The Monetary Policy Reaction Function for Taiwan: A Narrative Approach*

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This paper estimates the Taiwan's monetary policy reaction function using a unique data set of narrative-based monetary policy indicators. In particular, we introduce a probit model with autocorrelated errors to take into account the specific features of the discreteness of the dependent variable as well as the serial dependence in time series data. A practical sampling scheme via the Gibbs sampler with data augmentation algorithm is developed to make posterior inference. Empirical evidence shows that the monetary policy responds countercyclically to the inflation rate but not to the economic growth rate. In addition, we find that the autoregressive parameters are significantly positive in all cases. This suggests that estimating the binary monetary policy reaction function without considering the serially correlated errors would be inappropriate, if not incorrect.

Keywords: Gibbs sampler, data augmentation, narrative approach, monetary policy reaction function.
JEL classification codes: C11, C22, C25.

I. Introduction

Almost all studies of monetary policy reaction function assume that changes in macroeconomic conditions, e.g., inflation, economic growth or unemployment, will lead to a central bank response via changes in the monetary instruments such as monetary aggregate, nonborrowed reserve or federal funds rate. For instance, Barro (1978), Mishkin (1981), Melvin (1983) and Cochrane (1989) contend that monetary aggregate is an ideal proxy for monetary policy while

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Christiano and Eichenbaum (1992) and Strongin (1992) argue that monetary policy can be better served by the nonborrowed reserves. In contrast, Goodfriend (1993) and Clarida, Gali and Gertler (1998, 2000) take as the instrument of monetary policy the federal funds rate. However, as argued in Boschen and Mills (1995), there seems no general agreement on which money market variable may well proxy the policy. Even worse, these variables might fluctuate for reasons other than shifts in monetary policy. In order to avoid these problems, a unique narrative-based monetary policy index is constructed and used to represent the stance of monetary policy over a given time period. Although this approach appears to use less information relative to models involving quantitative (continuous) money market variables, it has the advantage of avoiding serious mis-specification problems.

Due to Romer and Romer (1989), recent empirical research has rejuvenated interest in the use of narrative-based monetary indicators. For example, Boschen and Mills (1995) compare the relation between the narrative-based and the widely used money-market indicators of monetary policy. Using a variety of narrative-based monetary indices, they are able to conclude that there is a high degree of conformity with regard to the effect of monetary policy decisions on monetary variables and interest rates. Shen, Hakes and Brown (1999) use binary time series indicators on monetary policy to examine whether the response of monetary policy to macroeconomic conditions is fixed or time-varying. Tests show that the fixed-coefficient reaction function can be rejected, implying that the response of the monetary authority to, say, inflation, may depend upon the level of inflation, the stance of business cycle, and so on.

Basically, a monetary policy index is a numerical scale in terms of discrete values which represent the stance of monetary policy. For example, the monetary policy can be classified as expansionary or contractionary actions which can then converted into a binary index with values 1 or 0, respectively. The advantages of the narrative-based indicators over commonly-used money market indicators of monetary policy are described as follows. First, 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. Second, it can 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 1 August 1990 whereas M1B decreases in the month. Finally, as indicated by Boschen and Mills (1995), the narrative-based indices appear to be appealing in terms of consistency-of-interpretation and robust in relation to money market activity. Shen, Hakes and Brown (1999) provide some other reasons to adopt the narrative-based policy indicators.

If the monetary response is better proxied by a binary variable, estimation of the monetary policy reaction function can be performed by the limited dependent variable model such as the probit method, e.g., Shen and Chen (1996). However, the application of probit approach to time-series data with binary dependent

variable might be inappropriate because of possible serially correlated errors. Despite recognizing this possible model mis-specification, however, Shen and Chen (1996) are unable to develop a feasible method to deal with this problem. The purpose of this paper is to propose a probit model with autocorrelated errors (PAR) to take into account the specific features of the binary time-series data. However, the likelihood function for the PAR model is difficult to evaluate due to the need for multiple integration. Alternatively, a practical simulation-based approach via the Gibbs sampler with data augmentation algorithm is developed to overcome the problems in fitting the PAR model. Our Bayesian approach is shown to be both conceptually simple and computationally feasible. In addition, the estimates exhibit exact finite-sample properties which are also desirable in many circumstances.

The rest of this paper is organized as follows. Section II gives a brief description of how the narrative-based monetary indicators are constructed. Section III reviews the setup of the binary reaction of monetary policy and related econometric modelling as well as methodology. Section IV introduces the Griddy-Gibbs sampler with data augmentation algorithm. Section V provides the relevant full conditional distributions needed in use of the Gibbs sampling scheme. Details of the derivations are given in the Appendix. Section VI provides the empirical results with interpretation. Concluding remarks are made in Section VII.

