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ENDOGENOUS MONETARY POLICY REGIMES
AND THE GREAT MODERATION

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Abstract

This paper contributes to the literature on the changing transmission mechanism of monetary policy by introducing a model whose parameter evolution explicitly depends on the conduct of monetary policy. We find that the model fits the data well, in particular when complemented with an estimated break around 1985 that could be associated with the re-gained credibility of the central bank. The responses of output and inflation to policy shocks change not only because of the break in 1985 but also according to the monetary policy stance: policy shocks have stronger negative effects when policy is tight. There is also evidence in favour of large changes in the volatility of the output equation, but not of inflation. A set of counterfactual experiments indicate that good policy and good luck contributed to the "great moderation", but neither of them can fully explain it. A more general variation in the model dynamics underlying the shock transmission mechanism is required.

1   Introduction

There is by now a vast literature on the relative role of good luck and good policy in determining the reduction in the volatility of key US macroeconomic aggregates, known as the "great moderation". In econometric terms, the debate is on whether changes in the parameters of the conditional mean of the variables matter more or less than changes in their conditional variances, and on how to model the pattern of time-variation. The conditional means have been modeled by means of VAR models in early contributions (e.g. Cogley and Sargent (2005), Sims and Zha (2006)) and of small scale DSGE models in more recent contributions (e.g., Justiniano and Primiceri (2008), Benati and Surico (2008), Inoue and Rossi (2009), Davig and Doh (2009), Bianchi (2009)). The pattern of time variation in the mean is captured either by slowly evolving parameters, typically modelled as random walks with small innovation variance, e.g. Cogley and Sargent (2005), or by abruptly changing parameters whose evolution is determined by an unobservable Markov chain, e.g., the Markov switching specification of Sims and Zha (2006), Davig and Doh (2009), Bianchi (2009). Time variation in the variance is typically modelled by means of a stochastic volatility specification, e.g., Sims and Zha (2006). While the results in the literature are mixed, overall there appears to be limited evidence of relevant changes in the conditional means, and more support for changing variance of the shocks. However, formal statistical tests to discriminate between the two hypotheses have in general low power (see e.g. the simulation results in Cogley and Sargent (2005)).

The contribution of our paper to this literature is that we explicitly link the parameter temporal evolution to the conduct of monetary policy. More specifically, since good monetary policy is typically associated to following a standard Taylor-type rule (e.g. Cecchetti et al. (2007)), we allow the parameters of the conditional mean and the conditional variance of key macroeconomic variables to vary depending on the extent of the deviation of actual monetary policy from that required by the adoption of the rule suggested by Taylor (1993). In other words, the model parameters can alternate depending on whether monetary policy is tight, neutral or loose, and the status of the policy is endogenously determined in the model, based on the distance of the actual interest rate from that required by the Taylor rule. Hence, in our model parameter time evolution is endogenously determined.

In addition, we allow for exogenous breaks in the parameters, since the consequences of monetary policy could depend not only on its stance but also on the credibility of the central bank and other factors, and it is difficult to explicitly model the latter. For example, a credible central bank can fight inflation with low output losses while a non credible central bank could suffer high output losses from adopting a tight monetary policy (e.g., Clarida, Gali and Gertler, (1999) and Goodfriend

and King (2005)). Hence, the dynamic responses of output and inflation to a monetary shock could differ not only when policy is loose or tight but also when it is credible or non credible.

In comparison with a range of specifications, our model fits the data quite well, and the main results we obtain are the following. First, there is strong evidence of an exogenous break in the parameters, whose date is estimated at 1985Q1. Interestingly, the credibility measure derived in Demertzis et al. (2008) steadily decreases from the early 70s until around 1985, and increases afterwards. The Laxton and Diaye (2002) credibility measure also shows a marked jump around 1985. Both measures are based on the fact that long-term inflation expectations should be anchored at the implicit or explicit inflation target of the central bank, when the latter is credible. The marked increase in both credibility measures in 1985 suggests that, notwithstanding the tight policy of the early '80s, it took some time to restore the central bank credibility lost in the '70s. This credibility interpretation of the break in 1985 is also supported by the fact that in our model changes in the policy rate during the restrictive regime have smaller effects on output and stronger negative effects on inflation after 1985. However, we are aware that there can be several other interpretations for the break in 1985, and therefore we stress that all our subsequent results are independent of our credibility interpretation of the 1985 break: in the model this break is treated as exogenous with an estimated timing.

Second, we find substantial evidence in favour of endogenous changes in the model parameters, triggered by the extent of the deviation of the actual interest rate from that prescribed by the Taylor rule. As a consequence, even when examining the transmission of monetary shocks with sizes that do not change with the regime, the computed responses suggest different transmission depending on whether the policy stance at the impact of the shock is loose, normal or tight. In particular, the reaction of output and prices to policy shocks is weaker in the loose regime. Moreover, and in contrast with models with only an exogenous break, we find evidence that restrictive monetary policy has a significantly negative effect on output and prices when the policy shock arises during the tight regime, even when considering the period after 1985. These differences in the monetary transmission depending on the policy stance are stronger after the break estimated in 1985.

Third, these detected differences in monetary transmission are complemented by significant shifts in the sizes of monetary policy shocks. The shifts in the variance-covariance matrix of the model disturbances are caused not only by the exogenous break, but also depending on the monetary policy stance. Before 1985, the volatility of output shocks during the loose policy of the '70s is twice as large as in the period of tight policy in the early '80s. Similarly, after 1985, the volatility of output when the policy rate is close to the value suggested by the Taylor rule is twice as large as in periods of tight policy. The model also captures a large decrease in the size of monetary policy

shocks after 1985, as well as differences related to the monetary policy stance.

Finally, a set of counterfactual experiments suggests that tight monetary policy is helpful in reducing growth volatility and the level of inflation. However, this is not sufficient to explain what happened to the US growth and inflation after 1985. The reduction in the volatility of the shocks ("good luck") is also not a sufficient explanation, according to our model, since using the pre-85 parameters with the post-85 shocks still generates substantial growth volatility and inflation after 1985. What is needed is a more general change in the model parameters, namely, in the contemporaneous and dynamic transmission of the shocks. This could be related to the increased credibility of monetary policy after 1985, or to other factors underlying the break in 1985, whose investigation is left for future research.

The rest of the paper is organized as follows. Section 2 discusses the theoretical model specification and estimation, and the method to compute (regime dependent and independent) impulse response functions and their standard errors. Section 3 presents empirical results on model specification, estimation, timing of the regimes and patterns of parameter time-variation. Section 4 illustrates the changing propagation of monetary shocks before and after 1985 and across policy regimes. Section 5 contains counterfactual analyses and discusses their implications for the debate on the sources of the great moderation. Section 6 summarizes and concludes.

2   The Model

This section describes our endogenous threshold VAR model and how to compute impulse response functions from this model; shows how to introduce additional exogenous breaks in the specification; and discusses how to determine the transition variable and the number of regimes.

2.1   Endogenous Threshold VARs

2.1.1   Specification and estimation

The model employed in this paper is a modification of Tsay's (1998) Threshold VAR. The main characteristic of the model in comparison with Markov-Switching specifications is that the variable that triggers regime switching is observed. This feature makes regime chagnes easier to interpret and estimation simpler, without loosing in terms of generality of the specification.

The threshold VAR specification of Tsay (1998) is a multivariate version of Self-Exciting Threshold Models (Tong, 1990). As a consequence, the variable that triggers the regime switching is one of the endogenous variables in the VAR. In contrast, our Endogenous Threshold Vector Autoregressive Model (ET-VAR) employs a combination of endogenous variables as transition variable.

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The combination of endogenous variables is computed using known (not estimated) weights, while the values of the transition variable that trigger the regime changes are endogenously estimated.[1]

Let us group the (endogenous) variables of interest observed at time t into the $m \times 1$ vector y_t, and label the transition variable as x_t. Recall that x_t contains a combination of endogenous variables. The ET-VAR is:

$$
y_t = \begin{cases} \phi_0^{(1)} + \sum_{i=1}^{p} \Phi_i^{(1)} y_{t-i} + \varepsilon_t^{(1)} \text{ if } x_{t-1} \leq c_1 \\ \phi_0^{(2)} + \sum_{i=1}^{p} \Phi_i^{(2)} y_{t-i} + \varepsilon_t^{(2)} \text{ if } c_1 < x_{t-1} \leq c_2 \\ \phi_0^{(3)} + \sum_{i=1}^{p} \Phi_i^{(3)} y_{t-i} + \varepsilon_t^{(3)} \text{ if } x_{t-1} > c_2 \end{cases} , \tag{1}
$$

where $\phi_0^{(r)}$ is an $m \times 1$ vector of intercepts for regime r $(r = 1, 2, 3)$, $\Phi_i^{(r)}$ is an $m \times m$ matrix of coefficients of lag i $(i = 1, ..., p)$, and c_1 and c_2 are (unknown) threshold values. Each regime has a specific full variance-covariance matrix, that is, $E(\varepsilon_t^{(r)} \varepsilon_t^{(r)\prime}) = \Sigma^{(r)}$, and we suppose that $\varepsilon_t^{(r)} \sim N(0, \Sigma^{(r)})$.

If the threshold values were known, the observations of the transition variable x_t combined with the threshold values could be used to split the sample of y_t and $(y_{t-1}, ..., y_{t-p})$ into subsamples (for $t = p + 1, ..., T$). Hence, the usual least squares formulae could be applied to obtain the estimates of the coefficient matrices and of the variance-covariance matrices, which are also equivalent to the maximum likelihood estimates of this reduced form model. However, the thresholds have also to be estimated. Following Galvão (2006), we use conditional maximum likelihood since it is an adequate estimation method (based on a Monte Carlo exercise) when the $\Sigma^{(r)}$ may differ across regimes. Hence, estimates of the unknown thresholds are obtained as:

$$
\hat{c}_1, \hat{c}_2 = \min_{\substack{c_1 \epsilon C_1 \\ c_2 \epsilon C_2}} \left[\frac{T_1}{2} \log |\hat{\Sigma}^{(1)}(c_1, c_2)| + \frac{T_2}{2} \log |\hat{\Sigma}^{(2)}(c_1, c_2)| + \frac{T_3}{2} \log |\hat{\Sigma}^{(3)}(c_1, c_2)| \right] , \tag{2}
$$

where $|\hat{\Sigma}^{(r)}|$ is the determinant of the estimated variance-covariance matrix computed as $\hat{\Sigma}^{(r)} = 1/T_r \sum_{t=1}^{T_r} \varepsilon_t^{(r)} \varepsilon_t^{(r)\prime}$, and T_r is the number of observations in each regime. The variance-covariance matrix is computed for each combination of threshold values in a grid, $\hat{\Sigma}^{(r)}(c_1, c_2)$, since if the threshold is known, least squares formulae can be used to estimate the coefficient matrices. The grid of threshold values is built based on restrictions on the minimum proportion of observations in each regime (Hansen, 2000). In the case of a model with three regimes, the value of one of the thresholds affects the grid of values available for the second threshold, so there is a large number of possible combinations that satisfy the restrictions on a given proportion of observations in each

---

[1]In our case the transition variable cannot be non-stationary (as Caner and Hansen (2001)), since we want to allow for the regimes to be possibly repeated over time. As a consequence, the transition variable cannot be a time trend, for example, since regimes defined by a time trend do not repeat over time, they just define structural breaks and subsamples.

regime. In this paper, we use the approach described by Hansen (1999), called "one-step-at-time", to reduce the computational burden.

Given the estimated thresholds, the remaining parameter estimates are obtained using standard OLS formulae. This procedure is equivalent to estimation by minimization of

$$\left[\frac{T_1}{2} \log |\hat{\Sigma}^{(1)}(\hat{c}_1, \hat{c}_2)| + \frac{T_2}{2} \log |\hat{\Sigma}^{(2)}(\hat{c}_1, \hat{c}_2)| + \frac{T_3}{2} \log |\hat{\Sigma}^{(3)}(\hat{c}_1, \hat{c}_2)| \right]. \tag{3}$$

Note that this analysis is conditional on the choice of the transition variable, x_t, and of the lag length, p. We will discuss their selection in the last subsection.

