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Real Effects of Inflation Uncertainty in the US

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Abstract

We empirically investigate the effects of inflation uncertainty on output growth for the US using both monthly and quarterly data over 1985-2009. Employing a Markov regime switching approach to model output dynamics, we show that inflation uncertainty obtained from a Markov regime switching GARCH model exerts a negative and regime dependant impact on output growth. In particular, we show that the negative impact of inflation uncertainty on output growth is almost 4.5 times higher during the low growth regime than that during the high growth regime. We verify the robustness of our findings using quarterly data.
Keywords: Growth; inflation uncertainty; Markov-switching modeling; Markov-switching GARCH.
JEL classification: E31, E32

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1 Introduction

Many economists agree that sustainable growth and low and stable inflation constitute two of the fundamental objectives of the macroeconomic policymakers. A reason behind this conviction is that high and unstable inflation leads to an increase in inflation uncertainty impeding the real economic activity (see Friedman (1977)). Hence, it is not surprising that the linkages between inflation, inflation uncertainty and economic growth have been extensively investigated on theoretical and empirical grounds.

Friedman (1977) emphases two arguments. First, he claims that the level of inflation is positively correlated with inflation uncertainty.[1] The rationale behind this view is the actions of the policymakers who use discretionary policy tools to reduce inflation because the use of discretionary policy tools lead to the widening of the gap between actual and anticipated inflation and induce future inflation uncertainty. As a consequence, in an environment where inflation uncertainty is high, economic agents would not be able to forecast the level of future prices accurately.[2] Second, he indicates that higher uncertainty distorts the information content of prices which plays a fundamental role in efficient allocation of resources.[3] In particular, it is argued that during periods of high inflation volatility it is harder to extract information about the relative prices of goods rendering managers unable to detect profitable investment opportunities. Furthermore, during periods of high uncertainty, it becomes prohibitively expensive to raise external funds due to heightened asymmetric information problems causing managers to delay or cancel fixed investment projects. In summary, high inflation and high inflation uncertainty hinder economic growth.

[1]However, Cukierman and Meltzer(1986) assume a reverse causation between inflation rate and inflation uncertainty.

[2]Ball (1992) formalizes the relation between inflation and inflation uncertainty with a model in which a rise in inflation raises uncertainty about future monetary policy, and thereby increases uncertainty about future inflation. He points out that when inflation is high, policymakers may apply disinflation policies or they fear of the recession that would result and may not trigger such policies. Since economic agents do not know the future preferences of policymakers, they do not know whether disinflation will occur.

[3]Beaudry et al. (2001) show that monetary instability exerts a negative effect on the allocation of resources across firms via price uncertainty channel.

Several researchers have investigated the association between inflation uncertainty and output growth. However, the empirical results do not allow us to arrive at a firm conclusion. Although some researchers provide evidence that inflation uncertainty affects output growth negatively, some others show that there is no or even a positive association. In general, it appears that empirical results are sensitive to various factors including the sample period, model specification and the proxies for inflation uncertainty that researchers use.

A review of the literature shows that some studies take advantage of survey data and employ the dispersion across forecasters' forecasts as a measure of uncertainty while others use a simple moving standard deviation of the inflation series at the same frequency as the data. Alternatively, researchers implement a GARCH model to mimic the volatility clustering often found in high-frequency series and use the generated conditional variance as a proxy for uncertainty. Among these three methodologies, use of GARCH models stands out as a more sophisticated approach whereas survey methods or the use of simple statistical tools to generate measures of uncertainty are criticized on various grounds. For instance, uncertainty proxies generated from survey data may not be able to gauge the true level of uncertainty and potentially contain sizable measurement errors. It is also pointed out that the standard deviation measures variability and expected fluctuations in inflation rate will cause an increase in this measure although there is no uncertainty in the economic environment (Jansen 1989, Grier and Perry, 2000).[4]

Despite the attractiveness of GARCH methodology to generate an uncertainty proxy one must be careful as the generated measure will be model dependant. In particular, it is well known that the standard ARCH/GARCH models take the economic structure as given and disregard the potential structural instabilities induced by regime changes over time. For instance, several researchers point out that when regime shifts are overlooked GARCH models may overstate the persistence in variance (Lamoureux and Lastrapes,

[4]Cukierman and Wachtel (1979), Cukierman (1983) show that inflation uncertainty measured by the dispersion of inflation forecasts gathered from survey data and standard deviation of inflation are highly correlated.

1990; Hamilton and Susmel, 1994; Gray, 1996) and understate the level of uncertainty (Giordani and Söderlind, 2003). To that end, Evans and Wachtel (1993) infer that, models which do not account for regime changes in the inflation process underestimates not only the level of uncertainty but also its effect on economic growth.

In the light of the above discussion and the previous empirical evidence which show that both output growth and inflation series are subject to regime shifts, we start our investigation by testing for the presence of regime shifts and structural breaks in the inflation series prior to committing to a particular approach to generate our measure of uncertainty. We also carefully investigate the properties of the output growth series because the true impact of inflation uncertainty on economic growth cannot be properly captured should we fail to account for the presence of regime shifts in output growth.

We carry out our empirical investigation using monthly US industrial production and inflation data which cover the period between 1985:03–2009:08. We implement robustness tests following a similar strategy using quarterly GDP series over 1985:QI– 2009:QIV.

Our results can be summarized as follows. We find that both inflation and output series exhibit regime dependance. Hence, we generate inflation uncertainty using a Markov switching GARCH model and we allow both inflation and inflation uncertainty to exert regime dependant impact on output growth. As a result, we find that inflation uncertainty has a negative impact on output growth during both regimes. Our investigation also shows that the magnitude of inflation uncertainty on output growth changes significantly across low- and high-growth regimes. In particular we find that inflation uncertainty has a greater negative impact on output growth during the low growth regime. In fact the impact of inflation uncertainty on output growth in a low growth regime is about 4.5 times greater than that in a high growth regime. We examine the robustness of our results by estimating a similar model using quarterly GDP growth series. Controlling for the state of the business cycles, we observe that inflation uncertainty exerts a negative and greater impact on economic growth during periods of contraction. We find that the adverse impact of inflation uncertainty on economic growth is almost 4 times higher in periods of contraction than that in periods of expansion. Furthermore, we find that the regimes captured by the model on the quarterly data fits well with periods of contraction and expansion as defined by NBER, providing further support to our empirical approach.

