Sources of Inflation Uncertainty and Real Economic Activity

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Abstract

This paper examines the effects of inflation uncertainties on real GDP. We argue that different sources of inflation uncertainty have different impacts on real GDP. The empirical evidence points out that uncertainty arising from changing regression coefficients has negative impacts on real GDP. However, the effect of uncertainty due to heteroscedasticity in disturbances on real GDP is insignificant. Moreover, we find that the survey-based measure of inflation uncertainty appears to be more associated with the uncertainty that arises from changing regression coefficients.

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1. Introduction

In his Nobel Prize lecture, Milton Friedman (1977) points out the potential for increased inflation to create nominal uncertainty that hinders the efficient allocation of resources and reduces real output. Ever since then, there have been several theoretical and empirical discussions on the relationship between inflation and inflation uncertainty (Ball, 1992; Cukierman and Meltzer, 1986; Evans, 1991 and Evans and Wachtel, 1993; Davis and Kanago, 2000). In addition, there are also several articles that empirically examine the impacts of inflation uncertainty on real economic activity, which can be categorized into two different approaches that differ in their proxy for inflation uncertainty.

The first one is the survey-based approach, in which inflation uncertainty is proxied by the variability across the individual forecasts. In other words, the standard deviation of inflation forecasts is used to measure inflation uncertainty.[1] The inflation uncertainty obtained from survey data tends to negatively correlate with real economic activities (Hafer, 1986 and Davis and Kanago, 1996).

The alternative approach measures uncertainty by estimating the time-varying conditional variance of a variable's unpredictable innovation. In this approach the autoregressive conditional heteroscedasticity (ARCH) model provided by Engle (1982) or the generalized ARCH (GARCH) model provided by Bollerslev (1986) is applied to estimate a time-varying conditional residual variance. Based on an ARCH model, Coulson and Robins (1985) find that uncertainty is positively correlated with real economic activity, but their correlation relationship is not significant. Applying a state-dependent conditional heteroscedasticity model provided by Brunner and Hess (1993), Lee and Ni (1995) find that inflation uncertainty is negatively correlated with real economic activities. Adopting a bivariate GARCH model, Grier and Perry

(2000) find that inflation uncertainty significantly lowers real output growth.

ARCH- or GARCH-type models provide estimates of how the conditional variance of inflation varies over time within a given structure and therefore they ignore the possibility of structural changes caused by changing regimes. Evans (1991) points out that there are many aspects to inflation uncertainty and applies a time-varying parameter model with an ARCH specification for the shocks to inflation in order to measure different types of uncertainty. Evans and Wachtel (1993) account for the prospects of changing inflation regimes by applying a Markov-switching model. They find that uncertainty about the inflation process contributes significantly to the overall degree of inflation uncertainty as measured by the conditional variance of future inflation. Furthermore, they show that their measure of inflation uncertainty has a significant influence on unemployment based on a vector autoregressive estimation.

According to the previous discussion, we find that there are two types of uncertainty within a regression context. These uncertainties arise due to heteroscedasticity in the disturbance terms and the unknown or changing regression coefficients, respectively. However, the previously-mentioned literature fail to consider that inflation uncertainty from different sources may have different effects on economic agents' decision-making and thus on economic activity. Most of the previously-mentioned literatures apply a conventional two-step approach in analyzing the impacts of uncertainties on real economic activity, except for the paper by Grier and Perry (2000). Pagan (1984) criticizes the inappropriateness of the two-step approach by showing that the estimates or standard errors from the second step are biased.

The purpose of this paper is two-fold. First, we examine the effects of different sources of inflation uncertainty on real economic activity measured by real GDP. Kim (1993) first applies a time-varying parameter model with Markov-switching heteroscedasticity to measure monetary growth uncertainty that arises from heteroscedasticity in disturbances and from changing regression coefficients, respectively. We therefore apply Kim's (1993) model to calculate different sources of inflation uncertainty and then examine their impacts on real GDP. To avoid Pagan's criticism of this approach, we jointly estimate the output equation and the inflation equation with the maximum likelihood estimation method. Second, we examine the information content embeded in the survey-based measure of inflation uncertainty by comparing the dynamic pattern of the survey-based measure with that of model-based measures.

Findings from our empirical investigation indicate that uncertainty due to changing regression coefficients has a negative impact on real GDP, but the impact of uncertainty arising from heteroscedasticity in disturbances is negligible. Moreover, we discover that the survey-based measure of inflation uncertainty appears more closely associated with the uncertainty that arises from changing regression coefficients than with the uncertainty arising from heteroscedasticity in disturbances.