II. Data Construction

The first Taiwan monetary policy indicator was constructed by Shen and Chen (1996), who follow the narrative approach by reading the minutes of the Central Bank of China (CBC) to develop the series. To construct the monetary indices in Taiwan, Shen and Chen (1996) studied the directive of the CBC Committee meeting. While the directives of the US Federal Open Market Committee (FOMC) are regularly recorded and made available to the public, the minutes of the CBC Committee meeting are usually not available. Although the CBC often announces its short-term monetary policy after the Committee meeting, its announcements are typically vague to avoid criticism of lack of credibility. For instance, it uses ‘easy within tight’, ‘tight within easy’, ‘growth under stability’ and ‘stability under growth’ to describe its intention of implementing the monetary policy. Since its true intention is blurred, assessing the current stance of the monetary policy solely on the basis of announcements is relatively difficult. Shen and Chen (1996) examined newspaper comments as for back as 1965. They also noted that the macroeconomic data must also be examined to gauge the Committee’s decision. They employed a lexicographic principle, which included four sequential rules, to complement the study of the announcements. The sequential rules are based on the authority’s announcement, changes of the required reserve ratio, the discount rate and the monetary base.

The first rule is based on the authority’s announcement. If the CBC articulated its intention without ambiguity, Shen and Chen (1996) assigned it as the top

Table 1 Indicators of Monetary Policy – Quarterly Data

Year	*First*	*Second*	*Third*	*Fourth*	*Year*	*First*	*Second*	*Third*	*Fourth*
1971	1	1	0	0	1985	1	1	1	1
1972	1	1	1	1	1986	1	1	1	1
1973	0	0	0	0	1987	1	1	1	1
1974	0	0	1	1	1988	0	1	1	0
1975	1	1	1	1	1989	0	0	0	0
1976	1	1	1	1	1990	0	0	1	1
1977	1	1	1	1	1991	1	1	1	1
1978	1	0	0	0	1992	1	0	1	1
1979	0	0	0	0	1993	0	1	1	1
1980	0	0	0	0	1994	1	1	0	1
1981	0	0	1	1	1995	0	0	1	1
1982	1	1	1	1	1996	1	1	1	1
1983	1	1	1	1	1997	1	0		
1984	1	1	1	1					

Note: Easy monetary policy is denoted by 1 and tight action is denoted by 0.

priority regardless of the changes in the above mentioned money market variables. With the exception of an institutional factor in May 1965, the change of the required reserve ratio is ranked as the second priority. Namely, if no announcement was made by the authority, the then stance of the monetary policy was evaluated by checking the required reserve ratio. The third priority was to verify the discount rate which might change in terms of both technical and non-technical adjustments. Since only the non-technical adjustment signalled the intention of the monetary authority, the change in it was employed to evaluate the tight (easy) monetary policy. Finally, they looked at the change in the monetary base during the periods when the stance of the monetary policy could not be identified by the above three rules. Based on the above four lexicographic rules, they were able to assess the intention of Taiwan monetary policy. For instance, if no clear announcement was made by the CBC, the increase (decrease) of the required ratio was judged as a signal of tight (easy) monetary policy no matter what the change of discount rate and the monetary base was.

The monetary policy indicator is mainly taken from Shen and Chen (1996) and then updated thereafter.[1] Both quarterly and monthly data are used in the paper. From Table 1, we can see that the sample period covers from the first quarter of 1971 to the second quarter of 1997 for the quarterly data. There are 106 observations in total of which 71 (denoted by 1) are classified as expansionary policies while the remaining 35 (denoted by 0) are treated as contractionary actions.

1. Shen and Chen (1996) explain more carefully and thoroughly for the criteria for constructing the narrative-based monetary policy indices.

Table 2 Indicators of Monetary Policy – Monthly Data

Year	*Jan.*	*Feb.*	*March*	*April*	*May*	*June*	*July*	*Aug.*	*Sept.*	*Oct.*	*Nov.*	*Dec.*
1978	1	1	1	1	1	0	0	0	0	0	0	0
1979	0	0	0	0	0	0	0	0	0	0	0	0
1980	0	0	0	0	0	0	0	0	0	0	0	0
1981	0	0	0	0	0	0	1	1	1	1	1	1
1982	1	1	1	1	1	1	1	1	1	1	1	1
1983	1	1	1	1	1	1	1	1	1	1	1	1
1984	1	1	1	1	1	1	1	1	1	1	1	1
1985	1	1	1	1	1	1	1	1	1	1	1	1
1986	1	1	1	1	1	1	1	1	1	1	1	1
1987	1	1	1	1	1	1	1	1	1	1	1	1
1988	0	0	0	1	1	0	1	1	1	0	0	0
1989	0	0	0	0	0	0	0	0	0	0	0	0
1990	0	0	0	0	0	0	1	1	1	1	1	1
1991	1	1	1	1	1	1	1	1	1	1	1	1
1992	1	1	1	0	0	0	1	1	1	1	1	1
1993	1	0	0	1	1	1	1	1	1	1	1	1
1994	1	1	1	1	1	1	0	0	0	0	1	1
1995	1	0	0	0	0	1	1	1	1	1	1	1
1996	1	1	1	1	1	1	1	1	1	1	1	1
1997	1	1	0	0	0	0						

Note: Easy monetary policy is denoted by 1 and tight action is denoted by 0.

Alternatively, from Table 2, we find that the monthly data begin in January, 1978 and end in June, 1997, with a total of 234 observations. Among which, 155 (denoted by 1) observations are considered to be easy monetary actions and the other 79 (denoted by 0) are regarded as tight policies.

