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Stability of Phillips Curve: The case of Taiwan

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Abstract

We study the time-varying slope of the Phillips curve by applying a tri-variate hybrid VAR model with time-varying parameter and stochastic volatility (hybrid TVP-VAR-SV, hereafter) to Taiwan's macroeconomic data. We follow Chan and Eisenstat (2018b) by using a Bayesian approach to approximate the posterior density of (time-varying) parameters and the marginal likelihood of a model, in which the latter one is used for the model comparison. We find that the fitness of a hybrid TVP-VAR-SV model to Taiwan's data is superior to a “non-hybrid” TVP-VAR-SV model of Primiceri (2005), a widely-used one in the current studies. In particular, the estimated parameters shown in the inflation equation, found in the best model and used to characterize the Phillips curve, are time-invariant, supporting the stability of Taiwan's Phillips curve over the past four decades. Moreover, we also find the stability of Phillips curve for China, the largest trading partner for Taiwan and similar to Taiwan in both language and culture, over the past two decades.

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1. Introduction

Quite a lot of macroeconomists recently observe that the Phillips curve has been flattened in the advanced economies over the post-global financial crisis, the so-called "Great Recession" period (Coibion and Gorodnichenko, 2015; Del Negro, Giannoni and Schorfheide, 2015; Bobeica and Jarociński, 2019; Van Zandweghe, 2019).[1] This phenomenon, also named "missing disinflation (inflation)", implies that the impact of the change in real economic activity, usually proxied by either the output gap or unemployment rate, on the inflation is quite small.[2] Occhino (2019) argue that understanding the change in the slope of Phillips curve, particularly the sources resulting to it, is very important to the policymakers for conducting the appropriate monetary policy.[3] Although many results are found in support of a flatter Phillips curve over the period of post-global financial crisis in advanced economies, we rarely find the discussion of it for Taiwan's economy, at least studied from a Bayesian perspective. Accordingly, we study the slope of Taiwan's Phillips curve and focus our attention on whether it exists time-varying or not over the past four decades when Taiwan experienced the structural change of the economy and multiple shifts of political regime.

Regarding the model that we use to study the time-varying slope of the curve, we use a reduced-form vector autoregression model with time-varying parameter and stochastic volatility (TVP-VAR-SV, hereafter), a useful model for characterizing the structural change of the economy. In particular, a TVP-VAR-SV model is widely adopted to study the time-varying interrelationship among the macroeconomic variables and the evolution of the transmission mechanism of the monetary policy since it is proposed by Cogley and Sargent (2005) and Primiceri (2005).[4] Using U.S. macroeconomic data, Chan and Eisenstat (2018a) find the in-sample fit, measured in terms of the marginal likelihood, of a TVP-VAR-SV model is far larger than a conventional VAR model but it seems that the increased goodness of fit in a model is mostly coming from the specification of the stochastic volatility rather than the time-varying parameters. Accordingly, Chan and Eisenstat

[1]Both the first and third cited papers adopt the reduced-form VAR models to study the time-varying slope of the Phillips curve. Instead, both the second and fourth cited papers study it in the structural Dynamic Stochastic General Equilibrium (DSGE) models.

[2]The Phillips curve, characterizing the negative relationship between inflation and unemployment rate, was named by Samuelson and Solow (1960) in remembrance of the empirical findings of Phillips (1958), when he found a negative relationship between nominal wage growth and unemployment rate in U.K. economy. The intuition behind the Phillips curve is that the firm hires more workers, lowering the unemployment rate, in response to a boom economy, and it lets workers to ask for higher wages and thus the firm raises the price.

[3]From the perspective of policy implementation, by altering the monetary policy to influence the aggregate demand, policymaker could choose any combination of two macroeconomic indicators, e.g., inflation and unemployment rate, along the curve, and the slope of the curve is particularly related to the effectiveness of the policy.

[4]Primiceri (2005) extends the model specification of Cogley and Sargent (2005) by additionally considering the evolution of the structural parameters, used to identify the structural shocks. The hybrid model of Chan and Eisenstat (2018b) that we consider in this paper is an extension of a Primiceri's model.

(2018b) further develop a hybrid TVP-VAR-SV model that allows the parameters in one or some equations to be time-invariant and find that, using U.S. data, the fit of a hybrid TVP-VAR-SV is better than that of both the TVP-VAR-SV and the VAR model with time-invariant parameters. Using Taiwan's macroeconomic data, Chin (2020) studies the goodness of fit in a TVP-VAR-SV model and find the results consistent with those of Chan and Eisenstat (2018a). However, it is unknown whether a hybrid TVP-VAR-SV model fits Taiwan's data even better. Thus, we also study this question in the paper.

We model the Phillips curve by specifying a tri-variate hybrid TVP-VAR-SV model, including the quarterly inflation, unemployment rate and rediscount rate.[5] More specifically, the macroeconomic time series data are collected from Taiwan's Economic and Statistical Database (AREMOS), ranging between 1978Q1 and 2022Q3. We use the Bayesian approach, particularly the posterior sampling algorithm of Chan and Eisenstat (2018b), to approximate the time-varying (time-invariant) posterior estimates of the parameters and the marginal likelihood of a model, in which both are respectively used for the computation of the time-varying slope in Phillips curve and the model comparison. In particular, we follow Karlsson and Österholm (2023) to define the stability of Phillips curve in the VAR model. That is, the Phillips curve is not stable when all the parameters, including the intercept, slope parameters of all the lagged variables are time-varying, in an inflation equation. We find the advantage of using a hybrid TVP-VAR-SV model to fit Taiwan's macroeconomic data. In particular, the goodness of fit in either a TVP-VAR-SV (the parameters in all the equations are time-varying) or a conventional model (the parameters in all the equations are time-invariant) is not the best one. Instead, the best model is the one that the parameters in only one of three equations, particularly the unemployment rate equation, are time-varying. That is, it implies the slope of Phillips curve, computed on the basis of the inflation equation, is approaching to time-invariant over the past decades, resulting to the stability of Taiwan's Phillips curve. Lastly, we turn to study whether Taiwan's Phillips curve becomes flatter by estimating a "non-hybrid" TVP-VAR-SV model of Primiceri (2005), and find that the slope of Taiwan's Phillips curve is relatively flatter during the post-global financial crisis.

The paper is organized as follows. Section 2 introduces a hybrid TVP-VAR-SV model. The Bayesian estimation procedure, proposed by Chan and Eisenstat (2018b), for the model is briefly introduced in Section 3. Section 4 provides a brief description of the data set, and the section is ended with the discussion of the empirical results. Finally, Section 5 concludes.

