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REGIME-SWITCHING APPROACH TO MONETARY POLICY EFFECTS: EMPIRICAL STUDIES USING A SMOOTH TRANSITION VECTOR AUTOREGRESSIVE MODEL

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Regime-Switching Approach to Monetary Policy Effects: Empirical Studies using a Smooth Transition Vector Autoregressive Model*†

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Abstract

Even though monetary policy has kept interest rates at historically low levels, the Japanese economy has experienced long lasting recessions since the 1990s. These recessions are commonly attributed to nominal interest rates coming up against the zero bound and to the delay in achieving necessary structural changes. However, since these two factors had not yet appeared in the early 1990s, there must also have been other factors acting to weaken the effectiveness of monetary policy. In this paper, we employ Japanese data to conduct an empirical analysis of changes in the effect of monetary policy on the real economy. We find that monetary policy effects vary depending on the phase of the business cycle (measured in terms of the rate of change in real output) and the lending attitudes DI. More precisely, policy effects are larger in recession but diminish in extreme recession, and monetary policy is more effective when lenders' attitudes are severe but less effective when they are excessively severe.

Keywords: monetary policy, policy effect, financial accelerator, nonlinearity, smooth transition model, multiple regime switching

JEL classification: E52, E32

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1 Introduction

Since the 1990s, the Japanese economy has experienced long-lasting recessions even with interest rates at historical lows under the continuously easy monetary policy. Fingers understandably point to the zero bound on nominal interest rates and the delay in carrying out necessary structural changes as the main factors behind the recessions. However, the fact that it is not until the late 1990s that these factors become severe suggests that there may well be other factors influencing monetary policy effects. In other words, the effects of monetary policy are unlikely to be constant. This paper employs Japanese data to determine empirically what factors affect the impact of the monetary policy on the real economy. Our empirical findings may provide possible lessons to promote economic recovery.[1]

The asymmetric effects of monetary policy have been an important topic for macroeconomic policy research, and they have been studied from both theoretical and empirical perspectives. The analysis here extends the "asymmetric effects" framework. Asymmetric effects, in the context of monetary policy, refer to a situation in which the effects of a given policy are not constant but vary depending on the circumstances. Typically the asymmetries discussed relate to either the phase of the business cycle or to the policy direction.

The paper has two valuable features.[2]

First, we provide a theoretical discussion of how the effects of monetary policy may not change monotonically with respect to some key factor variable, but may in fact be U-shaped (U-shaped effect). When credit constraints are binding, it has been argued that monetary policy has a greater effect on firms' investment plans.[3] However, these policy effects may weaken when credit constraints are excessively severe, by which we refer to situations in which lenders require especially high premiums from firms or perhaps refuse loans to them altogether. In such a case, even though monetary policy shifts the money supply curve upward, the extra money might not necessarily reach firms. The fact that fewer Japanese firms have been sufficiently strong in terms of self-financing since the 1990s might also explain

[1]Given our aim in this paper, we choose to focus on how policy affects real output. Analysis of how monetary policy affects prices is a subject for future study.

[2]See Miyagawa and Ishihara (1997), Kitasaka (2002) for empirical studies of asymmetric policy effects in Japan.

[3]See Tobin (1978) and Bernenke, Gertler and Gilchrist (1996,1999) for details. In particular, Bernenke, Gertler and Gilchrist (1996,1999) have developed what is termed the "financial accelerator mechanism." This mechanism is constructed under the assumption of asymmetric information, and introduces the idea that monetary policy effects could be amplified via their influence on firms' net worth, as a result affecting the external financing premium. Under this mechanism, tight monetary policy has three consequences: an increase in the number of credit constrained firms; deterioration in their net worth; and a higher external funding premium (for simplicity, these will be referred to as severe credit constraints).

the limited effectiveness of monetary policy.[4] In the past, the asymmetry of monetary policy effects has been discussed in the context of switching between two states: economic boom and recession. Since these are not precisely the "regimes" that we will be considering in this paper, we do not couch our discussion in the usual terms of asymmetric effects but, to avoid confusion, we adopt the terminology "regime switching".

Second, to detect changes in the extent to which monetary policy effects vary and which particular factors are responsible for this variation, we adopt Smooth Transition Vector Autoregressive models (ST-VAR models). These are nonlinear models which enable us to identify the appropriate factor variables. If monetary policy effects vary with respect to a certain economic variable, the ST-VAR model is more appropriate than the usual linear VAR model. However, there are, to date, few empirical studies of policy effects using ST-VAR models. Another unique aspect of the current research is the explicit treatment of the possibility that changes in policy effects may be non-monotonic, which we consider in addition to the more usual monotonic case.[5]

Our research uncovers significant changes in the effect of monetary policy depending on real output (rate of change) and the Diffusion Index (DI) describing the lending attitude of financial institutions. Policy effects are sharper when the rate of change of real output is smaller. Assuming that this rate of change can be taken to represents the business cycle, this finding offers support for the existence of asymmetric policy effects over the business cycle, as argued in previous studies.[6] Also, monetary effects are significantly larger when lenders' attitudes are severe. If a large negative value of the DI can be taken to represent a situation of severe credit constraint, this finding suggests that credit constraints also result in asymmetric policy effects, thus supporting arguments put forward in previous studies.

In addition, however, we find a contrary effect, namely that when growth in real output is too sluggish and/or when lending attitudes are excessively severe, monetary policy weakens. These results are consistent with our theoretical analyses.

The next section (section 2) investigates the theoretical reasons this sensitivity of monetary policy effects to regime-switching. In Section 3, we use

[4]The Bank of Japan's Financial Positions DI (all industries) ("Easy" minus "Tight", % point) recorded 8.2 % in the latter half of the 1980s, 1.2 % in the first half of the 1990s, and 7.25 % in the latter half of the 1990s. Using a VAR model to test for monetary policy effects, Miyao (2002) reports that policy effectiveness is likely to have weakened since the 90s.

[5]Weise (1999) makes use of ST-VAR models to analyze monetary policy effects, and Kitasaka (2003) applies them to the Japanese economy. However these papers only consider monotonic cases (increasing and decreasing, respectively).

[6]Asymmetry over the business cycle means that monetary policy in recessions is more effective than in economic booms, where "recession" denotes the period from Peak to Bottom and "economic boom" that from Bottom to Peak.

ST-VAR models to conduct an empirical analysis of asymmetrical monetary policy effects in Japan. Section 4 concludes the paper.

2 Reasons for regime-switching to influence monetary policy effects

Theoretical analyses of regime-switching effects in the context of monetary policy have been studied for decades. According to Karras (1996), reasons for these effects can be separated into two categories: nonlinearity of the aggregate supply curve and asymmetry in shifts of the aggregate demand curve. Our particular interest here is not only in the well known case where shifts in the aggregate demand curve are larger when production volume is low, but also in the case where these shifts could be small.

2.1 Nonlinearity of aggregate supply curve

Nonlinearity of the aggregate supply curve generally describes a condition where the aggregate demand curve becomes more elastic at higher production levels (see Chart 1). When the aggregate supply curve is nonlinear, the effects of monetary policy (captured by shifts in the aggregate demand curve) show asymmetry, with respect both to the direction of policy and the phase of the business cycle. As shown in the upper panel of Chart 1, although in both cases the size of the shift in the aggregate demand curve is the same, the effect (A) of a monetary tightening (downward shift) is greater than the effect (B) of a monetary loosening (upward shift). Also, as shown in the lower panel of Chart 1, the effect in recession (A) is larger than that in expansion (B). Downward rigidity of prices has been thought to cause the asymmetry (See Delong and Summers (1988), Senda (2001)). [7]

2.2 Asymmetry in shifts of aggregate demand curve

Whether the aggregate supply curve is nonlinear or not, there could be asymmetry in the shifts of the aggregate demand curve itself, and this would produce asymmetrical monetary policy effects. The common example in this context is of larger aggregate demand shifts at lower levels of production. However, it is also possible to envisage situations in which these shifts in fact become smaller at low levels of production.[8]

[7] The asymmetric monetary policy effects being discussed here are considered at current prices. Strictly speaking, the regime-switching point moves continuously along with changes in current prices. Continuous and smooth structural changes in ST-VAR models are able to capture this.

[8] The classification of production volume in terms of "low" and "high" levels is for the sake of simplicity. It does not necessarily mean that the production volume itself affects the impact of monetary policy.

When shifts in the aggregate demand curve are asymmetric, the direction of policy will depend upon the size of the shift. Let us look at the case where shifts in aggregate demand are larger at lower levels of production. As shown in the upper panel of Chart 2, the policy effects of downward shifts under tight monetary policy (effect (A) in Chart 2) are larger than those of upward shifts under easy policy (B). Also, as shown in the lower panel of the same chart, policy effects during recession (A) are larger than those during economic boom (B). We will examine possible factors that might cause aggregate demand curves to be asymmetric in the subsections that follow.

2.2.1 Factors causing larger shifts in aggregate demand at lower production levels

Two factors may be posited to explain why aggregate demand shifts might be larger at lower levels of production. One is credit constraints. The argument here is that monetary policy will have more effect the larger the proportion of undercapitalized firms (i.e., those for whom credit constraints are binding). Compared to an economy replete with firms of ample net worth, an economy with a greater proportion of highly indebted firms is thought to respond more sharply to monetary policy (see Tobin (1978)).

Asymmetric shifts induced by the "financial accelerator mechanism" recently introduced by Bernanke, Gertler and Gilchrist (1996,1999) also provide an explanation that appeals to credit constraint, as shown in Chart 3. With binding credit constraints (where the fund supply function is upward-sloping due to the existence of an external financing premium), the policy effect (2) is larger than the effect (1) seen in the corresponding case with no binding of credit constraints (where the fund supply function is flat). In particular, this mechanism will amplify policy effects since it lowers borrowers' net worth ($a' \to a$), heightens external finance premium and, as a result, makes the fund supply function more elastic.[9]

The other factor that may explain larger shifts in aggregate demand when production levels are lower is changes in expectations. In general, firms and consumers are more pessimistic during recessions than during booms. Therefore, the changes in expectations that occur during the period of tight monetary policy following the peaking of the economy will act to magnify the effects of monetary policy.[10]

[9] Traditional IS-LM analysis describes monetary policy taking effect via interest rate changes, in what is referred to as the "saving channel." However, there is another monetary policy transition mechanism through which changes in the amount of lending affect the real economy, and this is referred to as the "lending channel." The lending channel has importance when bank loans are not perfect substitutes due to asymmetricalinformation and regulations, and when monetary policy can affect bank loans. See Kashap-Stein (1994), Bernanke and Gertler (1995) and Hoshi (1997) for details.

[10] Okina, Shirakawa and Shiratsuka (2001) point out how monetary policy effects can

2.2.2 Factors causing smaller aggregate demand shifts at lower levels of production

On the other hand, we may also envisage cases where the aggregate demand shifts become smaller at lower levels of production. Such cases may occur if credit constrains bind excessively harshly. As shown in Chart 4, the amount of lending becomes less responsive to monetary control if the upward slope of the fund supply function steepens excessively due to an especially harsh loan premium.

With the excessive loan premium producing a very elastic fund supply function, there will be little difference in monetary policy effect between case (2), where credit constraints are binding, and case (1), where they are not.

We can verify this basic mechanism in the following simple model. We assume that the lending market can be characterized by the following supply function:

$$r = f(L, r_0; W), \tag{1}$$

where r is the interest rate on loans, r_0 is interest rate on risk-free assets (the policy variable), L is the lending volume, and W is borrowers' net worth.

The demand function is written as;

$$r = g(L), \tag{2}$$

We assume that the supply function f is increasing with respect to L, increasing in the risk-free rate, while the demand function is decreasing with respect to L, that is,

$$\partial f/\partial L > 0,\ \partial f/\partial r_0 > 0,\ \partial g/\partial L < 0 \tag{3}$$

Under the assumption of asymmetric information between lenders and borrowers, the borrowers' net worth functions as collateral. This is why the function f has W as an argument. The borrowers' net worth is assumed to be increasing with respect to r_0, with net worth at time zero (W_0) as given.

$$W = W(r_0; W_0), \partial W/\partial r_0 < 0. \tag{4}$$

When the borrowers' net worth W increases (decreases), we assume the expected marginal cost decreases (increases) through a reduced (increased) bankruptcy cost. This acts to soften (steepen) the slope of supply function $\partial f/\partial L$.

$$\frac{\partial\left(\partial f/\partial L\right)}{\partial W} < 0. \tag{5}$$

differ widely in response to changes in expectations held by economic agents.