The remainder of the paper is organized as follows. Section 2 provides a brief summary of the empirical literature. Section 3 presents the Markov switching GARCH methodology, the empirical model and the data. Section 4 reports the empirical results and some specification tests. Section 5 concludes the paper.

2 Literature Review

Following Okun (1971) and Friedman (1977), several researchers have examined the impact of inflation uncertainty on output growth for different countries. For example, Darrat and Lopez, (1989) investigate the relation between inflation uncertainty and output growth for Latin American countries. Ma (1998) scrutinizes the same question for Colombia, Bohara and Sauer (1994) and Grier and Grier (2006) examine it for Germany and Mexico, respectively. Fountas, Karanasos and Kim, (2002) and Wilson (2006) examine the data from Japan. Fountas, Karanasos and Kim (2002) investigate the link between inflation uncertainty and output growth for the G7 countries. Several other researchers, including Judson and Orphanides (1999), Grier and Perry 2000) and Elder (2004), scrutinize the US data in search for understanding the effects of inflation uncertainty on output growth.

However, the empirical evidence concerning the impact of inflation uncertainty on economic growth is mixed.[5] While some studies provide evidence that inflation uncertainty exerts a positive impact on output growth, some others show that the effect can be positive or non existent. Results seem to depend both on the method used to generate a measure of inflation uncertainty and on the model employed to examine the impact of uncertainty on output growth.

[5]See Holland (1993) and Davis and Kanago (1996) for a survey.

In what follows we first discuss the alternative methods that researchers use to generate a proxy for inflation uncertainty and then we briefly comment on how to model the association between inflation uncertainty and output growth.

2.1 Measuring inflation uncertainty

Researchers implement different strategies to measure inflation uncertainty. One approach is to exploit survey data and use the dispersion of inflation forecasts across the estimates of the surveyed forecasters as a measure of inflation uncertainty. Researchers using survey based uncertainty proxies in general report that real economic activity is negatively affected by inflation uncertainty. For instance Hafer (1986) provides evidence that the dispersion across the individual forecasts has a negative effect on output for the US. Hayford (2000) and Davis and Kanago (1996) show that the dispersion of inflation and unemployment forecast reduce output growth, at least temporarily. Holland (1988), using survey data, concludes that the adverse effects of inflation uncertainty on real GNP may be permanent. Although this approach is appealing, a survey based uncertainty measure may not gauge the true level of uncertainty as such a measure potentially contains sizable measurement errors.

Alternatively, researchers use the standard deviation or moving standard deviation of the inflation series, at the same frequency as the data, to proxy for inflation uncertainty. However, this approach imposes equal weights on all past observations and give rise to substantial serial correlation in the summary measure. It is also pointed out that standard deviation is a measure of variability and expected fluctuations in inflation rate will cause an increase in this uncertainty measure although there is no uncertainty. This method, due to its simplicity, is often implemented in the literature with mixed results. Barro (1996) using standard deviation of inflation as a measure of inflation uncertainty on a data set that includes over 100 countries from 1960 to 1990 fails to provide any significant effects of inflation uncertainty on growth. Similarly, Clark (1997) with cross-country growth regression analysis reports that there is no robust relationship between inflation uncertainty and growth. In contrast, using a cross country panel data, Judson and Orphanides (1999) stress that inflation and inflation uncertainty are both significantly and negatively correlated with growth.

A more sophisticated approach is to utilize ARCH/GARCH methodology and exploit the ability of these models to mimic the volatility clustering often found in high-frequency series. Given the advantages, several researchers use ARCH/GARCH models to examine the impact of inflation uncertainty on output growth. For instance, Fountas, Ioannidis and Karanasos (2004) generate a proxy for inflation uncertainty by employing an EGARCH model and then in the second step they show that inflation uncertainty exerts no significant negative output effects for Germany, the Netherlands, Italy, Spain, France except for the UK. One caveat against the use of this approach is that generated series will be model dependant. Hence, one should check for the properties of the underlying series very carefully. If the series exhibit structural breaks, ARCH/GARCH models must be modified to incorporate these shifts in the series. Otherwise the generated uncertainty proxy would be biased and can lead to wrong conclusions.

Several researchers, rather than using the two stage modeling, choose to employ bivariate GARCH models. This class of models offers the researcher to examine the behavior of inflation and output series simultaneously while the issue of generated regressors is internally resolved. For instance, Fountas, Karanasos, and Kim (2006), using a bivariate GARCH model of inflation and output growth, show that nominal uncertainty deters output growth in almost all of the G7 countries. Jansen (1989), implements a bivariate ARCH-M model for inflation and real output growth, and his results cannot refute an adverse effect of nominal uncertainty on growth. Grier and Perry (2000) and Grier et al. (2004) employ bivariate GARCH-M models for inflation and output growth and show that an increase in inflation uncertainty significantly reduces real output growth in US economy. Elder (2004) confirms this result for US economy by using a multivariate GARCH-M model and adds that an average shock to inflation uncertainty lowers output growth over three months by about 22 basis points.

Several other researchers use more sophisticated versions of ARCH/GARCH models. Wilson (2006) performs a bivariate EGARCH-M model while allowing the conditional variance to react to the direction of change in inflation and shows that increased inflation uncertainty is detrimental to the growth in Japanese economy.[6] Nevertheless there are various problems associated with the use of bivariate GARCH models. For instance, modeling is complicated and there are convergence problems which leads one to use parsimonious models. There is also the question of identification because, eventually, a bivariate model is a reduced form equation.[7] Thus, the generated measure of inflation uncertainty might embody volatility that arise from output growth.

One common weakness of all the approaches that we discussed above is that none of the uncertainty measures (measures based on surveys, standard deviation or ARCH/GARCH models) of inflation uncertainty are sensitive to the direction of changes in inflation. In particular, if the underlying series contain structural breaks, these methods would not capture the true nature of the impact of inflation uncertainty on growth. In fact many macroeconomic time series, possibly due to abrupt policy changes, exhibit regime shifts in their behavior and they behave differently during economic downturns, when resources are under-utilized, in contrast to expansionary periods as the economic agents use factors of production more efficiently. This is an important issue and several researchers point out that models which do not account for regime changes in the underlying series lead to wrong conclusions.

To scrutinize the economic series that display different behavior as the economy moves through the business cycle, researchers developed the so called the regime switching models. This class of models are developed in Goldfeld and Quandt (1973) which later led to the introduction of the Markov switching models by Hamilton (1989). Subsequently, Hamilton and Susmel

[6]Fountas, Karanasos and Kim (2002) also conclude that inflation uncertainty impedes output growth in Japan using a bivariate GARCH model.

