{h=m}^{\infty} I_y(\pi, h, \delta, \Omega_t)\right), \quad (11)$$

where

$$I_y(\pi, h, \delta, \Omega_t) = I[|GIRF_y(h, \delta, \Omega_t)| \leq \pi|\delta|], \quad (12)$$

with $I[A]$ being an indicator function that is one if the argument is true and zero otherwise.

Fig. 5 displays the impulse response functions for positive and negative shocks in y_τ for different regimes. The differences across regimes are relatively small, although the reaction to a shock in regime 2 has a longer absorption time. That is, it takes more than one quarter to absorb 50% of the shock. Across all regimes, it takes an average of three to nine quarters for 90% of the shock to be absorbed. Hence, an innovative shock has a small but relatively long-lasting effect on future US inflation.

Given the structure of the model, it is perhaps more interesting to examine the effect of a shock to the forecast $p_{t|t-1}$:

$$GIRF_p(h, \delta, \Omega_\tau) = E[y_{\tau+h}|\Omega_\tau, p_{\tau|\tau-1} = p_{\tau|\tau-1} + \delta] - E[y_{\tau+h}|\Omega_\tau]. \quad (13)$$

Fig. 6 shows the effects of such shocks of various magnitudes and for different regimes at time τ. It can be seen that a negative shock to the forecast has negative effects on future inflation rates. The differences between regimes are small, although the absorption time is larger in the outer regimes than in the intermediate regime. Hence, uncertainty in the outer regimes causes agents to react more to forecasts. Further, shocks in regime 2 last the longest (it is approximately four quarters before 90% is absorbed). In summary, the reactions to forecasts correspond to the expectations trap literature: positive (negative) shocks to forecasts accommodate an increase (decrease) in future US inflation.

Finally, we consider the hypothetical situation where we impose a shock on the forecast which makes the forecast equal to the realization. This analysis investigates the importance of forecast accuracy and determines whether an improved forecast accuracy could have circumvented extreme events. Fig. 7 displays impulse response functions for five data points where the forecast $p_{t|t-1}$ was inaccurate. For example, the lower inflation rate between the oil crises would have been higher if the inflation rate had been forecast correctly in 1975.Q1. Further, if US inflation had been forecast correctly in 1979.Q1, the inflation rate would have been lower for approximately two years. Finally, the financial crisis peaked in the second quarter of 2009, and the Michigan Series was not able to capture this downward spike in inflation. If the forecast $p_{t|t-1}$ had been correct, the inflation rate would have been lower for a long time period. This hypothetical analysis shows the importance of accurate forecasts: where forecasts have been inaccurate,

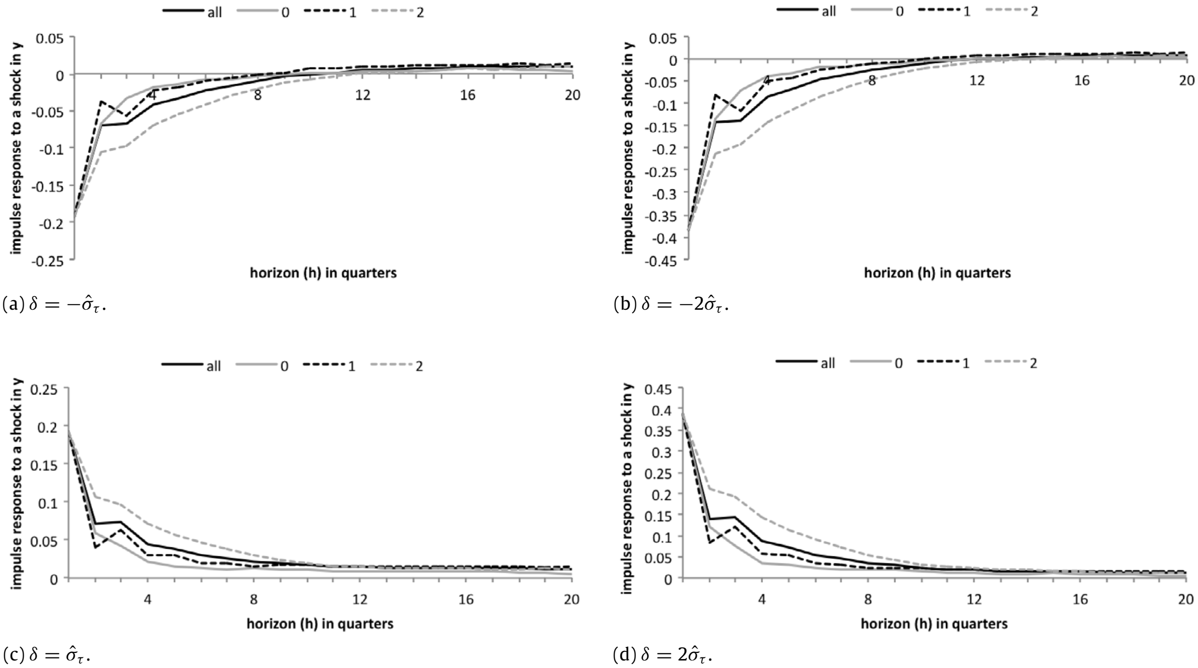


Fig. 5. Impulse response analysis for various shocks δ in y_t for the preferred model specification.