The goals of monetary policy are presumed to be price stability and adequate economic growth. These objectives are measured by the inflation rate and economic growth rate, respectively. In particular, the inflation rate is calculated by taking the (natural) log difference of the consumer price index (seasonally unadjusted) in the current period and the corresponding period in the previous year. Economic growth is proxied by growth rate on gross national product when the quarterly data are used and by industrial production once monthly data are considered. The data are also seasonally unadjusted. All the data are taken from the Taiwan AREMOS databank.

III. Econometric Methodology

III.1 Ordinary probit regression

The probit model is one of the popular qualitative response models discussed in Amemiya (1985). The applications of the models are numerous, e.g., whether to

buy a car or not, whether to take a job offer or not, and so on. The simplest form of the probit model can be described as

$$y_t^* = x_t'\beta + \varepsilon_t \tag{1}$$

$$y_t = \begin{cases} 1 & \text{if } y_t^* > 0 \\ 0 & \text{if } y_t^* \le 0 \end{cases} \tag{2}$$

The latent dependent variable y_t^*, measuring possibly the tendency or desire to make a particular decision, is commonly unobservable. However, it is assumed to be a function of a $k \times 1$ vector of explanatory variable denoted by x_t. The corresponding unknown parameter β, a $k \times 1$ vector, measures how the explanatory variable x_t affects the tendency y_t^*. The error term ε_t is commonly assumed to be distributed as $iid\mathcal{N}(0, 1)$. Note that the variance is normalized to be 1 for identification reasons. The observable y_t is assumed to take a value of 1 if the desire y_t^* is high enough to exceed a threshold value (normalized to be 0 in the simple case), otherwise, 0.

Estimation of the above model can be carried out routinely by the maximum likelihood method but there are many alternatives for estimating the simple probit model. For example, minimum chi-square method, generalized method of moments, maximum score estimation, and so on. In contrast, Albert and Chib (1993) introduce a simulation-based approach for computing the exact posterior distribution of β. Specifically, taking a diffuse prior and given the latent values $y^* = (y_1^*, y_2^*, \ldots, y_T^*)'$, we can simulate β from the following full conditional density

$$\beta | y, y^* \sim \mathcal{N}(\hat{\beta}, B^{-1}) \tag{3}$$

with $y = (y_1, y_2, \ldots, y_T)'$, $\hat{\beta} = (X'X)^{-1}X'y^*$, and $B = X'X$. The latent variables $y_1^*, y_2^*, \ldots, y_T^*$ are independent and can be shown to be distributed as

$$y_t^* \sim \mathcal{N}(x_t'\beta, 1) \tag{4}$$

Note that, by definition, y_t^* is truncated to $(-\infty, 0]$ if $y_t = 0$; $(0, \infty)$ if $y_t = 1$. Details of the sampling procedure and posterior inference are discussed in Section IV.

III.2 Probit model with autocorrelated errors

The above 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 used. Although Estrella and Rodrigues (1998) propose a GMM method to estimate the autocorrelation-consistent standard errors, the coefficient estimates from simple probit regressions may still lack efficiency. As a result, a probit model with autocorrelated errors (PAR) is formulated to allow for the time-series data with presence of the binary dependent variable. Due to the fact that the empirical literature is overwhelmingly dominated

by the first-order autoregressive process, we consider the following probit model with first-order serially correlated errors. In particular, the model is specified as,

$$y_t^* = \beta_0 + \beta_1 p_{t-1} + \beta_2 g_{t-1} + \varepsilon_t \tag{5}$$

$$y_t = \begin{cases} 0 & \text{if } y_t^* \le 0 \\ 1 & \text{if } y_t^* > 0 \end{cases} \tag{6}$$

$$\varepsilon_t = \rho \varepsilon_{t-1} + u_t \tag{7}$$

where $t = 1, 2, \ldots, T$, y_t^* is the true but unobserved intention of monetary authority for adopting an easy policy, p_{t-1} the inflation rate measured by the annual growth rate of consumer price index and g_{t-1} the economic growth rate. The use of lagged income and inflation in the reaction function can be accounted for by looking at the Central Bank's daily press release. Every day, starting at 4.30 pm, the Central Bank will call a half hour's press conference to announce its recent statistical figures and policy intention. Although the phrases in the press release are mostly vague and the usages are mostly stereotyped, the release sometimes reveals the Bank's major concerns and the plausible responses. For example, on 1 February 2001, the press release stated '. . . considering the slowdown of business cycle in the last several months, and because price and exchange markets are stable, the Bank decides to decrease the re-discount rate for 0.25% . . .'. This press release clearly stated that the Central Bank looked at the previous month's economic conditions to make its current decision. Hence, it justifies our use of the previous period's income and inflation as the explanatory variable.[2]

Equation (5) states that the authority adjusts to ease or tighten the monetary policy in response to the inflation rate and economic growth rate. Presumably, a higher inflation rate and higher economic growth rate would be expected to induce a tighter monetary policy. Thus, the hypothesized signs of β_1 and β_2 are both negative. The actual action taken by the monetary authority is recorded as y_t which is 0 (contractionary) if $y_t^* \le 0$; 1 (expansionary) if $y_t^* > 0$. In contrast with Shen and Chen (1996), we allow the policy to be persistent by considering a first-order autoregressive process in the error term ε_t as specified in Equation (7). Since monetary policy is expected to be consistent, the residuals are expected to be positively serially correlated, i.e., the autoregressive parameter ρ is hypothesized to be positive. The distribution of u_t is assumed to be *iid* normally distributed with mean 0 and variance, for identification reason, $1 - \rho^2$, i.e., $iid\mathcal{N}(0, 1 - \rho^2)$.