[7]Harvey, Ruiz and Shephard (1994) argue that multivariate generalization of ARCH model can be difficult to estimate and interpret. They suggest a multivariate stochastic volatility model where factor loading matrix was identified by rotating the estimated factors. Arestis and Mouratidis (2005) adopted the methodology suggested by Harvey, Ruiz and Shephard (1994) to model the trade-off between inflation and output-gap variability for ten European Union countries.

(1994), Cai (1994) proposed models that which allow the error component to follow Markov switching ARCH effects. These models and their variants are extensively used in the literature to examine the behavior of macroeconomic series which often contain non-linearities, asymmetries and structural breaks.

Within the context of our investigation, some studies raised this problem. For instance, Evans and Wachtel (1993), develop a Markov switching model that explains the behavior of inflation. They decompose inflation uncertainty into two components where the first one portrays the certainty equivalence component reflecting the variance of future shocks to the inflation process and the second one captures uncertainty about the future changes in the inflation regime. They then show that the second component of uncertainty which depend on regime lowers real economic activity. Wu et al. (2003) employ the time varying parameter model of Kim (1993) with Markov-switching heteroscedasticity for the US. Their results suggest that uncertainty due to the changing coefficients hinders growth of real GDP but uncertainty concerning heteroscedasticity in disturbances has an insignificant effect on growth.[8]

In this study, we first evaluate the underlying properties of the inflation series. Should we detect regime shifts in the series, we implement a Markov switching GARCH methodology to take into account the dynamic nature of the data as we allow for discrete shifts in the mean and the variance parameters of inflation.

2.2 Modeling output growth and inflation variability relation

There is a similar problem regarding the model that one employs to capture the impact of inflation uncertainty on output growth. If the output growth series follows a regime switching process, a linear reduced form regression model will not capture the true account of the relation between the variables. In that sense, it is likely that those studies in the literature which do

[8]Similarly, using state-dependent conditional variance model of Brunner and Hess (1993), Lee and Ni (1995) also conclude that inflation uncertainty significantly negatively correlated with economic activities in US economy.

not explore the possibility of changing output regimes may have arrived at misleading conclusions. Hence, prior to investigating the growth uncertainty relation, we test the null hypothesis of linearity of output growth against the regime switching alternative. Once we are certain of the properties of the output growth series, we construct a proper second stage model considering the time series movements of the growth series. In our case we resort to a Markov regime switching output growth model as the series exhibits regime shifts. The advantage of this model is that it allows us to determine the effects of inflation uncertainty across high and low growth regimes as we discuss in our empirical section below.

3 Data and Econometric Methodology

3.1 Data

To empirically analyze the link between inflation uncertainty and output growth, in the main, we use monthly consumer price index (CPI) and monthly seasonally adjusted industrial production index (IPI) for the United States. Data are obtained from the International Financial Statistics of the International Monetary Fund and spans the period 1985:03–2009:08. In the second part of the investigation we check for the robustness of our results using quarterly real GDP and CPI series that cover the period 1985:QI–2009:QIV.

We measure output growth (y_t) by the monthly (quarterly) difference of the log industrial production index $\left[y_t = log\left(\frac{IPI_t}{IPI_{t-1}}\right)\right]$. Similarly, we compute the inflation rate (π_t) as the monthly (quarterly) difference of the log of consumer price index $\left[\pi_t = log\left(\frac{CPI_t}{CPI_{t-1}}\right)\right]$. We check for the presence of GARCH effects in the inflation series by applying Lagrange Multiplier test. This test reveals significant GARCH effects in the inflation series. We then estimate a simple GARCH(1,1) model for inflation where the conditional variance follows $h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \alpha_2 h_{t-1}$. As the sum of ARCH coefficients and GARCH terms ($\alpha_1 + \alpha_2$) from this model is very close to one, we suspect that the effects of past shocks on current variance is very strong; i.e. the persistence of volatility shocks is strong. In this context, Lamoureux and

Lastrapes (1990) and Gray (1996) point out that the high volatility persistence may be due to the regime shifts in the conditional variance. In such circumstances, the use of a single regime model where there are regime shifts in the data is likely to yield parameters that show high volatility persistence.

To test for the presence of regime shifts in both inflation and output growth series, we implement a number of tests. The Hansen test rejects the null of linearity for the growth rate of industrial production series. In this context, we also implement a structural break test, the Quandt-Andrews breakpoint test (Andrews (1993)), which shows that inflation and growth of industrial production series exhibit structural breaks. Furthermore, the use of AIC (Akaike information criteria) as suggested by Psaradakis and Spagnolo (2003) provides evidence that both series contain two regimes. As a result of this investigation, we implement models that accommodate the presence of regime shifts in the inflation and output growth series as we investigate the linkages between inflation uncertainty and output growth as we discuss below.[9]

3.2 Generating inflation uncertainty

Among other macroeconomic series, inflation is known to exhibit different patterns over time. Sometimes, inflation tends to be high for a period of time and some other times it is subdued. To capture the regime shifts in inflation series, we apply the Markov switching GARCH methodology as proposed by Gray (1996). We do so because, the generalized regime switching (GRS) model suggested by Gray (1996) is independent of the entire history of the unobserved state variable $S\{t\}$. More concretely, Cai (1994) and Hamilton and Susmell (1994) argue that regime switching GARCH model is impossible to estimate due to the dependence of GARCH model on the entire history of the data. This is so because, a regime switching GARCH model at time t depends directly on the unobserved state $S\{t\}$and indirectly on the history of $S\{t\}$ (i.e., $\{S_{t-1}, S_{t-2,...,}S_1\}$). The problem of path dependence has been solved by the GRS model as described by equation (3) below. One advantage

[9] All test results are available from the authors upon request.

of Markov switching GARCH models is the ability of the GARCH term to capture persistence in a parsimonious way in place of a large number of ARCH terms.