[5]Regarding the choice of the macroeconomic variables used in studying the Phillips curve, one usually considers both inflation and unemployment rates in either a multivariate or univariate autoregressive model. Stock and Watson (1999) and Karlsson and Österholm (2023) particularly replace the inflation by its difference in the autoregressive distributed lag (ARDL) and vector autoregressive (VAR) models respectively. In a structural-type of the univariate Phillips curve, the so-called New Keynesian Phillips curve, both inflation and output gap are adopted as main variables to estimate the parameters. Specifically, Gali and Gertler (1999) replace output gap by the real marginal cost, proxied by labor share income.

2. Hybrid TVP-VAR-SV Model

Using the hybrid TVP-VAR-SV model of Chan and Eisenstat (2018b) to study the stability of the Phillips curve has the following benefits. First, it is a flexible model that allows none, some or all the parameters to be time-varying. Second, some empirical studies show that the fitness of the model to U.S. data is better than either the conventional VAR or the "non-hybrid" TVP-VAR-SV model (Karlsson and Österholm, 2023). A classical TVP-VAR-SV model with the lag length of p could be written as

$$y_t = \Phi_{0,t} + \Phi_{1,t} y_{t-1} + \Phi_{2,t} y_{t-2} + ... + \Phi_{p,t} y_{t-p} + u_t, \quad t = 1, ..., T, \tag{1}$$

where y_t is a $n \times 1$ vector of endogenous variables, and n is specified as three in the paper, representing the "inflation equation", "unemployment rate equation" and "interest rate equation" respectively; $\Phi_{0,t}$ is a $n \times 1$ vector of time-varying intercept and $\Phi_{i,t}$ is a $n \times n$ matrix of time-varying coefficients for the lagged j period of the variable, $j = 1, ..., p$; u_t is a $n \times 1$ vector of reduced-form error, assumed to follow a multivariate normal density with the zero mean vector and the covariance matrix of Ω_t. Chan and Eisenstat (2018b) rewrite the equation (1) as a structural form in a recursive representation,

$$A_t y_t = B_{0,t} + B_{1,t} y_{t-1} + B_{2,t} y_{t-2} + ... + B_{p,t} y_{t-p} + \varepsilon_t, \tag{2}$$

where A_t is a $n \times n$ lower-triangular matrix of structural parameters with ones on the main diagonal and is used to identify the structural shocks.[6] $B_{0,t}$, $B_{1,t}$, ..., $B_{p,t}$ are the corresponding time-varying intercept and coefficients; ε_t is a $n \times 1$ vector of structural errors, following a multivariate normal density with the zero mean vector and the diagonal covariance matrix of Σ_t, in which the diagonal elements are expressed as $e^{h_{1,t}}$, $e^{h_{2,t}}$,..., $e^{h_{n,t}}$. In particular, $h_{i,t}$ is a logarithmic form of time-varying volatility for the variable i, and it is assumed to follow a random-walk process without the drift,

$$h_{i,t} = h_{i,t-1} + \zeta_{i,t}, \quad \zeta_{i,t} \sim N\left(0, \sigma^2_{i,h}\right), \tag{3}$$

where the equation (3) is a state equation for the unobserved volatility, and $h_{i,0}$ is the initial state, treated as the parameters to be estimated. Given the structural-form expression and the diagonal covariance matrix of Σ_t, Chan and Eisenstat (2018b) state that the Bayesian inference could be applied to it equation-by-equation. Accordingly, Chan

[6] As stated in Chan and Eisenstat (2018b), using a recursive (structural) VAR model, obtained via the Cholesky decomposition, instead of a reduced-form one makes the estimation stage relatively easy since one could estimate the system based on equation by equation. Carriero, Clark and Marcellino (2016) adopt a similar model and argue that the triangular system is simply used for estimation stage, not for identifying the structural shocks. Once one obtains the posterior draws by using a MCMC approach, any identification method, including different Cholesky orderings (Stock and Watson, 2001), long-run restriction (Blanchard and Quah, 1989) and sign restriction (Uhlig, 2005), could be applied to conduct the structural analysis.

and Eisenstat (2018b) provide the following notation to a specific equation i. Technically, the coefficients in the equation i are stacked as $\alpha_{i,t}$ and $\beta_{i,t}$, in which we stack the parameters of matrix A_t and $B_{j,t}$ $(j = 0, 1, .., p)$ in $\alpha_{i,t}$, $\alpha_{i,t} = (A_{i,1,t}, A_{i,2,t}, ..., A_{i,i-1,t})^{'}$ and $\beta_{i,t} = (B_{i,0,t}, B_{i,1,t}, ..., B_{i,p,t})^{'}$ respectively, where $B_{i,j,t}$ is the coefficients in the i^{th} row of the matrix $B_{j,t}$. Accordingly, the i^{th} equation in the structural expression (2) could be represented as

$$y_{i,t} = w_{i,t}\alpha_{i,t} + \widetilde{x}_t\beta_{i,t} + \varepsilon_{i,t}, \quad \varepsilon_{i,t} \sim N\left(0, e^{h_{i,t}}\right) \tag{4}$$

where $w_{i,t} = (-y_{1,t}, -y_{2,t}, ..., -y_{i-1,t})$ and $\widetilde{x}_t = \left(y^{'}_{t-1}, y^{'}_{t-2}, ..., y^{'}_{t-p}\right)$. The equation (4) could be further written by using a new notation, $x_{i,t} = (w_{i,t}, \widetilde{x}_t)$,

$$y_{i,t} = x_{i,t}\phi_{i,t} + \varepsilon_{i,t}, \quad \varepsilon_{i,t} \sim N\left(0, e^{h_{i,t}}\right) \tag{5}$$

where $\phi_{i,t} = \left(\alpha^{'}_{i,t}, \beta^{'}_{i,t}\right)^{'}$ and it is assumed to follow a random-walk process without the drift as

$$\phi_{i,t} = \phi_{i,t-1} + \eta_{i,t}, \quad \eta_{i,t} \sim N\left(0, \Sigma_{\phi_i}\right) \tag{6}$$

where $\phi_{i,0}$ is the initial state, treated as the parameters to be estimated.[7]

Both equation (5) and (6) consist of a state-space representation for the time-varying parameters in a TVP-VAR-SV system, particularly expressed in a single-equation basis. For the variable i, Chan and Eisenstat (2018b) specify a vector consisting of $n \times 1$ vector of dummy variables, M,

$$M = (M_1, M_2, ..., M_n) \tag{7}$$

where $M_i \in \{0, 1\}$, $i = 1, ..., n$. Thus, a hybrid TVP-VAR-SV model is obtained by imposing the M vector on the above space-space model. In particular, when $M = 1$, we are estimating a TVP-VAR-SV model of Primiceri (2005), in which the parameters in all the equations are time-varying. However, when $M = 0$, we estimate a VAR model with time-invariant parameter but stochastic volatility,

$$y_{i,t} = x_{i,t}\phi_i + \varepsilon_{i,t}, \quad \varepsilon_{i,t} \sim N\left(0, e^{h_{i,t}}\right) \tag{8}$$

where $\phi_i = \left(\alpha^{'}_i, \beta^{'}_i\right)^{'}$, $i = 1, ..., n$.