When the net worth at time zero $W_0 = W_{0,1}$ and the equilibrium lending volume is L^*, the equilibrium condition satisfies

$$f(L^*, r_0; W) - g(L^*) = 0. \tag{6}$$

by differentiating Equation (6), we obtain

$$\left.\frac{dL^*}{dr_0}\right|_{W_0=W_{0,1}} = -\frac{\left(\frac{\partial f}{\partial r_0} + \frac{\partial\left(\frac{\partial f}{\partial L}\right)}{\partial W}\frac{\partial W}{\partial r_0}\right)}{\left(\left.\frac{\partial f}{\partial L^*}\right|_{W_0=W_{0,1}} - \frac{\partial g}{\partial L^*}\right)} < 0 \tag{7}$$

dL^*/dr_0 represents a shift of equilibrium lending volume L^* responding to a change in the policy interest rate r_0; in other words, it captures the effects of monetary policy. Note that dL^*/r_0 depends on W_0 since $\partial f/\partial L^*$ is determined by the net worth at time zero.[11]

Disregarding the effect of net worth as collateral, the monetary policy effect is defined as,

$$\left.\frac{dL^*}{dr_0}\right|_{W_0=W_{0,1}} = -\frac{\left(\frac{\partial f}{\partial r_0}\right)}{\left(\left.\frac{\partial f}{\partial L^*}\right|_{W_0=W_{0,1}} - \frac{\partial g}{\partial L^*}\right)} < 0 \tag{8}$$

Comparing policy effects when W_0 is fixed, the effect in Equation (7) is greater than that in Equation (8) by the amount of the second term in the numerator on the right-hand side of Equation (7). This corresponds to the financial accelerator mechanism proposed by Bernanke, Gertler and Gilchrist (1996,1999).

Next, we consider another value for net worth at time zero $W_{0,2}$, where $W_{0,1} > W_{0,2}$, Equation (7) is then rewritten as:

$$\left.\frac{dL^*}{dr_0}\right|_{W_0=W_{0,2}} = -\frac{\left(\frac{\partial f}{\partial r_0} + \frac{\partial\left(\frac{\partial f}{\partial L}\right)}{\partial W}\frac{\partial W}{\partial r_0}\right)}{\left(\left.\frac{\partial f}{\partial L^*}\right|_{W_0=W_{0,2}} - \frac{\partial g}{\partial L^*}\right)} < 0 \tag{9}$$

By assumption, we obtain

$$\left.\frac{\partial f}{\partial L^*}\right|_{W_0=W_{0,1}} < \left.\frac{\partial f}{\partial L^*}\right|_{W_0=W_{0,2}}. \tag{10}$$

That is, in so far as the smaller W_0 causes the first term in the denominator of Equation (9) to become larger, the policy effect diminishes. Therefore, the policy effect in Equation (9) is smaller than that in Equation (7) when

[11] For simplicity, we assume that no terms except $\partial f/\partial L^*$ respond to net worth at time zero W_0. This assumption does not affect our main results.

the net worth at time zero is lower. Whether Equation (9) or (8) produces a stronger policy effect depends on the parameters. The lower net worth case captures the situation where there is less collateral, a higher lending premium, and it is difficult to borrow (i.e., credit constraints are severely binding).

Another factor which might cause smaller aggregate demand shifts at lower levels of production is the interest rate elasticity of investment demand, depicted in Chart 5. If we suppose that the investment demand curve is inelastic when interest rates are high, monetary policy does not have much power to affect investment. In other words, effect (B), when the interest rate is high (less investment), is smaller than effect (A), when rates are low (more investment).

To sum up, our theoretical findings are as follows. First, the effects of monetary policy on the real economy may vary depending upon the policy direction and the particular phase of the business cycle. When factors such as downward price rigidity, credit constraints, and changes in expectations are dominant, these act to enhance policy effects. In contrast, when credit constraints bind excessively harshly or there is a high interest rate elasticity of investment, the effects of policy are reduced.

Moreover, with policy effects being determined by the interaction of these numerous factors, there is no reason to assume that changes in policy effects are monotonic. For instance, considering the role of credit constraints, we have seen how more binding credit constrains may act to increase the effectiveness of monetary policy up to a point, but when they become "excessively" binding the effect may be the reverse.[12]

3 Empirical Studies using a Smooth Transition VAR Model

In this section, based on the theoretical analyses in the previous section, we employ Japanese data to analyze empirically the changes in monetary policy effects.

In general, monetary policy effects are analyzed using a linear model with fixed parameters. However, as described in the previous section, fixed parameter analysis cannot adequately explain real economic activity when the effects of monetary policy alter along with economic conditions. It is for this reason that we adopt smooth transition models to analyze policy effects.

The smooth transition model has the following features.

- Parameters in smooth transition models may vary, which makes these

[12] As in many previous studies, household behavior is not explicitly analyzed here, but is left as a subject for future study.

models suitable vehicles for estimation of how regime-switching influences monetary policy effects.

- In smooth transition models, parameters are determined as functions of other key economic variables. This framework enables us to implement an empirical study theoretically consistent with structural change.[13]
- The model can detect both the smoothness of structural changes and threshold levels simultaneously. This is possible since functions determining parametric transition include parameters to capture both smooth changes and thresholds.
- Smooth transition models can detect and statistically distinguish both types of regime-switching: where changes are monotonic, and where they are U-shaped.

3.1 Analyses of Monetary Policy Effects using a Smooth Transition Vector Autoregressive Model

In this section, we adopt vector autoregressive models (VAR models) to analyze monetary policy effects. VAR models have been often applied in empirical studies of monetary policy effects.[14] Extending this VAR model approach, we empirically analyze monetary policy effects using smooth transition vector autoregressive models (ST-VAR models).

The structure of ST-VAR models may be explained as follows. First, let us consider the situation where there are two different regimes corresponding to two different economic conditions, then describe the two regimes by VAR model A and VAR model B. A switch from one regime to the other can be described as a shift from model A to model B and vice versa. Assuming that the regime described by model A occurs with probability G, then the other regime occurs with probability $1-G$. The whole system may thus be described as,[15]

$$G \times (VAR\ model\ A) + (1-G) \times (VAR\ model\ B) \tag{11}$$

Variation in probability G indicates structural change. Meanwhile, probability G itself is determined as a function of certain key economic variables.

$$\begin{aligned} G = f(&economic\ variables\ affecting \\ &structural\ changes; threshold(s),\ smoothness)\ , \end{aligned} \tag{12}$$

[13]The result is that equations (11) and (12) below become nonlinear with respect to the parameters, and this complicates the estimation in ways that are further discussed later.

[14]See Sims and Zha (1998) for empirical studies using VARs. See Miyao (2002) and Shioji (2000) for those that use Japanese data.

[15]For simplicity, G is interpreted as a probability. Of course we can also interpret G as a weight describing the economic structure.

where the function f is called a transition function, and is a continuous function bounded between 0 to 1. In general, a flexible functional form is adopted for function f, and neither threshold levels nor the smoothness of structural changes are given, but are estimated from actual data. Now by substituting Equation (12) into Equation (11), we can obtain our ST-VAR model. This model enables us to estimate structurals change in monetary policy effects, transition variables, threshold levels and smoothness simultaneously, and to implement hypothesis tests on them.

Now we will specify the regression model for estimations. Variables affecting monetary policy effects, "transition variables," are denoted by z_t. As in Bernanke and Blinder (1992) and Garcia and Schaller (2002), we adopt a policy effect model in which the policy interest rate i_t affects aggregate demand y_t^d. Furthermore, we extend the model by substituting the transition function for a coefficient of it, [16]

$$y_t^d = y_0 - \alpha(z_t)i_t + A(L)X_t + \eta_{y,t} \ , \tag{13}$$

where y_0 is constant, i_t is the call rate (the policy interest rate), X_t is a vector of other variables, and $\eta_{y,t}$ represents the shock to aggregate demand. Following Garcia and Shaller (2002), we adopt the vector of other variables $X_t = (y_t, m_t, p_t, i_t)'$, where y_t is equilibrium real output, m_t is the money supply, and p_t is the CPI. The parameter α is theoretically expected to be negative.

It must be noted that possible transition variables z_t are not necessarily explained by the endogenous four variables or their stationary shocks. However, in cases in which a transition variable cannot be explained by the four variables, the option to add that transition variable as a fifth endogenous variable may not be feasible because this would require too many parameters to be estimated and tested. [17]

Therefore, when we wish to include in a model a transition variable other than one of the existing 4 variables, we adopt a sampling method in which variations in the transition variables responding to the policy interest rate

[16] As in Cover (1988) and Weise (1999), the micro foundations for asymmetrical policy effects are not considered explicitly in this paper.

[17] Our sample comprises 324 observations on each variable from January 1975 to December 2001. The number of parameters that require estimation in an ST-VAR model surges if an additional endogenous variable is included. In the case of a four-variable VAR model with constants and three lagged variables, the number of parameters in each equation is 13 ($= 1 + 3 \times 4$). In the case of an ST-VAR model with a 2nd order logistic transition function, this number will surge to 28 ($= 1+12+12+3$) (103 parameters are required for the total system), and 5 times this number of parameters is required for model selection tests. Adding one variable to make a five-variable VAR model raises these figures to 34 ($= 1+15+15+3$) parameters required for the ST-VAR model (158 for the total system), and also 5 times this number for model selection tests. In fact, five-variable VAR models were estimated, but the results proved unreliable. These are left as a subject for future study.

are sampled from the following conditional probability,

$$z_t \sim \pi(z_t | h(i_t \in \Omega), D) \tag{14}$$

where $h(.)$ represents an indicator function of policy actions, Ω is a set of policy actions, and D is a matrix of other information matrix affecting z_t. D also includes the reactions of other economic variables to policy actions. This conditional probability is constructed from the observed data.

Next, by using the above aggregate demand equation, aggregate supply equation, policy reaction function and supply-demand balance equation, we can obtain the following VAR system.

$$X_t = (I - C_0)^{-1} X_0 + (I - C_0)^{-1} C(L) X_{t-1} + D(L)\epsilon_t \tag{15}$$

where C_0 are the parameters governing the simultaneous variables from the original equation, I is an identity matrix, C are parameters for the lagged variables from the original regression, $D(L)$ are the error term parameters, and ϵ_t represents innovations in period t. The nonlinear parameter $\alpha(z_t)$ is now contained not only in the real output function y_t but in parameter C_0 as well. This means that, to analyze nonlinear policy effects, we have to estimate Equation system (15) rather than Equation (13). The policy interest rate error term does not necessarily represent simple policy shocks, for it may be correlated with error terms in other equations. For this reason, following Bernanke and Blinder (1992) and Garcia and Schalla (2002), we adopt the simultaneous structure described in Appendix B.[18] [19]

Now, for analyzing structural changes, we adopt smooth transition vector autoregressive models (ST-VAR models).

An ST-VAR model can be specified as

$$\begin{aligned} X_t = {} & \Phi_1'(L) X_t (1 - G(s_t; \gamma, c)) \\ & + \Phi_2'(L) X_t G(s_t; \gamma, c) + \theta_t \end{aligned} \tag{16}$$

where Φ_i are $4 \times p$ parametric vectors (p is the number of lagged variables), and $\theta_t = (\theta_{1t}, ..., \theta_{4t})'$ is a 4-dimensional vector white noise process with mean zero and a 4×4 positive definite covariance matrix Σ. γ and c represent the smoothness of structural changes and threshold(s), respectively.

The transition function $G(s_t; \gamma, c)$ is a continuous function that is bounded between 0 and 1. In practice, the choice of transition function is between a first-order logistic function,

$$G(s_t; \gamma, c) = (1 + exp(-\gamma(s_t - c)))^{-1}, \gamma > 0, \tag{17}$$

[18] As has already been pointed out, single equation estimation is incapable of capturing the influence of regime-switching on monetary policy effects. However, the structural changes estimated from the VAR model may contain effects other than the influence of regime-switching. This is a subject for future study.

[19] The error term is heteroscedastic and is handled in the estimation procedure.

and a second-order logistic function,[20]

$$G(s_t;\gamma,c_1,c_2) = (1 + exp(-\gamma(s_t - c_1)(s_t - c_2)))^{-1},\ \gamma > 0,\ c_1 \leq c_2. \quad (18)$$

The first-order logistic function is a monotonic function weakly increasing with respect to the transition variable z_t. G represents the probability that the regime described by the VAR model $\Phi_2'(L)X_t$ occurs. c is interpreted as the threshold parameter, and the function G turns out to be greater than 0.5 when z_t is greater than c. The parameter γ determines the smoothness of the transition from one regime to the other. If $\gamma \to 0$, the model becomes linear and G converges to a constant. If $\gamma \to \infty$, G becomes an indicator function converging to 0 $(s_t < c)$ or $1(s_t > c)$. The first-order logistic function is therefore well-suited to describing the situation where monetary policy effects change monotonically, as described in Tobin (1978) and Bernanke, Gertler and Gilchrist (1996, 1999) and so on.

When we adopt the second-order logistic function, G varies from $1 \to 0 \to 1$ as z_t increases and, as a result, makes a U-shape. c_1 and c_2 are interpreted as structural change thresholds, and G turns out to be below 0.5 when z_t exceeds c_1, and to be above 0.5 when z_t exceeds c_2. Again, the parameter γ determines the smoothness of structural changes. If $\gamma \to 0$, the model becomes linear and again G converges to a constant. If $\gamma \to \infty$, G becomes an indicator function converging to 1 (when $s_t < c_1$ or $s_t > c_2$) or 0 (when $c_1 < s_t < c_2$). The second-order logistic function is therefore appropriate for describing a situation where changes in monetary policy effects are not monotonic: effects work in one direction first, but switch direction at a certain point. An example would be the situation, described in the previous section, in which stricter credit constraints act to increase the effectiveness of policy, but when these constraints become "excessively" strict, the effect is the opposite.[21] The above observation enables us to analyze whether changes in monetary policy effects have been monotonic or U-shaped, by testing which model (the first-order or second-order logistic function) is appropriate.