We use Markov switching GARCH(1,1) approach to model the conditional mean and the conditional volatility of the inflation process while we allow switching between two regimes: high- and low-inflation regimes. In this set up, conditional mean of inflation follows an AR(p) process:

$$\pi_{it} = \theta_{0i} + \sum_{j=1}^{p} \theta_{ji}\pi_{t-j} + \varepsilon_t, \tag{1}$$

where $i = 1, 2$ and

$$\pi_{it} \mid \Omega_{t-1} \sim \begin{cases} N\left(\theta_{01} + \sum_{j=1}^{p} \theta_{j1}\pi_{t-j}, h_{1t}\right) & \text{w.p. } p_{1t}, \\ \\ N\left(\theta_{02} + \sum_{j=1}^{p} \theta_{j2}\pi_{t-j}, h_{2t}\right) & \text{w.p. } 1 - p_{1t} \end{cases}$$

$$\varepsilon_t \mid \Omega_{t-1} \sim N\left(0, h_{it}\right), \text{i=1,2.}$$

In equation (1) i indicates the regime, π_t represents the inflation process and h_t denotes the conditional variance of inflation. Here, $p_{1t} = Pr\left(S_t = 1 \mid \Omega_{t-1}\right)$ is the probability that the unobserved state variable S_t is in regime 1 conditional on the information set available at time $t-1$ (Ω_{t-1}).[10]

Following Hamilton (1989) regime switches are assumed to be directed

[10]The t^{th} observation is classified in the i^{th} state if the smoothed probability of the occurrence of state i is greater than 0.5 for this observation.

by a first-order Markov process with fixed transition probabilities:[11]

$$\begin{aligned} Pr\left[S_t = 1 \mid S_{t-1} = 1\right] &= P_{11}, \\ Pr\left[S_t = 2 \mid S_{t-1} = 1\right] &= 1 - P_{11}, \\ Pr\left[S_t = 2 \mid S_{t-1} = 2\right] &= P_{22}, \\ Pr\left[S_t = 1 \mid S_{t-1} = 2\right] &= 1 - P_{22}. \end{aligned} \tag{2}$$

In his regime-switching GARCH model, Gray (1996) aggregates the conditional variances from the two regimes based on the regime probabilities at each step. In doing so, the aggregate conditional variance is not path dependent and can be used to calculate the conditional variances at the next time period. In this framework, the conditional variance, which follows a GARCH(1,1) process, can be expressed as:

$$h_{it} = \alpha_{0i} + \alpha_{1i}\varepsilon_{t-1}^2 + \alpha_{2i}h_{t-1} \tag{3}$$

where

$$\varepsilon_{t-1} = \pi_{t-1} - \left[p_{1t-1}\mu_{1t-1} + \left(1 - p_{1t-1}\right)\mu_{2t-1}\right],$$

$$\mu_{it-1} = \theta_{0i} + \sum_{j=1}^{p} \theta_{ji}\pi_{t-j-1}$$

and

$$\begin{aligned} h_{t-1} = {} & p_{1t-1}\left(\mu_{1t-1}^2 + h_{1t-1}\right) + \left(1 - p_{1t-1}\right)\left(\mu_{2t-1}^2 + h_{2t-1}\right) - \\ & \left[p_{1t-1}\mu_{1t-1} + \left(1 - p_{1t-1}\right)\mu_{2t-1}\right]^2. \end{aligned}$$

The non-negativity of h_t for all t, is ensured by assuming $\alpha_{0i} \geq 0$, $\alpha_{1i} \geq 0$ and $\alpha_{2i} \geq 0$. The necessary condition for stationarity is $\alpha_{1i} + \alpha_{2i} < 1$ as in a single-regime GARCH(1,1) model. Here, note that all parameters of the conditional variance of inflation are state-dependent.

We use the maximum likelihood methodology to estimate the model. The likelihood function for this generalized regime switching model is derived by

[11] For instance, if the economy is in the first state in the previous period ($S_{t-1} = 1$), P_{11} is the probability of switching to the first state in the present period ($S_t = 1$).

Gray (1996) and takes the form:

$$L = \sum_{t=1}^{T} log \left[p_{1t} \frac{1}{\sqrt{2\Pi h_{1t}}} exp \left\{ -\frac{(\pi_t - \mu_{1t})^2}{2h_{1t}} \right\} + (1 - p_{1t}) \frac{1}{\sqrt{2\Pi h_{2t}}} exp \left\{ -\frac{(\pi_t - \mu_{2t})^2}{2h_{2t}} \right\} \right].$$

Gray (1996) also shows that the regime probability p_{1t} can be written as a simple nonlinear recursive system as follows:

$$\begin{aligned} p_{1t} = P_{11} &\left[\frac{f_{1t-1} p_{1t-1}}{f_{1t-1} p_{1t-1} + f_{2t-1} (1 - p_{1t-1})} \right] + \\ (1 - P_{22}) &\left[\frac{f_{2t-1} (1 - p_{1t-1})}{f_{1t-1} p_{1t-1} + f_{2t-1} (1 - p_{1t-1})} \right]. \end{aligned} \tag{4}$$

Assuming conditional normality, the conditional distribution of inflation, f_{it} where $i = 1, 2$, can be written as:

$$f_{it} = f(\pi_t \mid S_t = i, \Omega_{t-1}) = \frac{1}{\sqrt{2\Pi h_{it}}} exp \left\{ -\frac{(\pi_t - \mu_{it})^2}{2h_{it}} \right\}.$$

The conditional variance of the inflation process obtained from the above procedure, is next used as a proxy for inflation uncertainty. It should be noted that the measure of inflation uncertainty that we use in the second stage regression is a generated regressor by the nature of its construction. Pagan (1984) and Pagan and Ullah (1988) argue that the generated regressor measures the true but unobserved regressor with error, hence biasing the coefficient estimates or the standard errors in the second step. As a solution to the errors in variables problem connected to the use of a generated regressor, Pagan and Ullah (1988) suggest instrumental variable estimation procedure. However, in our case where the generated regressor is the conditional variance of inflation estimated from a Markov Switching GARCH model, it is not possible to use the standard instrumental variable estimation approach where lags of the variable is used as instruments. The reason is that the conditional variance of inflation is a function of all previous history and hence there are no available instruments which can be used instead. In this case, Pagan and Ullah (1988) propose that specification tests are carried out to see whether the GARCH-type model is correctly specified.[12] Therefore, in section 4.5, we run diagnostic tests to check whether our Markov Switching GARCH model for inflation is well specified while properly capturing the conditional heteroscedasticity in inflation.