The remainder of the paper is organized as follows. Section 2 describes the inflation's time series model, in which parameters are time varying and the conditional variance of disturbances is Markov-switching. We then discuss our measure of inflation uncertainties based on the presented model. Section 3 begins by discussing the data before presenting the model estimates. The effects of different types of inflation uncertainty on real GDP are then examined empirically. We then decompose the total inflation uncertainty into two different sources of inflation uncertainty, and then examine their contribution to total uncertainty. In addition, we also examine the linkage between a survey-based measure of inflation uncertainty with the model-based measures. Finally, conclusions are summarized in the last section.

2. Measuring Inflation Uncertainties

There are two different types of uncertainty in conventional regression analysis. Over time, it is highly likely that changes in private sector behavior, economic policy, and/or institutions induce significant variations in the structure of the inflation process. Under the assumption of rational expectation, it is not reasonable to assume that coefficients in inflation regression are time invariant since the economy's structure may change over time. Economic agents will learn about the policy regime changes and respond accordingly if there are frequent policy shifts (Lucas, 1976). Taylor (1980) points out that the dynamics of inflation depend on the nature of wage contracts and the form of monetary policy rules. Therefore, time-varying coefficients in an inflation equation is one source of inflation uncertainty.

Second, most existing literature estimate inflation uncertainty by assuming that uncertainty is due to shocks to the inflation process, and hence they measure inflation uncertainty by using the conditional variance of inflation. An ARCH specification on disturbances fails to take into account the influence on uncertainty of possible future regime changes. Therefore, the second source of inflation uncertainty is measured by the conditional variance of inflation that will be affected by the possibility of switches in the inflation process.

To decompose the inflation uncertainty into two distinct sources mentioned previously, we apply a time-varying-parameter model with Markov-switching heteroscedasticity to describe the inflation process:

$$\begin{aligned}\pi_t &= \alpha_{0t} + \sum_{i=1}^{k} \pi_{t-i}\alpha_{it} + \varepsilon_t, \quad t = 1,2,\cdots T \\ &= X_t\alpha_t + \varepsilon_t, \;\; \varepsilon_t \sim N(0, h_t), \quad h_t = \sigma_0^2 + (\sigma_1^2 - \sigma_0^2)S_t^{\pi},\end{aligned} \tag{1}$$

$$\alpha_t = \alpha_{t-1} + \eta_t, \;\; \eta_t \sim \text{iid}N(0, \Omega), \tag{2}$$

with

$$\begin{aligned}&\Pr[S_t^{\pi} = 1 \mid S_{t-1}^{\pi} = 1] = p_{11}\,; \;\; \Pr[S_t^{\pi} = 0 \mid S_{t-1}^{\pi} = 1] = 1 - p_{11}, \\ &\Pr[S_t^{\pi} = 0 \mid S_{t-1}^{\pi} = 0] = p_{00}\,; \;\; \Pr[S_t^{\pi} = 1 \mid S_{t-1}^{\pi} = 0] = 1 - p_{00},\end{aligned} \tag{3}$$

where $X_t = (1 \;\; \pi_{t-1} \;\; \pi_{t-2} \;\; ... \;\; \pi_{t-k})$ is a $1 \times (k+1)$ vector of explanatory variables; α_t is a $(k+1) \times 1$ vector of time-varying regression coefficients; Ω is a positive definite matrix; and h_t is the conditional variance of ε_t. The state (S_t^{π}) is given by the two-state, first-order Markov process with the transition probabilities described in (3). The transition probability p_{ii} represents the probability that state i will be followed by state i.

Equation (1) is the measurement equation, which describes the relationship between the unobserved state α_t and a $T \times 1$ vector of measurement π_t. Equation (2) is the transition equation, which describes the evolution of coefficient α_t. A random walk specification is used for the time-varying coefficients following the specification of Kim and Nelson (1989) and Kim (1993). Markov-switching heteroscedasticity is reflected by the equation of h_t, which states that the unconditional variance itself is subject to shifts (structural changes). By considering Markov-switching heteroscedasticity, the change in unconditional variance is actually regarded as resulting from endogenous regime changes in the variance structure. However, if $\sigma_1^2 = \sigma_0^2$, then the model degenerates to the conventional time-varying parameter model. Equations (1) and (2) are easily recognized as state-space models, which can be recursively estimated by the Kalman filter. A detailed discussion of the estimation method can be found in Kim (1993) and hence is not described here.