2.1.2 Impulse Response Functions for Endogenous Threshold VARs.

An implication of the ET-VAR is that the responses to shocks are regime dependent. More precisely, the transmission of the shock relies on $\Phi_i^{(r)}$, $i = 1, ..., p$, and the impact of the shock on $\Sigma^{(r)}$, following eq. (1). In addition, the dynamic response to the shock can trigger a change in regime. Hence, the computation of the response functions and their standard errors can be fairly more complex than in the linear case, and the results quite different. We will now provide details on the required procedure.

To start with, let us suppose that each regime defines separate subsamples, as in the case of structural break models, such as Boivin and Giannoni (2006). We could then use a Cholesky decomposition conditional on the regime to identify the regime-specific structural shocks, $v_t^{(r)}$:

$$v_t^{(r)} = A^{(r)-1} \varepsilon_t^{(r)}, \tag{4}$$

where $\Sigma^{(r)} = A^{(r)} \Lambda^{(r)} A^{(r)\prime}$, $A^{(r)}$ is a lower triangular matrix with ones on the main diagonal, and $\Lambda^{(r)}$ is a diagonal matrix whose elements, $\lambda^{(r)}$, are the variances of the structural shocks $v_t^{(r)}$. The dynamic response to a one-unit structural shock is:

$$IRF_{r,j,s}^{cond} = \frac{\delta y_{t+s}}{\delta v_{j,t}^{(r)}} = \Psi_s^{(r)} a_j^{(r)}, \tag{5}$$

where $j = 1, ..., m$, s indicates the response horizon ($s = 1, ..., h$), $a_j^{(r)}$ is the jth column of $A^{(r)}$(Hamilton, 1994, p. 92 and 323), and $\Psi_s^{(r)}$ is the proper matrix in the MA(∞) representation obtained by inverting the $VAR(p)$ conditional on being in the regime r.

When computing the conditional impulse response as described, the implicit assumption is that a structural shock cannot not cause regime-switching. However, in practice regimes can change, since the transition variable is a combination of endogenous variables affected by the shock. The computation of dynamic responses that take into account the endogeneity of the regime switching of the ET-VAR is more complex. In fact, nonlinear models in general admit a Wold representation

(e.g., Potter (2000)), but it is not possible to derive the MA(∞) representation of an ET-VAR unconditional on the regime.

To compute unconditional dynamic responses, we must consider, for example, that a shock $v_{j,t}^{(r)}$ impacting the system in regime 1, that is, $x_t \leq c_1$, could generate an effect such that $x_{t+s-1} > c_1$ (so that the system switches to regime 2 in period $t + s$) or even $x_{t+s-1} > c_2$ (switch to regime 3). Moreover, whether or not the switch takes place depends not only on the impact and dynamic response to the shock, but also on the current and past values of the endogenous variables (since there is dependence on the past trough the VAR dynamics). Hence, contrary to the standard linear case, the history preceding the shock matters to determine its effects, and has to be considered for the computation of the dynamic responses. Finally, the realizations of the future shocks are also relevant, since they can also cause a regime change.

To compute the proper dynamic responses from the ET-VAR model, we make use of the concept of generalized responses introduced by Koop, Pesaran and Potter (1996). The response in period $t + s$ of regime r to a shock of size $\lambda_j^{(r)}$ hitting in $t + 1$ is:

$$IRF_{r,j,s} = E\left(y_{t+s}|\Omega_t^{(r)}, v_{j,t+1}^{(r)} = a_j^{(r)}\right) - E\left(y_{t+s}|\Omega_t^{(r)}\right), \tag{6}$$

where $\Omega_t^{(r)}$ is a matrix containing the set of relevant histories. More precisely, let us define $W_t = (y_t, ..., y_{t-p+1})$, and $\Omega_t = ((W_t, ..., W_T)')$. We then partition the matrix Ω_t so that $\Omega_t^{(r)}$ has the rows of Ω_t that correspond to regime r. Hence, $\Omega_t^{(r)}$ has dimension $T_r \times p$. The assumption that $v_{j,t+1}^{(r)} = a_j^{(r)}$ implies that the impact of the shock computed with the unconditional responses is the same as in the case of conditional responses.

The response to a shock with the definition in (6) is computed conditional on a specific regime history at the time of the shock with no restrictions on regime switches, and averaging out the effects of future shocks, which affect similarly both conditional means. The cost is that the conditional means in (6) cannot be evaluated analytically but need to be computed by simulation, using the following procedure.

Based on the estimates of $\Phi_i^{(r)}$ and of the thresholds, we can draw an $s \times m$ vector from each $N(0, \Sigma^{(r)})$ (for $r = 1, 2, 3$) such that sequences of $y_{t+1}^*, ..., y_{t+s}^*$ can be computed using one row of $\Omega_t^{(r)}$ as initial value. The $IRF_{r,j,s}$ will be the difference between two average sequences of $y_{t+1}^*, ..., y_{t+s}^*$: one with $v_{j,t+1}^{(r)} = a_j^{(r)}$ and the other with $v_{j,t+1}^{(r)} = 0$. By using the same draws from each $N(0, \Sigma^{(r)})$ to compute both conditional means, we guarantee that the only difference between them is the effect of the structural shock at $t+1$. Note also that the $IRF_{r,j,s}$ is the average across all vector of histories in $\Omega_t^{(r)}$. This means that if $T_j = 50$ and we draw 1000 times from $N(0, \Sigma^{(r)})$, the $IRF_{r,j,s}$ is computed using the average across $50 * 1000$ replications. Finally, notice that the size/sign of

the shock also matters in this context, since it can trigger a regime change. Hence, responses can differ across regimes both for the size of the shock and for its transmission to the economy.

2.1.3 Standard Errors for the Impulse Response Functions

Another important issue to be addressed is the impact of parameter uncertainty on the impulse response functions. This means that we would like to assess the impact of using $\hat{\Phi}_i^{(r)}$, $\hat{\Sigma}^{(r)}$, $\hat{c}_1$ and $\hat{c}_2$ obtained by conditional maximum likelihood when computing $IRF_{r,j,s}$. The normal distribution is a good approximation for that of $\hat{\Phi}_i^{(r)}$ and $\hat{\Sigma}^{(r)}$, provided that the threshold effect vanishes asymptotically, but the distribution of the threshold estimates is non-standard (Hansen, 2000). Therefore, we use the bootstrap to compute $100(1-\alpha)\%$ confidence intervals for the impulse response functions.

Let us label $\widehat{IRF}_{r,j,s}$ the impulse response function based on the conditional maximum likelihood estimates $\hat{\Phi}_i^{(r)}$, $\hat{\Sigma}^{(r)}$, $\hat{c}_1$ and $\hat{c}_2$. As described by Canova (2007, p. 134), a typical issue in applying the bootstrap to compute confidence intervals for impulse responses obtained from linear models is that the bootstrapped distributions are not scale invariant, implying that standard error bands may not include the point estimates. In addition, VAR estimates using small samples are severely downward biased. Unfortunately, techniques of bias correction such as those described in Kilian (1998) cannot be applied since the uncertainty in the ET-VAR parameters depends strongly on the uncertainty about the threshold estimation, while the empirical distribution of the threshold estimates may be quite asymmetric (Kapetanios, 2000).

Our bootstrap approach attempts to solve some of these issues. The first step is to draw with replacement sequences of length $T-p$ from all $\varepsilon_t^{(r)}$ ($r=1,2,3$), and use the estimates $\hat{\Phi}_i^{(r)}$, $\hat{\Sigma}^{(r)}$, $\hat{c}_1$ and $\hat{c}_2$ and initial values of y_t ($t=1,...,p$) to generate bootstrapped sequences of $y_{p+1}^{**},...,y_T^{**}$. For each of these sequences, conditional maximum likelihood is applied to obtain estimates of all the parameters, that is, $\hat{\Phi}_i^{**(r)}$, $\hat{\Sigma}^{**(r)}$, $\hat{c}_1^{**}$ and $\hat{c}_2^{**}$. Using these parameters and the specific bootstrapped sequence, we compute $IRF_{r,j,s}^{**}$ using the simulation procedure described previously. By repeating the bootstrapped procedure B times, an empirical distribution for the $IRF_{r,j,s}$ is obtained.

Using the B values of $IRF_{r,j,s}^{**}$, we compute $\mu_{IRF_{r,j,s}^{**}} = 1/B \sum_{b=1}^{B} IRF_{r,j,s,b}^{**}$ and the empirical quantiles $q_{IRF_{r,j,s}^{**}}^{\alpha/2}$ and $q_{IRF_{r,j,s}^{**}}^{(1-\alpha/2)}$ for $100(1-\alpha)\%$ confidence intervals. Using the empirical quantiles and the empirical mean of the impulse response function, the range of the $100(1-\alpha)\%$ confidence intervals is computed, that is, $rg_{LO} = abs(q_{IRF_{r,j,s}^{**}}^{\alpha/2} - \mu_{IRF_{r,j,s}^{**}})$ and $rg_{UP} = abs(q_{IRF_{r,j,s}^{**}}^{(1-\alpha/2)} - \mu_{IRF_{r,j,s}^{**}})$. As a result, centred confidence intervals, but potentially asymmetric and skewed, can be computed as $\left\{ \widehat{IRF}_{r,j,s} - rg_{LO}; \widehat{IRF}_{r,j,s} + rg_{UP} \right\}$. We emphasize that these intervals consider uncertainty on both coefficient and threshold estimates.

2.2 Endogenous Threshold VARs with a Break

There is by now strong statistical evidence on the existence of a "Great Moderation" in the variance of output and several other macroeconomic variables at around 1985 (e.g., McConnell and Perez-Quiros (2000), Sensier and van Dijk (2004)). Hence, it may be necessary to add an additional break in the specification of our ET-VAR, in order to capture parameter changes associated with the Great Moderation that are not explained by monetary policy stances. Since it is not clear whether the enhanced credibility of monetary policy or other phenomena underlie the Great Moderation, we prefer not to model the determinants of this additional break in the model parameters, but rather treat the break as exogenous, while its timing is endogenously determined.

Therefore, following Galvão (2006), we introduce a Structural Break-Endogenous Threshold-VAR model (SB-ET-VAR). In this model, the break date is estimated rather than exogenously assumed, since the exact starting date of the Great Moderation is uncertain, and the characteristics of the regimes and how regimes switch can also change after the break.

To simplify the notation, assume that $Y_{t-1} = (1, y_{t-1}, ..., y_{t-p})$ and $F^{(r)} = (\phi_0^{(r)\prime}, \Phi_1^{(r)}, ..., \Phi_p^{(r)})$ such that the ET-VAR can be written as:

$$
\begin{aligned}
y_t &= \left[(F^{(1)\prime} Y_{t-1} + \varepsilon_t^{(1)}) I\left(x_{t-1} \leq c_1\right) \right] + \left[(F^{(2)\prime} Y_{t-1} + \varepsilon_t^{(2)}) I((x_{t-1} > c_1)\,(x_{t-1} \leq c_2)) \right] \\
&\quad + \left[(F^{(3)\prime} Y_{t-1} + \varepsilon_t^{(3)}) I\left(x_{t-1} > c_2\right) \right],
\end{aligned}
$$

where $I(.)$ is an indicator function that is equal to one if the inequality is true. The inclusion of a break in the model, which yields our SB-ET-VAR specification, implies that:

$$
y_t = \left\{
\begin{array}{c}
\left[(F^{(1)\prime} Y_{t-1} + \varepsilon_t^{(1)}) I\left(x_{t-1} \leq c_1\right) \right] + \left[(F^{(2)\prime} Y_{t-1} + \varepsilon_t^{(2)}) I((x_{t-1} > c_1)\,(x_{t-1} \leq c_2)) \right] \\
+ \left[(F^{(3)\prime} Y_{t-1} + \varepsilon_t^{(3)}) I\left(x_{t-1} > c_2\right) \right]
\end{array}
\right\} I(t \leq b) +
$$

$$
\tag{7}
$$

$$
\left\{
\begin{array}{c}
\left[(F^{(4)\prime} Y_{t-1} + \varepsilon_t^{(4)}) I\left(x_{t-1} \leq c_3\right) \right] + \left[(F^{(5)\prime} Y_{t-1} + \varepsilon_t^{(5)}) I((x_{t-1} > c_3)\,(x_{t-1} \leq c_4)) \right] \\
+ \left[(F^{(6)\prime} Y_{t-1} + \varepsilon_t^{(6)}) I\left(x_{t-1} > c_4\right) \right]
\end{array}
\right\} I(t > b).
$$

The SB-ET-VAR is an ET-VAR in each of the two subsamples defined by the break date, b. The values of the thresholds before the break are different from the values after the break. Hence, the regimes defined by the thresholds c_1 and c_2 may repeat until $t \leq b$. When $t > b$, the threshold values are c_3 and c_4. The autoregressive coefficients $F^{(r)}$ and the variance-covariance matrix $\Sigma^{(r)}$ may differ for $r = 1, ..., 6$.