3.3 Empirical Model

To examine the real effects of uncertainty on output growth we entertain the possibility of changing output regimes, due to expansions and contractions over the business cycle and propose to use a Markov regime switching framework for the output model. Within the framework of this modeling strategy, our aim is to capture the regime dependent impact of inflation uncertainty on the output process as we control for periods of expansion and contraction in the economy. The specification for our baseline model takes the following form:

$$y_t = \phi_{0i} + \sum_{j=1}^{m} \beta_{ji} y_{t-j} + \sum_{j=1}^{k} \varphi_{ji} \pi_{t-j} + \delta_{0i} \sigma_{\pi_t} + \xi_t, \tag{5}$$

$$\xi_t \mid \Omega_{t-1} \sim N\left(0, \sigma_{0i}^2\right), \text{i=1,2 regimes,}$$

where y_t is the growth rate of output at time t and σ_{π_t} captures the effect of inflation uncertainty on output growth. The model includes lagged inflation rate to control for the level effects of inflation on output growth. Last but not least, the lagged dependent variable allows us to control for the persistence of output growth. Note that the appropriate number of lags of inflation and output growth rate are determined on the basis of the Akaike information criteria (AIC) and the Schwarz information criteria (SIC).

We next focus on determining the correct number of states required for the model. Standard likelihood ratio test can not be used to check for the

[12] Ruge-Murcia (2003) implements this approach to assess whether the GARCH(1,1) model in his study adequately captures the conditional heteroscedasticity in the US unemployment data.

null of linearity against the alternative of Markov switching model. The reason is that under the null of linearity the parameters of the transition probabilities are unidentified as the scores with respect to the parameters of interest are equal to zero and the information matrix is singular. However, we implement tests proposed by Hansen (1992, 1996) and Garcia (1998) which overcomes this problem. In addition, Psaradakis and Spagnolo (2003) suggest to select the number of regimes using the AIC, Bayesian information criterion (BIC) and three-pattern method (TPM).[13] In their study, using Monte Carlo analysis, Psaradakis and Spagnolo (2003) find that selection procedures based on the TPM and the AIC are generally successful in choosing the correct number of regimes, provided that the sample size and parameter changes are not too small. Here, we use both the Hansen test and AIC criteria to determine the number of states.

We apply the Hansen test to the growth rate of industrial production series and find out that the null of linearity is rejected.[14] In this context we also implement a structural break test, the Quandt-Andrews breakpoint test (Andrews (1993)), which shows that growth of industrial production series exhibit structural breaks. Furthermore, the use of AIC as suggested by Psaradakis and Spagnolo (2003) provides evidence that output growth contain two regimes. Hence, we allow all coefficients of the model (5), which are indexed by i, to vary over the high and low growth regimes. In this model, the key coefficients of interest are those of the conditional variance of inflation (δ_{01} and δ_{02}) which we use to test the Friedman hypothesis.

The error term ξ_t in equation (5), is assumed to be conditionally normal with a zero mean and a variance, σ_{0i}^2, which is also subject to regime shifts.

[13] Granger et al. (1996) and Sin and White (1996) argue that such methods are more appropriate for model selection than hypothesis testing procedures. The use of complexity-penalized criteria in model selection has been studied by Leroux (1992), Poskitt and Chung (1996) and Zhang and Stine (2001) among others. More concretely, Zhang and Stine (2001) show that any weekly stationary process generated by a Markov regime-switching model has a linear autoregressive ARMA representation. Psaradakis and Spagnolo (2003) using Monte-Carlo experiments investigate the properties of complexity-penalised criteria in determining the number of states.

[14] We did not apply the same test for the inflation process because inflation series contain GARCH components which require one to test the mean and the variance of the series simultaneously.

The variance of the error term, σ_{0i}^2, is allowed to change across the two regimes since the variability of output in recessions is generally different from the variability of output in expansions.

4 Empirical Results

4.1 Markov Switching GARCH model for Inflation

Table (1) reports the maximum likelihood estimates of the Markov Switching GARCH(1,1) model for inflation. The mean inflation rate is modeled as an AR(1) process as determined by the minimum AIC and SIC. Results show that coefficients in the mean equation for inflation are highly significant for both regimes. In State 1, the implied monthly inflation rate is around 0.26 per cent and in State 2, that rate is around 0.34 per cent.[15] Thus, State 1 is identified as the low inflation regime and State 2 is recognized as the high inflation regime.

Insert Table (1) about here

When we inspect the conditional variance of inflation over the two regimes we observe that all the parameters are significant at 1% significance level. Exception to this is the estimated coefficient on h_{t-1} for State 1, and the constant coefficient for State 2. Within each regime the GARCH processes are stationary as $\alpha_{1i} + \alpha_{2i} < 1$. In addition, low inflation regime is more sensitive to recent shocks (i.e. $\alpha_{11} > \alpha_{12}$). However, high inflation regime is more persistent to shocks than low inflation regime (i.e. $\alpha_{22} > \alpha_{21}$). This means that the effect of individual shocks do not die quickly in the high inflation regime. It is worth noting that a single regime GARCH model could not capture this difference.

We plot the conditional variances of inflation in high inflation and low inflation regimes in Figure (1). In line with the Friedman hypothesis, both series of inflation uncertainty increase in the high inflation periods which are

[15]The implied monthly inflation rate is equal to $\frac{\theta_{01}}{1-\theta_{11}} = 0.26\%$ in State 1 and $\frac{\theta_{02}}{1-\theta_{12}} = 0.34\%$ in State 2.

shaded in Figure (1). However inflation uncertainty in high inflation regime (H2) is significantly higher than the inflation uncertainty in low inflation regime (H1).

Insert Figure (1) about here

The estimates of the transition probabilities P_{11} and P_{22} are 0.991 and 0.995, respectively, which implies the presence of strong persistence of both regimes. Similar to Gray's findings, within-regime persistence of conditional variance is lower than the persistence of a single-regime GARCH model. More concretely, the sum of the coefficients of ARCH and GARCH terms ($\alpha_{1i}+\alpha_{2i}$) are 0.218 in State 1 and 0.886 in State 2 constituting an advantage of the regime-switching model over the single-regime GARCH model.

Insert Figure (2) about here

For comparison purposes in Figure (2) we plot the implied conditional variances of inflation generated from a single-regime GARCH(1,1) model and that from the Markov-switching GARCH(1,1) model. This figure shows us that inflation uncertainty obtained from the single-regime GARCH(1,1) model generally underestimates uncertainty at high inflation periods which are shaded. The figure also shows that a single regime GARCH(1,1) model overestimate both uncertainty and its persistence in the low inflation regime. The reason to these observations is that the simple GARCH(1,1) model does not account for the structural changes in the inflation process.

