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Bayesian inference of the dynamic ordered probit model with time-varying parameters

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計畫主持人：黃河泉

執行單位：淡江大學財務金融系

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一、中文摘要

本篇計畫建立一個相當一般化的動態排序 probit 模型 (dynamic ordered probit model), 且此模型中可允許迴歸參數為固定不變 (fixed) 或隨時間經過而改變 (time-varying)。由於傳統的方法如極大概似法 (maximum likelihood) 在計算時需要困難的多重積分, 在本文中, 我們將利用近年來相當受到注意的貝氏模擬 (simulation-based) 方法, 即馬可夫鍊蒙地卡羅 (Markov chain Monte Carlo) 法, 來從事參數的估計與模型的比較。

我們所考慮的模型設定與以往文獻所探討的情形有著以下幾個重要的相異之處。第一、我們將傳統靜態的排序 probit 模型延伸為動態的設定來處理下列兩個問題: 即被解釋變數只能觀察到間斷 (discrete) 的值且其為時間序列資料 (time series data), 應具有動態的特性。有別於其他研究, 通常只允許一階動態過程 (first-order process), 我們考慮更一般的"p"階過程 (order of p)。第二、我們的隨時間改變係數的模型, 由於可以允許迴歸參數隨著時間經過而有所不同, 其不僅考慮到迴歸參數的不穩定性, 同時也可以捕捉到整個經濟社會可能的結構性轉變。第三、我們將動態排序 probit 模型中區隔不同區間的分界點 (bin boundaries or cutoffs) 視為額外參數而予以估計。我們發覺, 這些分界點可被相當直接地估計。

我們將利用這個固定係數或隨時間改變係數的動態排序 probit 模型來估計台灣的貨幣政策反應函數。其 (可能) 使用的資料乃根據沈中華與陳華倫 (1996) 所建立貨幣政策指數 (monetary policy indicators)。其中, 貨幣政策指數所展現的可能值為間斷的, 分別以0、1和2來分別代表緊縮、中立和擴張的貨幣政策。

關鍵詞：動態排序probit 模型, 馬可夫鍊蒙地卡羅, 隨時間改變係數, 貨幣政策反應函數。

Abstract

This paper proposes a flexible dynamic ordered probit model which allows for the regression parameters to be either fixed or time-varying. The parameter estimation and model comparison are carried out using the simulation-based approach, namely, the Markov chain Monte Carlo technique.

Our model specification differs from existing studies in the following respects. First, the static ordered probit model is extended to a dynamic framework to deal with the specific discrete-valued feature of time series data. In particular, we consider a more general dynamic order of p instead of the first-order process commonly used in the literature. Second, our time-varying-parameter models permit the regression coefficients to evolve over time, so that they can be applied to discrete time series models with parameter instability and capture the possible change in the structure of the economy. Third, the bin-boundary coefficients of the ordered model are treated as additional parameters to be estimated rather than given in advance. It turns out that the estimation of those cut-offs is straightforward. Finally, the choice of appropriate dynamic order and the comparison of fixed-coefficient and time-varying-parameter models are made possible via the Bayes factor using by-product of the Gibbs simulation. We will apply the model to estimate the Taiwan's monetary policy reaction function using the unique narrative-based monetary policy indicators with discrete values of $0, 1$ and 2 for representing stances of tight, neutral and easy monetary policies, respectively.

Keywords: Dynamic ordered probit, Markov chain Monte Carlo, Time-varying parameters, Monetary policy reaction function.

1 Introduction

It is well known that the monetary policy is not independent of economic conditions but rather it responds actively to macroeconomic objectives such as price stability, sustainable economic growth, and so on. For example, Taylor (1993) shows that the monetary policy in the U.S. can be well described by a simple rule whereby the central bank adjusts the short-term nominal interest rate as a linear function of a measure of inflation as well as the output gap. Basically, as also argued in Clarida, Gali and Gertler (2000), the monetary authority raises the nominal interest rate by more than one-to-one in response to an increase in (expected) inflation so that the real interest rate is higher, thereby alleviating inflationary pressure. However, estimation of the monetary policy reaction functions often requires the selection of certain money market indicators, e.g., monetary aggregates, federal funds rates or nonborrowed reserves, to represent the stance of monetary policy. Unfortunately, there seems to be no general agreement on which variable serves as the best policy indicator. Furthermore, these money market indicators might fluctuate for reasons unrelated to changes in monetary policy stance. As a result, without appropriately taking into account the feedback of non-monetary policy shocks may result in misleading, or even incorrect, conclusions.

In this study, stimulated by Romer and Romer (1989), we consider an alternative measure of the monetary policy stance in Taiwan constructed by Shen and Chen (1996) and later extended in Huang and Shen (2001, 2002), using the narrative-based approach. To be more specific, Shen and Chen (1996) study the directive of the CBC (Central Bank of China, Taiwan) Committee meeting. While the directives of the U.S. FOMC are regularly recorded and made available to the public, the minutes of the CBC Committee meeting are usually not available. Despite the CBC often announces its short-term monetary policy after the Committee meeting, the announcements are typically vague to avoid criticism of lack of credibility. Since true intention of the monetary authority is blurred, assessment of the current policy stance based only on its announcements is relatively difficult, if not impossible. As a result, Shen and Chen (1996) read daily newspaper to examine the comments of newspapers and, moreover, they notice that the macroeconomic data must be examined to gauge the Committee's decision as well. Then, they employ a lexicographic principle, which includes four sequential rules, to complement the study of the announcements. The classification rules are sequentially based on the authority's announcement, changes of the required reserve ratio, the discount rate and the monetary base, and in that order. Similar methods are also implemented in estimating monetary policy reaction functions or deriving an indicator of monetary policy shocks, e.g., Hakes (1990), Shen, Hakes and Brown (1999), Shen (2000), and Romer and Romer (2003), to name a few.

Basically, an indicator of the monetary policy so constructed takes discrete values which represent the stance of monetary policy. Taken an example as in the appendix of Shen, Hakes and Brown (1999), the U.S. monetary policy can be classified into easy or tight actions represented by a binary index with values 1 or 0, respectively. Shen (2000) and Huang and Shen (2001, 2002) have also estimated the Taiwan monetary policy reaction function using such narrative-based monetary (binary) indicators by probit regression (without or with serially-correlated errors). As argued in Shen, Hakes and Brown (1999), the advantages of the narrative-based indicators over commonly-used money market indicators of monetary policy mentioned above are described as follows. First, it is shown in Boschen and Miller (1995) that the relationship between any of alternative narrative-based indicators and M2 is more persistent than that between money market indicators and M2, indicating the interest rate indicators such as the Federal funds rate containing more nonpolicy shocks than narrative indicators. Second, Boschen and Miller (1995) also find that there is a high degree of conformity across alternative narrative indicators, suggesting that the narrative indicators are lack of, if not free from, subjectivity. Thus, as pointed in Shen (2000) and Huang and Shen (2001, 2002), the use of monetary indicators constructed by the narrative approach can overcome the problem of endogeneity which arises because the changes of the money market variables are caused by reasons other than changes in monetary policy. Moreover, it can also avoid the problem of inconsistency caused by the contradictory relationship between those money market variables, e.g., the central bank of Taiwan reduces the reserve requirement on August 1, 1990 whereas M1B decreases in the month.

This paper extends the existing studies in the following directions. First, we classify the monetary policy stance into three categories, namely, expansionary, neutral, and contractionary, rather than the binary case as discussed above. As a matter of fact, there seems no reason to believe that monetary authority can only adopt either easy or tight actions. Allowing for neutral monetary policy (or inaction) might be closer to reality. Second, we consider inflation as well as output gap as the primary objectives of monetary policy. In particular, the output gap is measured by different filtering approaches to examine the robustness of the monetary policy reaction function. Those methods include the quadratic trend specification, the Hodrick-Prescott filter, the Band-Pass filter, and the structural time series approach. Third, we propose a dynamic ordered probit model with time-varying parameters to estimate the monetary policy reaction function in Taiwan using time series data on the discrete monetary indicators. Although the ordered probit models can account for the discreteness feature of the dependent variable, they may not be well suited for time series data as our trinomial monetary indicators for possible dynamics. For this purpose, we propose a dynamic ordered probit regression to capture the potential dynamics and serial correlation of time series data. [1] Moreover, as noted in McNees (1986), a policy reaction function is likely to be a fragile creature. Over time, the importance attached to conflicting objectives of the monetary policy may change. Thus, in order to examine the possibly changing responses of the policy to different economic conditions, we allow for the parameters to be time-varying so that the strength of policy responses to final macro objectives during different subperiods can vary over time. [2] The estimation and inference of the dynamic ordered probit model with time-varying parameters (TVP-DOP) is carried out via the recent advances in Bayesian simulation approach, namely, the Markov chain Monte Carlo (MCMC).

This paper is organized as follows. In section 2, we present the econometric modeling framework. We first present a simple Taylor rule to describe the monetary policy reaction function in Taiwan in the static ordered probit model. Then, we introduce our novel dynamic ordered probit model with time-varying parameters. Section 3 reviews the methodology for extracting the permanent as well as transitory components of output, thus, obtaining the output gap. Particularly, we first consider the baseline case using the quadratic trend specification. For robustness reason, we also investigate other techniques such as the Hodrick-Prescott filter, Band-Pass filter and the structural time series approach as well. Section 4 describes the Bayesian estimation technique. The simulation algorithm using the Markov-chain Monte Carlo approach is explained and the full conditional distributions needed for sampling are derived. Section 5 explains the data sources and construction and summarizes the empirical results. Final remarks are made in section 6.