As discussed previously, for our research here we specify a four-variable VAR model (the variables are real output (IIP), the money supply, the CPI (less foods), and the call rate), using monthly and seasonally adjusted data

[20] In general, we can also adopt an exponential function. In our research, however, the second-order logistic function is preferable because we have to analyze regime changes with unknown length of a median regime.

[21] This model is a three-regime model with the restriction that the outer regimes are identical. This means that our approach for detecting multiple changes in policy effects is an approximation unless the outer regimes are actually identical. There are two reasons for adopting this approximation approach, using the second-order logistic function. First, our main purpose is to test whether changes in policy effects are monotonic or not, rather than to estimate the exact path of regime changes. Second, there are already established theoretical foundations for statistical inference using model selection tests.

from January 1975 to December 2001.[22]

We adopt eight candidates as possible transition variables: real output (rate of change), the diffusion index (DI) of lending attitudes at financial institutions, the financial positions DI, of the business conditions DI, credit spreads (spreads between straight bond quotations by rating (Moody's Aa, Baa), over-the-counter corporate bond quotations by rating (12 years), and government bond yields), and stock prices (Topix).[23] [24]

There are some difficulties in carrying out statistical inference for smooth transition models, since regular statistical methods cannot be applied. Given these difficulties, we adopt the following estimation steps proposed in Van Dijk et al. (2002).

(i). Specify a linear VAR model, as a baseline, based on the Information Criteria and an LM test for serial correlation.[25]

(ii). Test the null hypothesis of linearity of the baseline model against the alternative with candidate transition variables. In this stage, we also select the lag order (delay parameter) and the length of the moving average for the transition variables (d and L in Equation (20)).[26]

(iii). If linearity is rejected and the appropriate transition variables are selected, test the form of the transition function: i.e., whether it is first order logistic (changes are monotonic) or second order logistic (U-shaped).

(iv). After specifying transition variables and the form of the transition function, estimate the ST-VAR model (estimating two regime VAR parameters, smoothness and threshold(s) simultaneously). Also, test the significance of the nonlinear parts.

(v). Estimate a generalized impulse response function (by stochastic simulation) to verify the effectiveness and the direction of monetary policy.

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[22]For all variables (variables other than interest rates are in logarithms), the null hypotheses of unit root tests are rejected. The null hypotheses of cointegration tests are also rejected. We are therefore able show estimation results for level variables in this paper. Although we also carried out estimations with differenced variables, considering size distortion of cointegration tests for multivariable model, our main results were not affected.

[23]Since the diffusion indices are quarterly statistics, the most recent value of the index is applied for the interim months, until the next release. Using Equation (20), the DI is calculated as shown in Chart 8.

[24]See Appendix for data. We analyze switching between regimes influenced by economic conditions. We do not directly analyze how effects change with policy direction. However, asymmetries with respect to policy direction can also be analyzed by impulse response functions as described later.

[25]In general, "general-to-specific" strategy is often adopted for building linear time series model. In the case of nonlinear time series models, "specific-to-general" strategy is recommended. See Granger (1993), Van Dijk et al. (2002) for details.

[26]If the transition variable selections are appropriate, LM-type tests, especially LM_3 test, have power against both alternatives: the first and second order logistic functions. Therefore, we can select the appropriate transition variable with the lowest p statistic based on LM-type nonlinear tests. See the section 5 in Van Dijk et al. (2002). Terasvirta (1994) has carried out simulations and reports that this method works well.

At step (v), it is important to implement a generalized impulse response function by stochastic simulation, and not the traditional impulse response function. This is because in nonlinear models the impact is known to differ depending upon data level, a characteristic often referred to as historical dependency. The traditional approach is not applicable to the ST-VAR model because of the latter's nonlinearity.[27] The generalized impulse response function is produced by calculating the difference between the case of "historical random variable shocks" (s_1) and the case with a specific shock (s_2).[28]

In carrying out step (i), we select a linear VAR model with 1, 2 and 10 lagged variables (the maximum lag was set to 13).[29] With this baseline model, we proceed to steps (ii) and (iii). The problem in testing is that the ST model contains parameters that are not restricted by the null hypothesis. For example, the null hypothesis $\Phi_1 = \Phi_2$ does not restrict the parameters in the transition function, γ and c. The likelihood is unaffected by the values of γ and c when the null hypothesis is valid. The main consequence of the presence of such nuisance parameters is that conventional statistical theory is not applicable, so that asymptotic null distributions for the classical likelihood ratio, Lagrange Multiplier and Wald statistics are not available.[30] We therefore follow Luukkonen, Saikkonen and Terasvirta (1988), and solve this problem by replacing the transition function $G(s_t; \gamma, c)$ by a suitable Taylor series approximation around $\gamma = 0$. Since the identification problem is no longer present in the reparameterized equation, linearity can be tested by means of a standard asymptotic distribution under the null hypothesis. Instead of testing the original null hypothesis $H_0 : \gamma = 0$, nonlinearity can be tested by using the null hypothesis $H_0' : \beta_1 = ... = \beta_k = 0$, where $\beta_j,\ j = 1, ..., k$, is the matrix of parameters in the following auxiliary regression which we obtain from the k-th order Taylor approximation around $\gamma = 0$,

$$X_t = \Phi_0(L)' X_t + \Phi_1(L)' X_t s_t^1 + ... + \Phi_k(L)' X_t s_t^k + \epsilon_t. \tag{19}$$

where s_t is a transformation of the original transition variable z_t. Based on this auxiliary regression approach, we can also implement model selection

[27] See Pesaran and Potter (1997).

[28] In cases where we include transition variables that are not among the endogenous variables of the VAR model, changes are sampled from the probability constructed from the observed data, as described previously.

[29] To identify the baseline model, we examined impulse response functions assigning standard deviations to account for tight monetary policy shocks. Real output turned out to decrease for about two years and there was also a decrease in the CPI, after a short lag, in line with theoretical expectations.

[30] See Davis (1977,1987), Andrews and Ploberger (1994), Hansen (1996) and Stinchcombe and White (1998) for the problem of undefined nuisance parameters under the null hypothesis.

tests between the 1st-order and the 2nd-order logistic transition function: specifically, tests by Terasvirta (1994) and Escribano and Jorda (1999).[31]

Following Skalin and Terasvirta (2002) and Van Dijk et al. (2002), we also adopt the following form for the transition variables. [32]

$$s_t = \Sigma_{j=0}^{L-1} z_{t-d-j}/L, \tag{20}$$

where z_t are the transition variables.

In testing nonlinearity and in model selection, we adopt the following strategy. We try all combinations of L and d for the z, setting the maximum level as 12, and select the appropriate transition variable, the one showing the most significant nonlinearity, from among candidates satisfying the following conditions;[33]

- in nonlinearity tests, at least one type of test shows significant nonlinearity,
- in the model selection tests by Terasvirta (1994), at least one null hypothesis is rejected,
- in the model selection tests by Escribano and Jorda (1999), at least one null hypothesis is rejected,
- both model selection tests suggest the same transition function.

In nonlinearity tests and model selection tests, the heteroscedasticity-robust estimator by Wooldridge (1990,1991) is adopted.

In the nonlinearity tests (step (ii)), two variables, real output (rate of change) and the lending attitudes DI, showed significant nonlinearity. The results are shown in Tables 1 and 2. The notation LM_i denotes a nonlinearity test conducted under the null hypothesis that the model is linear, using the i-th order Taylor approximation around $\gamma = 0$. The test results of step (iii) on selected transition variables are also shown in Tables 1 and 2.

H_{0i} denote model selection tests under the null hypothesis that the i-th order term $= 0$, given that the j-th terms $(j > i) = 0$, for the 3rd-order Taylor approximation around $\gamma = 0$. If the p-value for H_{02} is the smallest, the 2nd-order logistic transition function is preferable. In all other cases the 1st-order logistic function is preferable. H_{0E} and H_{0L} are model selection tests under, respectively, the null hypothesis that the 2nd-order term = 4th-order term = 0, and the null hypothesis that the 1st-order term = 3rd-order

[31] That is, the choice between a weakly-increasing monotonic function and a U-shaped function.

[32] Skalin and Terasvirta (2002) select the number of lags and the span depending on the data, after describing transition variables in the general form of Equation (20) to exclude possible short-term noise.

[33] With an alternative hypothesis for accepting the most appropriate transition variable, the test will show the highest power. See the section 5 in Van Dijk et al. (2002).

term = 0, for the 4th-order Taylor approximation around $\gamma = 0$. If the p-value for H_{0E} is smaller than for H_{0L}, the 2nd-order logistic transition function is preferable, and vice versa.

According to the results in Table 1, where real output (rate of change) is adopted as the transition variable, we can find significant nonlinearity in LM_1, LM_2 and LM_3, and both model selection tests come out in favor of the 2nd-order logistic function. These model selection test results are consistent with our hypothesis that policy effects are larger when business conditions are more constrained up to a certain point, but that after this point they start to diminish causing a U-shape to emerge.

In step (iii), we estimate a ST-VAR model (estimating two regime VAR parameters, smoothness and thresholds simultaneously).[34] Estimated ST-VAR models are shown in Tables 3 and 4. Estimated parameters (γ, c_1, c_2) of transition function G, diagnostic tests for nonlinear parts $(\Phi_2'(L)X_t - \Phi_1'(L)X_t)G$, tests of serial correlation, and estimated parameters for each function are shown in sequence. We use a heteroscedasticity-robust estimator.[35] Diagnostic tests for nonlinear parts shown in Tables 3 and 4 suggest significant regime-switching in both models.

In step (v), we evaluate the effects of monetary policy using impulse response functions. Due to the nonlinearity of the ST-VAR models, we cannot use traditional impulse response functions, as previously noted. Therefore, we adopt the generalized impulse response function introduced by Koop et al. (1996). The generalized impulse (GI) response for a specific shock $\varepsilon_t = \delta$ and history ω_{t-1} is defined as

$$GI_y(h, \delta, \omega_{t-1}) = E(y_{t+h}|\varepsilon_t = \delta, \omega_{t-1}) - E(y_{t+h}|\omega_{t-1}), \; for \; h = 0, 1, 2, ... \quad (21)$$

We have to carry out stochastic simulation in order to obtain estimates. In estimating the impulse response measures, following Garcia and Scaller (2002), we make use of a structural decomposition of the contemporaneous relationship among innovations, as show in Appendix B. To be more precise, we iteratively estimate the change in real output using the previously estimated ST-VAR model and adding one standard deviation at time zero as a policy shock as well as sampled historical shocks. [36]

When the transition variable is real output (rate of change), the variable is determined by changes in the four endogenous variables. When we select the lending attitudes DI as the transition variable, the changes in the variables are sampled from a conditional probability distribution, conditional

[34] We adopt maximum likelihood estimation here, and also the grid search method.

[35] See Davidson and MacKinnon (1985), Wooldridge (1990,1991) and Granger and Terasvirta (1993) for heteroscedasticity-robust estimators.

[36] By shifting the sampling period (46 periods for a round = 10 lag period + 36 estimation periods) by one, 279 (= the full 324 observations on each variable - 46 + 1) estimations are run for 40 rounds, and we sampled 11,160 (= 279×40) estimations in total. See Koop et al. (1996) for details.

on policy actions, constructed from the actual data as noted previously.[37]

Having carried out the stochastic simulation, we then subdivide our sample, based on the value of the transition variable at time zero, into observations where the transition variable z is: below the lower threshold value ($z_t < c_1$); greater than or equal to the lower and less than the upper threshold value ($c_1 \leq z_t < c_2$); and greater than or equal to the upper value ($c_2 \leq z_t$). The scale and direction of regime-switching are shown in Charts 6 to 9: Chart 6 shows the case with the real output growth rate as the transition variable; Chart 7 shows the results of the estimated general impulse responses. As shown in Chart 6, the estimated threshold (c_2) is about 0.5 which seems to be the border-line between economic boom and economic bust. Also, the lower threshold (c_1) turned out to be about -1.0, which corresponds to the case of excessive recession. For simplicity, we will refer to the case where $z_t < c_1$ as excessive recession, $c_1 \leq z_t < c_2$ as recession, and $c_2 \leq z_t$ as economic boom. The regime-switching estimates indicate the probability that the transition variable falls either below the lower threshold value, or takes a value greater than or equal to the upper threshold value. We therefore see that regime switching occurs frequently.

Estimated general impulse responses are shown in Chart 7: the responses of real output to a tight policy shock (Chart 7a), and to an easy policy shock (Chart 7b). To compare the impacts of different policy directions, Chart 7c describes responses to tight and easy policy shocks in one chart by assigning opposing signs to the respective responses.

From Chart 7a and 7b, we can conclude that policy effects in recessions are larger than those in economic booms, however this is not always true for excessive recessions. As Chart 7c shows, the impacts of different policy directions are not exactly identical, but do not differ much.