The two uncertainty terms of different sources can be calculated from the forecast error's conditional variance in equation (1) as:

$$\widetilde{U}_t = \widetilde{U}_{1t} + \widetilde{U}_{2t}, \tag{4}$$

where

$$\widetilde{U}_{1t} = X_{t-1}\widetilde{V}_{t|t-1}X'_{t-1}, \tag{5}$$

$$\widetilde{U}_{2t} = \sigma_0^2 + (\sigma_1^2 - \sigma_0^2)\Pr[S_t^{\pi} = 1 \mid \varphi_{t-1}], \tag{6}$$

$$\widetilde{V}_{t|t-1} = \sum_{i=0}^{1}\Pr[S_{t-1}^{\pi} = i \mid \varphi_{t-1}]\{V_{t|t-1}^{i} + (\widetilde{\alpha}_{t|t-1} - \alpha_{t|t-1}^{i})(\widetilde{\alpha}_{t|t-1} - \alpha_{t|t-1}^{i})'\}. \tag{7}$$

Here, $\widetilde{\alpha}_{t|t-1} = \sum_{i=0}^{1}\Pr[S_{t-1}^{\pi} = i \mid \varphi_{t-1}]\alpha_{t|t-1}^{i}$; $\alpha_{t|t-1}^{i}$ is the estimate of α_t based on information up to time t-1, given $S_{t-1}^{\pi} = i$; $V_{t|t-1}^{i}$ is the covariance matrix of $\alpha_{t|t-1}^{i}$ and φ_t is the information available at time t. Terms $\widetilde{U}_{1t}$ and $\widetilde{U}_{2t}$ are the conditional variances due to changing regression coefficients and the heteroscedisticity of the disturbance terms, respectively.

3. Inflation Uncertainties and Real Economic Activity: An Empirical Investigation

The purpose of this section is to empirically examine the effects of different types of uncertainty on real GDP.

3.1 Data Description

Quarterly data of real GDP and the consumer price index (CPI) for the United States (US) are obtained from IMF's International Financial Statistics. Inflation rates are computed from the CPI. The sample period starts from 1957Q1 and ends in 2000Q3. The one-quarter forecasts of the GDP deflator and CPI inflation rate are obtained from the Survey of Professional Forecasters published by the Federal Reserve Bank of Philadelphia. The forecasts of the GDP deflator start from the last quarter of 1968, while the forecasts of CPI inflation rates begin from the third quarter of 1981.

3.2 Model Estimation

We follow Hamilton (1989) and Kim (1993) by assuming that real GDP is composed of two unobserved components. The first component follows a random walk with drift, which evolves according to a two-state Markov process, and the second component follows an autoregressive process. Therefore, the specification for real GDP is given as follows:

$$y_t = y_t^{\tau} + y_t^{C}, \tag{8}$$

$$y_t^{\tau} = y_{t-1}^{\tau} + \gamma_{s_t} + \rho_1 \widetilde{U}_{1t} + \rho_2 \widetilde{U}_{2t}, \tag{9}$$

$$y_t^{C} = \beta_1 y_{t-1}^{C} + \beta_2 y_{t-2}^{C} + \beta_3 \widetilde{\psi}_{t|t-1} + \xi_t, \qquad \xi_t \sim \text{iid}N(0, \sigma^2), \tag{10}$$

$$\gamma_{s_t} = \gamma_0 + \gamma_1 S_t^y, \quad S_t^y = 0, 1, \tag{11}$$

$$\begin{aligned} &\Pr\left[S_t^y = 1 \mid S_{t-1}^y = 1\right] = q_{11} \text{ and } \Pr\left[S_t^y = 0 \mid S_{t-1}^y = 1\right] = 1 - q_{11}, \\ &\Pr\left[S_t^y = 0 \mid S_{t-1}^y = 0\right] = q_{00} \text{ and } \Pr\left[S_t^y = 1 \mid S_{t-1}^y = 0\right] = 1 - q_{00}, \end{aligned} \tag{12}$$

where y_t is the log of real GDP at time t; y_t^{τ} and y_t^{C} are the trend and cyclical components of real GDP, respectively; γ_{s_t} is the drift term, which changes according to a two-state Markov process; and $\widetilde{\psi}_{t|t-1}$ is the conditional forecast error of inflation. If Friedman's argument is correct, then we expect that ρ_1 and/or ρ_2 in (9) should be negative.

It is worth noting that Equation (10) is derived by using a Phillips curve which relates cyclical unemployment to the forecast error of inflation and Okun's law that relates cyclical output to cyclical unemployment. A Phillips curve presented in its empirical format is:

$$u_t - u_t^n = \sum_{l=1}^{p} \kappa_l (u_{t-l} - u_{t-l}^n) + \kappa_0 \widetilde{\psi}_{t|t-1} + \zeta_t, \quad \kappa_0 < 0, \tag{13}$$

in which u_t is the unemployment rate, u_t^n is its natural rate, and ζ_t is a serially-uncorrelated error term. Note that κ_0 measures the trade-off between the unemployment gap and inflation surprise. Okun's law relation, on the other hand, is

$$y_t - y_t^\tau = \theta(u_t - u_t^n), \quad \theta < 0. \tag{14}$$

Equation (10) is obtained by combining (13) and (14) together. Thus, $\beta_3 = \theta\kappa_0$ in equation (10) should be positive. In other words, the trade-off between inflation rates and unemployment rates is supported if β_3 is significantly positive.