2 The econometric modeling

In this section, we first specify a simple Taylor-type monetary policy reaction function in which the monetary indicators respond to economic

[1] In a similar way, extensions to dynamic ordered probit framework include Eichengreen, Watson and Grossman (1985) who consider a dynamic ordered probit model and develop a maximum likelihood estimation technique for analyzing the Bank of England's discount rate policy reaction function during the 'inter-war' period 1925-1931. Built on the work of Eichengreen, Watson and Grossman (1985), Davutyan and Parke (1995) analyze the 'pre-war' Bank rate behavior by using weekly data, allowing for asymmetric responses and applying the dynamic ordered probit to account for the discrete and dynamic nature of Bank rate policy.

[2] Similar applications can be found in Kim and Nelson (1989), Shen, Hakes and Brown (1999), Shen (2000), and Estrella and Fuhrer (2003).

conditions such as the inflation as well as the output gap. Notably, we adopt the narrative-based indicators to represent the stance of the monetary policy. Specifically, the indicators take discrete values -1, 0 and 1 and represent the easy, neutral and tight monetary actions,respectively. The model is first analyzed in a simple (static) ordered probit framework. We then propose two versions of dynamic ordered probit models, one with fixed-parameters and the other with time-varying coefficients, to account for possible dynamics and structural change. The estimation procedures for these two dynamic models are also discussed.

2.1 The ordered probit (OP) model

Consider the following monetary policy reaction function specified as the simplest (static) form of the (static) ordered probit model,

$$I_t^* = \beta_0 + \beta_1 \,\texttt{inf}_{t-1} + \beta_2 \,\texttt{gap}_{t-1} + \epsilon_t, \quad t = 1, 2, \cdots, T \tag{1}$$

where I_t^* is the latent variable denoting the intention of the monetary authority for adopting tight actions. In particular, its corresponding realized observation, I_t, takes the value of -1 if an expansionary policy is implemented, 0 if no or a neutral action is taken, and 1 if a contractionary policy is adopted. The policy indicators are assumed to respond to the macroeconomic objectives such lagged inflation ($\texttt{inf}_{t-1}$) as well as output gap ($\texttt{gap}_{t-1}$). Clearly, the reaction function in (1) is backward-looking in that the monetary authority in Taiwan is assumed to adjust the policy in response to lagged values rather than to forecasts. Similar rules are also considered in Taylor (1993), Choi (1999), Altavilla (2003) and Benhabib, Schmitt-Grohe and Uribe (2003).

For purpose of generality, we re-define $y_t^* = I_t^*$ and let $x_t = (1, \texttt{inf}_{t-1}, \texttt{gap}_{t-1})'$ be a $k(=3) \times 1$ vector with $k \times 1$ coefficient vector $\beta = (\beta_0, \beta_1, \beta_2)'$. Then, equation (1) can be rewritten as,

$$y_t^* = x_t'\beta + \epsilon_t \tag{2}$$

where the error term ϵ_t is assumed to be normally distributed as $\mathcal{N}(0, 1)$ with the variance being normalized to be 1 for identification reason. The observed outcome y_t is determined by,

$$y_t = \begin{cases} -1 & \text{if } y_t^* \leq 0 \\ 0 & \text{if } 0 < y_t^* \leq \gamma \\ 1 & \text{if } \gamma < y_t^* \end{cases} \tag{3}$$

As a result, there are 3 categories with additional unknown bin boundary (threshold) γ. [3] Therefore, the unknowns remain to be estimated are

[3] It is straightforward to allow for more than three categories, if necessary. Please see Albert and Chib (1993) for more details.

$\theta = (\beta', \gamma)'$. The estimation can be performed by maximum likelihood or generalized method of moments. In contrast, Albert and Chib (1993) introduces a simulation-based approach for computing the exact posterior distribution of θ based on the observed data.

2.2 The dynamic ordered probit model with fixed parameters (FP-DOP)

The above ordered probit model implicitly assumes that the error terms are serially uncorrelated. This is commonly true in the use of cross-sectional data but may not be appropriate when time series data are examined. In the case of reaction function considered in this study, we might expect that the adoption of a particular type of action by the monetary authority to be not only consistent but also persistent. As a result, it may seem more suitable to take into account the potential dynamics inherent in the model.

Consider the following flexible dynamic ordered probit model with the autoregressive order up to p. In particular, the model is designed explicitly for discretely valued time series data in which the intention of adopting a tight action is evolved over time. The FP-DOP model is specified as,

$$y_t^* = x_t'\beta + w_t'\phi + \epsilon_t \tag{4}$$

where the lagged latent variables measuring the policy intention are contained in the vector $w_t = (y_{t-1}^*, y_{t-2}^*, \cdots, y_{t-p}^*)'$ with corresponding coefficients vector $\phi = (\phi_1, \phi_2, \cdots, \phi_p)'$. Equation (4) can be reformulated as,

$$y_t^* = z_t'\alpha + \epsilon_t \tag{5}$$

where $z_t = (x_t', w_t')'$ and $\alpha = (\beta', \phi')'$. Again, as in the ordered probit case, the observed data y_t is determined by the criteria specified in equation (3). Thus, the parameter vector to be estimated is $\theta = (\alpha', \gamma')'$.

2.3 The dynamic ordered probit model with time-varying parameters (TVP-DOP)

The proposed dynamic ordered probit model in the evaluation of discrete monetary policy reaction functions seems to be promising, at least, in terms of capturing the dynamics of evolving policy intention. However, we are also concerned with possible changing weights attached to the conflicting final objectives as inflation and output gap (economic growth) over time. Since the FP-DOP approach is unable to take this important feature into account, we modify equation (5) to allow for time-varying parameters so that the monetary authority can change its reaction to various macroeconomic conditions in the presence of changing importance attached to potentially conflicting policy goals.

Specifically, the TVP-DOP mode is specified as,

$$y_t^* = z_t'\alpha_t + \epsilon_t \quad (6)$$

$$\alpha_t = \alpha_{t-1} + \eta_t \quad (7)$$

where $\alpha_t = (\beta_t', \phi_t')'$, $\beta_t = (\beta_{1t}, \cdots, \beta_{kt})'$ and $\phi_t = (\phi_{1t}, \cdots, \phi_{pt})', t = 1, 2, \cdots, T$. The coefficient vector α_t is assumed to follow a vector random walk process with disturbance term $\eta_t \sim \mathcal{N}(0, \Sigma)$ where Σ is a diagonal matrix with elements $(\sigma_1^2, \cdots, \sigma_k^2, \sigma_{k+1}^2, \cdots, \sigma_{k+p}^2)'$. If all the diagonal elements are equal, i.e., $\sigma_1^2 = \cdots = \sigma_{k+p}^2 = \sigma^2$, Σ can be simplified as $\sigma^2 I_{k+p}$. Note that the hyperparameter σ^2 determines the variability of all the regression coefficients over time. For instance, if $\sigma^2 = 0$, it would impose the regression coefficients to be fixed over time, i.e., $\alpha_t = \alpha_0$ for all t.

3 Extracting the cyclical components

In order to estimate equations (2), (5), or (6) and (7), we need a measure of the output gap which is defined as the cyclical component (μ_t^c) of the series of interest , namely, log real output (measured by GDP, μ_t). Although there are a variety of approaches for breaking a time series into trend and cyclical components, four detrending methods for extracting the cyclical components are considered in this paper. Specifically, they include the baseline case, e.g., the quadratic trend representation, the Band-Pass filter, the Hodrick and Prescott filter and the structural time series approach. [4] Canova (1998) provides a comprehensive comparison of a variety of different detrending methods.

3.1 The quadratic trend model

For comparison purpose, we use a quadratic trend representation to measure the trend and cyclical components of the log real output. For this baseline estimate, the cyclical component can be obtained by the deviation of fitting a quadratic function of time, i.e., the difference between the observed and trend output. A succinct specification is given as,

$$\mu_t = a_0 + a_1 t + a_2 t^2 + \epsilon_t \quad (8)$$

where μ_t is the observed output and $t = 1, 2, \cdots, T$, denotes time trend. Under this framework, trend output can be obtained by $\mu_t^t = \hat{a}_0 + \hat{a}_1 t + \hat{a}_2 t^2$ where $\hat{a}_i, i = 0, 1, 2$, denotes the least square estimates. Clearly, the cyclical output (gap) is nothing but the residuals from the quadratic regression, i.e., $\mu_t^c = \mu_t - \mu_t^t = \mu_t - \hat{a}_0 - \hat{a}_1 t - \hat{a}_2 t^2$.

[4] Two popular approaches for extracting the cyclical component are the Beveridge-Nelson (Beveridge and Nelson, 1981) and unobserved-component (Clark, 1987) methods, please see Morley, Nelson and Zivot (2003) for comparison.

3.2 The Hodrick-Prescott filter

Based on the hypothesis that the trend component of a time series varies smoothly over time, any given observed time series, e.g., the output μ_t, can be viewed as the sum of a trend component μ_t^t and a cyclical component μ_t^c. Hodrick and Prescott (1997) suggest to measure the smoothness of the $\{\mu_t^t\}$ path by the sum of the squares of its second difference while the cyclical components $\{\mu_t^c\}$ are deviations from the trend components $\{\mu_t^t\}$ and should have averages near zero over long time periods.

In particular, we can solve the following dynamic programming problem to determine the trend and cyclical components,

$$\min_{\{\mu_t^t\}_{t=1}^T} \left\{ \sum_{t=1}^T \left(\mu_t - \mu_t^t\right)^2 + \lambda \sum_{t=1}^T \left[\left(\mu_t^t - \mu_{t-1}^t\right) - \left(\mu_{t-1}^t - \mu_{t-2}^t\right)\right]^2 \right\} \tag{9}$$

where the smoothness parameter λ penalizes variation in the trend component series. For the quarterly data (will be) used in this paper, Hodrick and Prescott (1997) suggest to select a value of 1600 for the smoothing parameter λ.