Charts 8 and 9 show, respectively, regime-switching and general impulse responses for another transition variable (the lending attitudes DI). In Chart 8a, the upper threshold (c_2) is estimated to be 16.08, distinguishing the accommodative lending attitudes in the late 1970s and late 1980s from those in other periods. The lower threshold (c_1) is estimated to be -23.47, offering a plausible reflection of the severe lending attitudes in the mid 1970s, early 1980s, and at the end of 1990s.

For simplicity, we refer to cases where the transition variable is below the lower threshold as "excessively severe" cases; those where it is greater than or equal to the lower and less than the upper threshold as "severe" cases; and those where it is greater than or equal to the upper threshold as "accommodative" cases.

[37]Intuitively speaking, we can subdivide our sample into changes that take place under tight monetary policy and those that take place under easy policy. We can then, for example, estimate a DI change under tight policy by sampling rates of change from the tight policy sub-sample.

Regime switches, in Chart 8b, depict the probability that the transition variable falls between the lower and upper thresholds. Regime switching has occurred several times in the sample period and its probability range from zero to one indicates the remarkable switches.

Estimated general impulse responses are again shown in Chart 9, describing the response of real output to both a tight policy shock (Chart 9a), and to an easy policy shock (Chart 9b). To compare the impacts of different policy directions, Chart 9c again describes responses to both policy shocks in one chart by assigning opposite signs to each.

From Chart 9a and 9b, we can conclude that policy effects are larger when lending attitudes are more severe, although there is a remarkable turn around when lending attitudes become excessively severe. In Chart 9c, the impacts of different policy directions are not exactly identical, but they do not differ much.

Table 5 summarizes the differences among regimes. With real output as the transition variable, policy effects are larger in recession than in either economic boom or excessive recession. However, the differences are not significant. In contrast, for the lending attitudes DI, policy effects are larger when lending attitudes are severe than when they are either accommodative or excessively severe, and these differences are significant in both tight and easy policy phases.[38] [39]

As a result, we find that policy may be especially ineffective even in situations, such as excessive recession and/or excessively severe lending attitudes, where policy had been believed to be more powerful. The Japanese economy in the early 1990s and at the end of 1990s might have experienced this phenomenon. In July 1991, after a period of very tight policy responding to the so-called bubble economy, monetary policy was loosened, and it was during this particular period that our empirical results, using real output as a transition variable, suggest that there was a weakening in policy effects. In addition, the lending attitudes DI during this period approaches the threshold of "excessive" severity. Even though, on average, the DI variable does not exceed the threshold, there might be some individual firms that do exceed the threshold.[40]

At the end of the 1990s, the Japanese economy was in recession, causing bankruptcies at major banks and securities firms and triggering credit insecurity. Whether real output or the lending attitudes DI is adopted as the

[38] As already shown in Tables 1 and 3, both transition variables cause significant asymmetric policy effects. Therefore, the result that the difference among regimes is not significant for real output tends rather to suggest that the nonlinear model could be more appropriately constructed than to deny the existence of asymmetry.

[39] The lending attitudes DI resulted in significant regime differences while real output did not. This might be because the DI captures actual nonlinear factors more directly.

[40] Severer attitudes are said to have been experienced in this period particularly by larger firms. Stricter BIS regulation applied to large-scale banks (the main lenders to larger firms) provides one explanation for these severe lending attitudes.

transition variable, the indication is that excessive recession and excessively severe lending attitudes caused the effectiveness of policy to weaken.[41]

4 Implications

In this paper, we examine alterations in the effects of monetary policy on real output, using smooth transition vector autoregressive models. Specifically, we employ a four variable VAR model, with real output, M2+CDs, the CPI (excluding fresh foods), and the call rate forming the baseline VAR model. According to our empirical results, monetary policy effects vary significantly depending on real output and the lending attitudes diffusion index for financial institutions. More specifically, policy effects are magnified in recession (as argued in previous studies), but diminish in excessive recession. In the same way, policy effects are magnified when lending attitudes are severe, as has been pointed out, but diminish when attitudes grow "excessively" severe.

This paper focuses on the impact on real output. The impact on prices may be different from these results. The effect of monetary policy on prices remains an issue for future study.

Except in extreme cases, the results suggest that policy effects are magnified when credit constraints become stricter. This finding is consistent with the argument of Bevnanke and Gertler (1995) which takes into account paths for amplifying the effects of monetary policy through lending. However, it must be noted that the results cannot be taken to say anything about the sensitivity of policy effects to firm size. Kashyap and Stein (1995) and Gertler and Gilchrist (1994) argue that, if the lending channel is the key transmission mechanism for policy, larger policy effects would be found for smaller firms, which are highly dependent upon lending by financial institutions. However, since the threshold faced by each firm may differ depending upon their net worth level at time zero, it is not obvious where regime switching occurs for the smaller firms in this paper. The sensitivity of monetary policy effectiveness to firm size also remains an issue for future research.

Although there are some hurdles that need to be crossed in the application of smooth transition models, such as the absence of adequate asymptotic theory for statistical inference when testing null hypotheses regarding structural changes, as well as the inability to make use of traditional impulse

[41] Regime-switching in the context of a liquidity trap under low interest rate policy is a very important research topic for the current Japanese economy. However, dealing with the zero restriction on nominal interest rate is problematic, and it is not appropriate to use an ST-VAR model for numerical regimes which vary with the interest rate. This issue is therefore left as a subject for future study. In the meantime, however, the result does not differ when periods during which interest rate was extremely low at the end of the 1990s are excluded from the sample.

response functions because of historical dependence and nonlinearity, the ST model is a practical tool which allows us to derive useful implications from regime-switching analyses. Active application and development of ST-VAR models on several fields is expected.

A Data

Real output index of industrial production, compiled by the Ministry of Economy, Trade and Industry

Call rate the collateralized overnight call rate , compiled by the Bank of Japan

Credit spreads calculated using straight bond quotations by rating (Moody's Aa, Baa), over-the-counter corporate bond quotations by rating (12 years) and government bond yields, from the "Financial and Economic Statistics Monthly" published by the Bank of Japan

DI **of Lending Attitude of Financial Institutions** Diffusion Index of Lending Attitude of Financial Institutions, "Short-term Economic Survey of Enterprises in Japan (Tankan)," published by the Bank of Japan

DI **of Financial Positions** Diffusion Index of Financial Positions, "Short-term Economic Survey of Enterprises in Japan (Tankan)" published by the Bank of Japan

DI **of Business Conditions** Diffusion Index of Business Conditions, "Short-term Economic Survey of Enterprises in Japan (Tankan)" published by the Bank of Japan

CPI CPI less foods, complied by the Ministry of Public management, Home Affairs, Posts and Telecommunications

Money M2+CD, compiled by the Bank of Japan

Stock Prices (Topix) stock prices (Topix), "Financial and Economic Statistics Monthly" published by the Bank of Japan

B Structural Decomposition of VAR

In our structural decomposition, following Garcia and Schaller (2000), we adopt the following restrictions.[42]

$$\begin{pmatrix} e_Y \\ e_M \\ e_P \\ e_R \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ a_{21} & 1 & 0 & 0 \\ a_{31} & a_{32} & 1 & 0 \\ a_{41} & a_{42} & a_{43} & 1 \end{pmatrix} \begin{pmatrix} u_Y \\ u_M \\ u_P \\ u_R \end{pmatrix}$$

Y: Real output, M: M2+CD, P: CPI, R: Call rate, $e.$:structural shock, $u.$:error term of VAR estimation

[42]This is the same as the Cholesky decomposition.

C Nonlinearity Tests and Model Selection Test

C.1 Nonlinearity Tests

Consider the ST model in Equation (16). In order to derive nonlinearity tests for Equation (16), we approximate the logistic function using a Taylor approximation around $\gamma = 0$. Three types of nonlinearity tests are proposed by Luukkonen et al. (1988), Saikkonen and Luukkonen (1988) and Granger and Terasvirta (1993). Since these tests do not test the original null hypothesis $H_0 : \gamma = 0$ but rather the auxiliary null hypothesis $H_0' : \beta_. = 0$, these tests are usually referred to as LM-type statistics. In this section, the dependent variable is y_t and the independent variable is x_t.

(i) LM_1

In the following auxiliary regression,

$$y_t = \beta_0' x_t + \beta_1' x_t s_t + \epsilon_t, \tag{22}$$

nonlinearity of the 1st-order logistic transition function can be tested under the null hypothesis $H_1 : \beta_1 = 0$.

(ii)LM_2

In the following auxiliary regression,

$$y_t = \beta_0' x_t + \beta_1' x_t s_t + \beta_2' x_t s_t^2 + \epsilon_t \tag{23}$$

nonlinearity of the 2nd-order logistic transition function can be tested under the null hypothesis $H_2 : \beta_1 = \beta_2 = 0$.

(iii)LM_3

The LM_1 statistic does not have power in situations where only the intercept differs across regimes. This problem can be solved by approximating the transition function using a third-order Taylor approximation.

$$y_t = \beta_0' x_t + \beta_1' x_t s_t + \beta_2' x_t s_t^2 + \beta_3' x_t s_t^3 + \epsilon_t \tag{24}$$

Nonlinearity of the 1st-order logistic transition function can be tested under the null hypothesis, $H_3 : \beta_1 = \beta_2 = \beta_3 = 0$

C.2 Model Selection Tests

When linearity is rejected, the next decision concerns the appropriate formation of the transition function. In practice, the choice is limited to that between the first-order logistic function on the one hand and the second-order logistic function (or the exponential function) on the other. Two kinds of model selection tests are proposed by Terasvirta (1994) and Escribano and Jorda (1999).

(i) Model Selection Tests by Terasvirta (1994)

If we consider the following sequence of null hypotheses in equation (24):

$$\begin{aligned} H_{03} &: \beta_3 = 0, \\ H_{02} &: \beta_2 = 0 | \beta 3 = 0, \\ H_{01} &: \beta_1 = 0 | \beta_2 = \beta_3 = 0, \end{aligned} \tag{25}$$

the following decision rule is derived: if the p-value of the test corresponding to H_{02} is the smallest, the 2nd-order logistic function should be selected, while in all other cases the 1st-order logistic function is preferable.

(ii)Model Selection tests by Escribano and Jorda (1999)

In the following auxiliary regression of the 4th-order Taylor approximation,

$$y_t = \beta_0' x_t + \beta_1' x_t s_t + \beta_2' x_t s_t^2 + \beta_3' x_t s_t^3 + \beta_4' x_t s_t^4 + \epsilon_t \tag{26}$$

they suggest the two hypotheses:

$$\begin{aligned} H_{0E} &: \beta_2 = \beta_4 = 0, \\ H_{0L} &: \beta_1 = \beta_3 = 0, \end{aligned} \tag{27}$$

The 1st-order logistic transition function (2nd-order logistic function) should be selected if the minimum p-value is obtained for H_{0L} (H_{0E}).

In general, neither procedure for model selection dominates the other.

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Table 1: Tests for Nonlinearity and VAR Model Selection

Transition Variable: real output $\Sigma_{i=0}^{3}\Delta y_{1,t-9-i}/4$ Test	p-value[a]
Nonlinearity Tests[b]	
LM_1	0.0014
LM_2	4.199e-006
LM_3	5.167e-006
Model Selection Tests [Terasvirta (1994)][c]	
H_{01}	0.0014
H_{02}	0.0003
H_{03}	0.1017
Model Selection Tests [Escribano and Jorda (1999)] [d]	
H_{0E}	9.099e-006
H_{0L}	0.0718

[a]We adopted the heteroscedasticity robust estimator proposed by Wooldridge (1990,1991) and Granger and Terasvirta (1993).

[b]p-values of LM-type tests are for the ST-VAR model under the null hypothesis of no nonlinearity. LM_i is a test for the i-th order Taylor approximation around $\gamma = 0$. See Luukkonen et al. (1988), Granger and Terasvirta (1993) and Saikkonen and Lukkonen (1988).

[c]H_{0i} is the model selection test between the 1st-order and 2nd order logistic functions suggested by Terasvirta (1994). If H_{02} takes the lowest value, the 2nd-order logistic function is preferable. Otherwise, the 1st-order logistic function is preferable.

[d]H_{0E}, H_{0L} are the model selection tests between the 1st-order and 2nd order logistic functions suggested by Escribano and Jorda (1999). If H_{0E} is lower than H_{0L}, the 2nd-order logistic function is preferable, and vice versa.