Galvão (2006) provides Monte Carlo evidence that supports joint estimation of the thresholds and the break date by maximum likelihood, when there are large changes in the variance of the shocks across regimes. For each possible value of b in a grid, the sample is split and an ET-VAR

is estimated in each resulting subsample, by solving the grid minimization problem defined by (2), using the sequential approach to define the threshold grids. The grid of b ($b\epsilon(b_L, b_U)$) has to be defined such that there is a reasonable number of observations in each regime for the ET-VAR to be estimated. Formalizing:

$$\hat{b}, \hat{c}_1, \hat{c}_2, \hat{c}_3, \hat{c}_4 = \min_{\substack{b_L \leq b \leq b_U \\ c_1 \epsilon C_1 \\ c_2 \epsilon C_2 \\ c_3 \epsilon C_3 \\ c_4 \epsilon C_4}} \left[\begin{array}{c} \frac{T_1}{2} \log |\hat{\Sigma}^{(1)}(c_1, c_2)| + \frac{T_2}{2} \log |\hat{\Sigma}^{(2)}(c_1, c_2)| + \frac{T_3}{2} \log |\hat{\Sigma}^{(3)}(c_1, c_2)| \\ \frac{T_4}{2} \log |\hat{\Sigma}^{(4)}(c_3, c_4)| + \frac{T_5}{2} \log |\hat{\Sigma}^{(5)}(c_3, c_4)| + \frac{T_6}{2} \log |\hat{\Sigma}^{(6)}(c_3, c_4)| \end{array} \right]. \quad (8)$$

Finally, when computing impulse responses for SB-ET-VAR models, we apply the procedure described in Section 2.1 for each subsample separately.

2.3 Choosing the Number of Regimes and Transition Variables

The vast literature on choosing the number of thresholds and break dates relies on test statistics with non-standard distributions (e.g., Andrews (1993), Hansen (1996)), or on sequential procedures associated with asymptotic bounds (e.g., Altissimo and Corradi (2002), Gonzalo and Pitarakis (2002)). These methods are typically applied to univariate models, but they can be extended to multivariate models estimated by conditional least squares when changes in the variance of the disturbances across regimes are not important. In our application, changes in the variance-covariance matrix across regimes are instead potentially important, and the estimation procedure in (8) takes them into explicit account. As a consequence, the use of testing procedures based on the full sample sum of squared errors may be misleading. In addition, the sample size we have is rather short considering that we may have up to six different regimes, so that formal test statistics can be expected to have low power (see e.g. Cogley and Sargent (2005) in a related context).

An alternative simple approach is to use information criteria based on a penalised likelihood function, where the penalty depends on the number of estimated parameters, to compare specifications that differ for the assumed number of breaks and regimes. The same method can be also adopted for the selection of the transition variable, among the members of a pre-specified set.

We consider only the parameters in $F^{(r)}$ when computing the penalty function, as in Altissimo and Corradi (2002) and Gonzalo and Pitarakis (2002). Therefore, the inclusion of a further regime in the model requires the estimation of $m(mp + 1)$ additional parameters. The penalty function can be $2K/T$ (AIC), $2\log(\log(K))/T$ (HQC) or $\log(K)/T$ (SIC), where K is number of estimated parameters. Altissimo and Corradi (2002) suggest the HQC penalty to choose the number of regimes in a threshold model, while Gonzalo and Pitarakis (2002) suggest SIC. For comparison, we will compute all the three criteria, and use them also for the selection of the transition variable x_t,

which does not affect the penalty function but the value of the likelihood.

3 Model specification and estimation results

3.1 The Benchmark Model

The SB-ET-VAR model is built upon a small monetary VAR model, along the lines of Rudebusch and Svensson (1999), Cogley and Sargent (2005) or Boivin and Giannoni (2006). We focus on three endogenous variables: aggregate output, prices, and the policy interest rate. We use real GDP as the output variable, the PCE index as the price variable, and the FED fund rate as the policy interest rate. Output and prices are measured in log-levels (100*log). This implies that $y_t = (GDP_t, p_t, i_t)'$. We consider quarterly data for the period 1960-2008.

One of our aims is to check whether the stance of monetary policy can change the transmission of monetary policy shocks to output and prices. We identify policy shocks by means of a Cholesky decomposition based on the ordering $y_t = (GDP_t, p_t, i_t)'$, which assumes that it takes at least one quarter for monetary policy shocks to affect output and prices, with current values of prices and output affecting current monetary policy decisions.

As a starting point, Figure 1 presents the responses to the monetary shock in the full sample and in the two subsamples defined by a popular break date in the literature: 1985:Q1.[2] The responses before the break are familiar: an increase in interest rate decreases output and prices, but the effect on output is faster than on prices: output starts decreasing after a few quarters, prices after about two years. After the 1985 break, the size of the monetary policy shocks reduces dramatically, from about 100 to 25 basis points, the effect on prices becomes smaller and generally positive, and the effect on output is smaller, not statistically significant, and taking place after about 2 years. These findings are broadly consistent with those in Boivin and Giannoni (2006), though they split the sample in 1979 and use slightly different variables. If the VAR is estimated over the entire sample, there is a massive price puzzle, while the reactions of output and the dynamics of the interest rate are a mixture of those observed over the two subsamples. This finding suggests that a constant parameter model is not appropriate.

A potential weakness of the VAR specification with a break is the limited information set used to identify the monetary policy shock, since only three variables are employed. However, the fact that the shock has the expected effects on output and prices before 1985 suggests that this is not such a major problem. The cause of the counterintuitive results after 1985 could instead be due to

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[2]These results are based on a lag length of $p = 2$, which is the autogressive order chosen by HQC and AIC for both subsamples.

a modification of the VAR parameters, including the variance-covariance matrix of the shocks. In addition, even within each of the two subsamples the results could differ, depending for example on the monetary policy stance or on the business cycle conditions. Modelling the variables with our SB-ET-VAR could address these issues and improve our understanding of the effects of monetary policy.

3.2   Choosing a SB-ET-VAR Specification

An important step in specifying SB-ET-VAR models is the selection of the transition variable. Cechetti et al (2007) employ changes in the sign and size of the deviations from the Taylor rule as a measure of changes in the stance of the monetary policy. The time series of the deviations from the Taylor rule is then employed to assess whether changes in monetary policy can explain the great moderation in a group of countries. We use a similar measure as the first possible specification for the transition variable. Specifically, we define the deviations from the Taylor rule as:

$$x_t = 1 + 1.5(p_t - p_{t-4}) + 0.5(GDP_t - GDP_{t-4}) - i_t. \tag{9}$$

Our interpretation of using equation (9) as transition variable in the SB-ET-VAR is that x_t indicates how monetary policy should have been conducted, while the interest rate equation of the VAR tracks the actual monetary policy. If actual monetary policy followed exactly the Taylor rule underlying (9), the dynamics of the VAR could be described by a single regime. Instead, switches in the sign and size of x_t indicate that actual monetary policy evolves over time, being in some periods in line with the Taylor rule, and in other periods either looser or tighter than requested.

Two other possible choices for the transition variable in the SB-ET-VAR are the real interest rate, $x_t^a = i_t - (p_t - p_{t-4})$, and the growth rate of output, $x_t^b = (GDP_t - GDP_{t-4})$. The real interest rate provides another measure of the stance of monetary policy, without considering the economic activity; it can be considered as a policy rule that depends only on inflation. Both x_t and x_t^a were assessed by Gali (2008) within the context of a simple new-keynesian model. The output growth rate is a typical transition variable employed when measuring the effects of business cycle phases (expansions/contractions) on the responses to shocks.

A second key requirement for the specification of SB-ET-VAR models is to understand how many regimes are needed, and whether a simplified version without either the SB or the ET component would suffice. Note that the SB-VAR specification is similar to the split-sample benchmark model reported above, but with an estimated rather than a priori imposed break date.

Focusing first on the Taylor rule based transition variable, we compare a full sample VAR, an ET-VAR model with 2 or 3 regimes, an SB-VAR model with 2 or 3 regimes, and an SB-ET-VAR

model with one break and 2 or 3 regimes in the ET component (for a total of 4 and 6 regimes, respectively). When defining the grid to estimate the models with thresholds and breaks, we set restrictions based on the minimum proportion of observations in each regime in a given subsample. Specifically, we consider 15% or 30% proportions.[3] The two upper panels of Table 1 report information criteria for all these alternative specifications.

It turns out that the benchmark model with just one break (SB-VAR with 2 regimes) fits really well the data in comparison with a full sample VAR. The ET-VAR with three regimes is also better than the VAR, that is, there is evidence of endogenous regime switches when using the Taylor rule as transition variable. However, the SB-VAR is preferred to the ET-VAR. Putting together the break and threshold features to obtain the SB-ET-VAR model with six regimes yields the lowest AIC and HQC when at least 15% of observations are allowed in each regime. With 30% of observations, the SB-ET-VAR is best according to the AIC. In both cases, the other criteria are minimized by the SB-VAR with two regimes, that is close to the benchmark specification. However, as we will see, the SB-ET-VAR generates interesting differences in the shock responses within each of the two subsamples identified by the SB specification, and responses more in line with economic theory. Hence, we will adopt an SB-ET-VAR specification with one break and two thresholds (6 regimes).

When the SB-ET-VAR specification is estimated with either the real interest rate or output growth as transition variables, all the information criteria are higher than those corresponding to the Taylor rule based transition variable, x_t in equation (9), see the lower panel of Table 1. Hence, we will continue our analysis based on an SB-ET-VAR model with x_t as the transition variable.

A final interesting issue to consider is whether our approach manages to capture the heteroscedasticity usually found in the residuals of similar VAR models (Primiceri, 2006). We can test for remaining conditional heteroscedasticity by regressing the squared residuals from the (6-regime) SB-ET-VAR on dummies representing changes in the variance for each regime, and on lagged squared residuals. Under the null hypothesis of no remaining heteroscedasticity, an F-test for the non-significance of the coefficients of the lagged squared residuals should not reject. The results presented in Table 2 suggest no evidence of remaining heteroscedasticity in the output and price equations. There is instead some evidence of heteroscedasticity in the interest rate equation, but a split sample analysis reveals that it is a characteristic of the pre 1985 period only. Based on this analysis, we can conclude that our SB-ET-VAR captures sufficiently well also changes in the variances of the shocks affecting the three variables under analysis.

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[3]In the case of an SB-ET-VAR model, this restriction applies separately for each subsample. Other papers in the literature normally set the proportion equal to 10 or 15%. However, because of the relative short sample size and the impact that parameter estimates have on impulse responses, we also consider at least 30% of observations in each regime (which in a SB-ET-VAR model means 10% of T observations in each regime).

3.3 The Chronology of Regimes

In this subsection we discuss three main results. First, the break date for the SB-ET-VAR, which was estimated in 1985Q1. Second, the estimates of the thresholds, which are $\hat{c}_1 = 1.68$ and $\hat{c}_2 = 3.92$ before the break and $\hat{c}_3 = .18$ and $\hat{c}_4 = 2.25$ afterward. Third, the time series of the Taylor rule deviations (x_{t-1} using (9)), and the regime-switching function defining the chronology of the (six) regimes.

About the break date, the endogenously determined date of 1985Q1 is slightly later than the tightening of monetary policy and of the beginning of the great moderation. Figure 2 shows that after 1985Q1 there is a major increase in the credibility of the monetary policy authority, according to both the Laxton Diaye (2002) and the Demertzis et al. (2008) credibility measures. We are aware of the existence of several other possible explanations for the break in 1985, such as learning by the policy makers, faster globalization, improvements in inventory management, etc. As mentioned, we do not want to investigate this issue further since we want to focus on the consequences of the monetary regime changes, and therefore we treat the break as exogenous. However, we believe that our proposed credibility based explanation for the identified break in 1985 is sensible and in line with the response functions that we will compute later on. In particular, a more credible central bank that implements a restrictive policy should incur lower output losses and be more successful in fighting inflation, see e.g. Goodfriend and King (2005), which is exactly what we find on average after 1985.