3.3 The Band-Pass filter

As an alternative, Baxter and King (1999) show how to construct the moving averages so that the periodic components of an economic time series can be isolated in a specified band of frequencies. In fact, they are interested in constructing band-pass linear filters. In contrast, Christiano and Fitzgerald (2003) propose another approximation strategy to recover the trend as the component of the series with periodicity between a lower and an upper bound.

In particular, let the filter approximation of the output μ_t be μ_t^t which can be computed as follows,

$$\begin{aligned} \mu_t^t &= B_0\mu_t + B_1\mu_{t+1} + \cdots + B_{T-1-t}\mu_{T-1} + \widetilde{B}_{T-t}\mu_T \\ &\quad + B_1\mu_{t-1} + \cdots + B_{t-2}\mu_2 + \widetilde{B}_{t-1}\mu_1 \end{aligned} \tag{10}$$

for $t = 3, 4, \cdots, T-2$ and where

$$\begin{aligned} B_j &= \frac{\sin(jb) - \sin(ja)}{j\pi}, \quad j \geq 1 \\ B_0 &= \frac{b-a}{\pi}, \quad a = \frac{2\pi}{p_u}, \quad b = \frac{2\pi}{p_l} \\ \widetilde{B}_{T-t} &= -\frac{1}{2}B_0 - \sum_{j=1}^{T-t-1} B_j, \quad t = 3, 4, \cdots, T-2 \end{aligned}$$

and $\widetilde{B}_{t-1} = -(B_0 + B_1 + \cdots + B_{T-1-t} + \widetilde{B}_{T-t} + B_1 + \cdots + B_{t-2})$. For instance, the default case for Christiano and Fitzgerald (2003) is 1.5 and 8 years using quarterly data, corresponding to set $p_l = 6$ and $p_u = 32$. Please see Christiano and Fitzgerald (2003) for more details and Gallego and Johnson (2003) for building confidence intervals for the band-pass filters.

3.4 The structural time series approach

Another popular approach for extracting the trend as well as cyclical components of a time series is the structural time series (STS) approach proposed by Harvey (1989). Specifically, the model can be formulated as,

$$\mu_t = \mu_t^t + \mu_t^c + \epsilon_t \tag{11}$$

where μ_t is the output; μ_t^t, μ_t^c are the unobserved trend and cyclical components, respectively; and ϵ_t is an irregular component and is assumed to be white noise.

The trend component which represents the long-run movement of a series is assumed to be stochastic and linear and can be represented as,

$$\begin{bmatrix} \mu_t^t \\ \kappa_t \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \mu_{t-1}^t \\ \kappa_{t-1} \end{bmatrix} + \begin{bmatrix} \eta_t \\ \zeta_t \end{bmatrix} \tag{12}$$

where $\eta_t \sim \mathcal{N}(0, \sigma_\eta^2)$, $\zeta_t \sim \mathcal{N}(0, \sigma_\zeta^2)$, μ_t^t is a random walk with a drift factor, κ_t, which follows a first-order autoregressive process.

The cyclical component μ_t^c is assumed to be a stationary linear process and can be represented as,

$$\begin{bmatrix} \mu_t^c \\ \mu_t^{c*} \end{bmatrix} = \rho \begin{bmatrix} \cos\lambda & \sin\lambda \\ -\sin\lambda & \cos\lambda \end{bmatrix} \begin{bmatrix} \mu_{t-1}^c \\ \mu_{t-1}^{c*} \end{bmatrix} + \begin{bmatrix} \chi_t \\ \chi_t^* \end{bmatrix} \tag{13}$$

$$\begin{bmatrix} \chi_t \\ \chi_t^* \end{bmatrix} \sim \mathcal{N}\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \sigma_\chi^2(1-\rho^2)I_2\right] \tag{14}$$

As noted in Harvey (1989), the above equations can be cast into state-space form and we can calculate the likelihood function using the Kalman filter and obtain the parameters using the maximum likelihood approach. As a result, we can also derive the estimates of trend component μ_t^t and cyclical component μ_t^c, respectively.

4 Bayesian inference

In a Bayesian framework, inference about the unknown parameters θ is made via the posterior distribution of θ, which, according to Bayes theorem, is given by

$$\pi(\theta|y) = \frac{\pi(\theta)f(y|\theta)}{\int \pi(\theta)f(y|\theta)} \propto \pi(\theta)f(y|\theta)$$

where $\pi(\theta)$ denotes the prior beliefs about the parameters and $f(y|\theta)$ represents the sampling density (likelihood function) of the T observations given the parameters θ. As the theorem states, we update our prior beliefs of θ using information from the sample data, i.e., the likelihood function. Since the posterior distribution of θ is analytically intractable, direct inference is difficult, if not impossible, to implement using conventional Bayesian approach such numerical integration. [5] However, the recent advances in Bayesian simulation-based techniques, e.g., Markov-chain Monte Carlo (MCMC) approach, can be tailored to provide us a feasible and efficient method for making inference on the parameters θ. Although the joint posterior distribution is not in a standard form, the full conditional density of individual component of θ, conditional on the data and the other parameters, can be shown to take a simple and standard form. As a result, the Gibbs sampler, a special algorithm of the MCMC approach, is readily available for simulating from those "standard" full conditional densities. [6] We briefly discuss the Gibbs sampler along with data augmentation algorithm of Tanner and Wong (1987) in the next section. It turns out that the data augmentation algorithm will greatly facilitate the derivations of the relevant full conditional distributions needed for implementing the Gibbs sampler.

4.1 Gibbs sampler with data augmentation algorithm

The recent advance in the simulation-based approach, e.g., Markov chain Monte Carlo, has inspired a lot of empirical applications in Bayesian framework. Among which, the Gibbs sampler, first introduced by Geman and Geman (1984), is an algorithm for generating random variates from an intractable marginal distribution indirectly from the full conditional distributions which are usually available in a simple form.

In general, direct sampling from a posterior distribution $\theta|y$ is commonly infeasible. However, assuming that the full conditional distributions of the latent variable y^* along with the partitioned parameters $\theta = (\theta_1, \theta_2, \cdots, \theta_B)'$ are all available and in standard forms, the Gibbs sampler with data augmentation algorithm generates posterior sample variates $\left[y^{*(t)}, \theta^{(t)}\right]$ by recursively drawing from the following full conditional distributions,

$$y^*|y, \theta^{(t-1)}, \qquad \theta_i|y, y^{*(t)}, \theta_j^{(t)}, \theta_k^{(t-1)}$$

where $j < i, k > i$ and $i = 1, 2, \cdots, B$. Iteration of this process would

[5] The similar problem remains as well when one tries to estimate the model using classical methods such as maximum likelihood or generalized method of moments.

[6] Another popular variant of the MCMC approach is the Metropolis-Hastings algorithm which is particularly suitable for drawing from the "non-standard" full conditional density.

generate a sequence $\left[y^{*(t)}, \theta^{(t)}\right]$ which is a realization of a Markov chain. Under mild conditions, as $t \to \infty$, $\left[y^{*(t)}, \theta^{(t)}\right]$ converges in distribution to that of joint posterior density of the latent variable y^* and the parameters θ, namely $\pi(y^*, \theta)$, and each block $\left[\theta_i^{(t)}\right]$ also converges in distribution to its marginal density $\pi(\theta_i), i = 1, 2, \cdots, B$. In addition, given a sequence of N draws, according to the ergodic theorem, the function of interest, say $E\left[g(\theta_i)|y\right]$, can be consistently estimated by $\frac{1}{N}\sum_{j=1}^{N} g\left(\theta_i^{(j)}\right)$.

4.2 The FP-DOP model

As we have shown that all we need to implement the Gibbs sampler is the relevant full conditional densities of the parameters and, possibly, those of the latent variable. The OP model is considered in Albert and Chib (1993) and, thus, we refer the readers to the paper for details. For the remaining two versions of the DOP models, i.e., one with fixed-coefficients and the other with time-varying parameters, the specifications of priors and the derivations of full conditionals for these two models are both discussed. In particular, we first describe the FP-DOP case and, then, the TVP-DOP model on the next subsection.

To deal with the FP-DOP model, we note that, conditioned on y^*, the full conditional distributions of the remaining parameters, i.e., α and γ, can be derived in a very straightforward way. With regard to the specification of the prior for the model parameters, we assume that the priors on the unknowns α and γ are mutually independent. The prior of γ is diffuse and that of α is normally distributed as $\mathcal{N}(\alpha_0, A_0)$.

It can be shown that the full conditional density of α is normally distributed as,

$$\alpha|y^*, \gamma \sim \mathcal{N}(\hat{\alpha}, \hat{A}) \tag{15}$$

where $\hat{\alpha} = \hat{A}\left[A_0^{-1}\alpha_0 + \sum_t z_t y_t^*\right]$ and $\hat{A} = \left[A_0^{-1} + \sum_t z_t z_t'\right]^{-1}$.

Similarly, the full conditional density of $\gamma_j, j = 2, 3, \cdots, m-1$ can be seen to be uniformly distributed as

$$\gamma_j|y^*, \alpha, \gamma_{\kappa \neq j} \sim \mathcal{U}(\underline{u}, \overline{u}) \tag{16}$$

where $\underline{u} = \max\left[\max(y_t^* : y_t = j), \gamma_{j-1}\right]$ and $\overline{u} = \min\left[\min(y_t^* : y_t = j+1), \gamma_{j+1}\right]$.