[7] According to Leiva-Leon and Uzeda (2023), the TVP-VAR-SV model that we adopt is a "traditional" one, and that is also the one commonly used in the empirical research since the empirical works of Cogley and Sargent (2005) and Primiceri (2005). By taking the system of (5) and (6) for example, a "traditional" TVP-VAR-SV model assumes that $\varepsilon_{i,t}$ and $\eta_{i,t}$ are mutually independent, implying that "*changes in the transmission mechanism of economic shocks remain entirely driven by sources of information that are not identified within the VAR system*" (please refer to Leiva-Leon and Uzeda, 2023). Since we focus on the stability of Phillips curve instead of the parameter identification, the relaxation of the independent assumption is left for the future work.

3. Bayesian Approach

It is commonly known that the VAR model, particularly the large-scale one or the model with time-varying parameters, suffers from the "over-parameterization" problem, resulting to imprecise estimation since the number of parameters is much larger than the number of observations. With the use of the prior densities for the parameters, the Bayesian approach helps to solve the problem via parameter shrinkage in the models.[8]

In this paper, we apply the Bayesian approach to approximate the joint posterior density of the parameter of interest, including the time-invariant parameters (φ), time-varying parameters (ϕ) and stochastic volatility (h) in a hybrid TVP-VAR-SV model (we ignore the subscript t for simplicity). According to Bayes' rule, the posterior density of interest, $p\left(\phi, h, \varphi \mid y\right)$, is expressed as

$$p\left(\phi, h, \varphi \mid y\right) = \frac{p\left(y \mid \phi, h, \varphi\right) p\left(\phi, h, \varphi\right)}{p\left(y\right)} \tag{9}$$

$$\phi = \left\{\phi_i\right\}_{i=1}^{n}, \quad \phi_i = \left(\phi_{i,1}^{'}, \phi_{i,2}^{'}, ..., \phi_{i,T}^{'}\right)^{'}, \quad \phi_{i,t} = \left(\alpha_{i,t}^{'}, \beta_{i,t}^{'}\right)^{'}$$

$$h = \left\{h_i\right\}_{i=1}^{n}, \quad h_i = \left(h_{i,1}, h_{i,2}, ..., h_{i,T}\right)^{'}$$

$$\varphi = \left\{\phi^0, h^0, \Sigma_\phi, \Sigma_h\right\},$$

$$\phi^0 = \left(\phi_{1,0}^{'}, , .., \phi_{n,0}^{'}\right)^{'}, \quad h^0 = \left(h_{1,0}^{'}, .., h_{n,0}^{'}\right)^{'}, \quad \Sigma_\phi = \left\{\Sigma_{\phi_i}\right\}_{i=1}^{n}, \quad \Sigma_h = \left\{\sigma_{i,h}^2\right\}_{i=1}^{n},$$

$$y = \left\{y_i\right\}_{i=1}^{n}, \quad y_i = \left(y_{i,1}, y_{i,2}, ..., y_{i,T}\right)^{'},$$

where $p\left(y \mid \phi, h, \varphi\right)$, $p\left(\phi, h, \varphi\right)$, and $p\left(y\right)$ represent the likelihood function characterizing the density of the observables, the prior density of the parameter and the marginal likelihood (data density) respectively. With respect to the approximation of the posterior density of interest in a TVP-VAR-SV model, it is generally obtained by using the Markov Chain Monte Carlo (MCMC) approach, particularly the Gibbs sampler. That is, one repeatedly samples the draws from a set of conditional posterior densities, and the retained draws are used to approximate the posterior density. In particular, we follow the studies by adopting the algorithms of Carter and Kohn (1994) and Kim, Shephard and

[8]The "Bayesian shrinkage" refer to a scenario that the posterior estimate is obtained by shifting the sample mean toward the mean of the prior density via the tightening of the prior density. Regarding the application of a Bayesian approach on the parameter shrinkage, we particularly refer to a large-scale VAR model. Bańbura, Giannone and Reichlin (2010) specify a model that includes 131 monthly macroeconomic indicators and apply a Bayesian approach to estimate the model. In particular, the "Bayesian shrinkage" is usually implemented by using a Minnesota-type prior, taking into account the random-walk process of macroeconomic time series data for forming the prior belief of the researcher on the parameters. That is, a tight prior density for many of the parameters, associated with the lagged variables except for the first own lag, are specified around the values of zero. Instead, in a TVP-VAR-SV model, the specification of the prior density is standard across the studies for the initial state variables that characterize both the time-varying process of the parameter and volatility. The point when estimating a TVP-VAR-SV model is how to sample the time-varying state variables efficiently via the filtering algorithm.

Chib (1998) to sample the draws of time-varying parameter and volatility from their corresponding conditional posterior densities respectively, in which the former one is drawn by applying the Kalman filter to a linear Gaussian state-space model and the later one is drawn by using the mixture of seven normal densities to approximate the nonnormal density in a linear state-space model before the application of Kalman filter. One could refer to Cogley and Sargent (2005), Primiceri (2005), Koop and Korobilis (2010), Nakajima (2011) and Lubik and Matthes (2015) for the detailed derivation of the conditional posterior densities.[9]

Model comparison could be implemented in terms of the Bayesian perspective via the posterior odds ratio, the ratio of the posterior model probabilities of two competing models. More specifically, given the prior model probabilities for two competing models are the same, the posterior odds ratio reduces to the ratio of two marginal likelihoods for two competing models, the so-called Bayes factor.[10]