About the endogenously estimated thresholds, which induce switches in the monetary policy stance from loose to neutral and tight (and viceversa), it is noticeable that they are about 150 basis points lower after 1985. This implies, for example, that before 1985 a tight policy (regime 1) is associated with interest rate values that satisfy

$$i_t > 1.5(p_t - p_{t-4}) + 0.5(GDP_t - GDP_{t-4}) - .68 \ ,$$

while after 1985 (regime 4) it must be

$$i_t > 1.5(p_t - p_{t-4}) + 0.5(GDP_t - GDP_{t-4}) + 82 \ .$$

Therefore, for a given level of inflation and output growth, the interest rate must be about 150 basis points higher after 1985 for the policy to be classified as tight. In other words, what was considered a tight policy before 1985 could be no longer tight after 1985 but just neutral.

Similarly, a loose policy (regime 3) before 1985 requires

$$i_t < 1.5(p_t - p_{t-4}) + 0.5(GDP_t - GDP_{t-4}) - 2.92$$

while after 1985 (regime 6) it must be

$$i_t < 1.5(p_t - p_{t-4}) + 0.5(GDP_t - GDP_{t-4}) - 1.25$$

Hence, the interest rate should be much lower before 1985 for a policy to be considered as loose. Therefore, a loose policy after 1985 could have been considered neutral before 1985, and a neutral one tight.

Finally, the resulting chronology of regimes is plotted in Figure 3. It turns out that the tight monetary policy before 1985 (regime 1, $x_t < \hat{c}_1 = 1.68$) is mainly identified in the 1980-84 period, with some shorter episodes in the '60s, while the period of loose monetary policy (regime 3, $x_t > \hat{c}_2 = 3.92$) is largely associated with the 70's. After the 1985 break, it is harder to associate regimes with time periods, since the regime-switching is more frequent among all three regimes. However, the loose monetary policy (regime 6, $x_t > \hat{c}_4 = 2.25$) is mainly associated with the 2002-2006 period.

3.4   Time-varying estimates

We now discuss the estimated parameters of our SB-ET-VAR, starting with those of the conditional mean.

The three panels of Figure 4 report the evolution across regimes of the sum of the AR(1) and AR(2) estimated coefficients on GDP, prices and the interest rate for, respectively, the output, prices and interest rate equations.[4] We report the sum of the two coefficients rather than each of them separately in order to increase the readability. We have also standardized the values in order to make the relative sizes of the changes in parameters comparable across variables and equations. We use Figure 4 to evaluate whether parameter changes are concentrated in some key parameters or they are generalised.

Starting with the output equation, before 1985 there is little parameter movement across the loose, normal and tight regimes, while after 1985 there are large switches in all coefficients, with values also fairly different from those before 1985. A similar picture emerges for the price equation, while for the interest rate equation there are substantial differences across regimes also before 1985.

It is difficult to attribute a structural interpretation to the parameter movements at this stage, since the model is just a reduced form. However, Figure 4 suggests generalised changes in the conditional mean parameters both before and after 1985, and across regimes, even though the volatilities of the shocks are allowed to change over time.

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[4]The values are obtained from the estimates of $F^{(r)}$ in (8) for $r = 1, ..., 6$.

The next question we address is how much the variance of the shocks has changed, and whether the changes are only related to the great moderation or also to the monetary policy regimes. The upper panel of Figure 5 illustrates how the variance of the output shock was drastically reduced after 1985 (and we remember that in our model this date is endogenously determined rather than a priori imposed).[5] But there are also some interesting changes across regimes, in particular before 1985, with large values during the loose monetary policy period of the '70s in comparison with the tight regime in the beginning of the '80s. After 1985, the volatility of output when the current policy rate is in line with the Taylor rule (regime 5) is twice as large as during periods of tight policy (regime 4).

The reduction in the variance of the monetary shock after 1985 is even larger than that for the output shock, and also in this case the differences across regimes are more marked in the pre-1985 period. Interestingly, there are instead no major changes in the variance of the price shock.

The final question we address is whether the contemporaneous transmission of the output and price shocks to the interest rate has changed. The lower panel of Figure 5 reports the evolution of the relevant coefficients in the $A^{(r)}$ matrix (see section 2.2). The values are larger in absolute value and more volatile before 1985. After 1985 the role of output is approximately constant across regimes, while there are relevant swings in that of inflation.

In summary, this subsection provides evidence in favour of changes in the size of the shocks (in particular for output and the policy rate), in their contemporaneous transmission (in particular before and after 1985), and in their dynamic transmission, both before and after 1985 and across regimes. Hence, models that focus on changes in only one of these elements would have problems in properly estimating the consequences of monetary policy shocks.

4 The effects of monetary policy shocks across regimes

We now discuss how the effects of monetary policy have changed over time and across regimes, according to our estimated SB-ET-VAR model. In the previous section, we have detected substantial changes in the average size of the shocks that, due to the nonlinearity of the model, could by themselves determine also changes in their transmission. For example, a large shock can trigger more easily switches in regimes than a smaller shock. However, as argued by Boivin et al (2009), from an economic point of view it is more interesting and informative to focus on changes in the transmission of a monetary policy shock of a fixed size. Hence, Figures 6-8 present the dynamic response to a 25 basis point increase in the interest rate at time t of the interest rate (Figure 6),

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[5] The reported values are the estimates of the variances of the structural shocks $v_t(r)$ in (4), i.e., $\lambda_j^{(r)}$ for $r = 1, ..., 6$.

output (Figure 7) and prices (Figure 8).

The responses (black line) are computed as described in equation (6), that is, they are the average response over all histories from a specific regime allowing for regime-switching over the horizon of up to 20 quarters. All six regimes identified in the estimated SB-ET-VAR are represented in the figures. We recall that regimes 1 and 4 describe tight monetary policy before and after the 1985 break, while regimes 3 and 6 are associated with loose monetary policy. The plots also include 68% and 90% confidence intervals computed by the bootstrap procedure described in Section 2, and the responses computed without allowing for regime switching as a consequence of the shocks (eq. 5).

We use Figures 6-8 to answer two main questions. First, is there any statistical evidence in favour of significant differences in the transmission of shocks across regimes? Second, are there any changes in the transmission of shocks that can be associated with the "good policy" story?

With reference to the first question, Figures 6-8 present evidence that the transmission of monetary policy shocks is indeed affected by the monetary policy stance, in particular after 1985. In the tight regime (regime 4), the monetary shocks are substantially less persistent than in the loose regime 6 (marginal effect of .1 in contrast to .3 after 8 quarters). The effects on output and prices also differ, with a negative and significant reaction only in the tight regime. Before 1985, there are also some changes in the transmission across regimes, though less evident than after 1985. In particular, there is a reversion effect on the interest rate response in regimes 1 and 2 that is not observed in regime 3; a stronger negative effect on prices at long horizons in the tight regime in comparison with the loose regime; and a stronger effect on the output response after 8 quarters in the middle regime in comparison with the outer regimes.

About the second question, we also find some support for "good policy" as a driver of the great moderation. In particular, as mentioned before, Figure 3 illustrates that the early '80s were characterized by a long period of tight policy that likely re-established the credibility of the central bank, magnifying the effects of the continued tight policy after 1985 and up to about 1987 (again see Figure 3). Specifically, the dynamic response of the interest rate in the tight regimes 1 and 4 (Figure 6) are similar up to 8 quarters. However, the effects on prices and output are rather different. Before 1985, it takes 10 quarters to find evidence of a negative effect on prices, while this happens already after 1 quarter after 1985 (Figure 8). The transmission on output also changes. The negative effect on output is faster before 1985 than after 1985, although the marginal effect after 8 quarters (around -.3) is similar. Similar changes in the reaction of output and prices before and after 1985 are observed for the normal policy regimes 2 and 5, where the actual interest rate is close to that required by the Taylor rule.

In comparison with studies such as Boivin et al (2009), our model allows us to shift the focus from changes in the transmission of monetary policy shocks caused by changes of the chairman of the Federal Reserve Bank (around the end of 70's and beginning of the 80's) to endogenous changes caused by how strictly following a Taylor rule. The evidence provided in Figures 6-8 supports the claim that the monetary policy stance, measured by the size and sign of the deviations from the stabilizing Taylor rule, characterizes regimes where the same shock has a different effect on output, prices and the interest rate itself.

Finally, it is worth commenting on the responses that do not allow for a regime switch triggered by the dynamic transmission of the shock (the dashed lines in Figure 6-8). In a few cases, in particular during the loose regimes 3 and 6, they can be significantly different from the responses that we have commented so far. Hence, in order to avoid biased results, it is important to allow for the shock to trigger a change in regime rather than simply conditioning the responses on a given regime.

To conclude and summarize, using our SB-ET-VAR model, this Section has highlighted changes in the transmission of monetary policy shocks to output, inflation, and the interest rate itself, related to a different monetary policy stance. With fixed size shocks, there are statistically significant differences in shock tranmission across regimes only after 1985. However, when allowing also for the detected changes in shock size, the responses differ substantially across regimes even before 1985. In addition, the tight ("good") policy of the early and mid '80s contributed to the stabilization of inflation, by triggering a fast and negative impact of a restrictive policy on prices. We will further qualify this statement in the next section.

5   Counterfactual analysis

The previous Sections have shown that the contemporaneous and dynamic relationships across output, prices and interest rates are quite different before and after 1985 and across regimes of loose, normal and tight monetary policy. In this Section we speculate on what would have happened if a single monetary regime was in place over the entire sample period, or if the coefficients of a given regime did not change before and after 1985. The first type of experiment could shed light, for example, on what would have happened if the monetary policy followed rather closely a Taylor rule over the entire sample, a "good policy story". The second type of experiment would provide additional information about the role of the structural break in 1985, likely associated with the regained credibility of the central bank and often considered as the beginning of the great moderation.

Of course this kind of counterfactual analysis is open to a wide range of criticisms. Therefore, we do not want to provide any strong policy advice based on the results. We just think of these experiments as another useful way to analyze the properties of our SB-ET-VAR model, and to get information on the relative role of good policy and good luck in determining the lower volatility of output and the lower level and volatility of inflation after 1985.

Let us start with counterfactuals based on a single policy regime. From the computational point of view, we use the estimated coefficients from the regime of a given policy stance before and after 1985 (e.g., regimes 2 and 5 in the case of normal policy), the actual values for output, prices and interest rate in 1960Q1 and 1985Q1 as starting values, and then solve the model forward first for 1960Q2-1985Q1 and then for 1985Q2-2009Q1, adding in each period the estimated SB-ET-VAR residuals. In this way we obtain generated time series for the three variables, conditional on being always in a specific monetary policy stance. In Figure 9 we report the resulting series for output, prices and interest rate assuming normal policy for the entire period (small deviations from Taylor rule), together with the actual time series.

According to the upper panel of Figure 9, a Taylor rule based monetary policy would have increased the volatility of output during the 1960-1984 period, yielding in particular higher growth during the recoveries following the recessions of 1974 and 1981-82, and during the period 1978-79. The rationale for this positive growth result is the much lower interest rates resulting from the lower panel of Figure 9 around 1974 and 1981-82. But there is a cost: the much higher and persistent inflation during 1979-1984, see the middle panel of Figure 9. Interestingly, the interest rate spike in 1979-80 is compatible with a normal (Taylor rule based) policy, the difference is with the subsequent behaviour of the interest rate, which was kept at an higher level than that required by the Taylor rule (indeed the post 1980 period is identified as a tight regime, see Figure 3).

It is also important to mention that the decrease in inflation after 1985 resulting from Figure 9 is mostly due to the re-iniziatialization of the simulated series (based on the actual 1985Q1 value of inflation) and to the new set of parameters characterizing the normal regime (see Figure 4). In other words, without these changes, inflation would have remained at a higher level for a longer period. Hence, the parameter break in 1985 played an important role and good policy by itself (broadly following a Taylor rule) does not seem sufficient to lower inflation and the volatility of output.

Looking at the post 1985 period, being in a normal regime would have implied on average slightly lower interest rates over the 1995-2003 period, but higher ones afterwards (again in line with the timing of the regimes in Figure 3). Overall, there would have been slightly positive average effects on output, and no costs in terms of higher inflation.