The remaining problem is the derivation of the full conditional of the latent variable $y_t^*, t = 1, 2, \cdots, T$. By defining $N = \min(T, t+p)$, it can be shown that the relevant full conditional distribution of y_t^* is,

$$y_t^*|y_{\kappa \neq t}^*, y_t = j, \alpha, \gamma \sim \mathcal{TN}_{(\gamma_{j-1}, \gamma_j]}(\hat{\mu}_t, \hat{\sigma}_t^2) \tag{17}$$

i.e., a normal distribution truncated to the region $(\gamma_{j-1}, \gamma_j]$. The mean and variance, respectively, are

$$\hat{\mu}_t = \frac{z_{t,0} + \phi_1 z_{t,1} + \cdots + \phi_{N-t} z_{t,N-t}}{1 + \phi_1^2 + \cdots + \phi_{N-t}^2}$$

$$\hat{\sigma}_t^2 = \frac{1}{1+\phi_1^2+\cdots+\phi_{N-t}^2}$$

and

$$\begin{aligned} z_{t,0} &= x_t'\beta + \phi_1 y_{t-1}^* + \phi_2 y_{t-2}^* + \cdots + \phi_p y_{t-p}^* \\ z_{t,i} &= y_{t+i}^* - x_{t+i}'\beta - \sum_{j=1,j\neq i}^{p} \phi_j y_{t+i-j}^*, \quad i = 1,2,\cdots,N-t \end{aligned}$$

To implement the Gibbs sampler, we can simulate from the distributions (15), (16) and (17), in that order.

4.3 The TVP-DOP model

For latter use, we first rewrite equations (6) and (7) in a matrix form,

$$\begin{bmatrix} y_1^* \\ y_2^* \\ y_3^* \\ \vdots \\ y_T^* \end{bmatrix} = \begin{bmatrix} z_1' & 0 & 0 & \cdots & 0 \\ 0 & z_2' & 0 & \cdots & 0 \\ 0 & 0 & z_3' & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & z_T' \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \vdots \\ \alpha_T \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \epsilon_3 \\ \vdots \\ \epsilon_T \end{bmatrix}$$

$$\begin{bmatrix} I & 0 & 0 & \cdots & 0 & 0 \\ -I & I & 0 & \cdots & 0 & 0 \\ 0 & -I & I & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & -I & I \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \vdots \\ \alpha_T \end{bmatrix} = \begin{bmatrix} I \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \alpha_0 + \begin{bmatrix} \eta_1 \\ \eta_2 \\ \eta_3 \\ \vdots \\ \eta_T \end{bmatrix}$$

or, more compactly, as

$$\begin{aligned} y^* &= Z\theta + \epsilon, \quad \epsilon \sim \mathcal{N}(0, I_T) &(18) \\ A\theta &= J\alpha_0 + \eta, \quad \eta \sim \mathcal{N}(0, I_T \otimes \Sigma) &(19) \end{aligned}$$

where the definitions of $y^*, Z, \theta, \epsilon, A, J$ and η are obvious.

In order to obtain the full conditional densities for use of the Gibbs sampling procedures, we need to specify the priors. The priors of the bin boundaries γ are assumed to be diffuse as in Albert and Chib (1993). In addition, we follow Min (1998) to assume a diffuse prior for the α_0, i.e.,

$$\pi(\alpha_0|\Sigma) \propto \texttt{constant} \tag{20}$$

Regarding to the prior of θ, we first note that, from equation (19), we have,

$$\theta = A^{-1}J\alpha_0 + A^{-1}\eta \tag{21}$$

As a result, conditional on α_0, the prior of θ is normally distributed as,

$$\pi(\theta|\alpha_0, \Sigma) \sim \mathcal{N}\left(A^{-1}J\alpha_0, A^{-1}(I_T \otimes \Sigma)A^{-1'}\right) \tag{22}$$

Finally, the prior of Σ^{-1} is taken to be the product of $k+p$ independent gamma distributions with typical term denoted as,

$$\pi\left(\sigma_i^{-2}\right) \sim \mathcal{G}\left(\frac{v_{i0}}{2}, \frac{\delta_{i0}}{2}\right) \tag{23}$$

where $i = 1, 2, \cdots, p+k$.

4.3.1 The full conditional of y^*

The full conditional density of $y_t^*, t = 1, 2, \cdots, T$ takes a similar form as

$$y_t^*|y_{\kappa\neq t}^*, y_t = j, \alpha, \gamma, \Omega \sim \mathcal{TN}_{(\gamma_{j-1},\gamma_j]}(\hat{\mu}_t, \hat{\sigma}_t^2) \tag{24}$$

which is a truncated normal distribution restricted to the region $(\gamma_{j-1}, \gamma_j]$. The mean and variance, slightly different from those obtained above, are

$$\begin{aligned} \hat{\mu}_t &= \frac{z_{t,0} + \phi_{1t}z_{t,1} + \cdots + \phi_{N-t,t}z_{t,N-t}}{1 + \phi_{1t}^2 + \cdots + \phi_{N-t,t}^2} \\ \hat{\sigma}_t^2 &= \frac{1}{1 + \phi_{1t}^2 + \cdots + \phi_{N-t,t}^2} \end{aligned}$$

where $N = \min(T, t+p)$ and

$$\begin{aligned} z_{t,0} &= x_t'\beta_t + \phi_{1t}y_{t-1}^* + \phi_{2t}y_{t-2}^* + \cdots + \phi_{pt}y_{t-p}^* \\ z_{t,i} &= y_{t+i}^* - x_{t+i}'\beta_{t+i} - \sum_{j=1,j\neq i}^{p} \phi_{jt}y_{t+i-j}^*, \quad i = 1, 2, \cdots, N-t \end{aligned}$$

4.3.2 The full conditional of γ

The full conditional density of $\gamma_j, j = 2, 3, \cdots, m-1$ is identical as derived in equation (16). In particular, it is a uniform distribution as,

$$\gamma_j|y^*, \alpha, \gamma_{\kappa\neq j}, \Omega \sim \mathcal{U}(\underline{u}, \overline{u}) \tag{25}$$

where $\underline{u} = \max\left[\max(y_t^* : y_t = j), \gamma_{j-1}\right]$ and $\overline{u} = \min\left[\min(y_t^* : y_t = j+1), \gamma_{j+1}\right]$.

4.3.3 The full conditional of α_0

As shown in Min (1998), the full conditional of α_0 is normally distributed as,

$$\pi(\alpha_0|y^*, \gamma, \theta, \Sigma) \sim \mathcal{N}(\hat{\alpha}_0, V) \tag{26}$$

where

$$\begin{aligned} \hat{\alpha}_0 &= V \times \left(J' A^{-1'} Z' Q^{-1} y^*\right) \\ V &= \left(J' A^{-1'} Z' Q^{-1} Z A^{-1} J\right)^{-1} \end{aligned}$$

and $Q = ZA^{-1}(I_T \otimes \Sigma)A^{-1'}Z' + I_T$.

4.3.4 The full conditional of θ

In a similar way, we follow Min (1998) to obtain the full conditional of θ as,

$$\pi(\theta|y^*, \gamma, \alpha_0, \Sigma) \sim \mathcal{N}(\hat{\theta}, W) \tag{27}$$

where

$$\begin{aligned} \hat{\theta} &= W \times \left[Z'y^* + A'(I_T \otimes \Sigma)^{-1} J \alpha_0\right] \\ W &= \left[Z'Z + A'(I_T \otimes \Sigma)^{-1} A\right]^{-1} \end{aligned}$$

4.3.5 The full conditional of $\sigma_i^{-2}, i = 1, 2, \cdots, k + p$

By assuming independent gamma prior for each of the elements in Σ as above, the full conditional of $\sigma_i^{-2}, i = 1, 2, \cdots, k + p$ is gamma distributed as,

$$\sigma_i^{-2}|y^*, \gamma, \alpha_0, \theta \sim \mathcal{G}\left(\frac{v_i}{2}, \frac{\delta_i}{2}\right) \tag{28}$$

where

$$\begin{aligned} v_i &= v_{i0} + T \\ \delta_i &= \delta_{i0} + \sum_{t=1}^{T} (\alpha_{it} - \alpha_{it-1})^2 \end{aligned}$$

5 Data description and empirical results

5.1 Data

The data set used in this study is mainly taken from Shen and Chen (1996) and then updated thereafter as in Huang and Shen (2001, 2002). Interested readers are referred to the papers for details of constructing the narrative-based monetary indices. The sample period covers from the first quarter of 1971 to the second quarter of 1997 for the quarterly data. There are totally 106 observations, of which 58 (denoted by -1) are classified to be easy policies, 22 (denoted by 0) neutral actions, and the remaining 26 (denoted by 1) are treated as tight policies. Table 1 displays those indicators.

The macroeconomic targets of the monetary authority are assumed to be price stability as well as adequate economic growth. Those goals are measured by the inflation and output gap, respectively. In particular, the inflation is calculated by taking the (natural) log difference of the consumer price index (seasonally unadjusted) in the current period and the corresponding period last year. Output gap is proxied by the cyclical component of the (ln) real GDP. Four approaches, including the quadratic trend, HP filter, BP filter and the STS model, are used for this purpose. The time series plots of all data are displayed in Figure 1.

5.2 The OP model

The empirical results of the OP model, based on 5,000 simulated variates after discarding the first 5,000 iterations, are reported in Table 2. In particular, we present the means, standard errors, medians, 2.5%, 5.0%, 95% and 97.5% percentiles for each of the estimates. From Panels I to IV of Table 2, we find that the estimated parameters of the inflation variable (β_1) have mean values 9.4911, 10.7893, 11.1093 and 12.5265. The values are approximately equal and significantly positive judged by their corresponding 95% Bayesian confidence intervals. In other words, the probability of adopting a tight monetary action becomes higher when the inflation rate is larger. The evidence supports that the monetary policy responds counter-cyclically to curb inflation.