Regarding the computation of the marginal likelihood of a hybrid TVP-VAR-SV model, we follow the approach of Chan and Eisenstat (2018b). Technically, the objective of interest is expressed as

$$p\left(y\right) = \int p\left(y \mid \underbrace{\phi^0, h^0, \Sigma_\phi, \Sigma_h}_{\varphi}\right) p\left(\varphi\right) d\varphi \tag{10}$$

where $p\left(\varphi\right)$ is the prior density for the time-invariant parameters and $p\left(y \mid \varphi\right)$ is the integrated likelihood function, in which the time-varying parameter and volatility are both excluded from the conditional set. Chan and Eisenstat (2018b) adopt two-step approach to solve the integral problem.[11] In the first step, they approximate the integrated likelihood function by decomposing the high-dimensional integration into a low-dimensional one. Specifically, the integrated likelihood function could be written by using the rule of

[9] In a Bayesian TVP-VAR model, a special case of a TVP-VAR-SV model, the time-varying parameter could be written in a linear and Gaussian state-space representation, in which the parameter acts as the state variable, and one could sample it by using the filtering algorithm, particularly the Kalman filter. Carter and Kohn (1994) propose a method to apply the Kalman filter to efficiently generate the draws in a linear and Gaussian state-space system. However, sampling the time-varying volatility from its conditional posterior density is not straightforward in a TVP-VAR-SV model since it is expressed in a nonlinear Gaussian state-space model, in which one could not apply the Kalman filter to it directly. Kim, Shephard and Chib (1998) propose an efficient approach, an auxiliary mixture sampler, to sample all of the stochastic volatility at once. More specifically, they first linearize the nonlinear Gaussian state-space model, resulting to a linear but non-Gaussian state-space system. Then they propose a seven-component Gaussian mixture, summing seven Gaussian densities with the different weights, for approximating a logarithmic form of a chi-squared density of the measurement error. Regarding the specified weight, first and second (central) moment of seven normal densities, please refer to Page 371 in Kim, Shephard and Chib (1998). Lastly, one could apply the linear filtering algorithm, particularly the Kalman filter, to a Gaussian mixture approximation of the time-varying volatility.

[10] We adopt the Bayes factor to conduct the model comparison among a set of hybrid TVP-VAR-SV models. In particular, the appropriate guidance of using Bayes factor for model comparison could be found on page 777 in Kass and Raftery (1995).

[11] The importance sampling algorithm of Chan and Eisenstat (2018b), used to solve the integral problem in equation (10), is an improved version of Chan and Eisenstat (2018a).

conditional probability as

$$p(y \mid \varphi) = \int \underbrace{p(y \mid \phi, h, \varphi)}_{(I)} \underbrace{p(\phi, h \mid \varphi)}_{(II)} d(\phi, h) \tag{11}$$

where the component (I) in the integral problem can be decomposed into the multiplication of T univariate normal densities,

$$p(y \mid \phi, h, \varphi) = p(y \mid \phi, h) = \Pi_{i=1}^{n} p(y_i \mid \phi_i, h_i) \tag{12}$$

where $p(y_i \mid \phi_i, h_i)$ is implied by the equation (5). Moreover, the component (II) could be also divided into two conditional densities due to the independence between ϕ and h. Accordingly, we can simplify equation (11) as

$$p(y \mid \varphi) = \Pi_{i=1}^{n} \int \underbrace{p\left(y_i \mid h_i, \Sigma_{\phi_i}, \phi^0\right)}_{(III)} \underbrace{p\left(h_i \mid h_{i,0}, \sigma_{i,h}^2\right)}_{(IV)} dh_i \tag{13}$$

where Chan and Eisenstat (2018b) derive the analytical form of components (III) and (IV) and use importance sampler to solve the integral problem. Once the integrated likelihood function is approximated, one could apply the Cross-Entropy method of Chan and Eisenstat (2015) to integrate out the time-invariant parameters (φ) in equation (10), finally approximating the marginal likelihood of a model.

4. Empirical Data and Results

We collect macroeconomic time series data, ranging between 1978Q1 and 2022Q3, from Taiwan's Economic and Statistical Database (AREMOS), including monthly data of the seasonally adjusted consumer price index (base year: 2016), unemployment rate and rediscount rate (percent per annum). The monthly data is transformed into the quarterly basis by taking the simple average of the series over three months, and the inflation rate is computed by taking the first difference of the natural logarithm of the price level.[12] Accordingly, we specify a tri-variate hybrid TVP-VAR-SV model with two lags for Taiwan's economy.[13] Both the "improved importance sampling" algorithm of Chan and Eisenstat (2018b) and Gibbs sampler of Primiceri (2005) are adopted to approximate the marginal likelihood of the model and the posterior estimates of the time-varying (time-invariant) parameter for a total of eight models. In particular, we follow the setting proposed by Chan and Eisenstat (2018b) for the hyperparameter of the prior density and obtain 100,000 posterior draws for approximating the posterior density

[12] We simply divide the annualized rediscount rate by four to obtain the quarterly rate.

[13] We follow Stock and Watson (1999) and Karlsson and Österholm (2023) by replacing the inflation with the first difference of inflation.

Table 1.1. Log Marginal Likelihood in Hybrid TVP-VAR-SV Models

$\Delta\pi$ Equation	u Equation	i Equation	Log Marginal Likelihood	S.E.
Constant	Constant	Constant	-10.5	0.71
Constant	Constant	Time-Varying	-113.9	0.26
Constant	***Time-Varying***	***Constant***	***-8.3***	***0.72***
Constant	Time-Varying	Time-Varying	-111.7	0.14
Time-Varying	Time-Varying	Time-Varying	-117.6	0.21
Time-Varying	Time-Varying	Constant	-16.0	0.38
Time-Varying	Constant	Time-Varying	-120.3	0.10
Time-Varying	Constant	Constant	-17.8	0.21

Footnote: "$\Delta\pi$ Equation", "u Equation" and "i Equation" represent the "Inflation Equation", "Unemployment Rate Equation" and "Interest Rate Equation" in a hybrid TVP-VAR-SV model respectively. "S.E." refers to the corresponding numerical standard errors.

of interest, in which we take 25,000 as the burn-in sample. To compute the Bayes factor empirically, we apply the Importance Sampling (IS) algorithm of Chan and Eisenstat (2018b) to approximate the marginal likelihood of the model in two steps. In step 1, the IS algorithm is applied to evaluate the integrated likelihood function by 100,000 times. Once we obtain the integrated likelihood function, the cross-entropy method, an adaptive IS algorithm, is applied to completely obtain the marginal likelihood for the model in step 2, in which we sample 100,000 posterior draws after a burn-in sample of 25,000.