Equations (1)-(3) and (8)-(12) can be estimated by a conventional two-step method. As such, we can estimate $\widetilde{U}_{1t}$ and $\widetilde{U}_{2t}$ from (1)-(3) in the first step and then use them to estimate parameters of (9) and (10) in the second step. However, as we stated before, Pagan (1984) points out that we may get biased parameter estimates or biased standard errors from the second step estimation procedure. To avoid Pagan’s critique, we therefore estimate the inflation equation and the output equation jointly by employing a maximum likelihood estimation method.

The lag order of inflation equation (1) needs to be determined, and it is selected by choosing the maximum value of the log likelihood function from the joint estimation. The lag order in the inflation equation (1) is then set to 3. To justify the model in equations (1)-(3) and (8)-(12), it would seem appropriate to show that the estimated disturbances from equation (1) by the ordinary least square (OLS) method are serially correlated and conditionally heteroscedastic. We therefore estimate (1) by OLS and then examine the serial correlation of residuals and squared residuals by using the Q statistic of Ljung and Box (1978). We also apply the ARCH test provided by Engle (1982) to examine the null hypothesis of no autoregressive conditional heteroscedasticity in the estimated residuals.

Findings from Table 1 indicate no significant serial correlation since the Q-statistics are not significant at the 5% level for the residuals from OLS. However, the Q-statistics are significant at the 1% level for the squared residuals. The ARCH test also rejects the null of no ARCH effects in the residuals. Table 1 further reports the diagnostic checks for residuals from a conventional time-varying-parameter model. Again, Q-statistics are insignificant for standardized residuals, but significant at the 1% level for squared residuals. The ARCH test reveals a significant ARCH effect at the 5% level in the estimated residuals. Therefore, findings from Table 1 imply that some of the dynamics of conditional variance are not fully captured by a constant parameter model or a conventional time-varying parameter model. To take into account the heteroscedasticity in disturbances, we assume that the conditional variance of disturbances is Markov-switching.

The joint estimations of the generalized model in equations (1)-(3) and (8)-(12) are reported in Table 2, which indicates that both types of uncertainty have a negative impact on real GDP. Uncertainty arising from changing parameters has significantly negative impacts on real GDP, but the effect of uncertainty from heteroscedasticity in disturbances is negligible. Therefore, the hypothesis that uncertainty due to changing coefficients discourages economic activity is strongly supported.

3.3 Robustness of the empirical estimates

The period starting from 1970 in general has higher average inflation uncertainty than the period of pre-1970. To check the robustness of our finding, we re-examine the effects of inflation uncertainty on real GDP growth based on the period 1970Q1–2000Q3. The specification of the inflation equation over the sub-sample period is similar to that over the full sample period. Findings from the last column of Table 2 indicate that the effect of uncertainty arising from changing parameters is significant at the 10% level, but the size of the estimate is 1/4th of that in the whole period. Again, the impact of the uncertainty from heteroscedasticity of disturbances is insignificant at conventional levels. The trade-off between inflation rates and unemployment rates is supported since the estimated coefficient of β_3 is positive.

The previous two findings are the same as those in the whole period's estimation. As for the diagnostic tests, there is no serial correlation in the residuals and squared residuals, and no ARCH effect in the residuals. Overall, our finding that uncertainty arising from changing parameters has a negative impact on real GDP is supported, and this finding is robust for different sample periods. We also find that uncertainty due to heteroscedasticity in disturbances is negligible in affecting real GDP, and that there is a trade-off between inflation and unemployment rates. These two findings are robust to the sample periods.

One may argue that our finding of a significant negative impact of the regime uncertainty component of inflation uncertainty may be due to our failure of controlling oil price shocks. Following Hamilton (1996), we therefore include nominal oil price changes and net oil price changes in equation (10), respectively, and then re-estimate the model simultaneously.[2] Empirical findings indicate that the impact of oil price changes on real output is not significant at the conventional significance level. Although our findings from Table 2 are not significantly affected when we include either nominal oil price changes or net oil price changes, the residual diagnostic checks reveal the existence of ARCH effects in estimated residuals.

(results are not reported here, but are available upon request). Therefore, this indicates that our findings from Table 2 are not due to our failure of controlling oil price shocks.