Table 2: Tests for Nonlinearity and Model Selection

Transition Variable: DI of lending attitude	
$\Sigma_{i=0}^{5} DI_{t-5-i}/6$	
Test[a]	p-value
Nonlinearity Tests	
LM_1	4.377e-007
LM_2	2.478e-014
LM_3	1.598e-015
Model Selection Tests [Terasvirta (1994)]	
H_{01}	4.377e-007
H_{02}	3.757e-009
H_{03}	0.0020
Model Selection Tests [Escribano and Jorda (1999)]	
H_{0E}	6.896e-017
H_{0L}	3.553e-011

[a]See footnote in Table 1

Table 3: Estimation of ST-VAR model (Transition Variable: real output)

variables				
y1: real output, y2: M2+CD				
y3: CPI, y4: call rate				
lags: 1,2, 10				
estimation period: 1975/Jan.-2001/Dec.				
Transition Variable: real output $\Sigma_{i=0}^{3}\Delta y_{1,t-9-i}/4$				
Estimated parameters of Transition Function				
Variable	Estimate	SE(heteroscedastic robust estimate)		
γ	40.305	0.575		
c_1	-0.011	0.000206		
c_2	0.003	0.000197		
Diagnostic Tests for Nonlinear Parts $((\Phi_2'(L)X_t - \Phi_1'(L)X_t)G)$ (LR tests)				
LR statistics	89.730	p-value	0.007	
Tests for q-th order serial correlation (p-value)				
Order	Eqn. 1	Eqn. 2	Eqn. 3	Eqn.4
4	0.099	0.313	0.207	0.056
8	0.321	0.503	0.237	0.159
12	0.281	0.389	0.382	0.138

Table 3: (continued)

Equation 1. Dependent Variable: y1(real output)

Variable	Estimate	HR-t-value
Linear part		
constant	-1.016	-4.022
Nonlinear part		
Central Area ($c_1 \leq TransitionVariable(TV) < c_2$)		
y1(t-1)	0.588	2.055
y1(t-2)	-0.172	-0.312
y1(t-10)	0.547	1.858
y2(t-1)	-0.130	-0.228
y2(t-2)	-0.283	-1.750
y2(t-10)	0.288	0.849
y3(t-1)	2.416	1.613
y3(t-2)	-3.665	-1.252
y3(t-10)	-2.589	-1.565
y4(t-1)	4.224	1.311
y4(t-2)	0.301	1.033
y4(t-10)	-0.576	-0.970
End Areas($TV < c_1, c_2 \leq TV$)		
y1(t-1)	0.015	0.009
y1(t-2)	0.666	0.220
y1(t-10)	-0.074	-0.038
y2(t-1)	-0.724	-0.204
y2(t-2)	-0.000	-0.000
y2(t-10)	0.129	0.178
y3(t-1)	-0.003	-0.272
y3(t-2)	0.006	0.211
y3(t-10)	0.002	0.131
y4(t-1)	-0.003	-0.115
y4(t-2)	-0.001	-0.356
y4(t-10)	0.003	0.421

Table 3: (continued)

Equation 2: Dependent Variable: y2(M2+CD)		
Variable	Estimate	HR-t-value
Linear Part		
Constant	0.027	0.609
Nonlinear Part		
Central Area($c_1 \leq TV < c_2$)		
y1(t-1)	0.031	0.557
y1(t-2)	-0.073	-0.662
y1(t-10)	-0.013	-0.218
y2(t-1)	0.024	0.209
y2(t-2)	-0.045	-1.371
y2(t-10)	0.126	1.843
y3(t-1)	1.359	3.321
y3(t-2)	-0.583	-0.718
y3(t-10)	-0.239	-0.540
y4(t-1)	0.531	0.611
y4(t-2)	-0.125	-2.065
y4(t-10)	0.045	0.377
End Areas($TV < c_1, c_2 \leq TV$)		
y1(t-1)	0.122	0.460
y1(t-2)	-0.063	-0.129
y1(t-10)	-0.146	-0.494
y2(t-1)	0.114	0.212
y2(t-2)	0.060	1.091
y2(t-10)	-0.110	-1.031
y3(t-1)	-0.002	-1.057
y3(t-2)	0.005	1.084
y3(t-10)	0.001	0.454
y4(t-1)	-0.003	-0.677
y4(t-2)	0.000	1.392
y4(t-10)	-0.001	-1.102

Table 3: (continued)

Equation 3. Dependent Variable: y3(CPI)

Variable	Estimate	HR-t-value
	Linear part	
constant	-0.012	-0.480
	Nonlinear part	
	Central Area ($c_1 \leq TV < c_2$)	
y1(t-1)	-0.019	-0.392
y1(t-2)	0.041	0.388
y1(t-10)	0.021	0.379
y2(t-1)	-0.040	-0.323
y2(t-2)	0.008	0.304
y2(t-10)	-0.029	-0.481
y3(t-1)	0.355	1.462
y3(t-2)	-0.622	-1.181
y3(t-10)	-0.386	-1.435
y4(t-1)	0.699	1.192
y4(t-2)	0.030	0.779
y4(t-10)	-0.072	-0.812
	End Areas($TV < c_1, c_2 \leq TV$)	
y1(t-1)	1.920	3.895
y1(t-2)	-1.784	-1.799
y1(t-10)	-1.001	-1.811
y2(t-1)	2.102	1.880
y2(t-2)	0.071	0.920
y2(t-10)	-0.306	-1.879
y3(t-1)	-0.008	-2.043
y3(t-2)	0.020	2.132
y3(t-10)	0.009	2.083
y4(t-1)	-0.021	-2.153
y4(t-2)	0.000	0.220
y4(t-10)	-5.704E-005	-0.044

Table 3: (continued)

Equation 4.Dependent Variable: y4 (call rates)

Variable	Estimate	HR-t-value
Linear part		
constant	1.440	0.334
Nonlinear part		
Central Area($c_1 \leq TV < c_2$)		
y1(t-1)	-4.383	-0.440
y1(t-2)	14.467	0.642
y1(t-10)	-0.271	-0.028
y2(t-1)	-3.112	-0.146
y2(t-2)	5.286	1.617
y2(t-10)	-11.300	-1.585
y3(t-1)	-27.822	-0.748
y3(t-2)	64.476	0.825
y3(t-10)	31.733	0.755
y4(t-1)	-72.560	-0.816
y4(t-2)	-3.783	-0.546
y4(t-10)	7.488	0.482
End Areas($TV < c_1, c_2 \leq TV$)		
y1(t-1)	8.817	0.170
y1(t-2)	-11.804	-0.113
y1(t-10)	-5.919	-0.100
y2(t-1)	3.121	0.026
y2(t-2)	-4.284	-0.444
y2(t-10)	10.716	0.539
y3(t-1)	0.390	0.720
y3(t-2)	1.709	1.516
y3(t-10)	0.731	1.293
y4(t-1)	-1.950	-1.650
y4(t-2)	-0.093	-0.859
y4(t-10)	0.110	0.482

note:HR-t-value is a heteroscedastic consistent t-value.

Table 4: Estimated Parameters of ST-VAR Model(Transition Variable: lending attitude DI)

Variables				
y1: Real Output, y2: M2+CD				
y3: CPI, y4: Call Rates				
lags: 1,2, 10				
Estimation period: 1975/Jan.-2001/Dec.				
Transition Variable: $\Sigma_{i=0}^{5} DI_{t-5-i}/6$				
Estimated parameters of Transition Function				
Variable	Estimate	SE(heteroscedastic robust estimate)		
γ	50.644	0.225		
c_1	-23.467	0.026		
c_2	16.079	0.037		
Diagnostic Tests for Nonlinear Parts $((\Phi_2'(L)X_t - \Phi_1'(L)X_t)G)$ (LR tests)				
LR statistics	88.752	p-value	0.009	
Tests for q-th order serial correlation (p-value)				
Order	Eqn. 1	Eqn. 2	Eqn. 3	Eqn. 4
4	0.099	0.677	0.584	0.999
8	0.321	0.787	0.742	0.616
12	0.281	0.683	0.888	0.196

Table 4: (continued)

Equation 1. Dependent Variable: y1(Real Output)

Variable	Estimate	HR-t-value
	Linear part	
constant	-1.183	-4.524
	Nonlinear part	
	Central Area ($c_1 \leq TV < c_2$)	
y1(t-1)	0.528	7.379
y1(t-2)	-0.070	-0.666
y1(t-10)	0.485	6.541
y2(t-1)	-0.018	-0.165
y2(t-2)	-0.163	-4.301
y2(t-10)	0.024	0.424
y3(t-1)	0.578	1.521
y3(t-2)	0.171	0.298
y3(t-10)	-0.486	-1.173
y4(t-1)	-0.122	-0.192
y4(t-2)	0.045	0.656
y4(t-10)	-0.044	-0.388
	End Areas($TV < c_1, c_2 \leq TV$)	
y1(t-1)	-0.191	-0.432
y1(t-2)	1.037	1.566
y1(t-10)	0.146	0.289
y2(t-1)	-1.056	-1.467
y2(t-2)	0.000	-0.005
y2(t-10)	0.064	0.458
y3(t-1)	0.006	1.725
y3(t-2)	-0.008	-1.786
y3(t-10)	-0.008	-1.902
y4(t-1)	0.011	2.167
y4(t-2)	0.000	0.214
y4(t-10)	-0.001	-0.517

Table 4: (continued)

Equation 2. Dependent Variable: y2 (M2+CD)		
Variable	Estimate	HR-t-value
Linear part		
constant	0.025	0.582
Nonlinear part		
Central Area ($c_1 \leq TV < c_2$)		
y1(t-1)	0.006	0.484
y1(t-2)	-0.024	-1.057
y1(t-10)	-0.008	-0.582
y2(t-1)	0.013	0.590
y2(t-2)	-0.002	-0.207
y2(t-10)	0.033	2.765
y3(t-1)	1.031	12.081
y3(t-2)	-0.033	-0.232
y3(t-10)	0.038	0.399
y4(t-1)	0.068	0.445
y4(t-2)	-0.073	-5.085
y4(t-10)	-0.037	-1.239
End Areas($TV < c_1, c_2 \leq TV$)		
y1(t-1)	0.064	0.686
y1(t-2)	0.099	0.712
y1(t-10)	-0.024	-0.236
y2(t-1)	-0.138	-0.909
y2(t-2)	-0.028	-1.594
y2(t-10)	0.025	0.720
y3(t-1)	0.002	3.085
y3(t-2)	-0.002	-1.868
y3(t-10)	-0.002	-3.874
y4(t-1)	0.002	2.295
y4(t-2)	0.000	2.311
y4(t-10)	0.000	0.005

Table 4: (continued)

Variable	Estimate	HR-t-value
	Equation 3. Dependent Variable: y3 (CPI)	
	Linear part	
constant	-0.018	-0.616
	Nonlinear part	
	Central Area ($c_1 \leq TV < c_2$)	
y1(t-1)	-0.010	-0.921
y1(t-2)	0.014	0.978
y1(t-10)	0.016	1.332
y2(t-1)	-0.029	-1.818
y2(t-2)	-0.003	-0.635
y2(t-10)	-0.001	-0.108
y3(t-1)	0.119	2.837
y3(t-2)	-0.097	-1.268
y3(t-10)	-0.116	-2.544
y4(t-1)	0.134	1.587
y4(t-2)	-0.001	-0.161
y4(t-10)	-0.031	-1.972
	End Areas($TV < c_1, c_2 \leq TV$)	
y1(t-1)	1.134	10.343
y1(t-2)	-0.200	-1.122
y1(t-10)	-0.068	-0.567
y2(t-1)	0.213	1.099
y2(t-2)	-0.071	-4.648
y2(t-10)	-0.015	-0.540
y3(t-1)	0.002	1.189
y3(t-2)	-0.001	-0.447
y3(t-10)	-0.002	-1.185
y4(t-1)	0.001	0.572
y4(t-2)	0.000	0.434
y4(t-10)	0.000	0.123

Table 4: (continued)

Equation 4. Dependent Variable: y4 (Call Rates)

Variable	Estimate	HR-t-value
Linear part		
constant	3.700	0.887
Nonlinear part		
Central Area ($c_1 \leq TV < c_2$)		
y1(t-1)	2.017	1.052
y1(t-2)	0.718	0.269
y1(t-10)	-1.311	-0.642
y2(t-1)	1.110	0.402
y2(t-2)	0.281	0.450
y2(t-10)	0.698	0.595
y3(t-1)	8.181	1.266
y3(t-2)	-2.593	-0.198
y3(t-10)	-7.395	-1.043
y4(t-1)	-3.967	-0.260
y4(t-2)	-1.396	-1.300
y4(t-10)	6.440	1.614
End Areas ($TV < c_1, c_2 \leq TV$)		
y1(t-1)	11.042	0.848
y1(t-2)	2.885	0.158
y1(t-10)	-14.996	-1.079
y2(t-1)	0.868	0.043
y2(t-2)	4.226	1.942
y2(t-10)	-5.757	-1.193
y3(t-1)	1.305	9.417
y3(t-2)	-0.272	-1.347
y3(t-10)	-0.298	-2.103
y4(t-1)	0.177	0.932
y4(t-2)	-0.022	-0.958
y4(t-10)	-0.026	-0.759

note:HR-t-value is a heteroscedasticity consistent t-value.