The message of Table 1.1 is that the TVP-VAR-SV of Primiceri (2005) with all its parameters being time-varying, has the worse fit when it is compared to the VAR model with time-invariant parameters and stochastic volatility. Instead, one type of hybrid TVP-VAR-SV model, in which only the parameters in the "unemployment rate equation" are time-varying, has the best goodness of fit. The above results are supported by using the guidance of Kass and Raftery (1995) in the computation of Bayes factor. Specifically, we find a very strong evidence that the hybrid TVP-VAR-SV model outperforms the pure TVP-VAR-SV model and the positive evidence that the data fitness of a hybrid TVP-VAR-SV model is better than a conventional VAR model. Thus, we suggest using a hybrid TVP-VAR-SV model to study the evolution of Taiwan's macroeconomy.[14] In addition, for the best model we pick up from the model comparison, we find the parameters in the inflation equation, characterizing the Phillips curve, are time-invariant. As a result,

[14]We perform a sensitivity analysis on reducing the influence of the specification of prior density on the estimated results. More specifically, we re-estimate a set of hybrid TVP-VAR-SV models by increasing the uncertainty of the prior density for the parameters. Compare to the relatively informative prior, we find the log marginal likelihoods for eight types of hybrid TVP-VAR-SV models are relatively smaller (relatively larger in the absolute value). Moreover, the rank of eight types of hybrid TVP-VAR-SV models is identical to the case of the relatively informative prior. In particular, the best fitness of model to Taiwan's data is still the one in which only the parameters are time-varying in the unemployment rate equation. All the results are available upon request.

Table 1.2. Log Marginal Likelihood in a Hybrid TVP-VAR-SV

$\Delta\pi$ Equation	u Equation	i Equation	Log ML	
			China	Taiwan
Constant	***Constant***	***Constant***	***-12.6***	-10.5
Constant	Constant	Time-Varying	-81.6	-113.9
Constant	***Time-Varying***	***Constant***	-48.9	***-8.3***
Constant	Time-Varying	Time-Varying	-114.2	-111.7
Time-Varying	Time-Varying	Time-Varying	-114.5	-117.6
Time-Varying	Time-Varying	Constant	-49.0	-16.0
Time-Varying	Constant	Time-Varying	-81.7	-120.3
Time-Varying	Constant	Constant	-17.92	-17.8

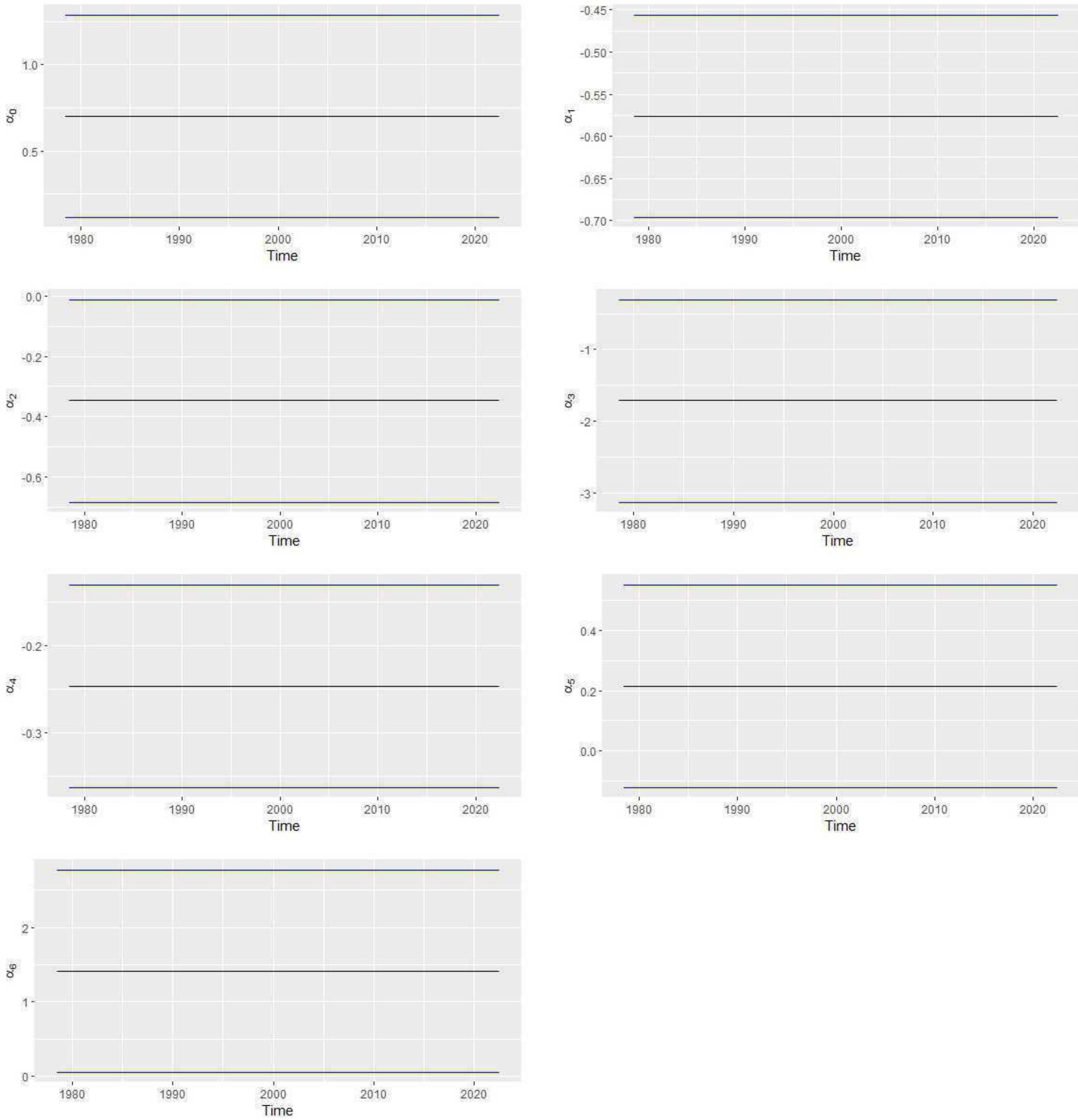
Footnote: "$\Delta\pi$ Equation", "u Equation" and "i Equation" represent the "Inflation Equation", "Unemployment Rate Equation" and "Interest Rate Equation" in a hybrid TVP-VAR-SV model respectively. The log marginal likelihood is denoted as "Log ML".

we argue that the slope of Taiwan's Phillips curve has a stable pattern over the past four decades. In Figure 1.1, 1.2 and 1.3, we simply plot both the time-varying and time-invariant parameters for each one of the equations in the "best" hybrid TVP-VAR-SV model.