Given the important consequences of the 1985 break emerging from the first type of counter-factual, we now consider an experiment that let us better assess its role. From the computational point of view, we use the estimated coefficients for the tight, normal and loose regimes before 1985 (including the estimated thresholds) for the entire sample period, actual values for output, prices and interest rate in 1985Q1, and then solve the model forward for the period 1985Q2-2009Q1, adding in each period the estimated SB-ET-VAR residuals. In this way we obtain generated time series for the three variables, conditional on the pre-1985 parameters but on the post-1985 shocks. The resulting series for output, prices and interest rate are reported in Figure 10.

If the Great Moderation, that is, the reduction in the volatility of output and inflation (and other variables), was purely due to "good luck", namely to smaller shocks, it should emerge from Figure 10, since the simulated values are based on the post-1985 shocks, whose variance is indeed smaller than in the pre-1985 period (see Figure 5). Instead, both the levels and the volatility of output and inflation are fairly close to the pre-1985 values, actually even higher.

The final exercise we consider is a mixture of the first two cases. Specifically, we use the pre-1985 parameters coming from the tight policy regime only, to simulate data for the post-1985 period, conditional on the post-1985 SB-ET-VAR residuals. The goal is to understand whether a tight policy enforced over the entire post-1985 period, combined with the smaller post-85 shocks, could have reduced the volatility of output and the level and volatility of inflation, in the absence of the parameter changes that took place around 1985. The results are reported in Figure 11.

A comparison of Figures 10 and 11 shows that the tighter monetary policy is indeed helpful in reducing the volatility of output and the level of inflation, but it is definitely not sufficient to replicate the actual behaviour, of growth, inflation, and the interest rate.

Overall, the lesson from this Section is that good monetary policy is helpful in reducing growth volatility and the level of inflation. However, this is not sufficient to explain what happened to the US growth and inflation after 1985. The reduction in the volatility of the shocks is also not a sufficient explanation, according to our model, since using the pre-85 VAR parameters with the post-85 shocks still generates substantial growth volatility and inflation after 1985. What is needed is a more general change in the VAR parameters, namely, in the contemporaneous and dynamic transmission of the shocks. This could be related to the increased credibility of monetary policy, or to other factors, whose investigation is beyond the scope of the present paper.

6 Conclusions

This paper contributes to the literature on the changing transmission mechanism of monetary policy by introducing a model whose parameter evolution explicitly depends on the conduct of monetary policy. More precisely, we model prices, aggregate output, and the policy interest rate with a structural break endogenous threshold VAR specification (SB-ET-VAR), whose parameters are subject to a structural break at an estimated date and to periodic changes related to how close or far the interest rate is from the level prescribed by the Taylor rule.

The resulting model, with a break in the first quarter of 1985 and three regimes in each of the subperiods identified by the break date, fits the data well. In addition, we find substantial evidence of changes both in the parameters of the conditional means of the three variables, and in the variances of the output and interest rate shocks.

The model generates responses of output and prices to monetary policy shocks changing not only before and after 1985 but also according to the monetary policy stance. Restrictive monetary policy has stronger negative effects on output before 1985, but takes time to reduce prices, even during the tight policy regime. After 1985, on average across regimes, the effects on output are smaller and prices decrease faster, particularly so during a tight or normal policy regime. These results suggest that the 1985 break could be associated with the regained credibility of the central bank, which makes monetary policy more effective in fighting inflation and less costly in terms of output loss. In addition, they indicate that good policy matters when the central bank is credible: after 1985 the FED could indeed decrease inflation with small output costs by increasing the interest rate.

A set of counterfactual experiments confirms that good monetary policy is helpful for reducing the level of inflation, and also the volatility of output growth. However, the extent of the reduction is not sufficient to explain what happened to the US growth and inflation after 1985. The reduction in the volatility of the shocks is also not a sufficient explanation, according to our model, since using the pre-85 VAR parameters with the post-85 shocks still generates substantial growth volatility and inflation after 1985.

Therefore, we conclude that good policy and good luck were relevant to explain part of the reduction in the level and volatility of inflation and growth. However, the bulk of the reduction seems to be due to a more general change in the model parameters, namely, in the contemporaneous and dynamic transmission of the monetary shocks and output and inflation. We suggest that the change is related to the regained credibility of the FED, but this is an issue that deserves additional investigation in future research.

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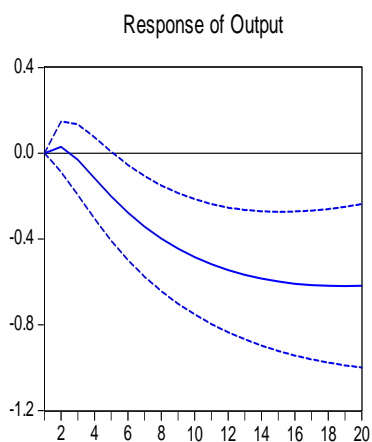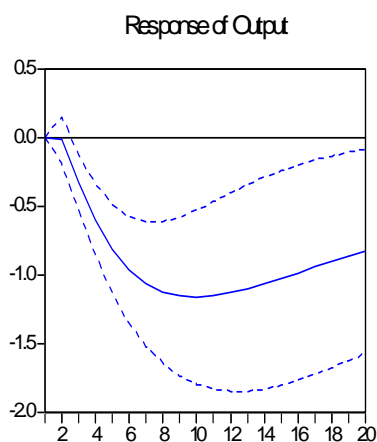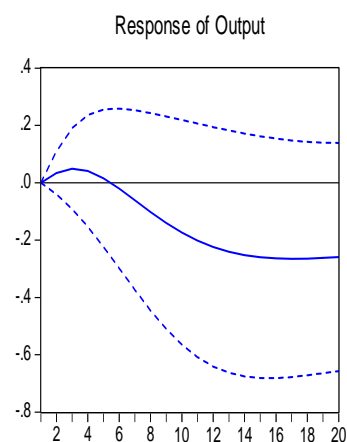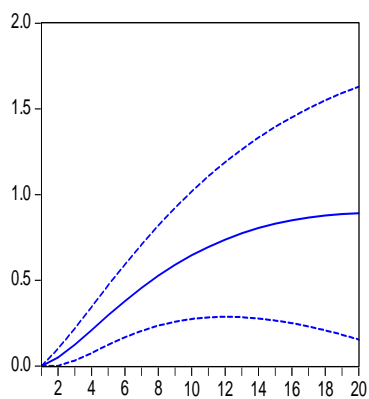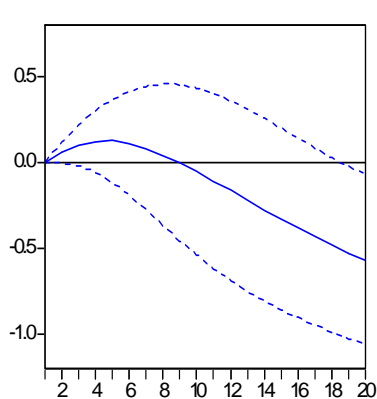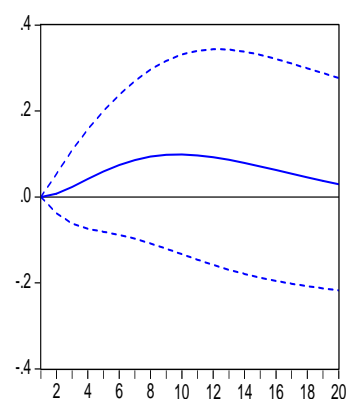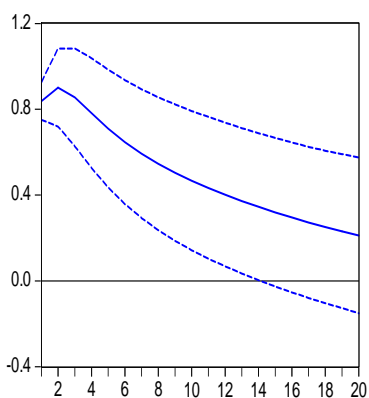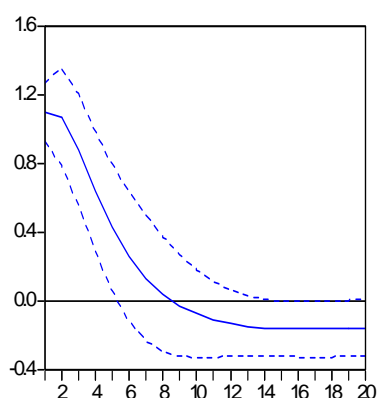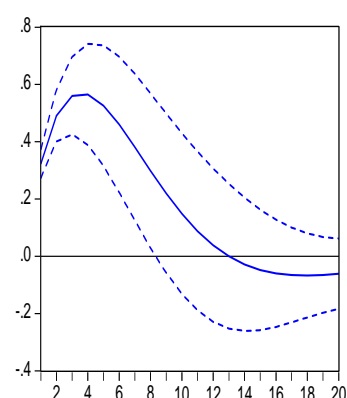
Figure 1: The effects of (one-standard deviation) monetary policy shocks in a constant parameter VAR and in a SB-VAR
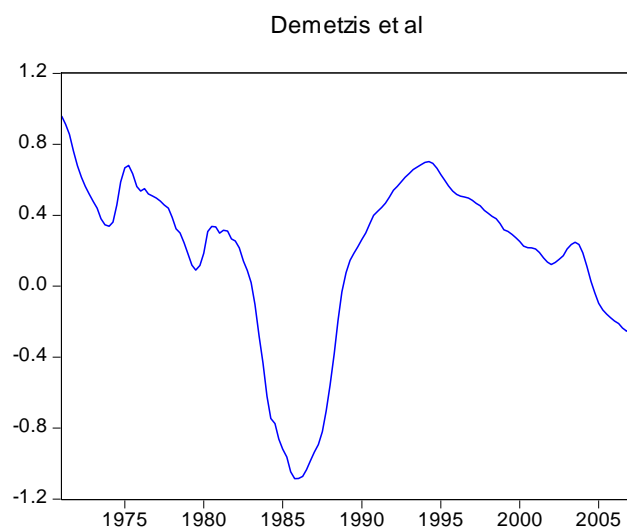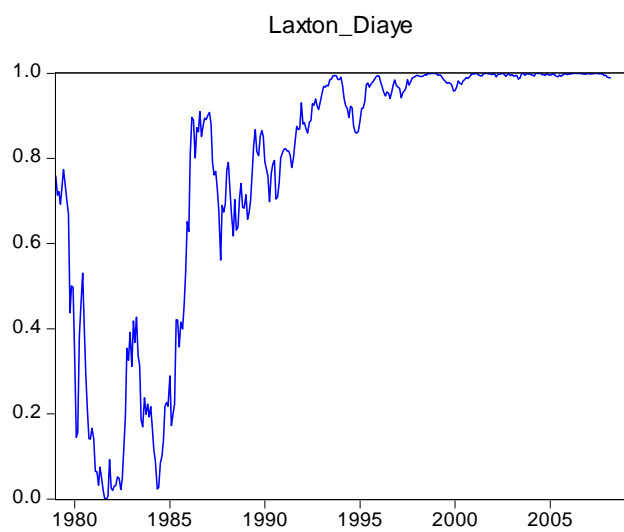
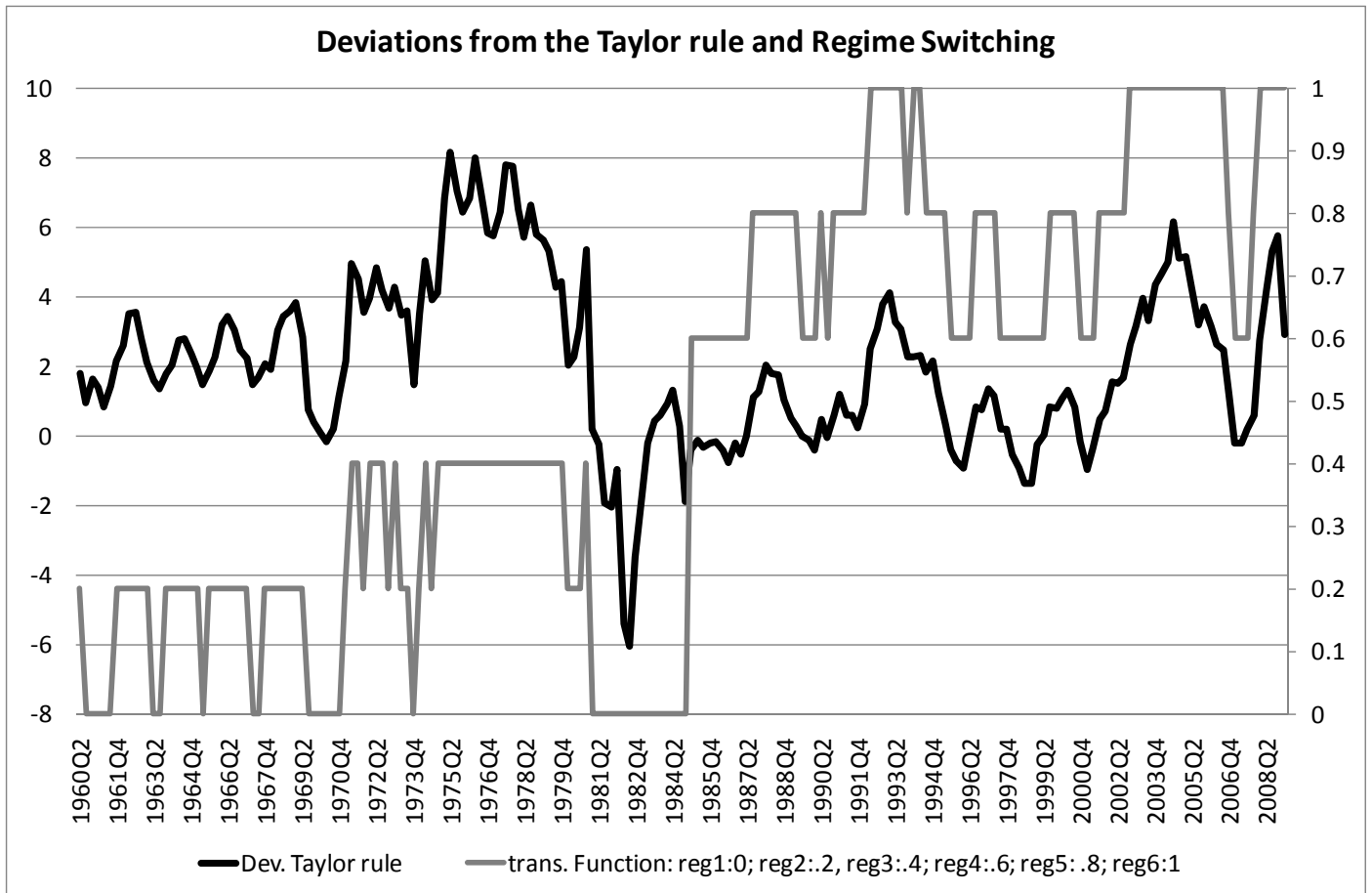Figure 2: Two measures of monetary policy credibility