Regarding the output gap variables, the results are somewhat inconsistent. For example, the parameter (β_2) in the quadratic trend case (Panel I) is estimated to have a mean value of 13.5430 which is significantly positive at 95% confidence level. Similarly, the mean coefficient in the HP filter case (Panel II) is 10.0661 and is significantly positive at 90% confidence level as well. Both results imply that the monetary authority conducts policy counter-cyclically to influence output. In contrast, the mean coefficients of the output gap variable in the BP filter case and the STS case have the expected (positive) signs but neither is significant at either 95% or 90% confidence level. Thus, the mixing results show some weak, if any, evidence in support that the monetary authority adopts counter-cyclical policies to stimulate economic growth rate.

Next, the estimated mean coefficients (γ) on the bin (threshold) variable for the quadratic trend, HP filter, BP filter and STS cases are 0.8334, 0.7955, 0.7815 and 0.7730, respectively. All the estimates are significantly positive and approximately equal, indicating that the estimates are robust to the filtered approaches used. Finally, we also present the boxplots for the estimates of the OP models using four filtering approaches in Figure 2.

5.3 The FP-DOP model

Due to the fact that the empirical literature is overwhelmingly dominated by the first-order autoregressive process, we summarize the empirical results of the first-order FP-DOP model in Table 3. Similarly, we discard the first $5,000$ sample variates and collect the last $5,000$ Gibbs output for making posterior inference of the parameters.

First, the estimates of β_1, i.e., the coefficients of the inflation variable, in four cases, are in accordance with those obtained in the OP model. Namely, the signs are all positive as expected and significantly different from 0 according to 95% confidence intervals. However, the mean estimates on the inflation variable in the DOP model are all smaller than those from the OP model. It indicates that the counter-cyclical monetary policy is again confirmed in the DOP model but the response of the authority to the inflation may be less strong than that in the OP model.

Second, as in the OP model, all of the coefficients on the output gap variable have the expected positive signs. Same patterns regarding the significance of those estimates as in the OP regression have appeared in the DOP model as well. The coefficients are significant at 95% and 90% levels for the quadratic trend and HP filter cases, respectively. No evidence of significance at conventional levels for the BP filter and STS model is found as in the OP model. Similar to the inflation variable case, the mean coefficients on the output variable in the DOP model are generally smaller than those in the OP model, except for the BP filter case. Overall, the results, to some extent, seem to provide weak evidence in support of the counter-cyclical behavior adopted by the monetary authority.

Furthermore, the posterior mean estimates of the bin variable are 0.9605, 0.9537, 0.8971 and 0.9310 for the quadratic trend, HP filter, BP filter and STS cases, respectively. All the estimates are significantly positive, approximately equal and are larger than those from the OP model. More importantly, the mean values of the first-order autoregressive coefficients for the four approaches are 0.4397, 0.4911, 0.4911 and 0.5198 with corresponding 95% confidence intervals being $[0.2321, 0.6433]$, $[0.2787, 0.7045]$, $[0.2708, 0.7078]$ and $[0.3071, 0.7224]$, respectively. Clearly, those significant, positive coefficients on the autoregressive term justify the use of a dynamic version of the ordered probit model and are also consistent with the fact that the authority adopts a consistent and persistent monetary policy. Figure 3 displays the boxplots for the estimates of the DOP models using alternative output gap measures.

5.4 The TVP-DOP model

As argued in many studies, e.g., Shen, Hakes and Brown (1999) and Shen (2000), the constant-coefficient estimates of the monetary policy reaction function may over-simplify the authority's actual response to macroeconomic conditions. As a result, we consider an alternative time-varying-parameter version of the DOP model which allows the Central Bank to respond to the same change in either inflation or output gap in a different way or magnitude at different time horizons.

Table 4 and Figure 4 summarize the estimation results of the TVP-DOP model. From each panel of Table 4, the first four coefficients, i.e., $\beta_{00}, \beta_{01}, \beta_{02}$ and ϕ_0, denote the estimates of the initial state variable α_0 at time 0. Clearly, we find that the coefficient of the inflation variable, i.e., β_{01}, are all significantly positive at 95% level according to Bayesian confidence interval, except for the quadratic trend case. In contrast, no evidence is found in support of the significance of the parameter estimates on the output gap, i.e., β_{02}, except for the quadratic trend specification. The next four coefficients, i.e., $\sigma_1^2, \cdots, \sigma_4^2$, are the variance (diagonal elements) estimates of the Σ. Specifically, they control for the evolving processes and variations of the time-varying-parameters of the DOP model.

More importantly, we also find the following interesting observations. First, we check for the time path of the coefficient on the inflation variable. By examining the estimates of σ_2^2 for each panel, we find little evidence in support of large variations of the coefficients judged by their small posterior mean estimates, expect for the quadratic trend case. This observation is further confirmed by the small variations (looking at the value on the y-axis) of the second graph for each panel of Figure 4. Moreover, the mean estimates are positive in every case, confirming that a counter-cyclical monetary policy is adopted to curb inflation. The above results may be interpreted as evidence supporting that the inflation is always the major concern of the monetary authority in Taiwan as found in the OP as well as the FP-DOP model. Second, more encouraging evidence of significant time variations is found on the output gap variable. This is particularly true for the HP filter and STS model cases. In other words, the monetary policy responds to economic growth in a more diverse way. Since all the posterior mean estimates are positive, we may regard this as evidence, if any, in favor of a counter-cyclical monetary policy. Finally, the estimated bin coefficients in the TVP-DOP model are approximately equal to their counterparts as in the FP-DOP model.

6 Conclusions

This paper proposes a novel dynamic ordered probit model, with either fixed parameters or time-varying parameters, to estimate a discrete policy reaction function with monetary indices constructed by the narrative-based approach. The motivating factors of the monetary authority are presumably to be price stability (measured by inflation) and economic growth (measured by output gap). For robustness reason, alternative methods including the quadratic trend specification, the Hodrick-Prescott filter, the Band-Pass filter and the structural time series model are used to extract the cyclical components of the (ln) real GDP as a proxy for the output gap. The estimation and inference of the model is made possible via the simulation-based Bayesian techniques, i.e., the Markov chain Monte Carlo approach.

Taking above results from the OP, FP-DOP and TVP-DOP models together, we find that the monetary authority in Taiwan adopts a "leaning-against-the-wind" policy. In particular, significant and consistent evidence indicates that the intention of adopting a tight action becomes higher when the inflation becomes larger. In contrast, the response of the monetary authority to output gap (measuring economic growth objective) appears to be weaker, if any. The overall results may be interpreted as evidence in support that price stability is the primary concern of the Central Bank in Taiwan. Furthermore, the significance of the positive autoregressive coefficient suggests that the monetary authority is reasonably persistent and consistent in policy making. In addition, it also implies that studies of the discrete monetary policy reaction functions without explicitly considering the possible dynamics inherent in the time series data may be inappropriate, if not incorrect. Finally, the estimates of the TVP-DOP model reveal some evidence in support that some of the parameters are time-varying, although not all. The latter findings suggest that the attached weights to alternative ultimate policy objectives by the monetary authority do not remain constant but rather change over time. As a consequence, the estimates of fixed-coefficient reaction function of the monetary policy may produce misleading, if not incorrect, results.

References

Albert, J. H. and Chib, S. (1993), "Bayesian analysis of binary and polychotomous response data." *Journal of the American Statistical Association* 88, 669-679.

Altavilla, C. (2003), "Assessing monetary rules performance across EMU countries." *International Journal of Finance and Economics* 8, 131-151.

Baxter, M. and King, R. G. (1999), "Measuring business cycles: Approximate Band-Pass filters for economic time series." *Review of Economics and Statistics* 81, 575-593.

Benhabib, J., Schmitt-Grohe, S. and Uribe, M. (2003), "Backward-looking interest-rate rules, interest-rate smoothing, and macroeconomic instability." Working paper.

Beveridge, S. and Nelson, C. R. (1981), "A new approach to decomposition of economic time series into permanent and transitory components with particular attention to measurement of the business cycle." *Journal of Monetary Economics* 7, 151-174.

Boschen, J. F. and Mills, L. O. (1995), "The relationship between narrative and money market indicators of monetary policy." *Economic Inquiry* 33, 23-44.

Canova, F. (1998), "Detrending and business cycle facts." *Journal of Monetary Economics* 41, 475-512.

Choi, W. G. (1999), "Estimating the discount rate policy reaction function of the monetary authority." *Journal of Applied Econometrics* 14, 379-401.

Christiano, L. J. and Fitzgerald, T. J. (2003), "The Band Pass filter." *International Economic Review* 44, 435-465.

Clarida, R., Gali, J. and Gertler, M. (2000), "Monetary policy rules and macroeconomic stability: Evidence and some theory." *Quarterly Journal of Economics* 115, 147-180.

Clark, P. K. (1987), The cyclical component of U.S. economic activity." *Quarterly Journal of Economics* 102, 797-814.

Davutyan, N. and Parke, M. R. (1995), "The operations of the Bank of England, 1890-1908: A dynamic probit approach." *Journal of Money, Credit and Banking* 27, 1099-1112.

Eichengreen, B., Watson, M. W. and Grossman, R. S. (1985), "Bank rate policy under the interwar gold standard: A dynamic probit model." *Economic Journal* 95, 725-745.