Since Taiwan is a small open economy, and its economic growth heavily relied on economic transactions with foreign countries. In particular, not only does China currently becomes the largest trading partner for Taiwan, but also both China and Taiwan have the similar language and culture. Accordingly, we are also interested in whether the slope of China's Phillips curve display a significant change over the past decades? We re-estimate a hybrid TVP-VAR-SV model by using China's quarterly data, including the inflation, unemployment and interest rate and spanning from 2002Q1 to 2023Q2.[15] The estimates of the log marginal likelihood in a set of hybrid TVP-VAR-SV models for both China and Taiwan are shown in Table 1.2, and some interesting findings are read from it. First of all, we do not find any benefit of fitting a hybrid TVP-VAR-SV model to China's economy. Instead, a VAR model with time-invariant parameter (and stochastic volatility) is the one has the best fitness to the data, implying the China's Phillips curve, characterized by the inflation equation in a trivariate VAR model, is stable over the past two decades. Secondly, we find that allowing for the parameters to be time-varying in the "Interest Rate Equation" results to the worse fitness of model to both Mainland China and Taiwan. Accordingly, we find the conduct of monetary in both Mainland China and Taiwan to combat the fluctuations of inflation and output growth does not move toward an aggressive attitude.[16]

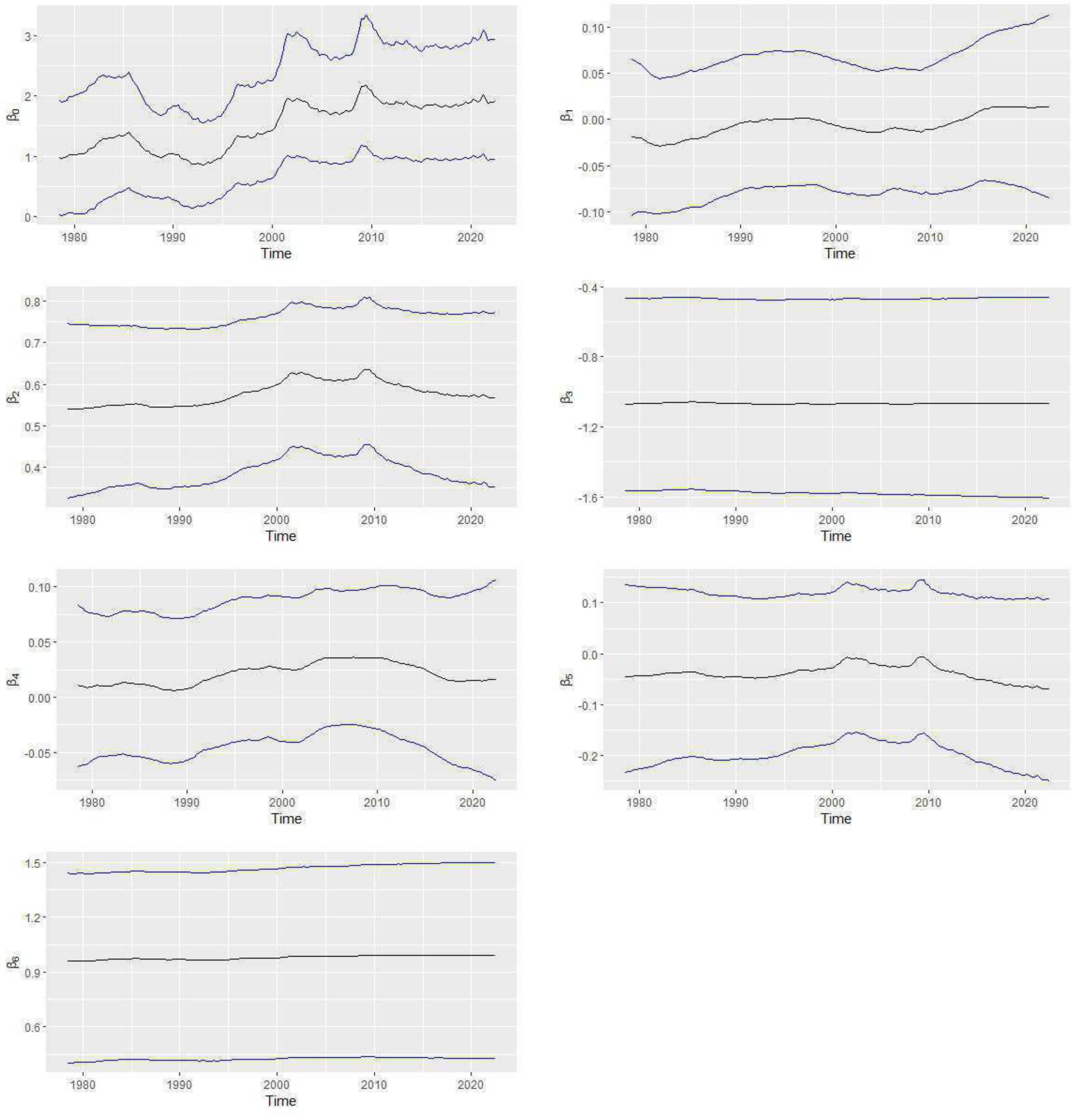
[15]Due to the data availability, that is the largest sample size we could collect from AREMOS.

[16]Primiceri (2005) finds in a TVP-VAR-SV model that the monetary policymakers in U.S. conduct an