4.2 Effects of Inflation Uncertainty on Output Growth

In section 3.1 we demonstrate that the null of linearity is rejected for output growth series as it exhibits changes over time. Hence, prior to estimating the impact of inflation uncertainty on output growth, we must first identify the low and high growth periods for the US economy. To do that we estimate an autoregressive Markov switching model for output growth rate. The model takes the following form:

$$y_t = \phi_{0i} + \sum_{j=1}^{m} \beta_{ji} y_{t-j} + \xi_t,$$

$$\xi_t \mid \Omega_{t-1} \sim N\left(0, \sigma_{0i}^2\right),$$

where y_t is the growth rate of output at time t. The error term, ξ_t, is assumed to be conditionally normal with a zero mean and a variance, σ_{0i}^2, which is subject to regime shifts. Here, we set the number of lags (m) for the lagged dependent variable to 3 based on the AIC and SIC.

Table (2) provides the parameter estimates of the benchmark model in equation (6). These results suggest that during State 1, the US economy experiences a steady-state output growth rate of around 0.25 per cent and that during State 2, output growth declines at a steady-state rate of around -0.05 per cent. Given these figures, we can therefore classify State 1 as the high growth regime and State 2 as the low growth regime. According to the estimated smoothed probabilities, 1985:12-1986:03, 1990:10-1990:12, 1991:05-1991:07, 1998:06-1998:08, 2005:09-2006:01, 2008:08-2009:01, 2009:07 are identified as low growth periods. The remaining periods are recognized as high growth periods.

Insert Table (2) about here

Having distinguished the low and high growth periods for the US economy, in the next step we estimate the model in equation (5). In doing so we investigate the real effects of inflation uncertainty on output growth. The smoothed probabilities for State 1 and for State 2 obtained from the estimation of model (5) are shown in Figure (3). As depicted in Figure (3), State 1 coincides with high growth periods and State 2 coincides with low growth periods.

Insert Figure (3) about here

Insert Table (3) about here

In Table (3), we observe that the impact of inflation uncertainty over both regimes is significant and negative. The effect of inflation uncertainty in regime one (δ_{01}), the high growth regime, is -0.087 and significant at the 10% level. Alternatively, the impact of inflation uncertainty on output in regime two (δ_{02}), the low growth regime, is -0.383 and significant at the 1% level. In other words, the magnitude of the adverse impact of inflation uncertainty on output growth in the low growth regime is about 4.4 times greater than that in the high growth regime. This is an interesting finding and has not been shown in the literature: the impact of inflation uncertainty on output growth can vary depending on the growth phase of the economy. In particular, the negative impact of inflation uncertainty on real economic activity is more profound during periods of low growth. These findings support the Friedman hypothesis which claims that inflation uncertainty exerts a negative impact on output growth.

Another interesting finding that arises from Table (3) is the impact of inflation on the growth rate of output. The effect of inflation on economic performance is positive and significantly different from zero at the 10% significance level during the low growth regime as captured by φ_{12} while its impact (φ_{11}) is negative and insignificant at the high growth regime. That is during periods of low growth, inflation helps the economy to recover whereas during expansionary periods inflation affects the economy adversely but the adverse effect of inflation is insignificant. This observation is similar to that of Grier and Grier (2006) who report that while inflation uncertainty significantly lowers output growth, lagged average inflation actually raises it.

4.3 Robustness Analysis

To investigate the robustness of our results, we estimate equation (5) using quarterly real GDP and CPI series. The data cover the period between 1985:QI–2009:QIV. We measure the growth rate of real GDP in period t, Y_t, as the quarterly difference of the log of real GDP, RGDP, $\left[Y_t = log\left(\frac{RGDP_t}{RGDP_{t-1}}\right)\right]$. Working with growth of real GDP enables us to compare the detected periods of contraction and expansion through the model with the dates provided by the NBER.[16] A match between the implied dates for contraction that we infer from the Markov Switching model with that announced by the NBER would indicate a success. As a result, this will provide more conviction to the results regarding the impact of inflation uncertainty on output growth.

Insert Table (4) about here

Table (4) provides the NBER dates covering the period under investigation in this study. We see that between 1985-2000, the US economy experienced three recessionary episodes. Based on the AIC and SIC, we select the number of lags for the lagged dependent variable (m) as 3 and the number of lags for inflation (k) as 1. Table (5) presents the results for our model in equation (5).

Insert Table (5) about here

The smoothed probabilities for this model are shown in Figure (4). When we examine the smoothed probabilities of the occurrence of State 1 we see that contraction persists during 1990:QIII-1991:QI, 1995:QI-1995:QII, 2000:QIII-2001:QIV, 2002:QIII-2002:QIV, 2006:QIV, 2007:QIV-2008:QI, 2008:QIII-2009:QIII. Comparing these periods with the business cycle dates provided by the NBER which we report in Table (4), we observe that our model captures the economic contractions over 1990/1991, 2000/2001, 2008/2009. It also picks up several additional turning points in the data including 1995:QI-1995:QII, 2000:QIII-2001:QI, 2002:QIII-2002:QIV, 2006:QIII, 2007:QIV, 2009:QIII as periods of contraction. However, following the censoring rule of Harding and Pagan (2002), we assume that a completed cycle (peak to peak or through to through) last at least five quarters.[17] Thus, we

[16] Recession is generally defined as a period when GDP falls for at least two consecutive quarters. However NBER defines an economic recession as: "a significant decline in economic activity spread across the country, lasting more than a few months, normally visible in real GDP growth, real personal income, employment (non-farm payrolls), industrial production, and wholesale-retail sales."

[17] Harding and Pagan (2002) specify a censoring rule such that phases last at least 2 quarters and the completed cycle last at least 5 quarters. Mitchell and Mouratidis (2004) using alternative measures of business cycles for 12 European Union (EU) countries show that recession and expansion last on average 18 and 60 months respectively.

can not classified the above episodes as periods of recession. Overall we think that the model is useful in captures the business cycle peaks and troughs in the US economy over the period of our investigation as dated by NBER. Additionally, inspecting the data closely, we can observe that the additional dates which the model suggests as periods of contraction are due to rapid changes in output growth series and do not necessarily imply that the model is improperly specified.

Insert Figure (4) about here

We next turn to examine how economic growth is affected by inflation uncertainty and whether this effect would change across periods of contraction and expansion. As we can observe from Table (5), results for the quarterly data are stronger compared to the case of monthly data. This may be due to the fact that industrial production represents only a portion of output generated in the economy whereas GDP provides us the full economic performance. As a consequence, we capture the true impact of inflation uncertainty on real output growth within the context of this model.