Rewriting Equation (5) as a matrix form, we obtain

$$y_t^* = x_t'\beta + \varepsilon_t \tag{8}$$

2. We thank the referee for pointing out that allowing an information lag would be more appropriate when estimating the monetary policy reaction function.

where $x_t = (1, p_{t-1}, g_{t-1})'$ a 3×1 vector of regressors with corresponding regression parameters vector $\beta = (\beta_0, \beta_1, \beta_2)'$.

In order to illustrate why our Bayesian approach should be appreciated, it would be helpful to investigate the complexity involved in obtaining the maximum likelihood estimates. According to Poirier and Ruud (1988), the likelihood for the PAR model is given by the following T-dimensional integral

$$L = \int_{a_1}^{b_1} \cdots \int_{a_T}^{b_T} \mathcal{N}_T(X\beta, \Sigma)\, dy_T^* \cdots dy_1^* \tag{9}$$

where $\mathcal{N}_T(X\beta, \Sigma)$ represents a T-dimensional multivariate normal density function with mean $X\beta$ and covariance matrix Σ.[3] In addition

$$(a_t, b_t) = \begin{cases} (-\infty, 0] & \text{if } y_t = 0 \\ (0, \infty) & \text{if } y_t = 1 \end{cases} \tag{10}$$

Obviously, the estimation appears to be intractable even for moderate time periods T and commonly used structure of Σ.

However, the estimation problem of the PAR model can be easily dealt with via Gibbs sampler with data augmentation algorithm. By treating the latent dependent variable as an additional parameter along with the other parameters to be simulated from their respective full conditional distribution, the posterior inference can be made directly using the Gibbs output from the Markov chain once it has converged. As will become clear in the subsequent section, the Bayesian approach is not only conceptually simple but also computationally feasible. In addition, our method exhibits exact finite sample properties. The algorithm is briefly reviewed in the next section.

IV. Griddy-Gibbs Sampler with Data Augmentation

The recent advance in the simulation-based approach, e.g., Markov chain Monte Carlo, has inspired many empirical applications in Bayesian framework. Among these, 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, assume that the full conditional distributions of the latent variable y^* along with the partitioned parameters $\theta = (\theta_1, \theta_2, \ldots, \theta_p)'$ are all available and in standard forms. The Gibbs sampler with data augmentation algorithm generates posterior variates $(y^{*(t)}, \theta^{(t)})$ by recursively drawing from the following distributions

3. X is obtained by stacking $x_1', x_2', \ldots, x_T'$.

$$y^*|y, \theta^{(t-1)}, \quad \theta_i|y, y^{*(t)}, \theta_j^{(t)}, \theta_k^{(t-1)} \tag{11}$$

where $j < i$, $k > i$ and $i = 1, 2, \ldots, p$. As shown in Gelfand and Smith (1990), the random variate $(y^{*(t)}, \theta^{(t)})$, converges in distribution to that of joint posterior density of the latent variable y^* and the parameter θ as $t \to \infty$.

However, in some practical situations, the full conditional, say $\theta_i|\theta_{\neg i}, y^{*(t)}$, is nonstandard which is difficult to sample directly. The Griddy-Gibbs sampling algorithm suggested by Ritter and Tanner (1992) can be implemented to overcome this problem. The procedures are:

- Evaluate $\theta_i|\theta_{\neg i}, y^{*(t)}$ at a set of grid points, e.g., $\theta_i^1, \theta_i^2, \ldots, \theta_i^n$, to obtain $w_1, w_2, \ldots, w_n$.
- Use $w_1, w_2, \ldots, w_n$ to approximate the inverse CDF of $\theta_i|\theta_{\neg i}, y^{*(t)}$.
- Sample from the uniform distribution, $U(0, 1)$, and transform the observation via the approximate inverse CDF to obtain a sample of θ_i.

Particularly, we only need to know the function $\theta_i|\theta_{\neg i}, y^{*(t)}$ up to a proportionality constant since the normalization can be obtained from the $w_1, w_2, \ldots, w_n$ directly.

V. Full Conditional Distributions

As discussed previously, our objective is to estimate the parameters $\theta = (\beta', \rho)'$ based on the observed values y_t and explanatory variables x_t. The strategy is provided by the Griddy-Gibbs sampler with data augmentation algorithm from the Bayesian point of view. For the purpose of later analysis, we assume prior independence between β and ρ. Let the prior of β be normally distributed with mean β_0 and precision matrix B_0, i.e., $\mathcal{N}(\beta_0, B_0^{-1})$. The prior of ρ is assumed to lie in the stationary region, i.e., $\rho \in (-1, 1)$. Direct Bayesian inference about β and ρ seems difficult, if not impossible. Nonetheless, we can treat the latent variable y_t^* as an additional parameter to be simulated along with β and ρ from their individual full conditional density. It turns out that this augmentation step greatly simplifies the analysis.