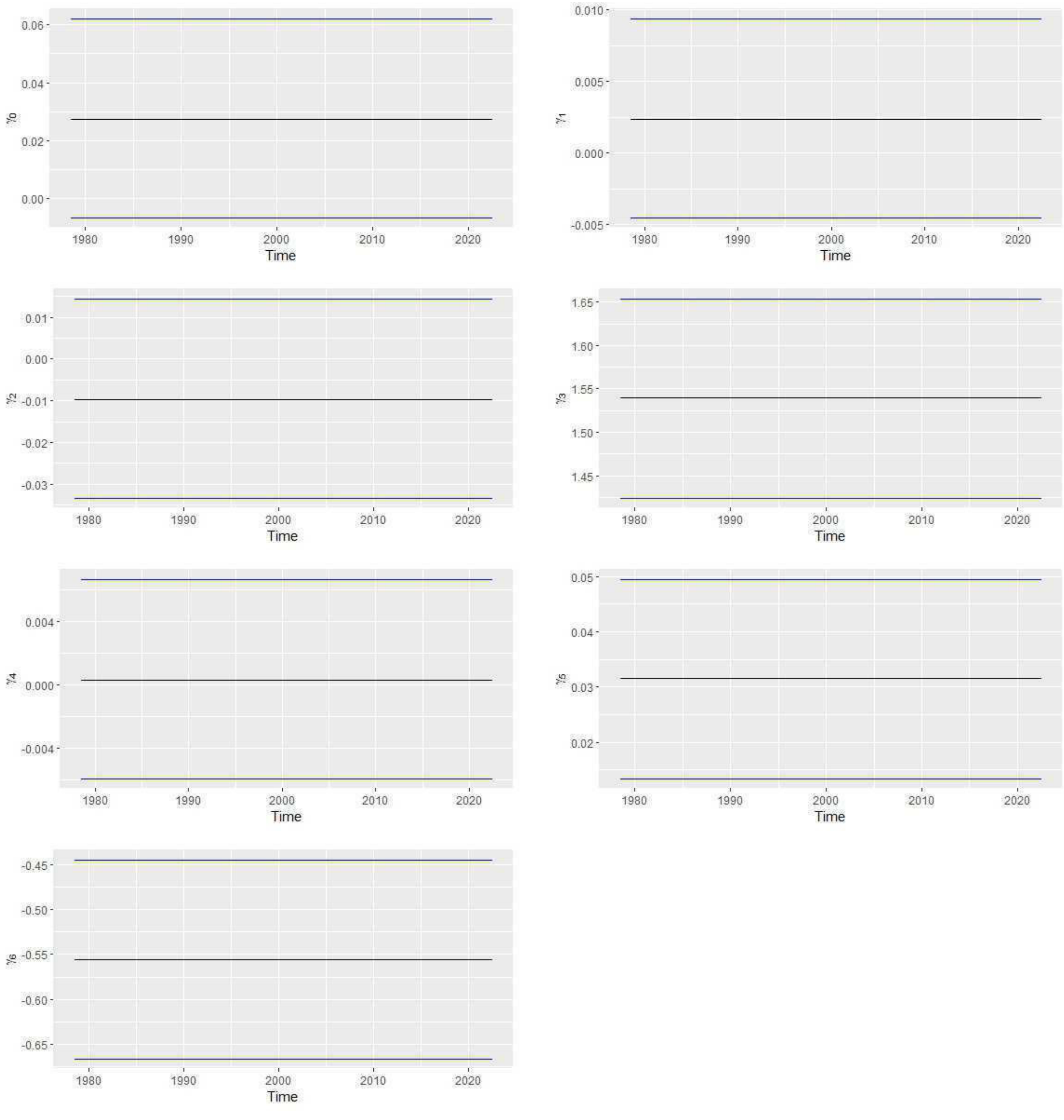
Footnote: "Inflation Equation" is expressed as $\Delta\pi_t = \alpha_0 + \alpha_1\Delta\pi_{t-1} + \alpha_2 u_{t-1} + \alpha_3 i_{t-1} + \alpha_4\Delta\pi_{t-2} + \alpha_5 u_{t-2} + \alpha_6 i_{t-2} + \varepsilon_{1,t}$*, and the goodness of fit for the best model is the one that all the parameters in the "Inflation Equation" are time-invariant.* π_t*,* u_t*, and* i_t *represent the inflation rate, unemployment rate and interest rate respectively.*

Figure 1.1. Time-Varying Parameter in "Inflation Equation"



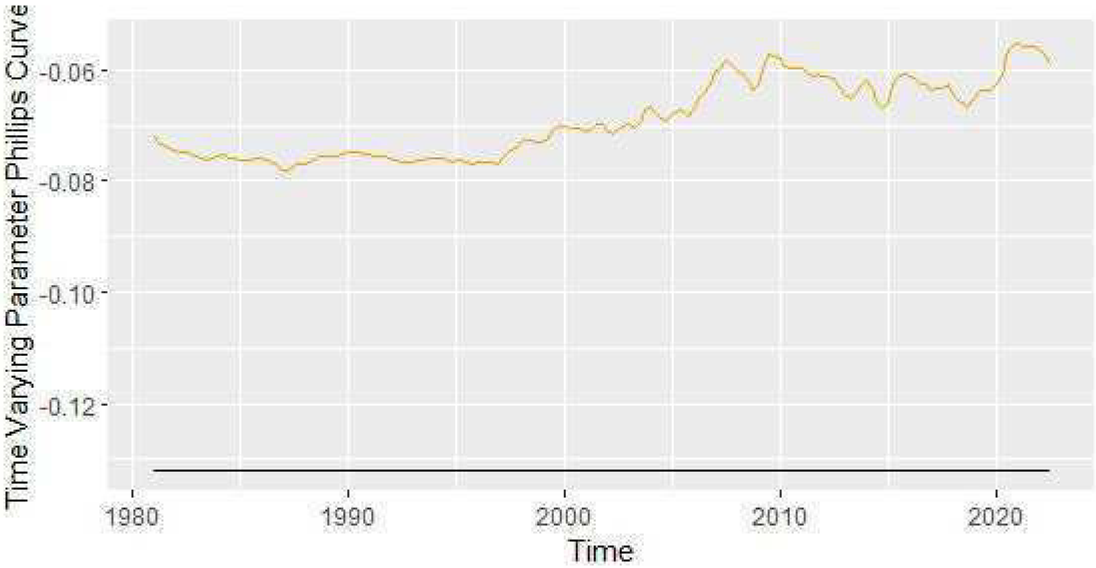
Footnote: "Unemployment Rate Equation" is expressed as $u_t = \beta_0 + \beta_1 \Delta\pi_{t-1} + \beta_2 u_{t-1} + \beta_3 i_{t-1} + \beta_4 \Delta\pi_{t-2} + \beta_5 u_{t-2} + \beta_6 i_{t-2} + \varepsilon_{2,t}$, *and the goodness of fit for the best model is the one that all the parameters in the "Unemployment Rate Equation" are time-varying.* π_t, u_t, *and* i_t *represent the inflation rate, unemployment rate and interest rate respectively.*

Figure 1.2. Time-Varying Parameter in "Unemployment Rate Equation"