Table (5) shows that during the low regime, inflation uncertainty has a negative effect ($\delta_{02} = -0.603$) which is significantly different from zero at the 1% significance level. From Table (5) we also observe the effect of inflation uncertainty on growth during the period of expansion is also negative ($\delta_{01} = -0.152$) and significant at the 10% significance level. Comparing the magnitude of inflation uncertainty on output growth, *ceteris paribus*, we see that the adverse impact of inflation uncertainty on economic growth is 4 times more in a period of contraction than that in an expansion. Finally, we observe inflation has a positive but insignificant effect on economic growth at during periods of contraction while it is negative but insignificant during periods of expansion. Overall, we conclude that inflation uncertainty has a negative impact on output growth supporting the Friedman hypothesis.

4.4 Specification Tests

To check if the standardized residuals obtained from the Markow switching GARCH(1,1) model and the Markow switching output growth model are correctly specified, we apply the standard LM test. For both series we cannot reject the hypothesis of no conditional heteroscedasticity. Thus, we conclude that the Markov switching GARCH(1,1) model for inflation captures the conditional heteroscedasticity in both monthly and quarterly US inflation data adequately. Furthermore, the Markov switching model for output growth is properly specified and does not contain any ARCH effects.

Insert Table (6) about here

5 Conclusion

In this paper, we examine the impact of inflation uncertainty on output growth for the US economy. To carry out our investigation, we use two sets of data. The main investigation is carried out on monthly US inflation and industrial production series covering the period 1985:03–2009:08. We then check the robustness of our findings using quarterly GDP series over 1985:QI–2009:QIV. Prior to estimating any model, we investigate the properties of inflation and output growth series. Detecting that both series can be characterized by regime shifts we implement Markov switching models. In particular, we apply a Markov switching GARCH model to inflation so that we can obtain a measure of uncertainty which considers the shifts in the inflation process. We then construct a Markov switching model for the output series to fully capture the growth dynamics as we investigate the impact of uncertainty on growth.

This approach enables us to examine whether the effects of inflation uncertainty change across different regimes as the economy expands and contracts. Similar to the earlier research, we observe a significant and negative effect of inflation uncertainty on output growth. Furthermore, different from the earlier research we show that the negative effect of inflation uncertainty is more pronounced during periods of contraction. In particular, the negative impact of inflation uncertainty on output growth in low growth regimes is about 4.5 times greater than that in a high growth regimes. We also show that the direct effect of inflation on output growth is positive and significant during low growth regimes while it is negative and insignificant during high growth regimes.

We examine the robustness of our results by re-estimating the model on quarterly GDP series. Once more we detect low and high growth regimes which coincide well with the NBER dates of contraction and expansion for the US economy. The results from this investigation are similar to those findings reported for monthly industrial production data. We observe that inflation uncertainty exerts a negative and larger impact (almost 4 times higher in periods of contraction than that in periods of expansion) on economic growth when the economy contracts. Specification tests provide further evidence that the model is properly specified.

Overall our findings verify that inflation uncertainty exerts a negative impact on output growth through the business cycle. We also observe that uncertainty has stronger negative effects on real economic activity during periods of bottlenecks in economic growth. Our results also show that it is important to use a model that captures the proper behavior of the underlying series to capture the interlinkages between the variables accurately.

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Figure 1: The Inflation Uncertainties in State 1 and State 2

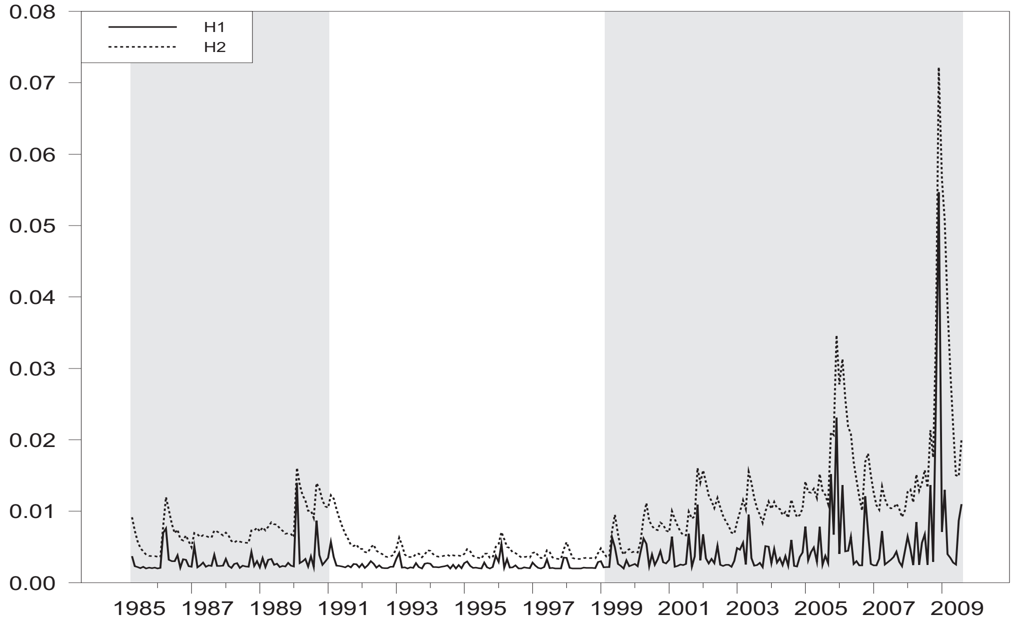

Figure 2: The Inflation Uncertainties Estimated with Single Regime GARCH(1,1) Model and Markov Switching GARCH(1,1) Model