In particular, given the latent data $Y_T^* = (y_1^*, y_2^*, \ldots, y_T^*)'$, the full conditional distribution of β is multivariate normal such that

$$\beta|Y_T^*, \rho \sim \mathcal{N}(\hat{\beta}, B_T^{-1}) \tag{12}$$

where $\hat{\beta} = B_T^{-1}[B_0\beta_0 + (1 - \rho^2)^{-1}X^{*\prime}W]$ and $B_T = B_0 + (1 - \rho^2)^{-1}X^{*\prime}X^*$. The first element of W is $W_1 = (1 - \rho^2)^{-\frac{1}{2}}y_1^*$, the other elements are $W_t = y_t^* - \rho y_{t-1}^*$, $2 \le t \le T$; X^* is defined accordingly.

Similarly, the full conditional distribution of ρ is

$$\rho|Y_T^*, \beta \propto L(Y_T^*|\beta, \rho)I(-1, 1) \tag{13}$$

which is proportional to

$$(1-\rho^2)^{-\frac{T-1}{2}} \exp\left\{-\frac{1}{2}(y_1^* - x_1'\beta)^2 - \frac{1}{2(1-\rho^2)} \sum_{t=2}^{T} [(y_t^* - x_t'\beta) - \rho(y_{t-1}^* - x_{t-1}'\beta)]^2\right\} I(-1, 1) \quad (14)$$

Finally, the latent values Y_T^* can be obtained via two steps. We can draw the first p latent values $Y_1^* = (y_1^*, y_2^*, \ldots, y_p^*)'$, conditional on the realized values $Y_1 = (y_1, y_2, \ldots, y_p)'$, from the following stationary distribution,

$$Y_1^* | Y_1, \beta, \phi \sim \mathcal{TN}(X_1\beta, \Sigma) \quad (15)$$

and then take subsequent draws from

$$f(y_t^* | y_1^*, \ldots, y_{t-1}^*, y_{t+1}^*, \ldots, y_T^*; y_t \in \{0, 1\}) \sim \mathcal{TN}(x_t'\beta + \bar{y}, \sigma_y^2) \quad (16)$$

where $t = p+1, p+2, \ldots, T$. The definition of Σ, $\bar{y}$ and σ_y^2 and details for derivations of the relevant full densities can be found in the Appendix.

VI. Empirical Results

In this section, we present the estimation results via the Griddy-Gibbs sampler with data augmentation algorithm. In every case, the priors on the model parameters β and ρ are taken to be very diffuse so that the estimation results reflect mainly the information from the data, not the priors. In particular, the prior on β is assumed to be normally distributed with zero mean and precision matrix $0.0001 \times I_k$ where I_k is a $k \times k$ identity matrix and k is the dimension of β. The prior of ρ is assumed to be uniformly distributed in the region $(-1, 1)$ to ensure the stationarity of the process. Then, we run the Markov chain and collect 10,000 random variates for subsequent analysis after discarding the first 10,000 draws. Therefore, the following results are all based on 10,000 sampled values. We first present results for probit model and then PAR model, using both quarterly and monthly data.

VI.1 The ordinary probit model

The empirical results using quarterly data are reported in the upper panel of Table 3. The estimated parameter of the inflation variable, $\hat{\beta}_1$, has a mean value -25.3700 with standard error 5.7686. The value is significantly negative judged by the 95% Bayesian confidence interval $[-37.1416, -14.7711]$. On the other hand, the coefficient of the growth rate variable, $\hat{\beta}_2$, has an estimated mean value -0.6160 with standard error 4.4329. Although the mean value is negative, it is not significantly different from 0 either judged by 95% confidence interval

Table 3 Probit Model

	Quarterly Data					
	mean	std	2.5%	5%	95%	97.5%
β_0	1.6588	0.3945	0.9144	1.0295	2.3291	2.4601
β_1	−25.3700	5.7686	−37.1416	−35.0766	−16.2962	−14.7711
β_2	−0.6160	4.4329	−9.4183	−7.9411	6.6100	7.9166
	Monthly Data					
	mean	std	2.5%	5%	95%	97.5%
β_0	1.2417	0.1651	0.9206	0.9718	1.5166	1.5686
β_1	−15.8766	2.4311	−20.7978	−19.9634	−11.9839	−11.2953
β_2	−1.8657	1.2773	−4.3084	−3.9655	0.2477	0.6641

Note: The results are based on 10,000 iterations after discarding the first 10,000 draws.

[−9.4183, 7.9166] or 90% confidence interval [−7.9411, 6.6100]. The implication is that the monetary authority responds countercyclically to inflation but not to economic growth rate.

We also present the results using monthly data in the lower panel of Table 3. Note that the estimated mean value of the parameter of the inflation variable, $\hat{\beta}_1$, is −15.8766 with standard error 2.4311. According to 95% Bayesian confidence interval, [−20.7978, −11.2953], we can conclude that the estimate is significantly negative. This finding is in accordance with the one using quarterly data, namely, a tight monetary policy is adopted if the inflation is high and vice versa. The posterior mean of the estimated coefficient of the growth rate variable, $\hat{\beta}_2$, is −1.8657 with standard error 1.2773. Again, the mean value is negative but is not significantly different from 0 according to either 95% or 90% confidence levels. Similar to the case using quarterly data, we do not find significant evidence to support the view that the monetary authority adopts countercyclical policies to stimulate the economic growth rate.