Estrella, A. and Fuhrer, J. C. (2003), "Monetary policy shifts and the stability of monetary policy models." *Review of Economics and Statistics* 85, 94-104.

Gallego, F. A. and Johnson, C. A. (2003), "Building confidence intervals for the Band-Pass and Hodrick-Prescott filters: An application using bootstrapping." Working paper.

Geman and Geman (1984), "Stochastic relaxation, Gibbs distributions and the Bayesian restoration of images." *IEEE Transactions on Pattern Analysis and Machine Intelligence* 6, 721-741.

Hakes, D. R. (1990), "The objectives and priorities of monetary policy under different Federal Reserve chairmen." *Journal of Money, Credit and Banking* 22, 327-337.

Harvey, A. C. (1989), *Forecasting, structural time series models and the Kalman filter*, Cambridge: Cambridge University Press.

Hodrick, R. J. and Prescott, E. C. (1997), "Postwar U.S. business cycles: An empirical investigation." *Journal of Money, Credit and Banking* 29, 1-16.

Huang, River H. C. and Shen, C. H. (2002), "Estimation of Taiwan's binary monetary policy reaction function." *Journal of Economic Studies* 29, 222-239.

Huang, River H. C. and Shen, C. H. (2001), "The monetary policy reaction function in Taiwan: A narrative approach." *Asian Economic Journal* 15, 199-215.

Kim, C. J. and Nelson, C. R. (1989), "The time-varying-parameter model for modeling changing conditional variance: The case of the Lucas hypothesis." *Journal of Business & Economic Statistics* 7, 433-440.

McNees, S. K. (1986), "Modeling the Fed: A forward-looking monetary policy reaction function." *New England Economic Review* 3-8.

Min, C. K. (1998), "A Gibbs sampling approach to estimation and prediction of time-varying-parameter models." *Computational Statistics & Data Analysis* 27, 171-194.

Morley, J. C., Nelson, C. R. and Zivot, E. (2003), "Why are Beveridge-Nelson and unobserved-component decompositions of GDP so different?" *Review of Economics and Statistics* 85, 235-243.

Romer, C. D. and Romer, D. H. (2003), "A new measure of monetary shocks: Derivation and implications." Working paper.

Romer, C. D. and Romer, D. H. (1989), "Does monetary policy matter? A new test in the spirit of Friedman and Schwartz." *NBER Macroeconomics Annual* 121-183.

Shen, C. H. (2000), "Estimation of a Taiwan monetary reaction function with time varying parameters." *Applied Economics* 32, 459-466.

Shen, C. H. and Chen, H. R. (1996), "Monetary policy index and policy reaction function." *Academia Economic Papers* 24, 559-590.

Shen, C. H., Hakes, D. R. and Brown, K. (1999), "Time-varying response of monetary policy to macroeconomic conditions." *Southern Economic Journal* 65, 584-593.

Tanner, M. A. and Wong, W. H. (1987), "The calculation of posterior distributions by data augmentation." *Journal of the American Statistical Association* 82, 528-540.

Taylor, J. B. (1993), "Discretion versus policy rules in practice." *Carnegie-Rochester Conference Series on Public Policy* 39, 195-214.

Table 1: Indicators of the monetary policy stance

	Q1	Q2	Q3	Q4		Q1	Q2	Q3	Q4
1971	−1	−1	1	0	1985	−1	−1	−1	−1
1972	0	0	−1	−1	1986	−1	0	−1	−1
1973	1	1	1	1	1987	−1	−1	−1	−1
1974	1	1	−1	−1	1988	0	0	−1	1
1975	−1	−1	−1	0	1989	1	1	1	1
1976	0	0	−1	−1	1990	1	1	0	−1
1977	−1	−1	−1	−1	1991	−1	0	−1	−1
1978	0	0	1	1	1992	0	1	−1	−1
1979	1	1	1	1	1993	0	0	−1	−1
1980	0	0	0	1	1994	−1	−1	1	−1
1981	1	1	−1	−1	1995	0	0	−1	−1
1982	−1	−1	−1	−1	1996	−1	−1	−1	−1
1983	−1	−1	−1	−1	1997	0	1		
1984	−1	−1	−1	−1					

* $-1, 0$ and 1 denotes an easy, a neutral or a tight monetary policy, respectively.

Table 2: Estimation results of the OP model

	mean	std err	median	2.5%	5%	95%	97.5%
	Panel I: The quadratic trend approach						
β_0	-0.5636	0.1790	-0.5608	-0.9247	-0.8603	-0.2725	-0.2147
β_1	9.4911	2.7155	9.4103	4.3553	5.1366	14.0748	14.9664
β_2	13.5430	4.0552	13.4292	5.7443	7.0515	20.4436	21.6165
γ	0.8334	0.1519	0.8228	0.5530	0.5957	1.0918	1.1450
	Panel II: The Hodrick-Prescott filter approach						
	mean	std err	median	2.5%	5%	95%	97.5%
β_0	-0.5991	0.1786	-0.5949	-0.9513	-0.8952	-0.3070	-0.2550
β_1	10.7893	2.7447	10.7543	5.5043	6.3711	15.4133	16.2884
β_2	10.0661	5.1649	10.0530	-0.0728	1.5120	18.5955	20.2525
γ	0.7955	0.1615	0.7929	0.5023	0.5376	1.0734	1.1252
	Panel III: The Band-Pass filter approach						
	mean	std err	median	2.5%	5%	95%	97.5%
β_0	-0.6182	0.1768	-0.6179	-0.9661	-0.9080	-0.3258	-0.2709
β_1	11.1093	2.7947	11.1217	5.6873	6.5455	15.7472	16.6050
β_2	9.4664	6.6772	9.4031	-3.2549	-1.4185	20.5909	22.6983
γ	0.7815	0.1461	0.7754	0.5141	0.5548	1.0399	1.0901
	Panel IV: The structural time series approach						
	mean	std err	median	2.5%	5%	95%	97.5%
β_0	-0.6829	0.1653	-0.6821	-1.0113	-0.9556	-0.4133	-0.3640
β_1	12.5265	2.5759	12.4979	7.6685	8.4048	16.8211	17.6684
β_2	3.7092	8.7203	3.7303	-13.3366	-10.5604	17.9767	20.7922
γ	0.7730	0.1433	0.7734	0.4958	0.5307	1.0177	1.0625

* Results are based on 5,000 simulated values after discarding the first 5,000 draws.

Table 3: Estimation results of the FP-DOP model

	Panel I: The quadratic trend approach						
	mean	std err	median	2.5%	5%	95%	97.5%
ϕ	0.4397	0.1044	0.4404	0.2321	0.2659	0.6086	0.6433
β_0	−0.3298	0.1686	−0.3273	−0.6688	−0.6083	−0.0550	−0.0071
β_1	5.6348	2.5255	5.5493	0.9883	1.6693	10.0275	10.9261
β_2	10.3819	3.8943	10.3710	2.8427	3.9590	16.9001	17.9729
γ	0.9605	0.1756	0.9510	0.6528	0.6919	1.2633	1.3312
	Panel II: The Hodrick-Prescott filter approach						
	mean	std err	median	2.5%	5%	95%	97.5%
ϕ	0.4911	0.1070	0.4922	0.2787	0.3148	0.6672	0.7045
β_0	−0.3168	0.1707	−0.3146	−0.6632	−0.6014	−0.0430	0.0041
β_1	5.7688	2.6681	5.6203	0.9911	1.6190	10.3886	11.4826
β_2	9.1489	5.0977	9.0802	−0.8237	0.8337	17.6354	19.4085
γ	0.9537	0.1702	0.9499	0.6372	0.6794	1.2359	1.2887
	Panel III: The Band-Pass filter approach						
	mean	std err	median	2.5%	5%	95%	97.5%
ϕ	0.4911	0.1115	0.4905	0.2708	0.3073	0.6719	0.7078
β_0	−0.3748	0.1704	−0.3725	−0.7134	−0.6579	−0.0947	−0.0452
β_1	6.6803	2.7065	6.5655	1.7319	2.4475	11.3109	12.2495
β_2	4.2253	5.9207	4.1459	−7.3446	−5.4593	14.0789	15.8944
γ	0.8971	0.1752	0.8895	0.5842	0.6235	1.2079	1.2676
	Panel IV: The structural time series approach						
	mean	std err	median	2.5%	5%	95%	97.5%
ϕ	0.5198	0.1065	0.5209	0.3071	0.3413	0.6917	0.7224
β_0	−0.3807	0.1686	−0.3801	−0.7185	−0.6637	−0.1077	−0.0554
β_1	6.9248	2.4987	6.8108	2.4166	3.0281	11.2452	12.1333
β_2	9.6641	9.9891	9.6966	−9.8092	−6.8888	26.0781	29.2153
γ	0.9310	0.1750	0.9250	0.6144	0.6511	1.2363	1.2887

* Results are based on 5,000 simulated values after discarding the first 5,000 draws.