3.4 Decomposition of Inflation Uncertainty

Equation (4) indicates that the conditional variance of disturbances consists of two distinct terms. They are the conditional variance arising from changing regression coefficients and the conditional variance due to the heteroscedasticity of the disturbance terms. These two different sources of uncertainty can be calculated based on equation (5) and (6), respectively. The plot of the total uncertainty, $\widetilde{U}_t$, and the decomposed uncertainty, $\widetilde{U}_{1t}$ and $\widetilde{U}_{2t}$, based on (5) and (6), respectively, is given in Figure 1.

From Figure 1 we observe that the overall inflation uncertainty is higher during the periods of 1973–1975, 1978-1983, and 1985-1991 than in other periods, which reflects basically two oil price shocks that occurred in 1973 and 1979, financial deregulation starting from 1979, the switching of the Fed's monetary policy target in 1982, and the Plaza accord in 1985. We also observe that uncertainty due to changing regression coefficients is in general higher than that arising from the heteroscedasticity of disturbances during the period of 1974-1983. The average level of inflation uncertainty during the period of 1974-1983 is 0.246, approximately 58% of which is due to the uncertainty arising from changing regression coefficients. However, the average level of inflation uncertainty is 0.151 during the sample period of 1984-2000, approximately 65% of which is due to the heteroscedasticity of residuals.

Conventional literature construct inflation uncertainty from survey forecasts, in which the standard deviation of inflation forecasts is used to measure inflation uncertainty. Based on this approach, Hafer (1986) and Davis and Kanago (1996) support Friedman's hypothesis. It is therefore quite interesting to examine the dynamic patterns of our estimated inflation uncertainty with that from a survey measure by plotting them together. First of all, we construct the survey-based measure of inflation uncertainty from the GDP deflator and CPI inflation rate, respectively. According to Figure 2, we find that the size of the model-based measure of total inflation uncertainty is in general higher than (with several exceptions) that of survey-based measures, but the fluctuation of the latter is much larger than that of the former. The switching of the Fed's monetary policy target in 1982, the Plaza Accord in 1985, and Iraq's invasion of Kuwait in 1990 are the periods with high uncertainty according to the CPI survey-based measure of inflation uncertainty.[3] The two oil price shocks in the 1970s, the onset of the Iran-Iraq war in 1980, the switching of the Fed's monetary policy target in 1982, and the Iraq's invasion of Kuwait in 1990 are the periods with high inflation uncertainty according to the survey-based measure from the GDP deflator. The previously-mentioned periods with high inflation uncertainty are also consistent with those from the model–based measure of total inflation uncertainty.

In Figure 3, we compare the survey-based measure of inflation uncertainty from the GDP deflator with different sources of model-based measures. We find that the movement of the survey-based measure of inflation uncertainty is more associated with the uncertainty arising from changing regression coefficients. The correlation coefficient between the survey-based measure of inflation uncertainty and the measure of uncertainty arising from changing regression coefficients is 0.425. This is higher than the correlation coefficient between the survey-based measure of inflation uncertainty and the uncertainty arising from the heteroscedasticity of disturbances which is 0.233.

Figure 4 plots the model-based measure of inflation uncertainty and the survey-based measure from the forecast of the CPI inflation rate. Again, we find that the survey-based measure of inflation uncertainty is more associated with that arising from changing regression coefficients. The correlation coefficient between the survey-based measure of inflation uncertainty and the uncertainty arising from changing regression coefficients is 0.629. This is higher than the correlation coefficient between the survey-based measure of inflation uncertainty and the uncertainty arising from the heteroscedasticity of disturbances which is 0.559. Findings from Figures 2 to 4 are interesting since they indicate that the survey-based measure of inflation uncertainty is more associated with the uncertainty from changing regression coefficients which can be characterized by a model with time-varying-parameters in coefficients and Markov-switching in disturbances.

4. Conclusions

Inflation uncertainty is conventionally measured as the conditional variance of inflation in most existing literature. The effects of inflation uncertainty on real economic activity are then examined by the conventional two-step approach. In this paper we apply a time-varying-parameter model with Markov-Switching variance to measure two different types of uncertainty. The effects of uncertainties on real GDP are then examined by a joint estimation of the maximum likelihood. Empirically, our joint estimation method sidesteps Pagan’s critique on the conventional two-step approach. The empirical findings point out that uncertainty due to changing regression coefficients has a significant influence on real GDP, but the effects of uncertainty arising from heteroscedasticity of disturbances are negligible. Moreover, we also find that the survey-based measure of inflation uncertainty appears more associated with the uncertainty arising from changing regression coefficients.

Endnotes

[1] The survey-based inflation uncertainty is given by $\gamma^d = [\sum(\pi_i - \overline{\pi})^2]/n$, where π_i is the forecast of the ith forecaster and $\overline{\pi}$ is the average forecast across n forecasters.