VI.2 The PAR model

In Table 4 we report the empirical results of the PAR model using quarterly and monthly data. The prior of the AR(1) coefficient, ρ, is taken to be uniform with value between −1 and 1 while the priors of the other parameters are the same as in the previous case. Similarly, we discard the first 10,000 sample variates and collect the last 10,000 Gibbs output for making posterior inference of the parameters.

First, we consider the case of using quarterly data. Results from the upper panel of Table 4 show that the posterior mean of $\hat{\beta}_1$ is −22.3931 with standard error 7.2588. The 95% Bayesian confidence interval ranges from −38.2108 to

Table 4 PAR Model

	Quarterly Data					
	mean	std	2.5%	5%	95%	97.5%
β_0	1.5612	0.5093	0.5754	0.7341	2.4151	2.5878
β_1	−22.3931	7.2588	−38.2108	−35.1593	−11.5172	−9.8743
β_2	−0.9773	5.5574	−11.7586	−10.1185	8.1162	9.7712
ρ	0.3408	0.1425	0.0419	0.0954	0.5644	0.5992
	Monthly Data					
	mean	std	2.5%	5%	95%	97.5%
β_0	1.0899	0.3006	0.5096	0.6007	1.5922	1.6947
β_1	−14.5012	4.5896	−23.8611	−22.3174	−7.2049	−5.7814
β_2	−0.5970	1.3208	−3.2034	−2.7754	1.5684	1.9499
ρ	0.7039	0.0569	0.5841	0.6064	0.7907	0.8037

Note: The results are based on 10,000 iterations after discarding the first 10,000 draws.

−9.8743, suggesting that the coefficient is significantly negative as expected. This significantly negative coefficient of the inflation variable implies that the central bank demonstrates countercyclical response to inflation. The posterior mean of the parameter of the growth rate variable ($\hat{\beta}_2$) is −0.9773 which is not significantly different from 0 at any reasonable Bayesian confidence interval. It shows no significant evidence being supportive of countercyclical response to real economic activity by the central bank. Taking the above results together, the stronger response of the monetary authority to inflation and no (weaker) response to economic growth seem to suggest that the inflation rate is the primary concern of the central bank. Besides, the posterior mean of the autoregressive parameter, $\hat{\rho}$, has a value 0.3408 which is significantly positive according to the 95% Bayesian confidence interval [0.1425, 0.5992]. The finding suggests that the residuals are positively serially correlated and studies of the binary monetary reaction function which do not consider possible serial dependence in the errors may be inappropriate, if not incorrect.

Turning to the empirical findings using monthly data in the lower panel of Table 4, similar results are found. The coefficient of inflation ($\hat{\beta}_1$) is estimated to be −14.5012 with standard error 4.5896. The sign is as expected and the estimate is, again, significantly negative. The growth rate variable has an estimated coefficient ($\hat{\beta}_2$) with posterior mean −0.5970 and standard error 1.3208. As found previously, it is negative but not significantly different from 0. The posterior mean of $\hat{\rho}$ is 0.7107 which is not only significantly positive but also much larger than the value 0.3408 in the quarterly data case. This suggests, not surprisingly, that serial dependence is more serious when monthly data are used.

These results are surprising to some extent since central banks in most developing countries are concerned not only with inflation but also with economic growth. In particular, the second article in Taiwan's Central Bank Law stipulates that the goal of the central bank is to pursue economic growth when the inflation rate is not in danger (Shen and Hakes, 1995). That is, while the inflation rate is still the first priority, economic growth should not be overlooked when inflation rate is stable. Thus, the unresponsiveness of monetary policy to the output variable deserves further explanations. We offer two possibilities below.

First, the Central Bank may respond to economic growth but the responses occur only when the inflation rate and exchange rate are not threatened. These hierarchy conditions may cause the responses to output to be relatively few and even sporadic since inflation may be deemed unstable by the Central Bank most of the time. These few or even sporadic responses may further cause our estimated output coefficients to be not significant enough to exceed the 10% level, though the coefficients still have the expected signs. Thus, even though we incorporate an autocorrelation coefficient, which is supposed to make our estimation more efficient, the results are not overturned.

The second explanation is that the Central Bank responds to economic growth in a nonlinear way. The nonlinear responses of monetary policy to economic conditions are often found in the US (Hakes, Gamber and Shen, 1998; Shen, Hakes and Brown, 1999) and also in Taiwan (Shen and Hakes, 1995; Shen, 2000). For example, the monetary policy may respond differently during recessions and during recovery. Thus, nonlinear responses may be another possible explanation for the unresponsive-coefficient on output. While it is an interesting topic, it is not easy to take both nonlinearity and PAR into account simultaneously. We would leave it for future study.

In summary, what stands out is that the monetary policy is consistently associated with countercyclical movement to inflation but not to economic growth rate. Furthermore, the significantly positive coefficients of the autoregressive terms in both cases strongly suggest that the residuals tend to be serially correlated over time and that this has to be taken into account when a binary monetary policy reaction function is estimated. More specifically, the strong autocorrelation found in our paper indicates that today's easy (tight) monetary policy is also influenced by the yesterday's easy (tight) monetary policy. Past studies which ignore this aspect, even though it may not have affected their main results, miss the spirit of the policy's self-momentum. That is, the policy change is hardly dramatic but is affected by the previous policy.