Table 4: Estimation results of the TVP-DOP model

	mean	std err	median	2.5%	5%	95%	97.5%
	Panel I: The quadratic trend approach						
β_{00}	−0.3006	0.3850	−0.3151	−1.0427	−0.8898	0.3936	0.5553
β_{01}	7.0896	4.9244	6.4513	−0.7552	0.6315	15.7707	19.2533
β_{02}	9.5332	5.0203	9.5895	−0.8267	1.0318	17.5663	19.2965
ϕ_0	0.4014	0.1139	0.4014	0.1770	0.2139	0.5907	0.6208
σ_1^2	0.0136	0.0190	0.0052	0.0002	0.0002	0.0493	0.0654
σ_2^2	1.3018	2.5528	0.1089	0.0010	0.0013	6.1569	9.1307
σ_3^2	0.0746	0.1288	0.0069	0.0002	0.0002	0.3549	0.4441
σ_4^2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
γ	0.9681	0.1876	0.9582	0.6642	0.7167	1.3000	1.3716
	Panel II: The Hodrick-Prescott filter approach						
	mean	std err	median	2.5%	5%	95%	97.5%
β_{00}	−0.3343	0.2474	−0.3294	−0.8420	−0.7369	0.0497	0.1404
β_{01}	6.2747	2.9737	6.1295	0.9457	1.6749	11.2891	12.5840
β_{02}	11.9813	11.6842	11.9259	−12.1590	−7.2526	31.0884	36.2199
ϕ_0	0.2745	0.3064	0.3286	−0.4653	−0.2919	0.6954	0.7768
σ_1^2	0.0010	0.0015	0.0004	0.0000	0.0000	0.0038	0.0055
σ_2^2	0.0006	0.0012	0.0002	0.0000	0.0000	0.0024	0.0037
σ_3^2	10.5111	18.8378	3.8440	0.4567	0.5703	34.6358	80.8127
σ_4^2	0.0054	0.0070	0.0027	0.0002	0.0002	0.0196	0.0246
γ	0.9777	0.1733	0.9547	0.6680	0.7211	1.2854	1.4002
	Panel III: The Band-Pass filter approach						
	mean	std err	median	2.5%	5%	95%	97.5%
β_{00}	−0.4076	0.2936	−0.4048	−0.9970	−0.8794	0.0397	0.1847
β_{01}	7.6488	3.3030	7.3167	1.8699	2.7592	13.4509	15.3645
β_{02}	4.0783	6.6842	3.9609	−8.2937	−6.1961	15.5143	17.6448
ϕ_0	0.4408	0.1706	0.4556	−0.0218	0.1570	0.6647	0.7260
σ_1^2	0.0052	0.0145	0.0011	0.0001	0.0001	0.0150	0.0390
σ_2^2	0.0009	0.0016	0.0001	0.0000	0.0000	0.0041	0.0052
σ_3^2	0.0331	0.0333	0.0220	0.0001	0.0002	0.0983	0.1115
σ_4^2	0.0005	0.0015	0.0001	0.0000	0.0000	0.0038	0.0051
γ	0.9818	0.1878	0.9715	0.6117	0.6771	1.3190	1.3830
	Panel IV: The structural time series approach						
	mean	std err	median	2.5%	5%	95%	97.5%
β_{00}	−0.2855	0.9947	−0.3810	−2.3118	−1.6681	1.5349	1.9658
β_{01}	10.7528	5.1657	9.7416	3.2834	4.2670	20.2588	23.0988
β_{02}	14.0957	18.1672	13.1927	−18.0183	−13.1274	46.5597	53.4997
ϕ_0	0.3791	0.1781	0.4040	−0.0279	0.0240	0.6290	0.6526
σ_1^2	0.4483	0.7650	0.0359	0.0005	0.0006	2.1662	2.7747
σ_2^2	0.0008	0.0016	0.0001	0.0000	0.0000	0.0045	0.0059
σ_3^2	9.2103	9.8487	6.2361	0.0990	0.1761	31.3076	36.8528
σ_4^2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
γ	1.2025	0.3979	1.0874	0.7025	0.7312	1.9130	2.0476

* Results are based on 1,000 simulated values after discarding the first 1,000 draws.

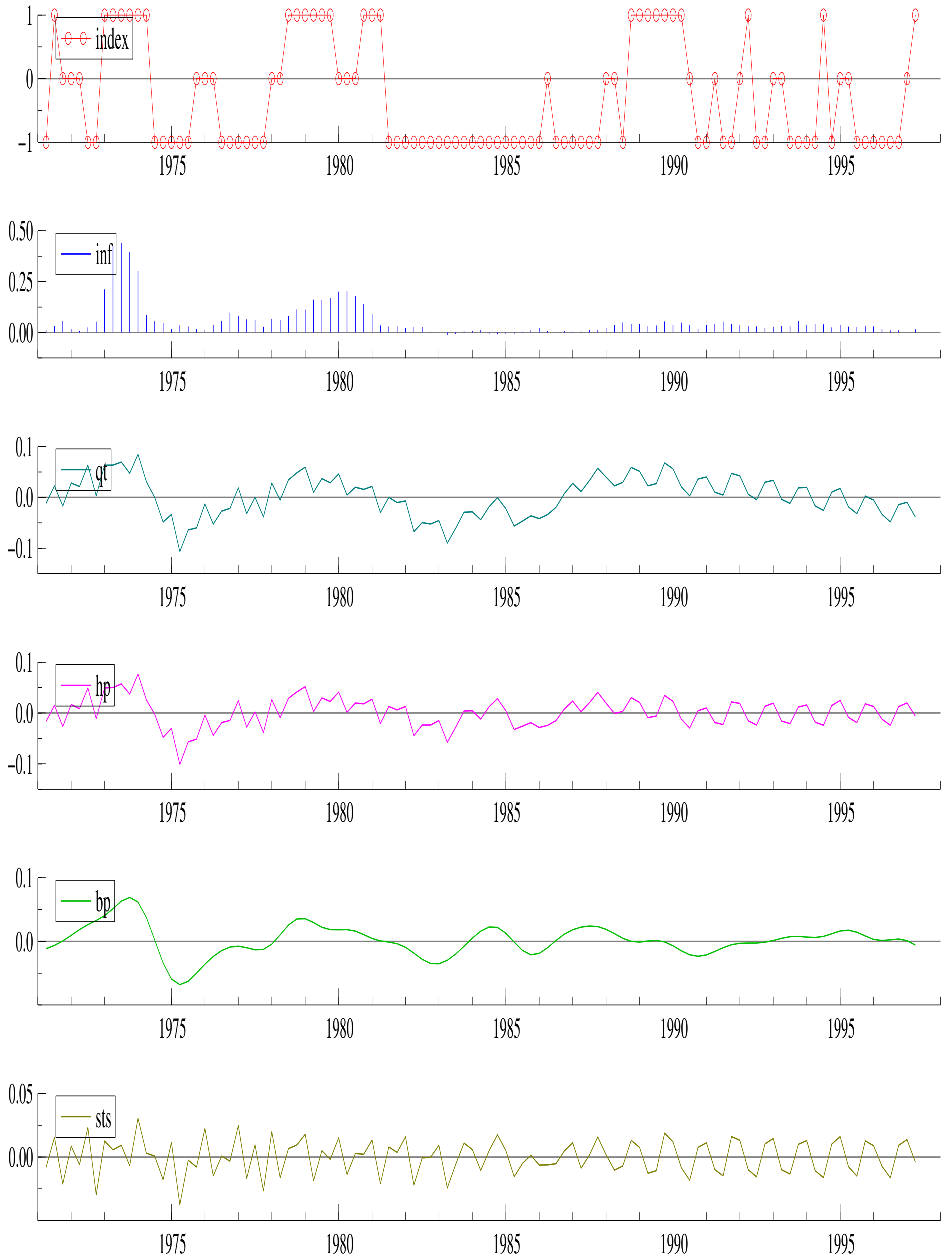

圖 1: From top to bottom panels are the time series plots of the monetary indicators, inflation, the output gaps using the quadratic trend, HP filter, BP filter, and STS approaches, respectively.