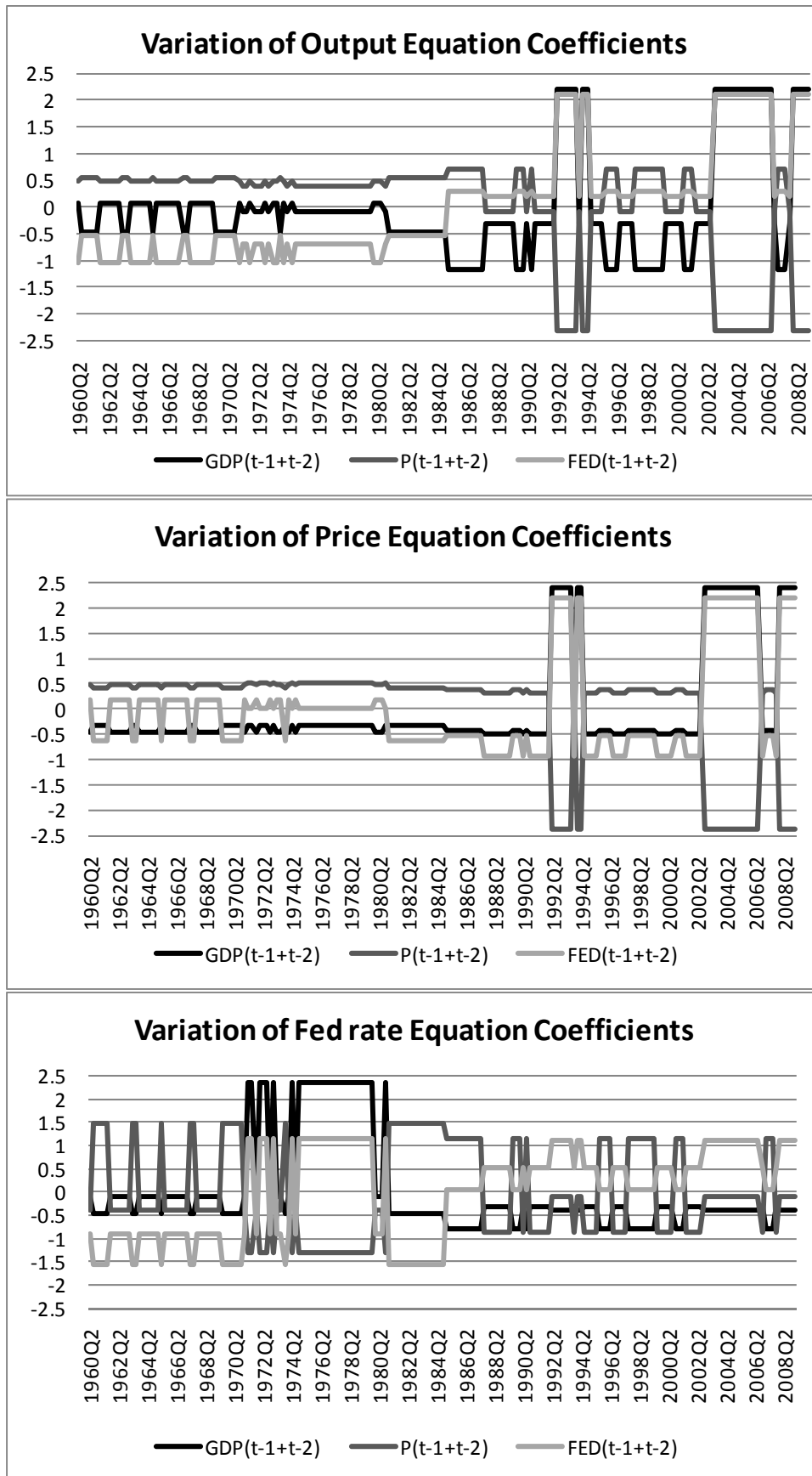Figure 3: The six regimes identified by the SB-ET-VAR model.