VII. Conclusions

This paper re-examines the monetary policy reaction function in Taiwan using a novel binary monetary policy indicator and allows for the possibility of serially correlated errors. In particular, a probit model with autocorrelated errors is proposed to make possible posterior inference of the interested parameters.

Our findings are that the central bank in Taiwan responds countercyclically to inflation but not to economic growth rate using both quarterly and monthly data. In addition, we find that the primary concern of the monetary authority appears to be price stability. We also observe that the errors tend to positively autocorrelated over time. The discovery of the first-order serial correlation in the residuals suggests that estimating the binary monetary policy reaction function without considering possibly autocorrelated errors would be inappropriate, if not incorrect.

However, the paper can be extended in many directions. First, more convincing discrete indicators should classify the monetary policy into, say, easing, neutral and firming actions. An inference can then be drawn by considering an ordered (dynamic) probit model with autocorrelated errors. Second, the central bank may respond asymmetrically to a particular policy objective, e.g., the authority may concentrate on reducing inflation when it is above some threshold value but take no action when it is lower than the threshold value. In this case, a threshold regression should be combined with our PAR model to deal with the problem. Finally, a time-varying parameter or Markov-switching in the parameter combined with the PAR model can be implemented to allow for possible structural change in the structure of the monetary policy reaction function.

Appendix

Full conditional densities of β *and* ρ

Given the augmented data $Y_T^* = (y_1^*, y_2^*, \ldots, y_T^*)'$, the complete-data likelihood function of the PAR model is

$$L(y_1^*, y_2^*, \ldots, y_T^* | \beta, \rho) = f(y_1^* | \beta, \rho) \prod_{t=2}^{T} f(y_t^* | y_{t-1}^*, \beta, \rho) \tag{A1}$$

Since the autoregressive process is assumed to be stationary, the density of the first observation y_1^* is

$$f(y_1^* | \beta, \rho) = (2\pi)^{-\frac{1}{2}} \exp\left[-\frac{1}{2}(y_1^* - x_1'\beta)^2\right] \tag{A2}$$

Alternatively, the density of y_t^* conditional on its preceding observation y_{t-1}^*, takes the form,

$$(2\pi)^{-\frac{1}{2}}(1-\rho^2)^{-\frac{1}{2}} \exp\left\{-\frac{1}{2(1-\rho^2)}[(y_t^* - x_t'\beta) - \rho(y_{t-1}^* - x_{t-1}'\beta)]^2\right\} \tag{A3}$$

where $t = 2, 3, \ldots, T$. Thus, the likelihood function of the complete data in Equation (A1) can be obtained from Equations (A2) and (A3).

By combining the prior of β with the likelihood, the full conditional distribution of β is multivariate normal such that

$$\beta|Y_T^*, \rho \sim \mathcal{N}(\hat{\beta}, B_T^{-1}) \tag{A4}$$

where $\hat{\beta} = B_T^{-1}[B_0\beta_0 + (1-\rho^2)^{-1}X^{*\prime}W]$ and $B_T = B_0 + (1-\rho^2)^{-1}X^{*\prime}X^*$. The first element of W is $W_1 = (1-\rho^2)^{-\frac{1}{2}}y_1^*$, the other elements are $W_t = y_t^* - \rho y_{t-1}^*$, $2 \le t \le T$; X^* is defined similarly.

Similarly, the full conditional distribution of ρ can be obtained by observing the following fact,

$$\rho|Y_T^*, \beta \propto L(Y_T^*|\beta, \rho)I(-1, 1) \tag{A5}$$

which is proportional to,

$$(1-\rho^2)^{-\frac{T-1}{2}} \exp\left\{-\frac{1}{2}(y_1^* - x_1'\beta)^2 - \frac{1}{2(1-\rho^2)}\sum_{t=2}^{T}[(y_t^* - x_t'\beta) - \rho(y_{t-1}^* - x_{t-1}'\beta)]^2\right\}I(-1, 1) \tag{A6}$$

where $I(-1, 1)$ means that one makes a draw of ρ from (A6), accepting it if it lies in the stationary region $(-1, 1)$. It is clear that this full conditional density does not take any simple form so that it is not easy to make the draw directly. However, as discussed earlier, the 'Griddy–Gibbs sampler' can be readily applied to simulate from this non-standard univariate distribution.

Full conditionals of the latent variable Y_T^*

In this subsection, we show how to derive the full conditional density of the latent variable Y_T^*. By the law of total probability, we can decompose the joint density of Y_T^* into the product of conditional densities as,

$$p(Y_T^*|\beta, \phi) = p(y_1^*, y_2^*, \ldots, y_p^*|\beta, \phi)\prod_{t=p+1}^{T} p(y_t^*|y_{t-1}^*, y_{t-2}^*, \ldots, y_{t-p}^*|\beta, \phi) \tag{A7}$$

where $y^* = (y_1^*, y_2^*, \ldots, y_T^*)'$ denotes the augmented or complete data.