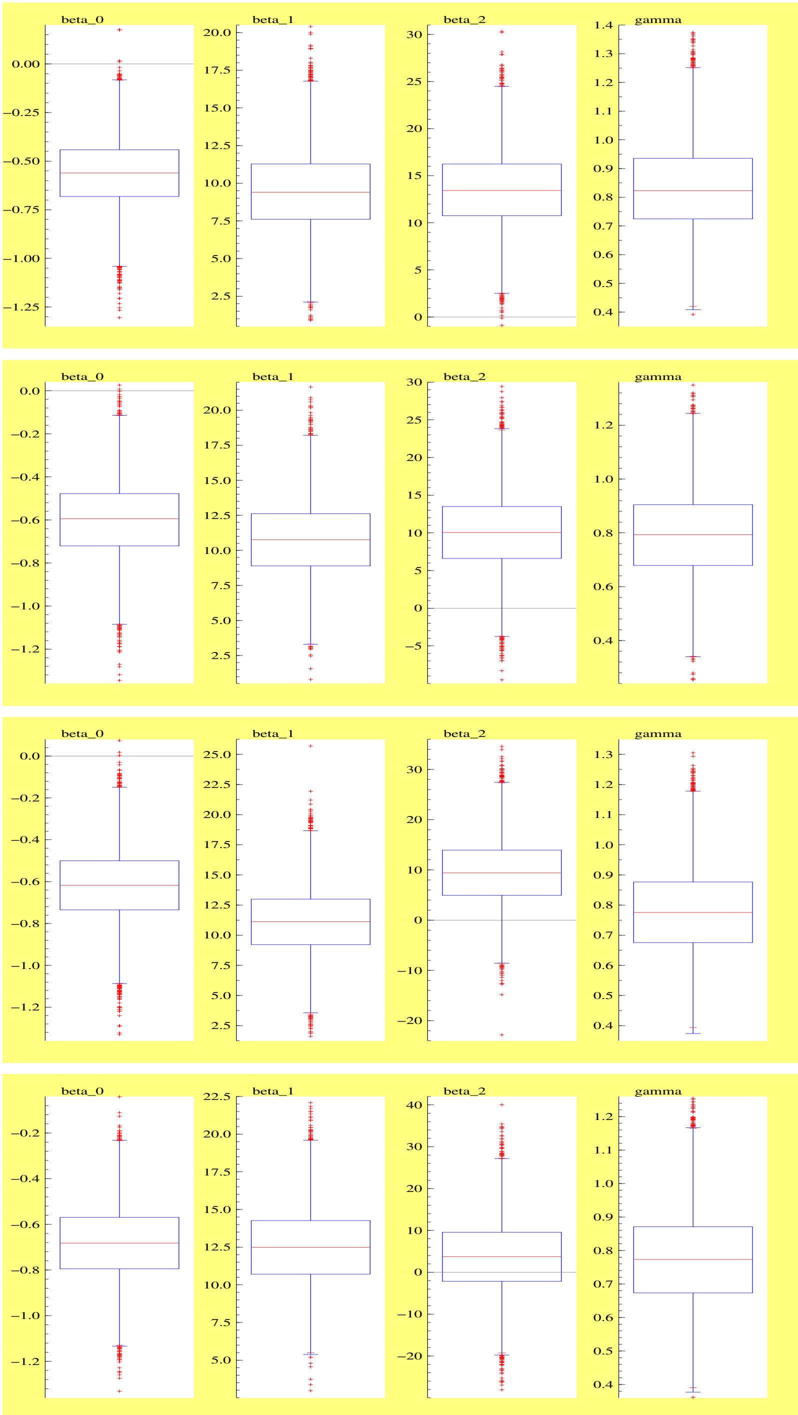

圖 2: The OP model: From top to bottom panels are the quadratic trend, HP filter, BP filter, and the STS cases, respectively. For each panel, the boxplots for $\beta_0, \beta_1, \beta_2$ and γ are shown from left to right subpanels.

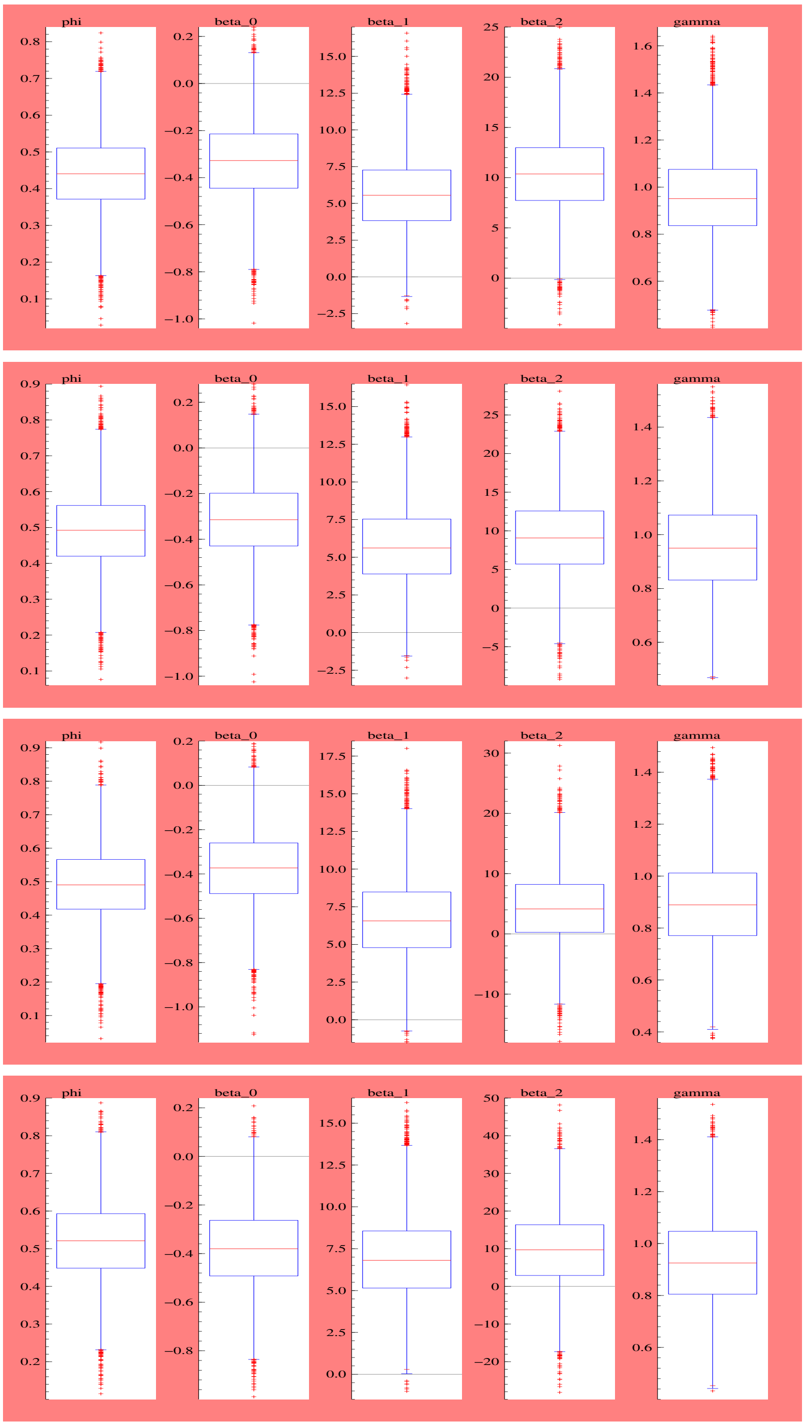

圖 3: The FP-DOP case: From top to bottom panels are the quadratic trend, HP filter, BP filter, and the STS cases, respectively. For each panel, the boxplots for $\phi, \beta_0, \beta_1, \beta_2$ and γ are shown from left to right subpanels.

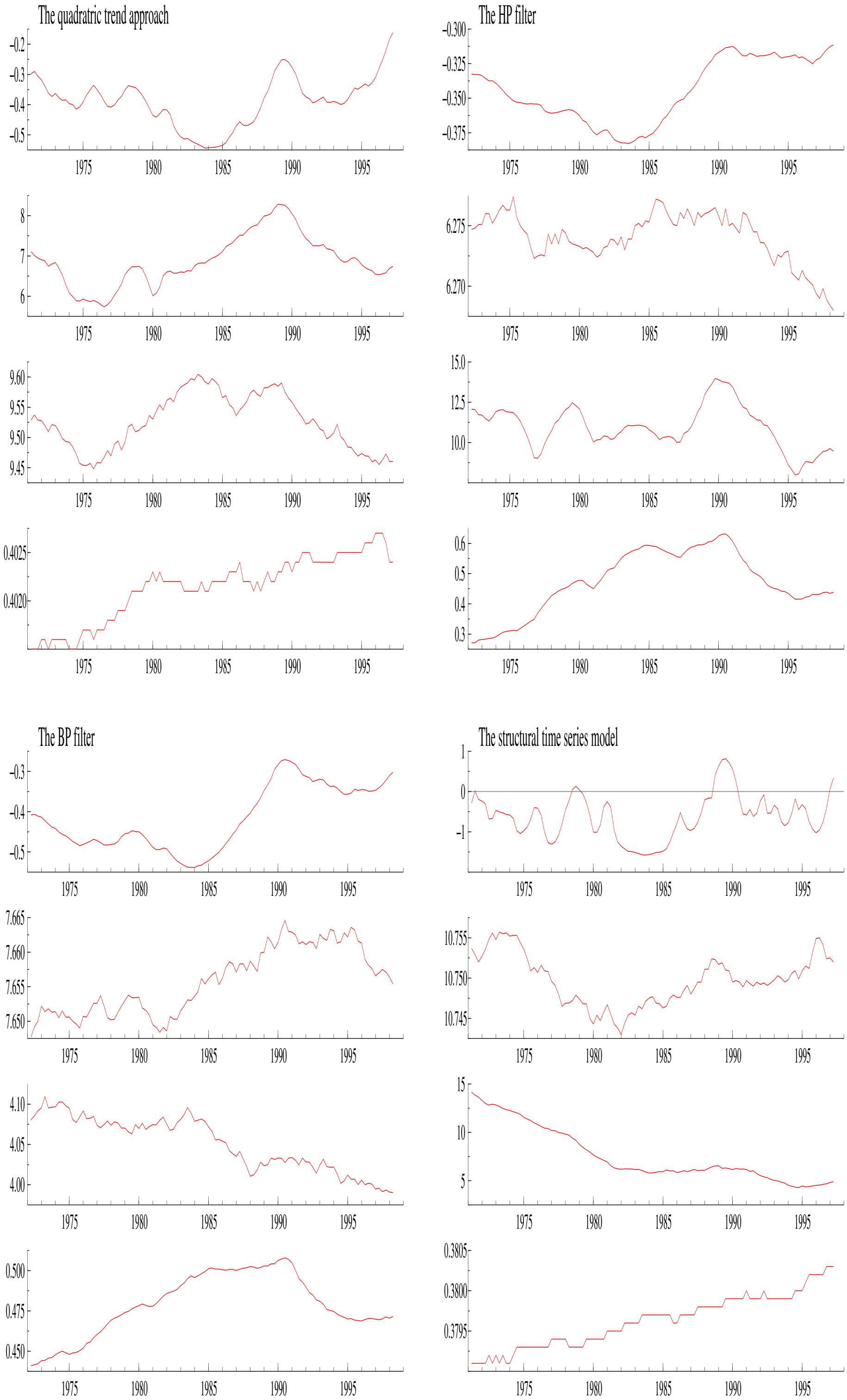

圖 4: The TVP-DOP case: The time series plots of the TVP-DOP estimates for the quadratic trend (top left panel), HP filter (top right panel), BP filter (bottom left panel), and the STS (bottom right panel) cases, respectively. For each panel, the boxplots for $\beta_0, \beta_1, \beta_2$ and ϕ are shown from top to bottom subpanels.