Figure 4: Time-varying estimates: sum of coefficients of both lags of each variable in each equation of the SB-ET-VAR model; standardized values.
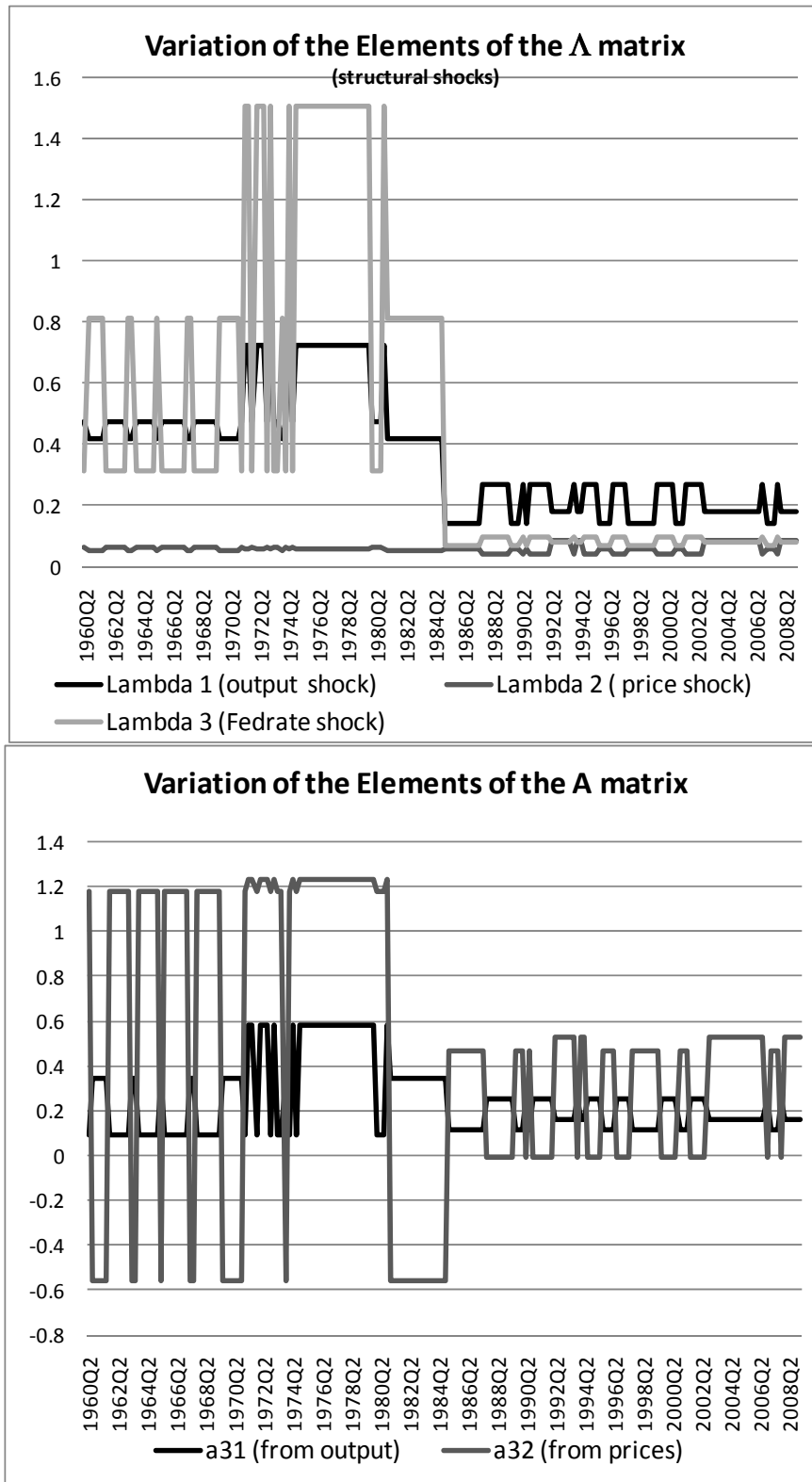
Figure 5: Time-varying estimates: Variance of structural shocks (upper panel) and of coefficients in Choleski decomposition(lower panel).
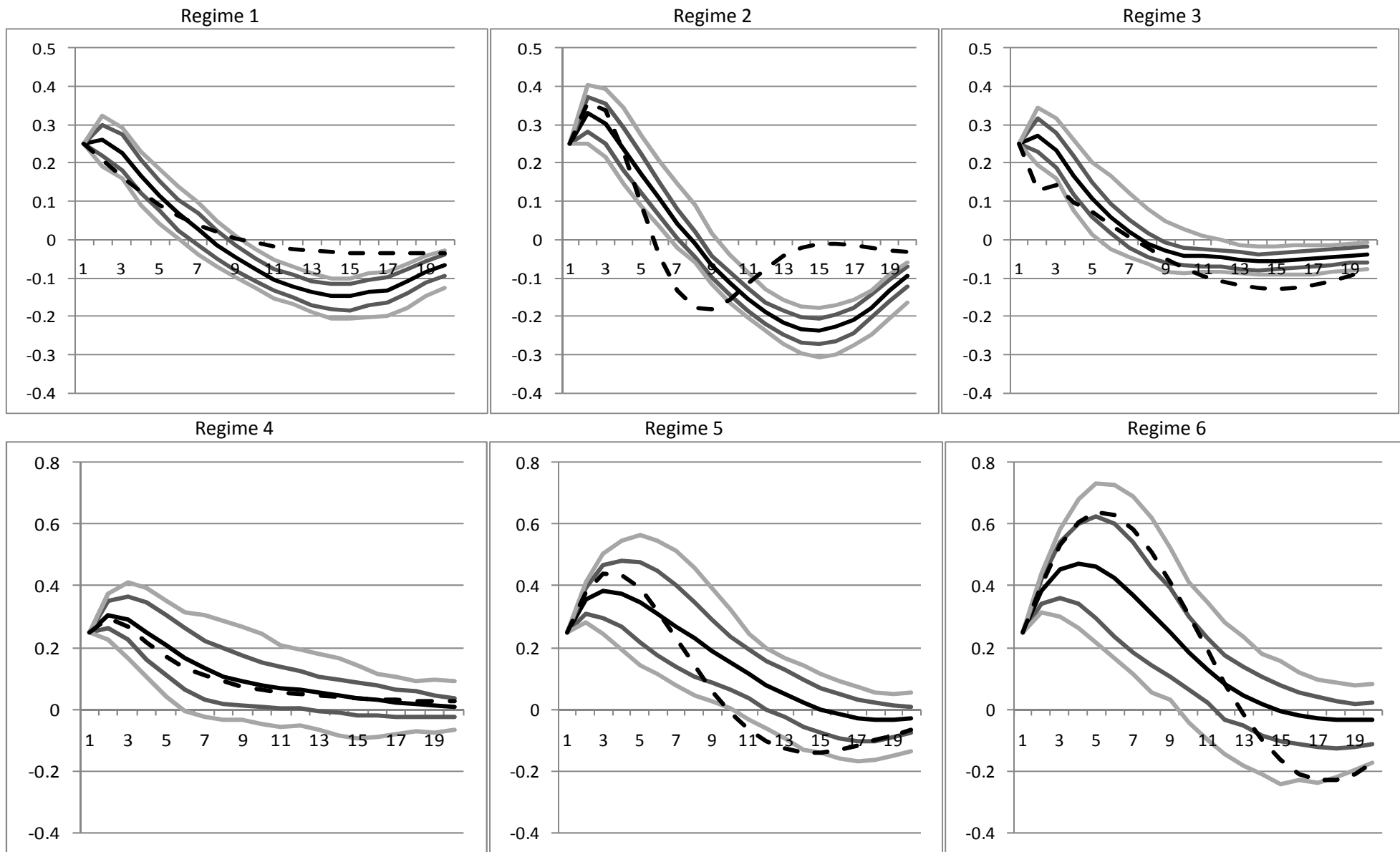
Figure 6: Monetary Policy Shocks (25 basis point shock): IRFs with 68% (dark grey) and 90% (light grey) confidence intervals. Dashed black line is response when regime-switching is not allowed. Regimes 1 (4), 2 (5) and 3 (6) correspond to tight, normal and loose monetary policy before 1985Q1 (after 1985Q1).
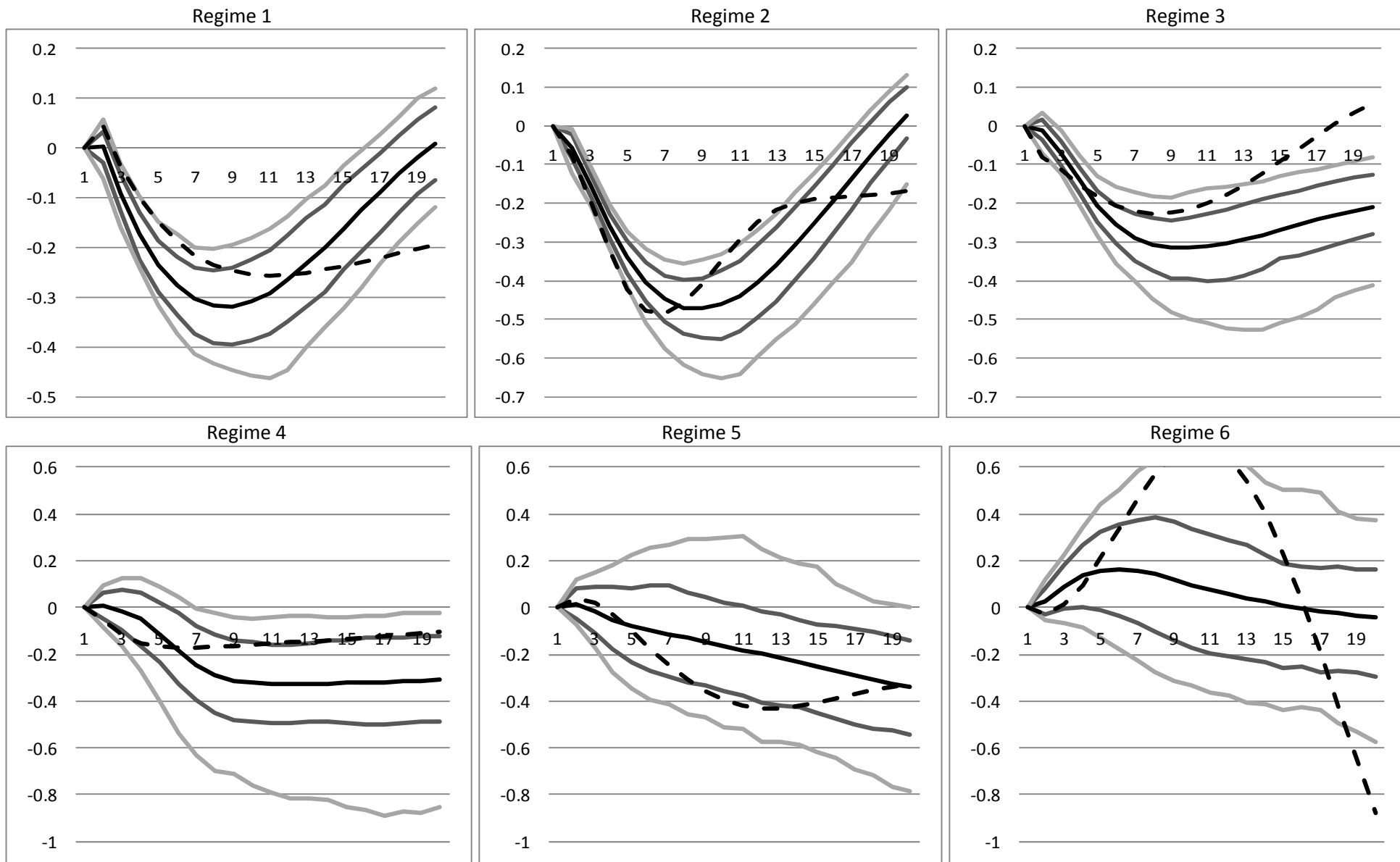
Figure 7: Responses of output to monetary policy shocks (25 basis point shock): IRFs with 68% (dark grey) and 90% (light grey) confidence intervals. Dashed black line is response when regime-switching is not allowed. Regimes 1 (4), 2 (5) and 3 (6) correspond to tight, normal and loose monetary policy before 1985Q1 (after 1985Q1).
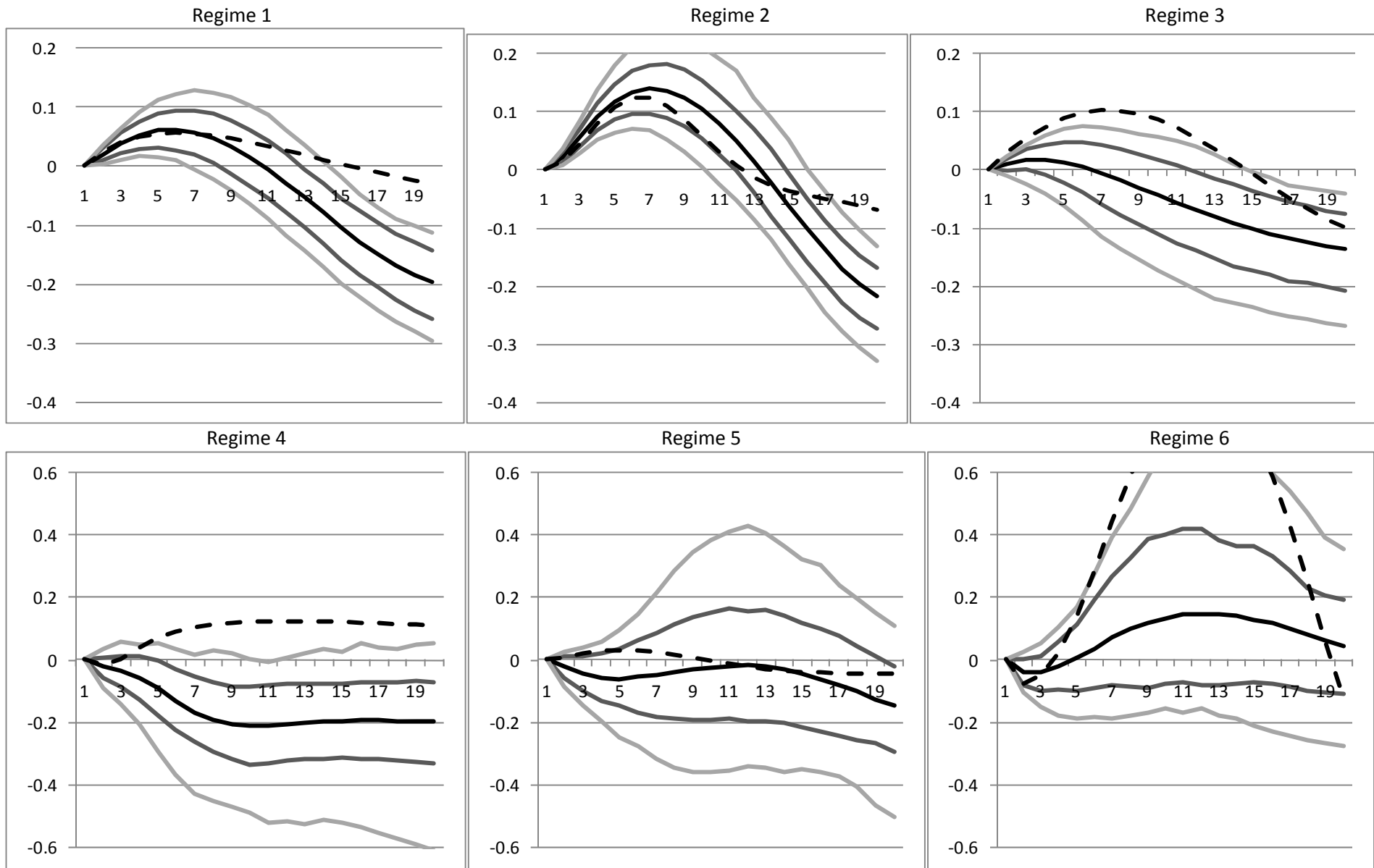
Figure 8: Responses of Prices to Monetary Policy Shocks (25 basis point shock): IRFs with 68% (dark grey) and 90% (light grey) confidence intervals. Dashed black line is response when regime-switching is not allowed. Regimes 1 (4), 2 (5) and 3 (6) correspond to tight, normal and loose monetary policy before 1985 (after 1985).
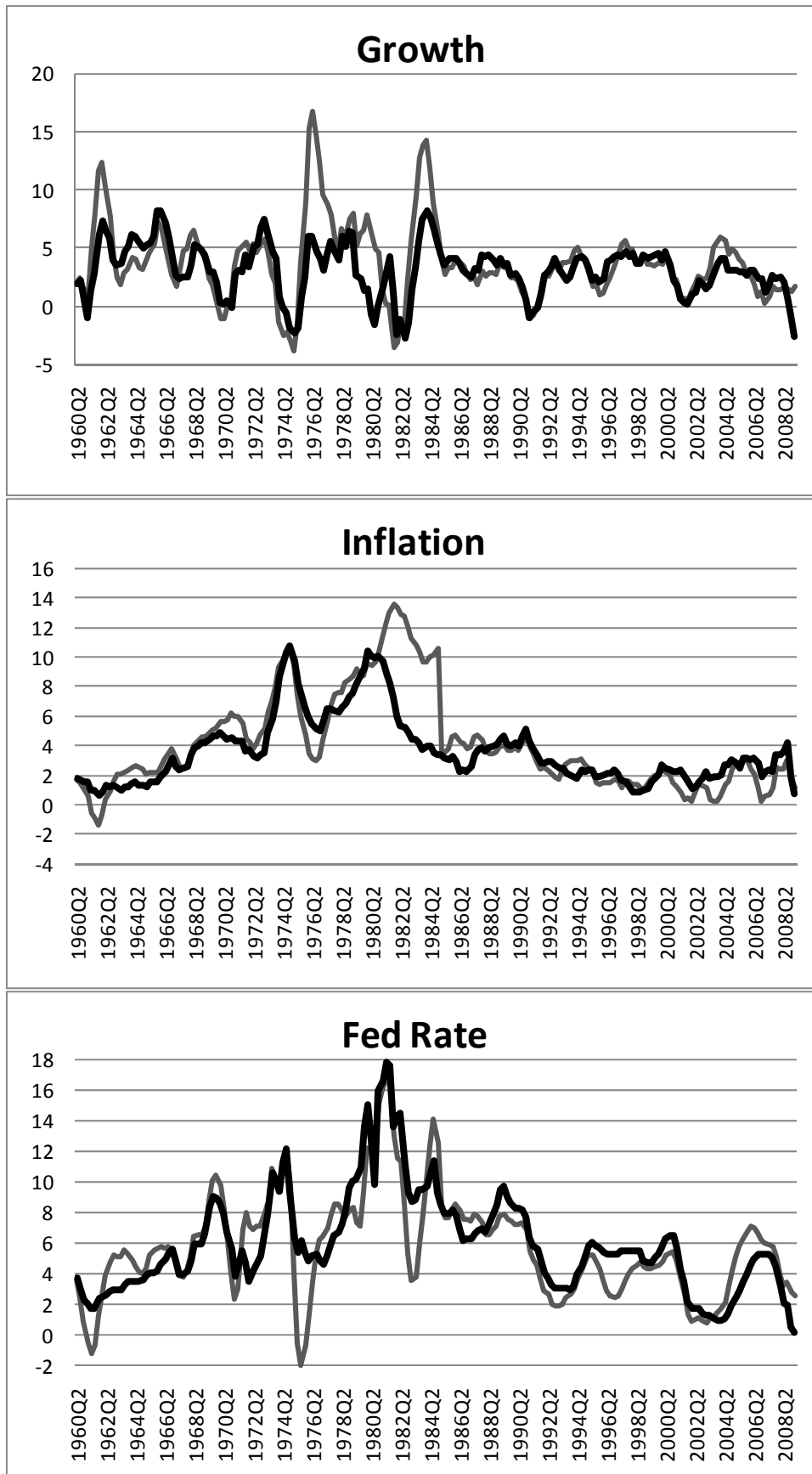
Figure 9. Counterfactual: Always in the normal regime (reg2 and reg5) in each subsample. Black line is observed data; grey line is the simulated counterfactual.
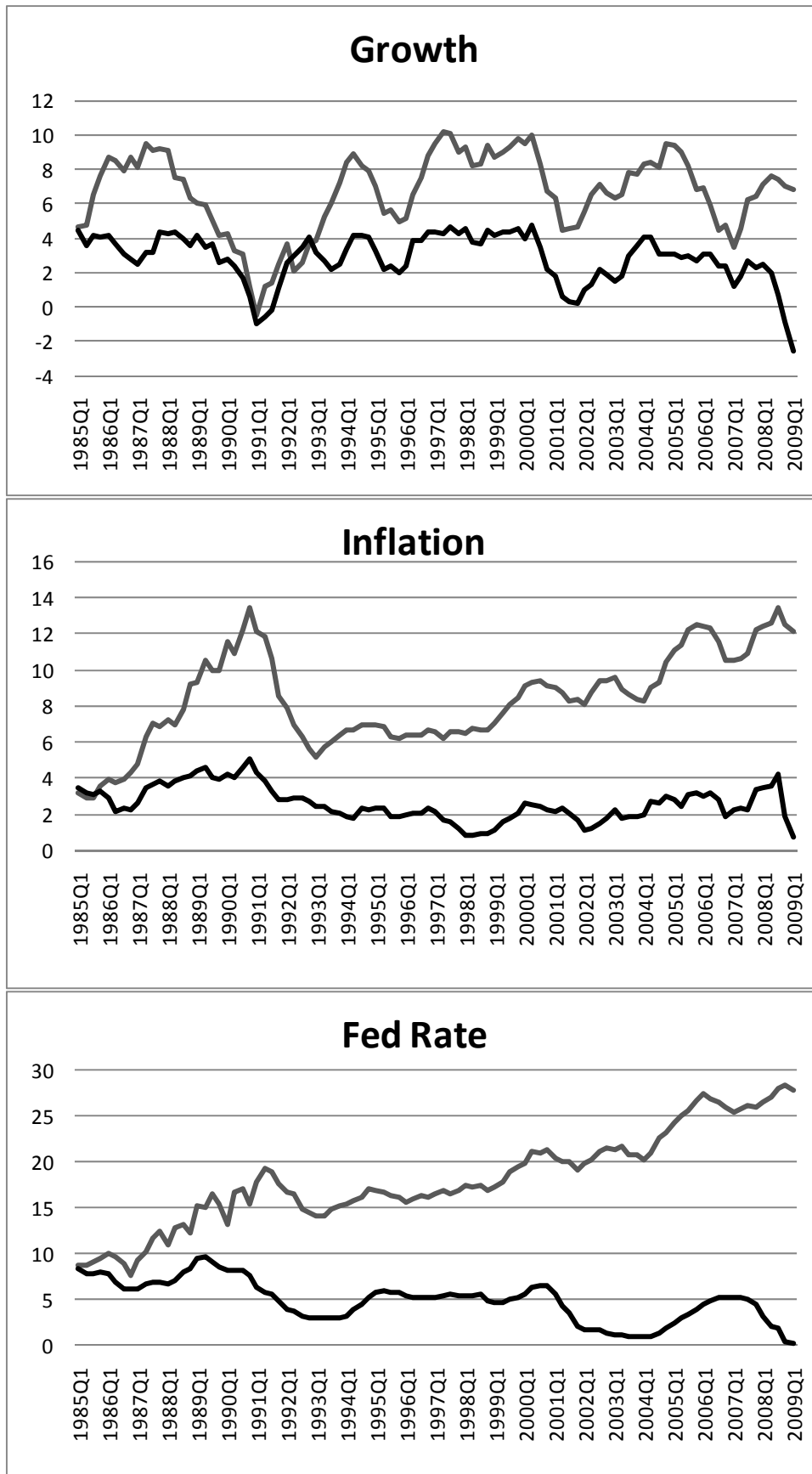
Figure 10. Counterfactual: Using pre-1985 estimates (including threshold values) for the period after 1985
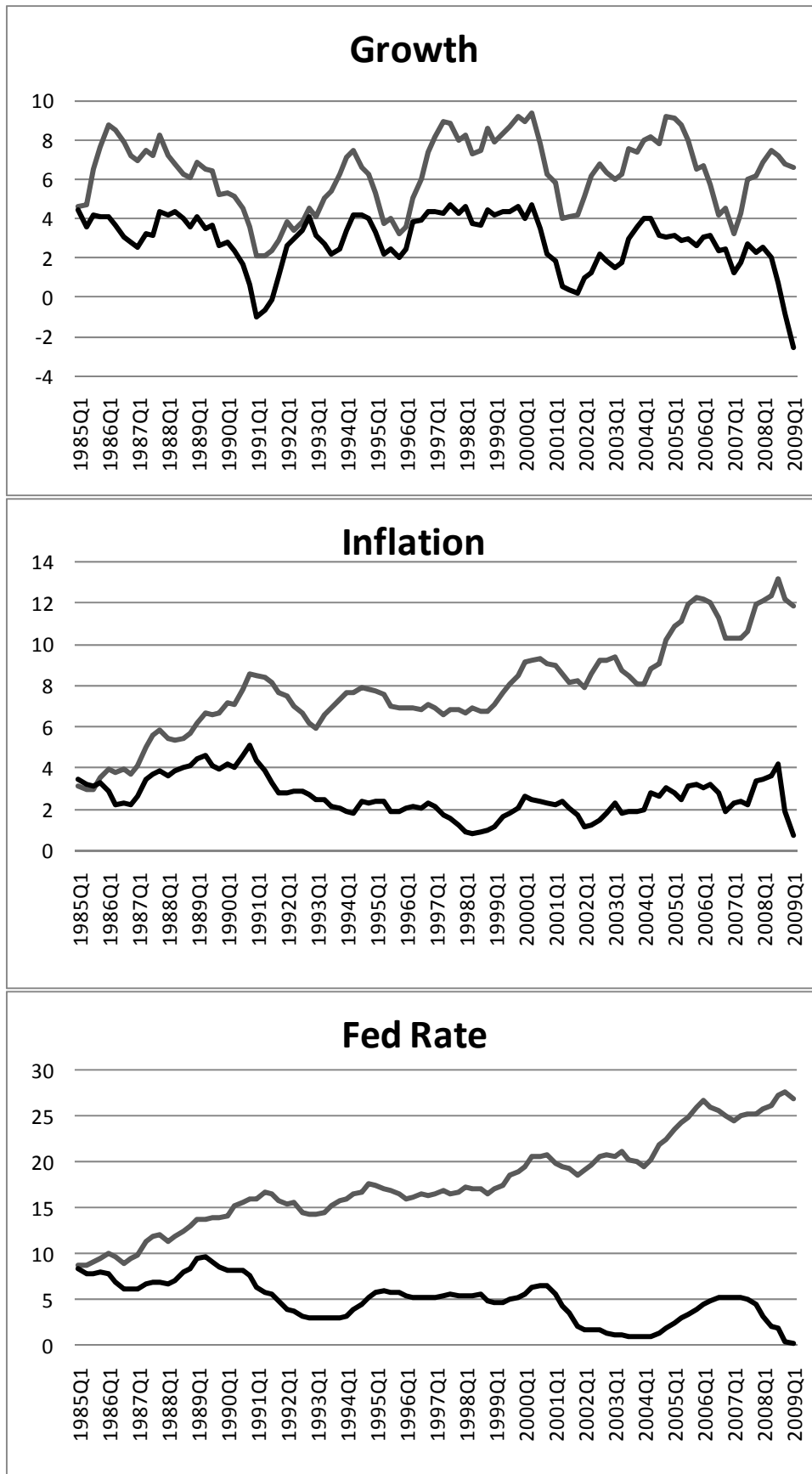Black line is observed data; grey line is simulated counterfactual.