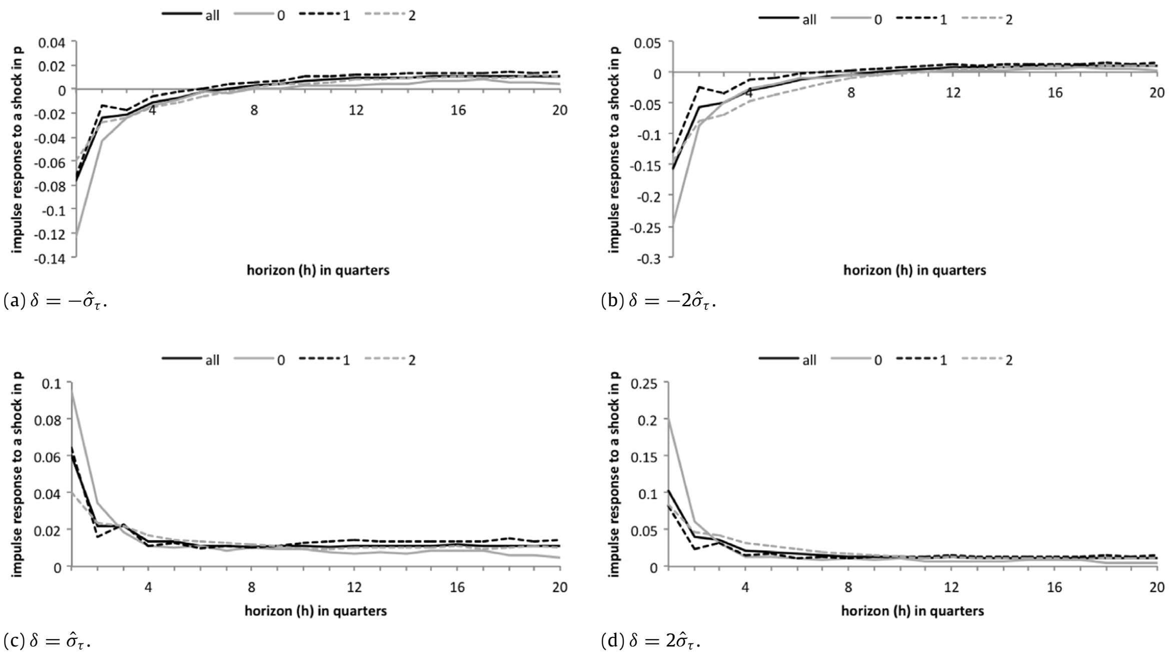


Fig. 6. Impulse response analysis for various shocks δ in $p_{t|t-1}$ for the preferred model specification.

a more accurate forecast would have considerably changed agents' reactions, and therefore future inflation rates.

In summary, we find that the model we propose in Section 2 is capable of capturing the familiar aspects of US inflation. Marginal effects and impulse response analyses show that agents take the forecast of the dependent variable into account when they take action in the economic market. In particular, the model shows that agents follow the direction of the forecast.

5. Concluding remarks

In this paper we have introduced a STAR-type time series model for inflation, where regime switches are based on the relative size of the forecast of the underlying series. The specification allows low and high inflation forecasts to have different impacts on future values of inflation.

The model is applied to GDP deflator-based US inflation rate, where we use the Michigan Inflation Expectation

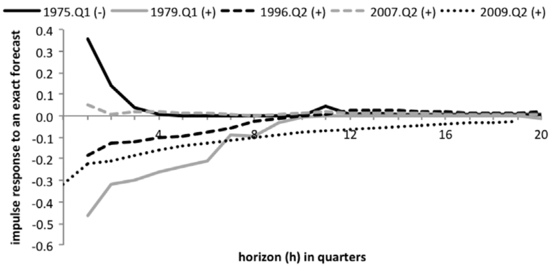


Fig. 7. Impulse response analysis of a shock in $p_{\tau|\tau-1}$ that makes the forecast exactly equal to the dependent variable. Five quarters where the forecast of inflation is far from the realization are displayed ((−) underestimation, (+) overestimation).

Series as inflation forecasts. Since the level of inflation changes over time, we include a time-varying threshold parameter in the L-STAR specification, such that the relative size of the forecast determines regime changes. Our empirical results show that (i) forecasts lead to regime changes, and have an impact on the level of inflation; (ii) forecasts seem to signal regime switches better than lagged inflation in economically stable periods, and similarly well in other periods; (iii) a positive (negative) shock to the inflation forecast results in actions that increase (decrease) the inflation rate, which is in line with the expectations trap literature; (iv) the absorption time of shocks in the forecast of inflation is about four quarters; and (v) a counterfactual scenario where forecasts during the financial crisis in 2009 were assumed to be correct would have resulted in a lower level of inflation in the subsequent quarters.

The model and analysis in this paper are applicable to (macroeconomic) variables that are likely to react to forecasts. The impacts of forecasts of other key variables is a topic for future study. Furthermore, the current assumption is that the reaction to one-step-ahead forecasts takes place in the next quarter. However, in actual fact, agents' reactions may be slow. Hence, today's forecast may lead to regime changes in later quarters.

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Koen Bel obtained his Ph.D. degree in Econometrics at Erasmus University Rotterdam in 2015 and is currently researcher and consultant at Erasmus Q-Intelligence, Erasmus School of Economics, Erasmus University Rotterdam, The Netherlands.

Richard Paap is professor in Econometrics at Econometric Institute, Erasmus University Rotterdam. He has publications in several econometric, economic and statistical journals and is coauthor of two econometric textbooks.