[2] The series of net oil price increases is the difference between the level of oil prices for quarter t and the maximum price observed during the preceding four quarters, if this difference is positive. Otherwise, the series of net oil prices is defined to be zero.

[3] The data for the survey forecasts of the CPI inflation rate start from the third quarter of 1981, and hence their uncertainty is available from the same time.

Table 1. Diagnostic Checks of Residuals

	CPM	TVPM
Q(12)	11.883 [0.46]	13.825 [0.31]
Q(24)	28.276 [0.25]	30.257 [0.18]
$Q^2(12)$	41.231 [0.00]	38.606 [0.00]
$Q^2(24)$	63.413 [0.00]	56.075 [0.00]
ARCH(1)	0.998 [0.32]	2.139 [0.14]
ARCH(4)	13.719 [0.01]	21.758 [0.00]

Notes: 1. CPM and TVPM indicate the constant parameter model and the time-varying parameter model, respectively. The CPM is estimated by the ordinary least square method and the TVPM is estimated by a Kalman filter.

2. Numbers in brackets are p-values.

3. Terms Q(p) and $Q^2(p)$ are the Ljung-Box autocorrelation test statisitics for residuals and residuals squared, respectively, for up to pth-order autocorrelations, which have a chi-square distribution with p degrees of freedom. ARCH(q) is the Lagrange multiplier test of Engle (1992) for up to qth-order autoregressive conditional heteroscedasticity, which has a chi-square distribution with q degrees of freedom.

Table2. Joint Estimation Results with Output and Inflation Equations

$$y_t = y_t^{\tau} + y_t^{C},$$
$$y_t^{\tau} = y_{t-1}^{\tau} + \gamma_{s_t} + \rho_1 \widetilde{U}_{1t} + \rho_2 \widetilde{U}_{2t},$$
$$y_t^{C} = \beta_1 y_{t-1}^{C} + \beta_2 y_{t-2}^{C} + \beta_3 \widetilde{\psi}_{t|t-1} + \xi_t, \qquad \xi_t \sim \text{iidN}(0, \sigma^2),$$
$$\gamma_{s_t} = \gamma_0 + \gamma_1 S_t^y, \qquad \Pr\left[S_t^y = 0 \mid S_{t-1}^y = 0\right] = q_{00}, \ \Pr\left[S_t^y = 1 \mid S_{t-1}^y = 1\right] = q_{11},$$
$$\Pr\left[S_t^y = 1 \mid S_{t-1}^y = 0\right] = 1 - q_{00}, \ \Pr\left[S_t^y = 0 \mid S_{t-1}^y = 1\right] = 1 - q_{11}.$$

	57Q1~2000Q3	70Q1~2000Q3
ρ_1	-6.070*	-1.522#
	(2.271)	(0.841)
ρ_2	-1.209	-1.739
	(1.960)	(1.391)
β_1	1.037*	1.416*
	(0.104)	(0.085)
β_2	-0.096	-0.471*
	(0.102)	(0.084)
β_3	0. 543*	0.437*
	(0.146)	(0.145)
σ^2	0.608*	0.638*
	(0.050)	(0.045)
γ_0	2.596*	3.423*
	(0.325)	(0.452)
γ_1	-1.409*	-2.427*
	(0.214)	(0.413)
q_{00}	0.917*	0.970*
	(0.042)	(0.017)
q_{11}	0.517*	0.237*
	(0.127)	(0.118)
Q(12)	10.774 [0.548]	10.902 [0.537]
Q(24)	32.936 [0.105]	22.710 [0.537]
$Q^2(12)$	10.647 [0.559]	9.917 [0.623]
$Q^2(24)$	25.269 [0.391]	17.580 [0.823]
ARCH(1)	0.880 [0.927]	0.305 [0.581]
ARCH(4)	0.054 [0.817]	4.070 [0.400]

Note: 1. The output equation is estimated using 100 times the log-difference in quarterly real GDP. Standard errors are in parenthesis and numbers in the brackets are p-values.

2. '*' and '#' indicate significance at the 5% and 10% level, respectively.

3. Terms Q(p) and $Q^2(p)$ are the Ljung-Box autocorrelation test statisitics for residuals and residuals squared, respectively, for up to pth-order autocorrelations, which have a chi-square distribution with p degrees of freedom. ARCH(q) is the Lagrange multiplier test of Engle (1992) for up to qth-order autoregressive conditional heteroscedasticity, which has a chi-square distribution with q degrees of freedom.