Figure 11: Counterfactual: Using the tight regime estimated with data before 1985 (regime 1) during the post-1985 period. Black line is observed data; grey line is simulated counterfactual.

Table 1: Measures of Fit of Different Specifications

Model	N. Regimes	Lik	AIC	HQC	SIC
Specifications with **Taylor rule** as Transition Variable (with at least 15% obs. in each regime in each subsample)					
VAR	1	-537.673	5.70	5.84	6.05
ET-VAR	2	-874.180	9.35	9.63	10.05
SB-VAR	2	-422.533	4.74	5.02	**5.44**
ET-VAR	3	-440.664	5.14	5.57	6.19
SB-VAR	3	-383.481	4.56	4.98	5.61
SB-ET-VAR	4	-466.281	5.62	6.18	7.02
SB-ET-VAR	6	-261.917	**3.96**	**4.81**	6.07
Specifications with **Taylor rule** as Transition Variable (with at least 30% obs. in each regime in each subsample)					
ET-VAR	2	-689.114	7.46	7.74	8.16
SB-VAR	2	-422.533	4.74	**5.02**	**5.44**
ET-VAR	3	-452.218	5.26	5.68	6.31
SB-VAR	3	-392.211	4.65	5.07	5.70
SB-ET-VAR	4	-466.281	5.62	6.18	7.02
SB-ET-VAR	6	-305.687	**4.41**	5.26	6.51
Specification with **Real Interest Rate** as Transition Variable (with at least 30% obs. in each regime in each subsample)					
SB-ET-VAR	6	-315.813	4.51	5.36	6.62
Specification with **Output Growth** as Transition Variable (with at least 30% obs. in each regime in each subsample)					
SB-ET-VAR	6	-313.113	4.48	5.33	6.59

Note: All estimates are with p=2; effective sample period: 1960:Q2-2009:Q1.

Table 2: Tests for remaining heteroscedasticity in the SB-ET-VAR (6 regimes)

Test on Disturbances from:	Wald [pv]
Output equation	4.39 [.11]
Price equation	3.99[.14]
Fed fund equation	17.80[.01]
Fed fund equation (first subsample)	9.07[.01]
Fed fund equation (second subsample)	1.62[0.44]

Note: The test statistics are computed with an auxiliary regression (LM) of squared residuals on dummies to capture regime-dependent changes and with two lags of squared residuals. The null hypothesis of homoscedasticity is that the coefficients on the lag-squared disturbances are zero.

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