Table 5: Regime-Switching Estimated by General Impulse Responses

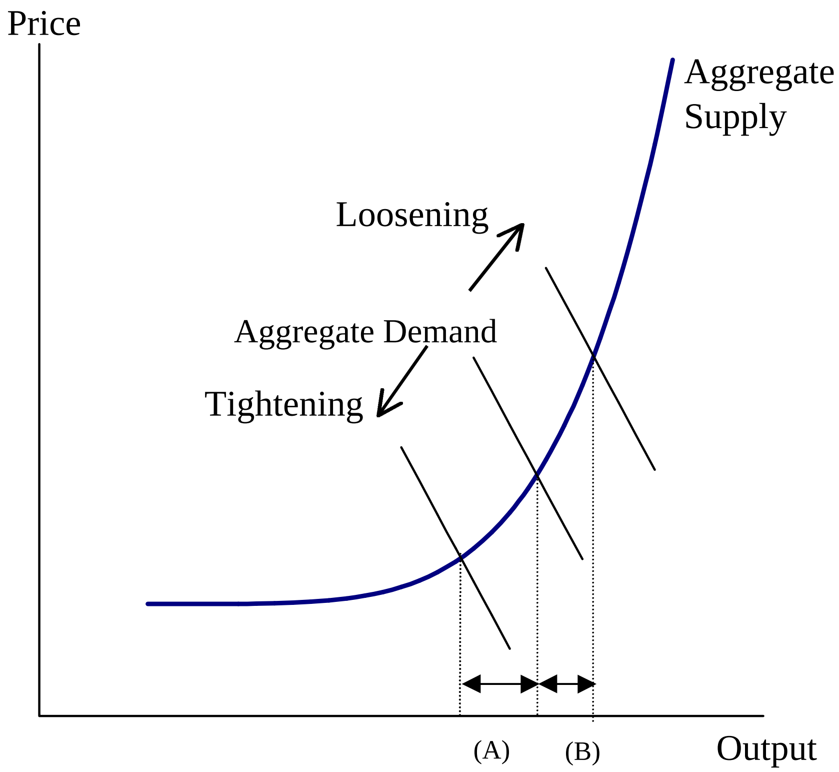
difference of responses (maximal value)[a]		tight policy	easy policy
	period	Estimate	Estimate
Transition Variable: Real Output (rate of change)[b]			
recession - economic boom	26	-0.00087	0.000989
recession - excessive recession	36	-0.0068	0.000804
Transition Variable: lending attitude DI [c]			
difference of responses	period	Estimate	Estimate
severe - accommodative	22	-0.00844*	0.00846*
severe - excessively severe	22	-0.00846*	0.00847*

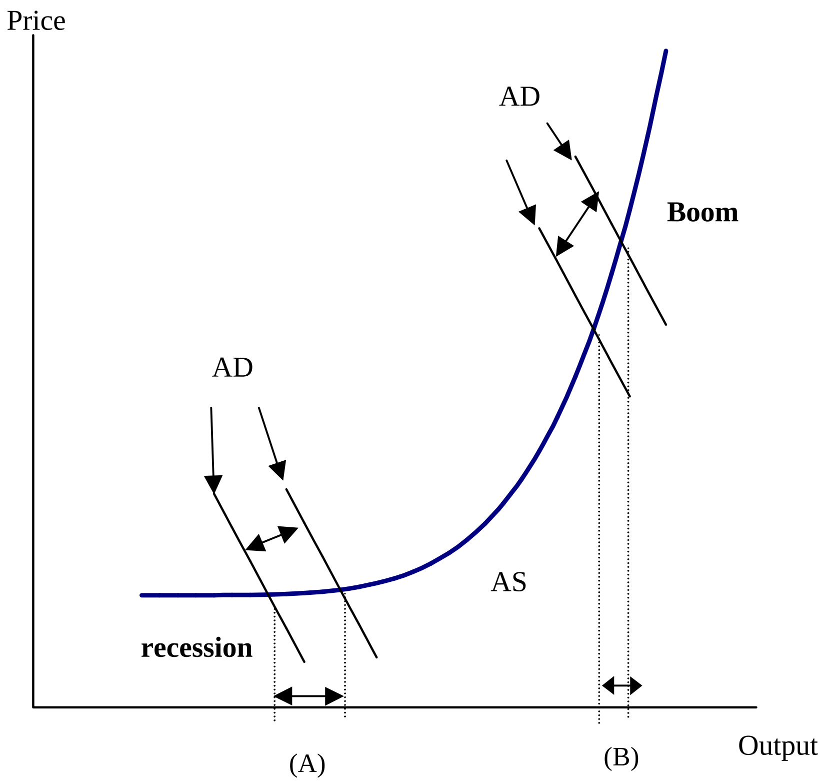
[a]* denotes 5 % significance

[b]Economic boom, recession, excessive recession correspond to cases when transition variables are greater than or equal to the upper threshold, greater or equal to lower threshold and less than upper threshold, and less than lower threshold, respectively.

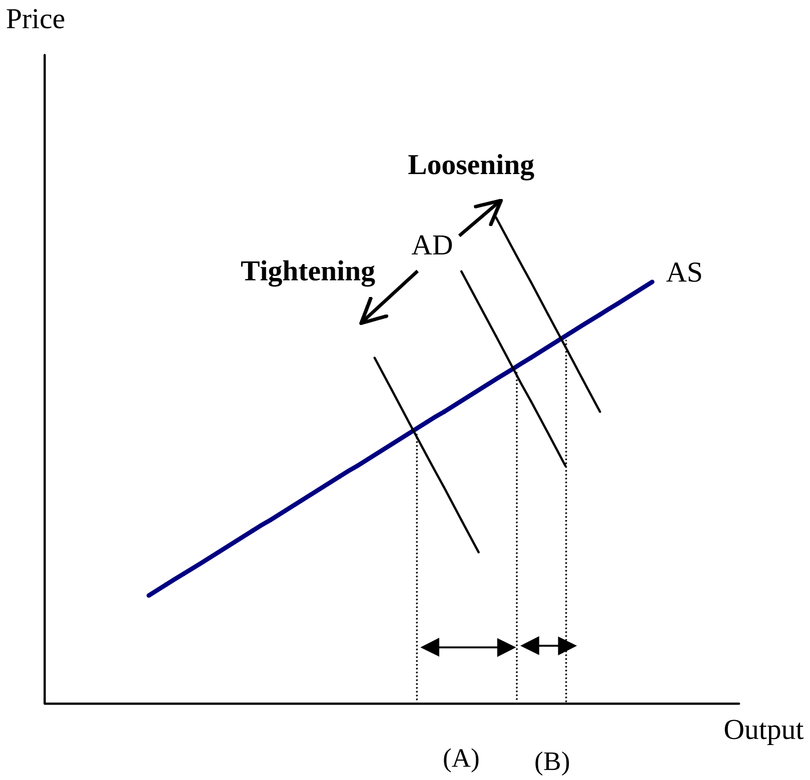
[c]Accommodative, severe, excessively severe correspond to cases when transition variables are greater than or equal to the upper threshold, greater than or equal to the lower threshold and less than the upper threshold, and less than the lower threshold respectively.