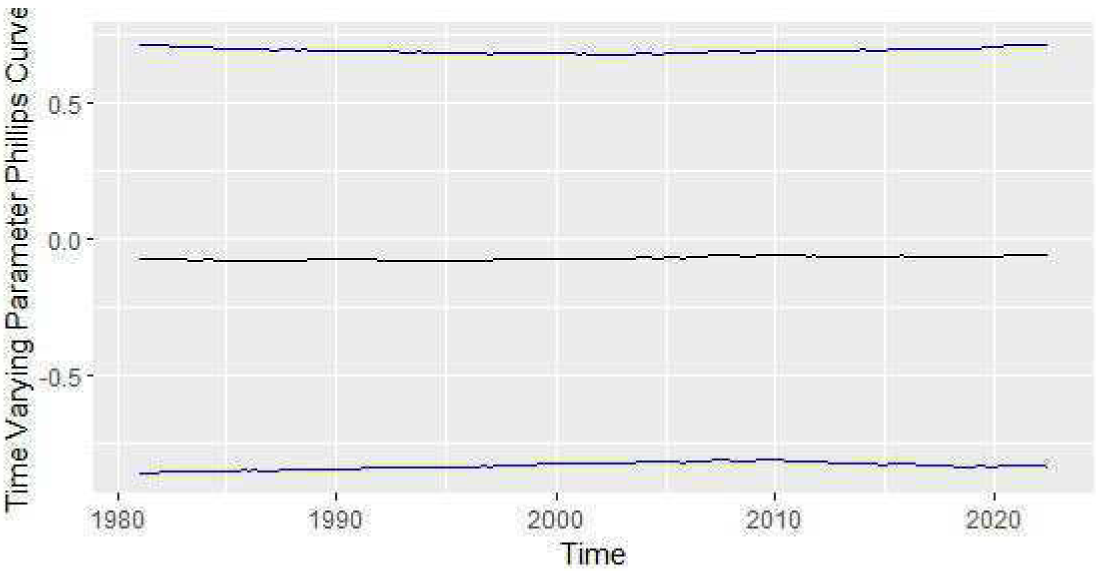
Footnote: "Interest Rate Equation" is expressed as $i_t = \gamma_0 + \gamma_1 \Delta\pi_{t-1} + \gamma_2 u_{t-1} + \gamma_3 i_{t-1} + \gamma_4 \Delta\pi_{t-2} + \gamma_5 u_{t-2} + \gamma_6 i_{t-2} + \varepsilon_{3,t}$, *and the goodness of fit for the best model is the one that all the parameters in the "Interest Rate Equation" are time-invariant.* π_t, u_t, *and* i_t *represent the inflation rate, unemployment rate and interest rate respectively.*

Figure 1.3. Time-Varying Parameter in "Interest Rate Equation"



Footnote: the "Best" hybrid TVP-VAR-SV model indicates that all the parameters in the "Inflation Equation" are time-invariant, implying the constant slope of Phillips curve, labelled as the black color; "TVP-VAR-SV" model of Primiceri (2005)" indicates that all the parameters in the hybrid TVP-VAR-SV model are time-varying, implying a time-varying slope of Phillips curve, labelled as the orange color.

Figure 2.1. Time-Varying (Time-Invariant) Slope of Taiwan's Phillips Curve



Footnote: the 90% credible interval is provided for the time-varying slope of Phillips curve obtained from the "TVP-VAR-SV" model of Primiceri (2005)".

Figure 2.2. 90% Credible Interval for Time-Varying Slope of Taiwan's Phillips Curve

Lastly we plot in Figure 2.1 the slopes of Phillips curve over time, derived on the basis of the "purely" TVP-VAR-SV model of Primiceri (2005), a widely-used model in the academia, and one type of hybrid TVP-VAR-SV model that fits Taiwan's macroeconomic data the best. Specifically, we compute the slope of Phillips curve by summing up the lagged coefficients of the unemployment rate in the "inflation equation" and are interested in studying whether Taiwan's Phillips curve has been flattened after the 2008-2009 global financial crisis.[17] As we expect that the slopes of Taiwan's Phillips curve, obtaining based on the "purely" TVP-VAR-SV model, are all negative. In particular, it becomes flatter recently, in consistent with most of the current studies. However, by taking into consideration the 90% credible interval for the time-varying slopes of Taiwan's Phillips curve, given in Figure 2.2, those time-varying values are not significantly different from zero, and this result is consistent with our previous results on Bayesian model comparison.

5. Conclusion

In recent years, many macroeconomic empirics pay attention to the flatter Phillips curve, appeared in the "Great Recession" period and closely associated with the "missing inflation (disinflation)" phenomenon, when the impact of the change in real economic activity, possibly caused by the conduct of monetary policy, on inflation is quite small. The occurrence of "flattering Phillips curve" had been found in some of advanced economies by recent studies, but the discussion of it for the Taiwan's economy is rarely found, at least studied from a Bayesian perspective. Accordingly, we study the time-varying slope of Phillips curve over the past four decades for Taiwan's economy. More specifically, we follow the Bayesian approach of Chan and Eisenstat (2018b) by fitting a tri-variate hybrid TVP-VAR-SV model, in which time-varying volatility is built-in but either some or all of the parameters are allowed to change over time, with Taiwan's macroeconomic time series data, including the first difference of inflation, unemployment rate and rediscount rate. The posterior estimates of time-varying (time-invariant) and the marginal likelihood of a model are respectively adopted to compute the slope of Taiwan's Phillips over time and to implement the Bayesian model comparison.

In terms of the fitness of model to Taiwan's data, we find the benefit of using a hybrid TVP-VAR-SV model since it is superior to the TVP-VAR-SV model of Primiceri (2005), in which parameters in all the equations are time-varying, and a VAR-SV model, in which parameters in all the equations are time-invariant but the volatility of the stochastic error is time-varying. In particular, the best model is the one that only the parameters in unemployment rate equation are time-varying but all the parameters in

aggressive attitude toward combating the fluctuation of inflation and output growth since the early of 1980s.

[17] We implement MATLAB code, provided by Chan and Eisenstat (2018b), several times and find the identical time-varying pattern of Phillips curve with the different scale of values.

other equations are constant over time. Accordingly, the estimated parameters shown in the inflation equation, found in the best model and used to characterize the Phillips curve, are time-invariant, supporting the stability of Taiwan's Phillips curve over the past four decades. We obtain the similar results when we apply a hybrid TVP-VAR-SV model to China's macroeconomic data over the past two decades. Lastly, we turn to study whether Taiwan's Phillips curve becomes flatter by estimating a TVP-VAR-SV model of Primiceri (2005), a widely-used model in the academia but its data fitness is found to be worse than a hybrid TVP-VAR-SV model in this paper. We find that the slope of Taiwan's Phillips curve is relatively flatter during the post-global financial crisis. However, by taking into account the 90% credible interval for its time-varying slopes, we find those values are not significantly different from zero, and this result supports our previous finding, Taiwan's Phillips curve is stable over the past four decades.

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