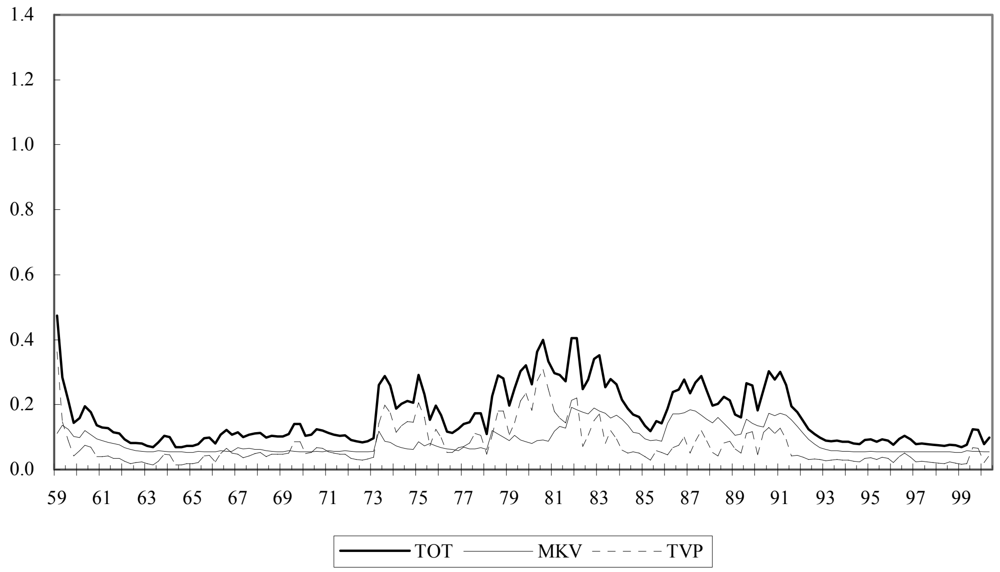

Figure 1. Model-based Measures of Inflation Uncertainty. TOT: model-based total uncertainty. MKV: uncertainty arising from heteroscedasticity of disturbances. TVP: uncertainty arising from changing regression coefficients.

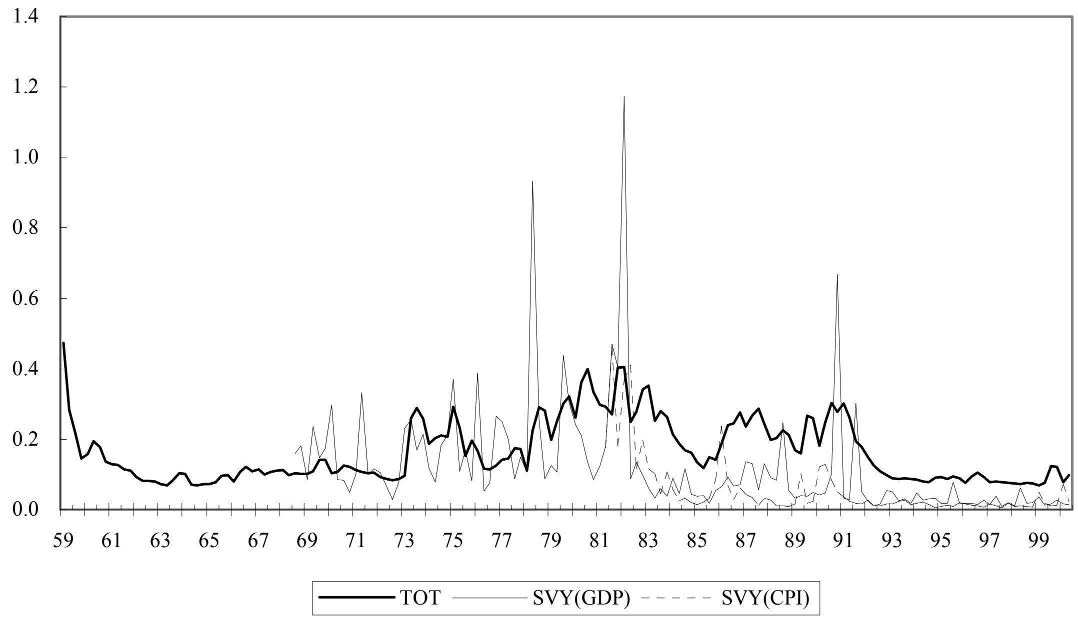

Figure 2. Model-based vs. Survey-based Measures of Inflation Uncertainty. TOT: model-based total uncertainty. SVY(GDP): survey-based measure of inflation uncertainty from a GDP deflator. SVY(CPI): survey-based measure of inflation uncertainty from CPI inflation rates.