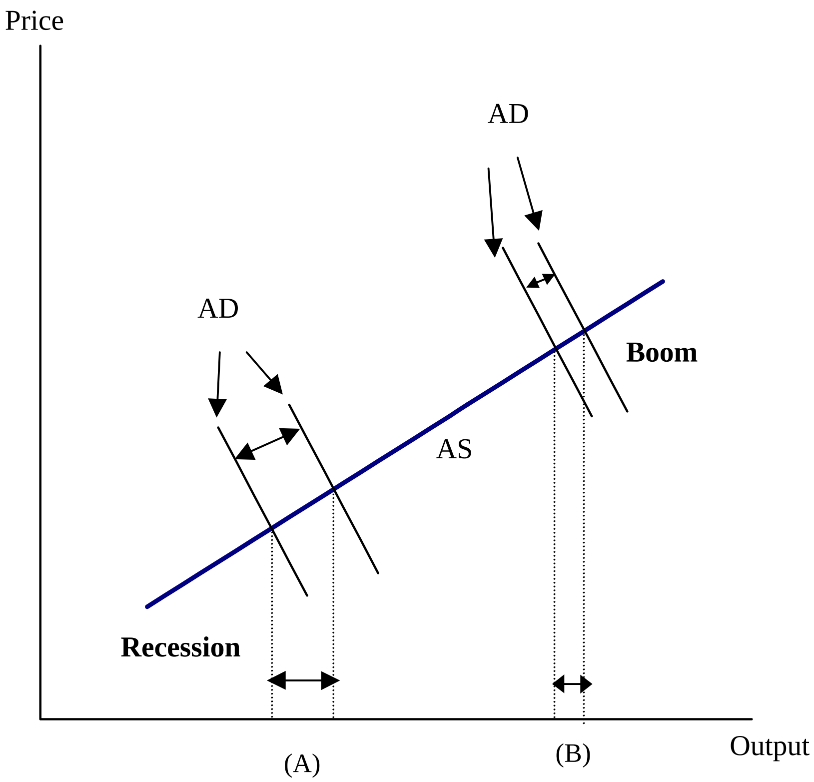
(Chart 1) Asymmetry of Aggregate Supply



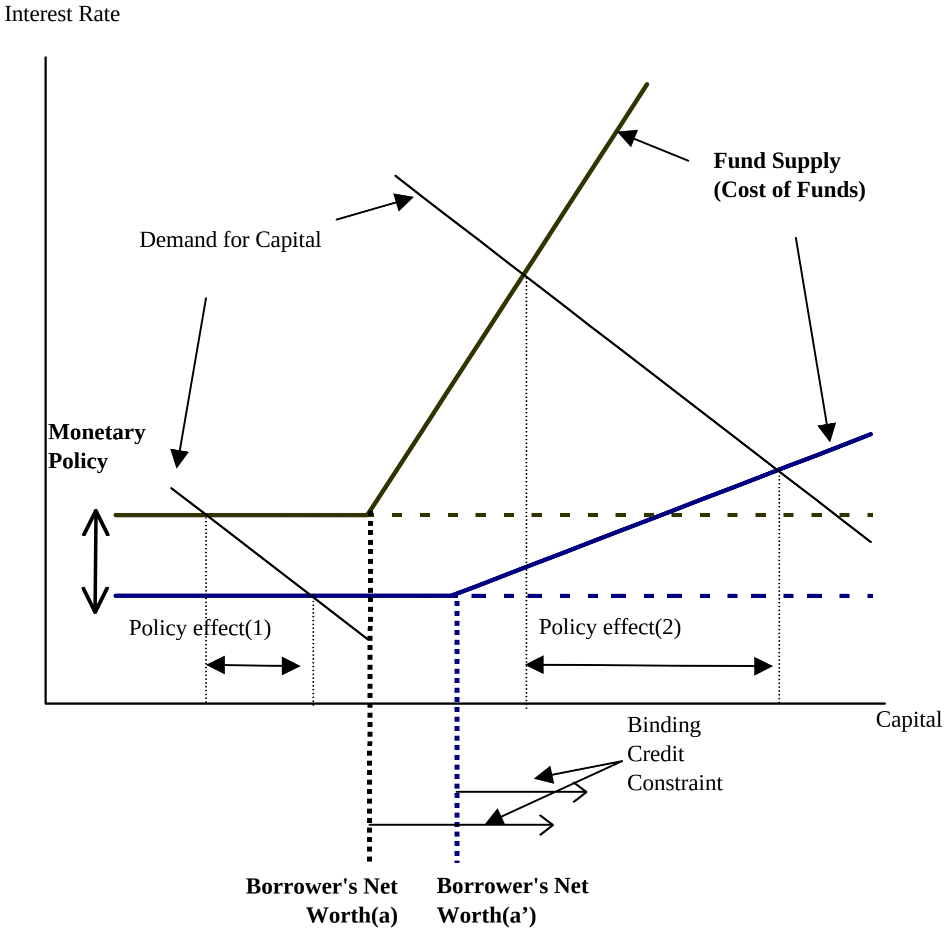


(Chart 2) Asymmetry in Shifts of Aggregate Demand

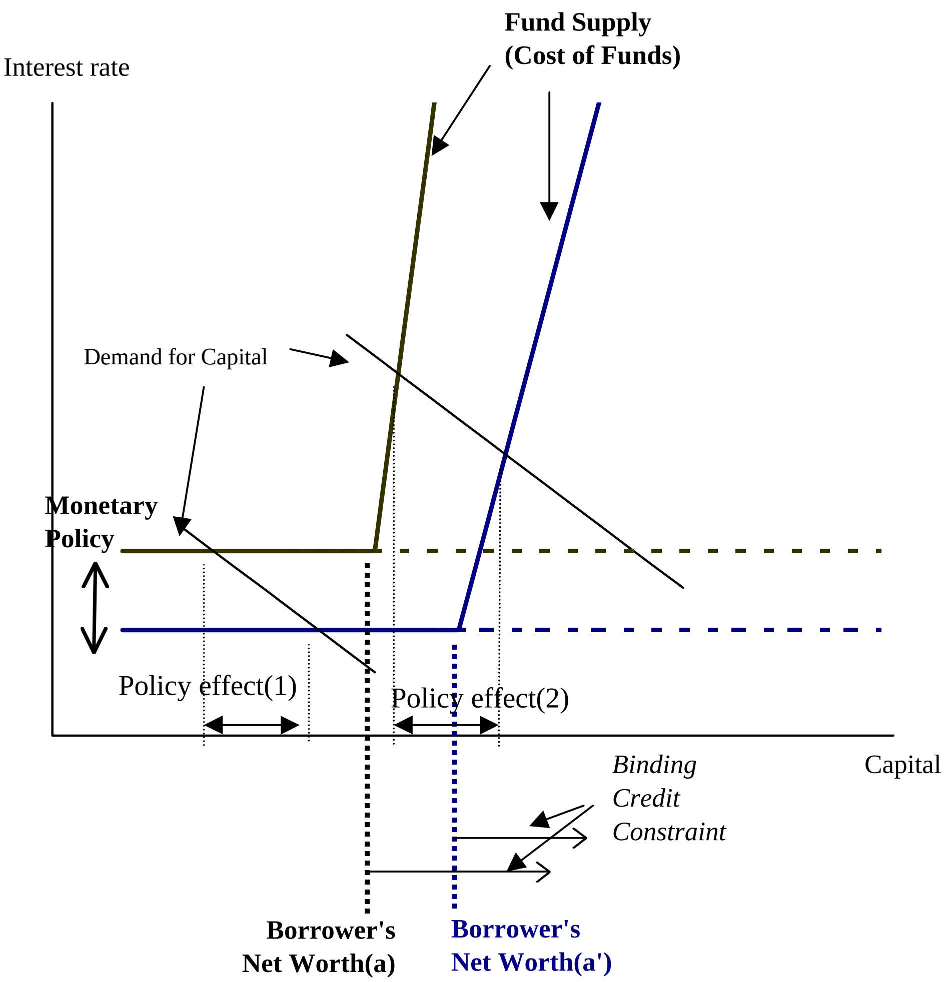




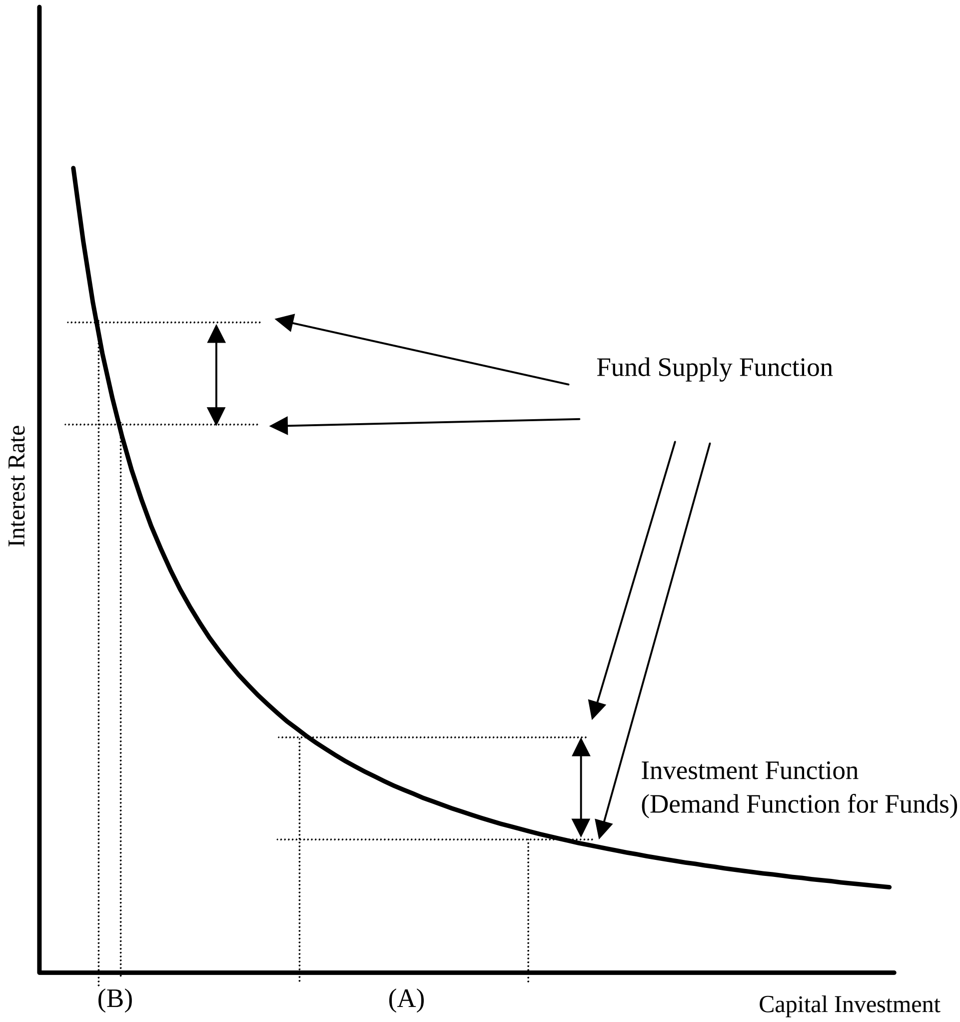
(Chart 3) Financial Accelerator



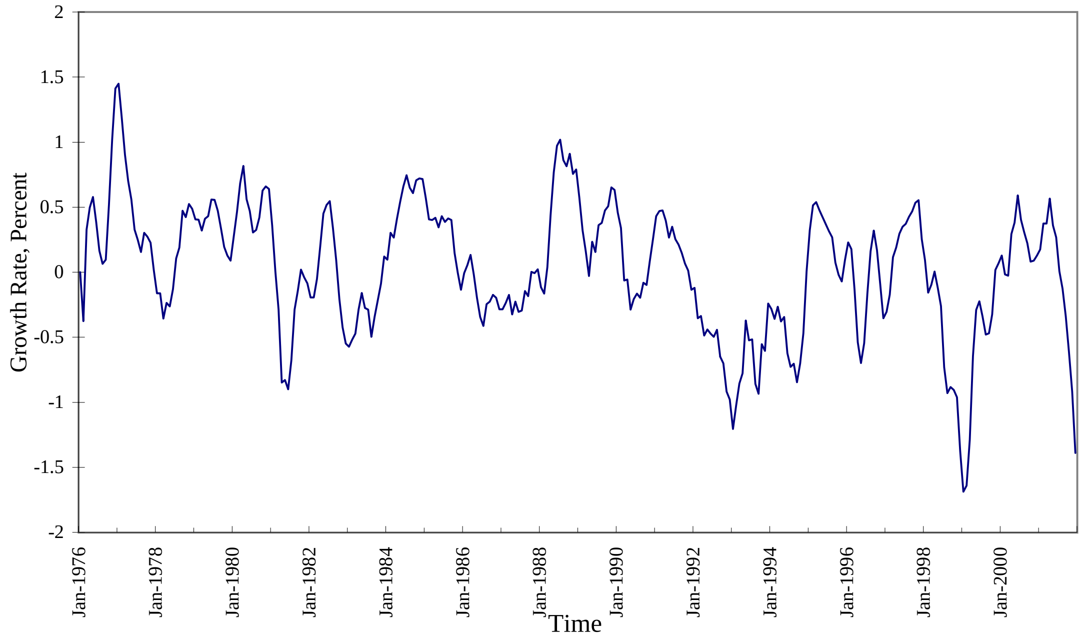
(Chart 4) Excessive External Financing Premium



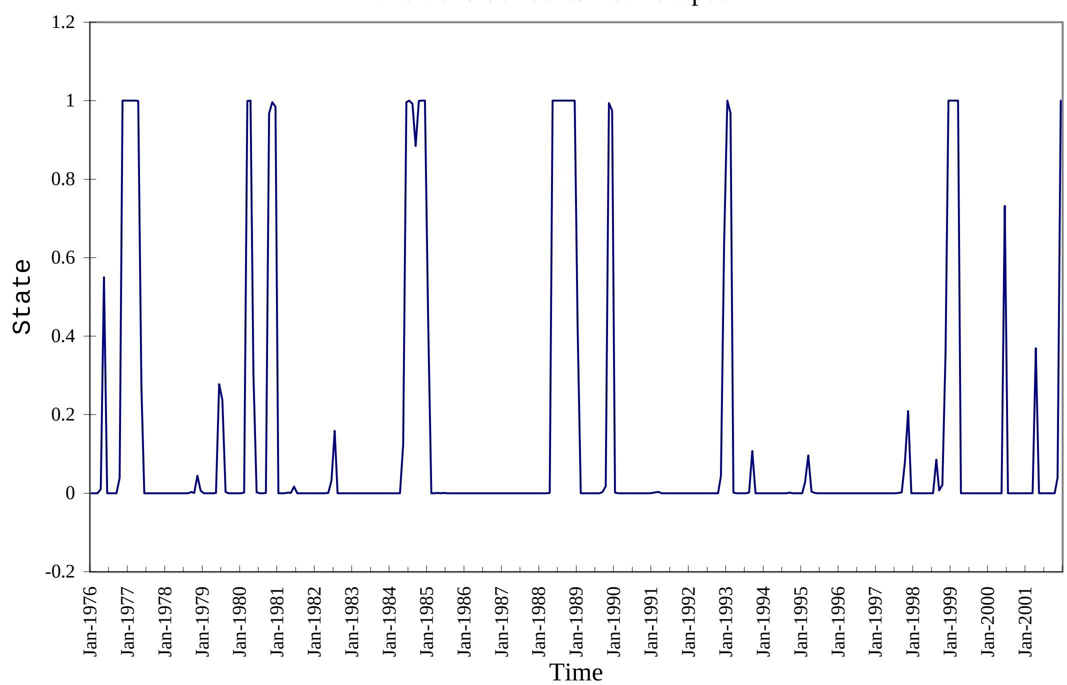
(Chart 5) Asymmetric Demand Shifts
according to the Interest Elasticity Hypothesis



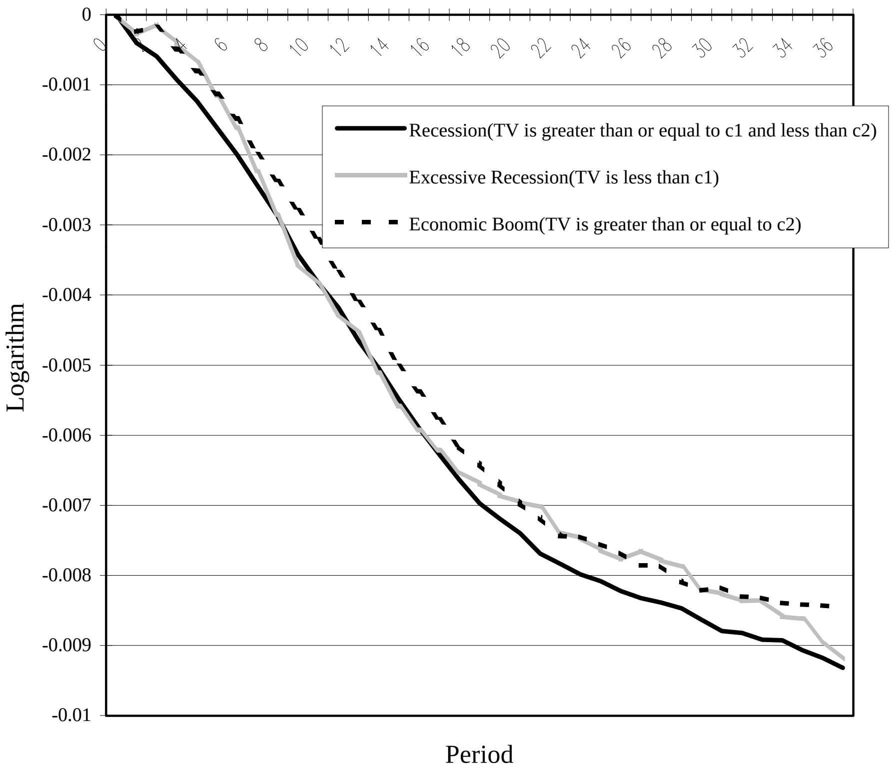
(Chart 6a) Transition Variable: Real Output



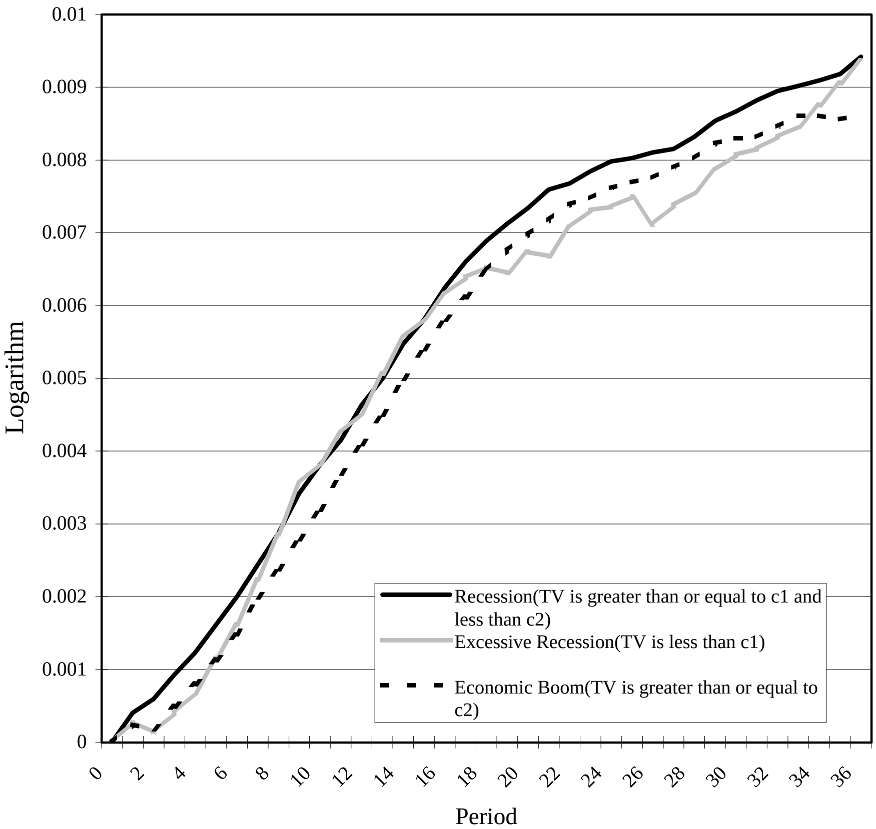
(Chart 6b) Regime Switching
Transition: Variable: Real Output