Since the process is assumed to be stationary, following Chib and Greenberg (1994), we can draw the first p latent values $Y_1^* = (y_1^*, y_2^*, \ldots, y_p^*)'$, conditional on the realized values $Y_1 = (y_1, y_2, \ldots, y_p)'$, from the following stationary distribution

$$Y_1^*|Y_1, \beta, \phi \sim \mathcal{TN}(X_1\beta, \Sigma) \tag{A8}$$

where X_1 is a $p \times k$ matrix with tth row x_t', $t = 1, 2, \ldots, p$, and $\sum = \Phi \sum \Phi' + e_1(p)e_1(p)'$,

$$\Phi = \begin{bmatrix} \phi_{-p}' & \phi_p \\ I_{p-1} & 0 \end{bmatrix}$$

$e_1(p) = (1, 0, \ldots, 0)'$ and $\phi_{-p} = (\phi_1, \phi_2, \ldots, \phi_{p-1})'$.

Due to sequential nature of the Gibbs sampler, we then take subsequent draws from

$$f(y_t^* | y_1^*, \ldots, y_{t-1}^*, y_{t+1}^*, \ldots, y_T^*; y_t \in \{0, 1\}) \tag{A9}$$

where $t = p + 1, p + 2, \ldots, T$. By letting $N = \min(T, t + p)$, it can be shown that the above full conditional density is

$$\mathcal{TN}(x_t'\beta + \bar{y}, \sigma_y^2) \tag{A10}$$

with $\bar{y} = z_t'\phi^*/\phi^{*\prime}\phi^*$, $\sigma_y^2 = 1/\phi^{*\prime}\phi^*$, $z_t = (z_{t,1}, z_{t,2}, \ldots, z_{t,N-t+1})'$, $\phi^* = (1, \phi_1, \ldots, \phi_{N-t})'$,

$$z_{t,1} = \phi_1\varepsilon_{t-1} + \phi_2\varepsilon_{t-2} + \ldots + \phi_p\varepsilon_{t-p}$$

$$z_{t,i} = \varepsilon_{t+i-1} - \sum_{j=1, j\neq i-1}^{p} \phi_j \varepsilon_{t+i-1-j}, \quad i = 2, 3, \ldots, N - t + 1.$$

and $\varepsilon_t = y_t^* - x_t'\beta$. As a result, we can simulate a value for y_t^* from the range $(-\infty, 0]$ if $y_t = 0$ and from the range $(0, \infty)$ if $y_t = 1$.

References

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

Amemiya, T., 1985, *Advanced Econometrics*. Harvard University Press, Cambridge, MA.

Barro, R. J., 1978, Unanticipated money, output, and the price level in the United States. *Journal of Political Economy*, **86**, pp. 549–580.

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

Chib, S. and E. Greenberg, 1994, Bayes inference in regression models with ARMA(p, q) errors. *Journal of Econometrics*, **64**, pp. 183–206.

Christiano, L. and M. Eichenbaum, 1992, Liquidity effects and the monetary transmission mechanism. *American Economic Review*, **82**, pp. 346–353.

Clarida, R., J. Gali and M. Gertler, 1998, Monetary policy rules in practice: some international evidence. *European Economic Review*, **42**, pp. 1033–1067.

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

Cochrane, J. H., 1989, The return of the liquidity effect: a study of the short-run relation between money growth and interest rates. *Journal of Business & Economic Statistics*, **7**, pp. 75–83.

Estrella, A. and A. P. Rodrigues, 1998, *Consistent Covariance Matrix Estimation in Probit Model with Autocorrelated Errors*. Working paper.

Gelfand, A. E. and A. F. M. Smith, 1990, Sampling-based approaches to calculating marginal densities. *Journal of the American Statistical Association*, **85**, pp. 398–409.

Geman, D. and S. Geman, 1984, Stochastic relaxation, Gibbs distributions and the Bayesian restoration of images. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **6**, pp. 721–741.

Goodfriend, M., 1993, Interest rate policy and the inflation scare problem: 1979–1992. *Federal Reserve Bank of Richmond Economic Quarterly*, **79**, pp. 1–24.

Hakes, D. R., E. N. Gamber and C. H. Shen, 1998, Does the Federal Reserve lexico-graphically order its policy objectives? *Eastern Economic Journal*, **24**, pp. 195–206.

Melvin, M., 1983, The vanishing liquidity effect of money on interest: analysis and implications for policy. *Economic Inquiry*, **21**, pp. 188–202.

Mishkin, F. S., 1981, Monetary policy and long-term interest rates: an efficient markets approach. *Journal of Monetary Economics*, **7**, pp. 29–55.

Poirier, D. J. and P. A. Ruud, 1988, Probit with dependent observations. *Review of Economic Studies*, **15**, pp. 593–614.

Ritter, C. and M. A. Tanner, 1992, Facilitating the Gibbs sampler: The Gibbs stopper and the Griddy-Gibbs sampler. *Journal of the American Statistical Association*, **87**, pp. 861–868.

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

Shen, C. H., 2000, Estimation of Taiwan monetary reaction function: The nonlinear time varying parameter model. *Applied Economics*, **32**, pp. 459–466.

Shen, C. H. and H. R. Chen, 1996, Monetary policy index and policy reaction function. *Academia Economic Papers*, **24**, pp. 559–590.

Shen, C. H. and D. Hakes, 1995, Monetary policy as a decision-making hierarchy: the case of Taiwan. *Journal of Macroeconomics*, **17**, pp. 357–368.

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

Strongin, S., 1992, *The Identification of Monetary Policy Disturbance: Explaining the Liquidity Puzzle*. Manuscript, Federal Reserve Bank of Chicago.