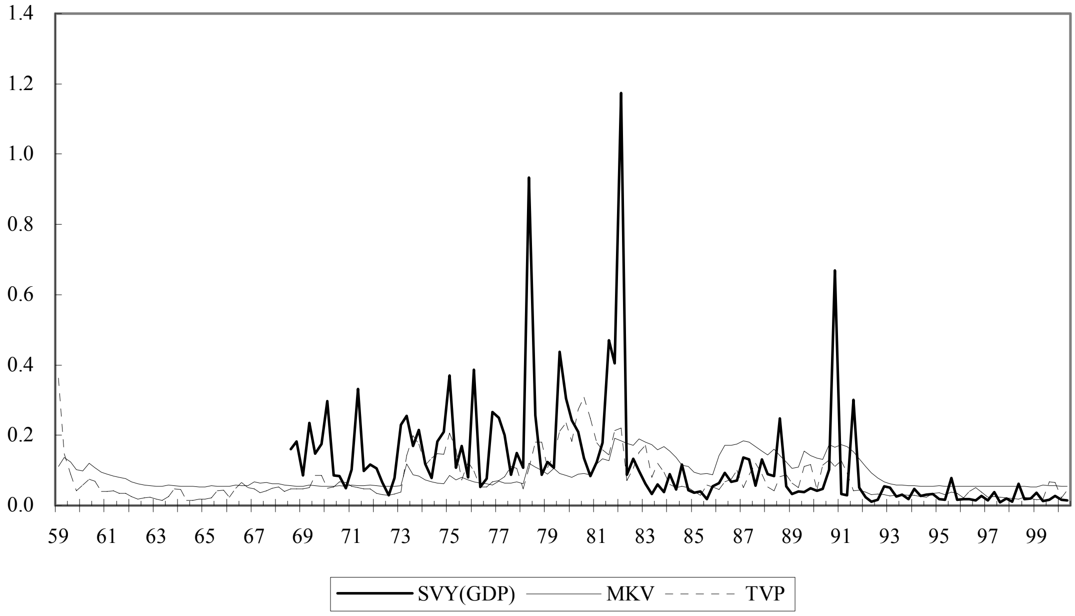

Figure 3. Survey-based vs. Model-based Measures of Inflation Uncertainty with a GDP deflator in the Survey. SVY(GDP): survey-based measure of inflation uncertainty from GDP deflator. MKV: uncertainty arising from heteroscedasticity of disturbances. TVP: uncertainty arising from changing regression coefficients.

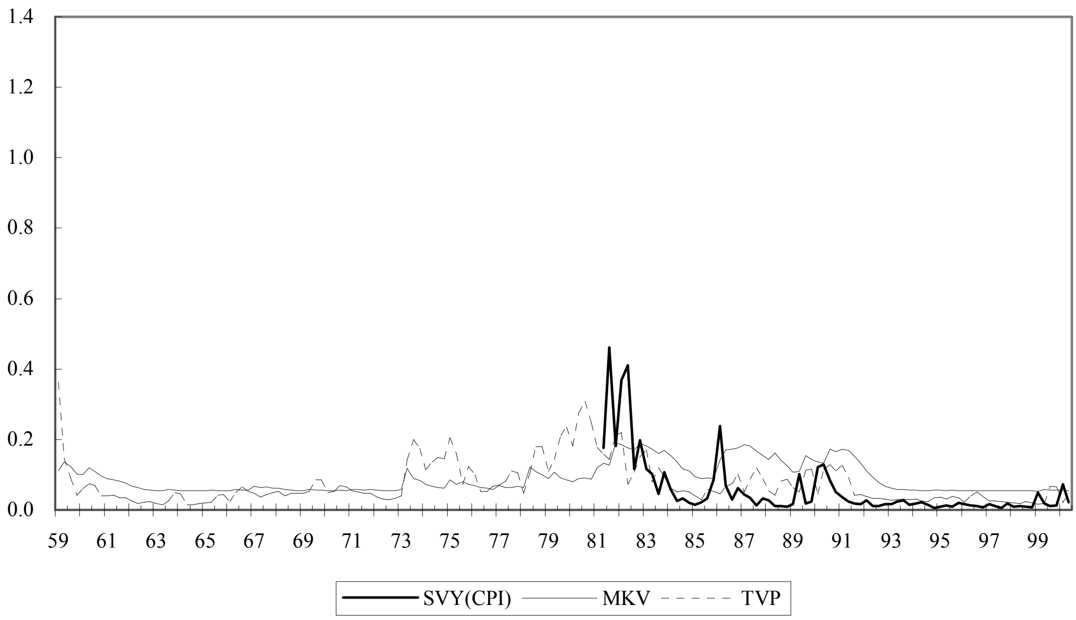

Figure 4. Model-based vs. Survey-based Inflation Uncertainty with CPI Inflation Rate in the Survey. SVY(CPI): survey-based measure of inflation uncertainty from CPI inflation rates. MKV: uncertainty arising from heteroscedasticity of disturbances. TVP: uncertainty arising from changing regression coefficients.

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