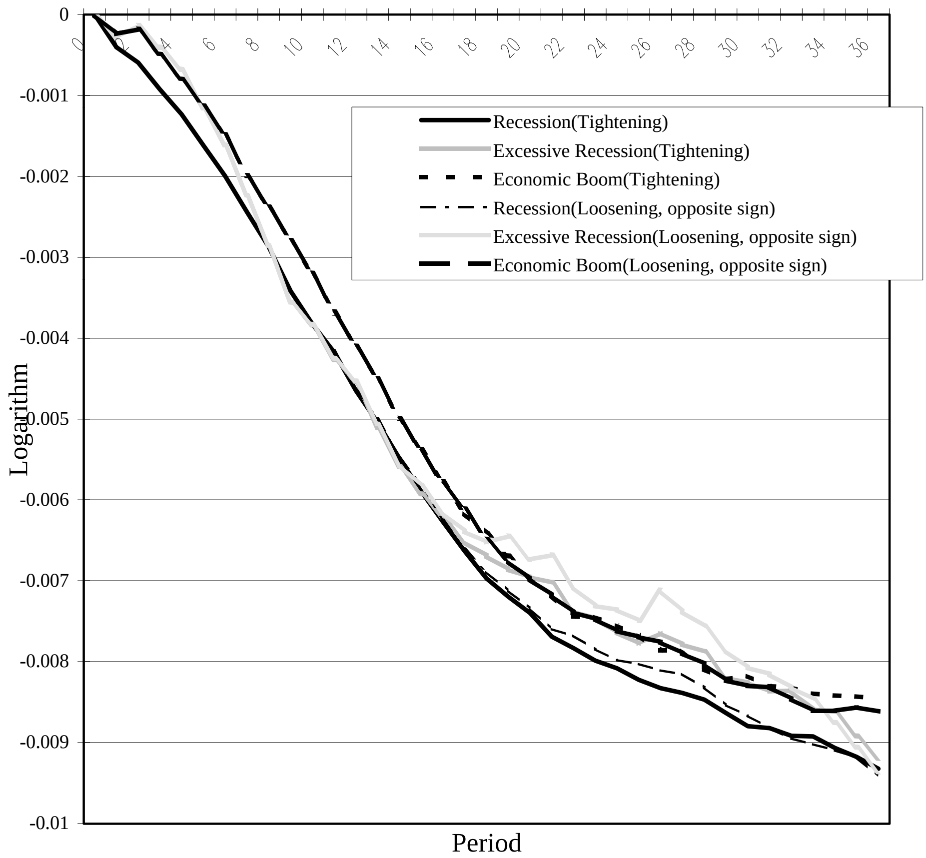
(Chart 7a) Real Output Response to Tight Policy Shock
Transition Variable(TV): Real Output



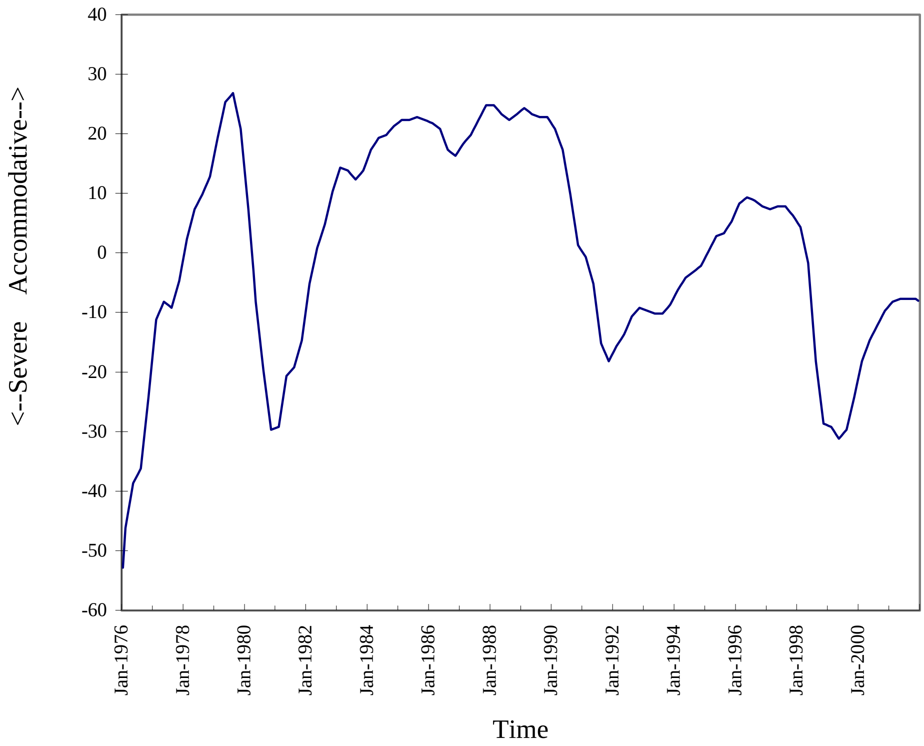
(Chart 7b) Real Output Response to Easy Policy Shock
Transition Variable: Real Output



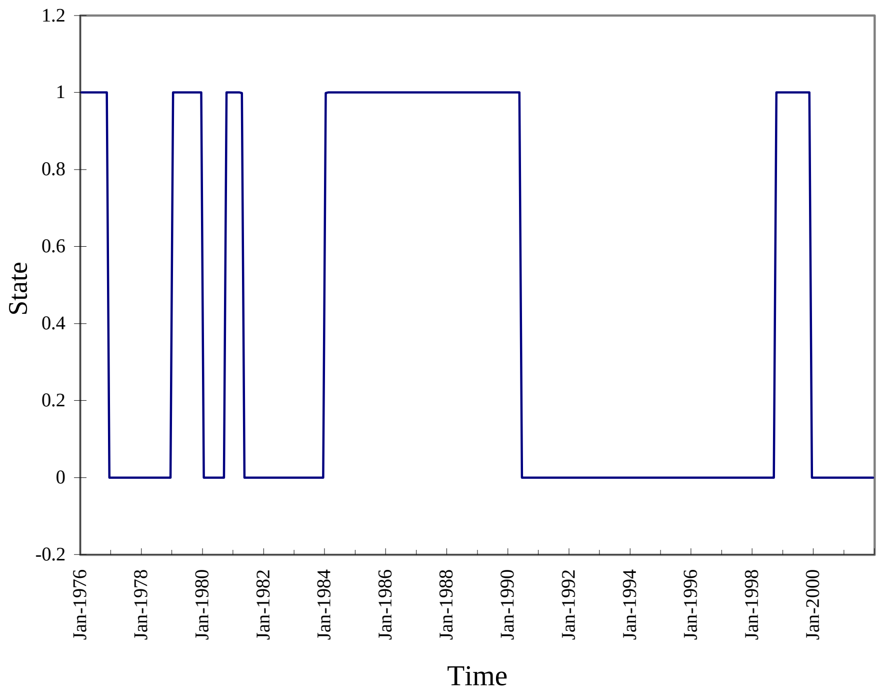
(Chart 7c) Real Output Response to Policy Shocks
Transition Variable: Real Output



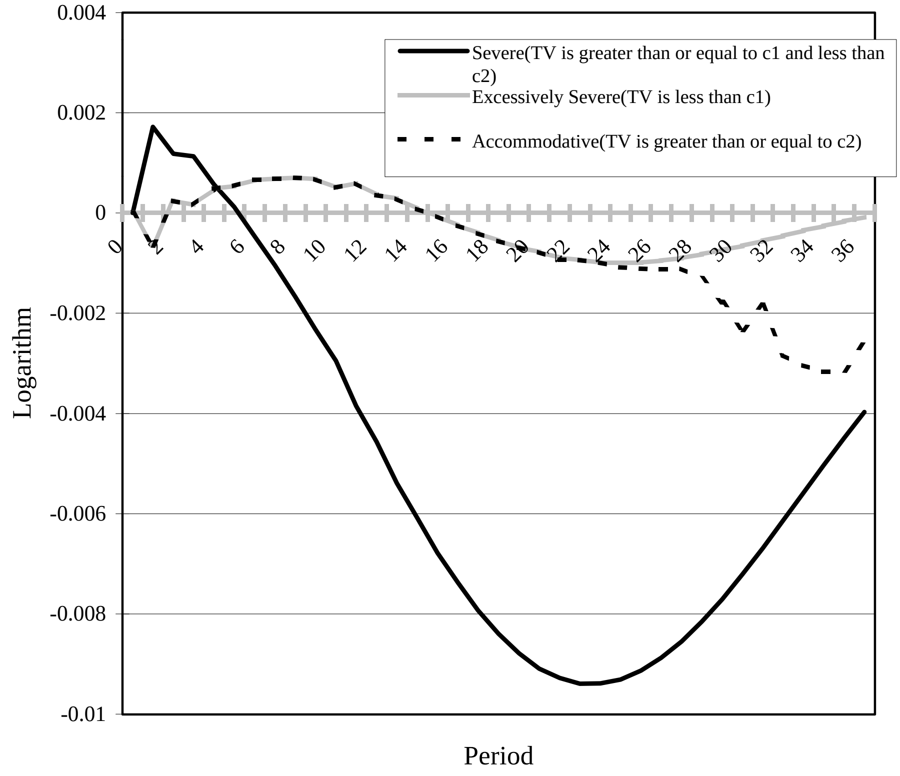
(Chart 8a) Transition Variable: Lending Attitudes DI



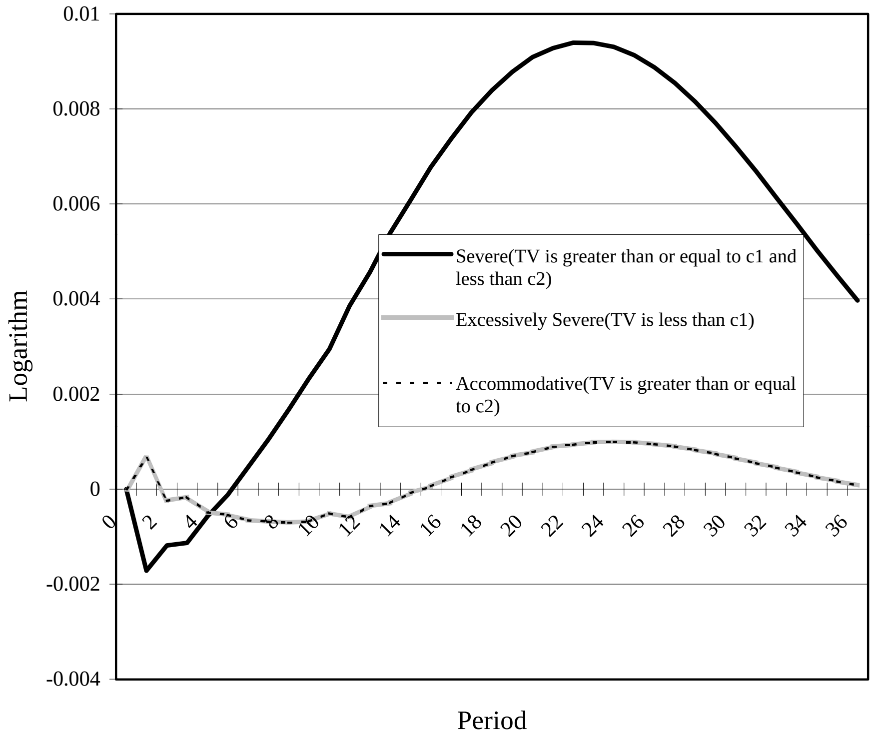
(Chart 8b) Regime-Switching
Transition Variable: Lending Attitudes DI



(Chart 9a) Real Output Response to Tight Policy Shock
Transition Varibale(TV): Lending Attitude DI



(Chart 9b) Real Output Response to Easy Policy Shock
Transition Variable: Lending Attitude DI



(Chart 9c)Real Output Response to Policy Shock
Transition Variable: Lending Attitude DI