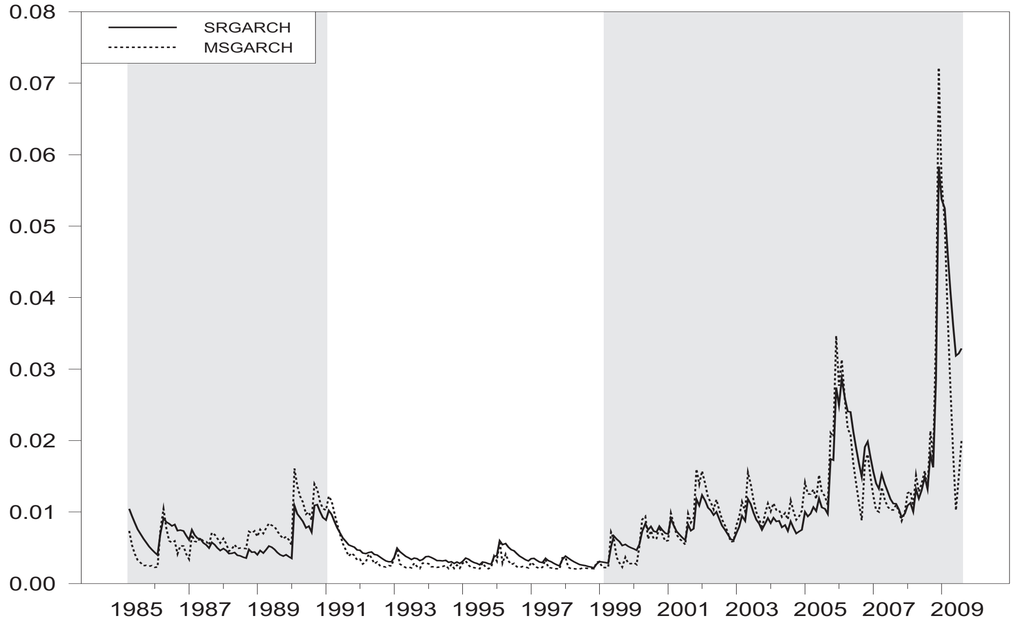

Figure 3: Smoothed Probabilities for State 1–1985:03-2009:08

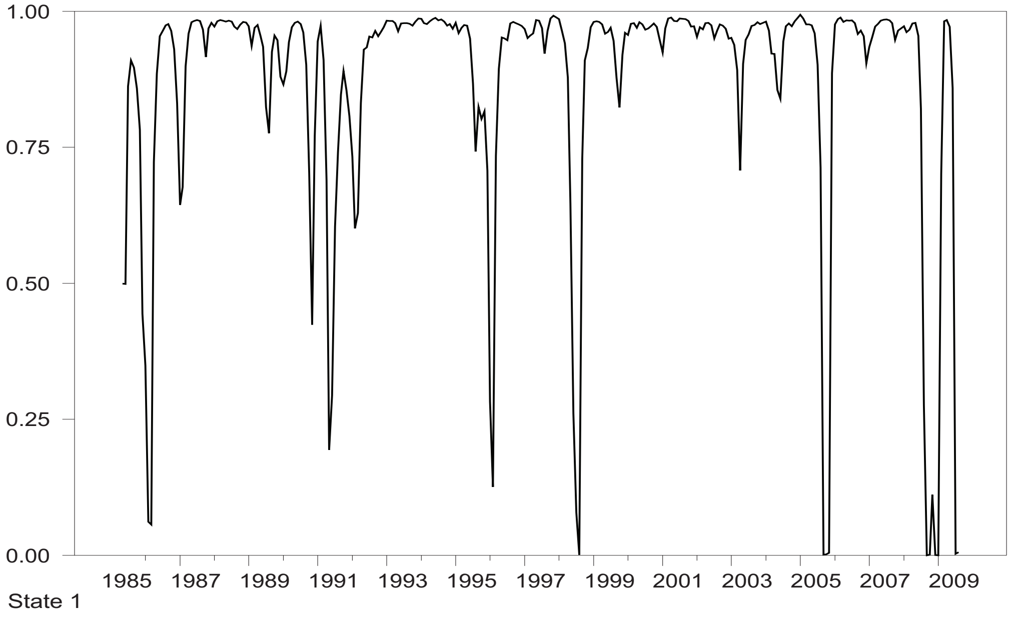

Figure 4: Smoothed Probabilities for State 1–1985:QI-2009:QIV

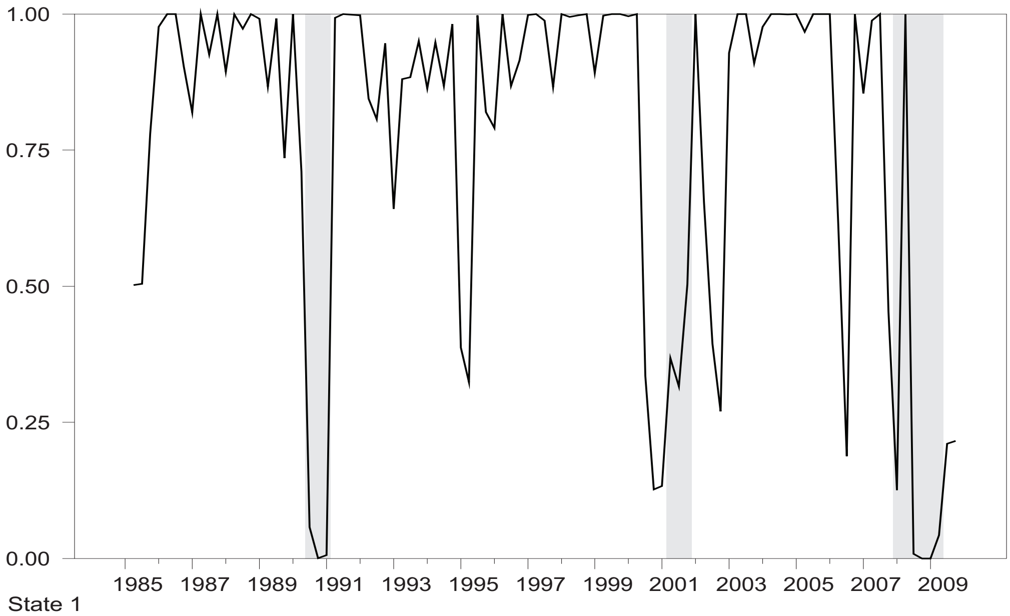

Table 1: Estimation Results for Markov Switching GARCH Model

Parameter	**Estimate**	**Standard Error**
θ_{01}	0.002***	0.000
θ_{11}	0.218***	0.089
θ_{02}	0.002***	0.000
θ_{12}	0.420***	0.065
α_{01}	0.000***	0.000
α_{11}	0.185*	0.103
α_{21}	0.033	0.125
α_{02}	0.000	0.000
α_{12}	0.162***	0.057
α_{22}	0.724***	0.155
P_{11}	0.991‡	0.009
P_{22}	0.995‡	0.004
Log-likelihood	1343.151	

Notes: *, **, *** denote significance at the 10%, 5% and 1% levels.
‡ significance of P_{11} and P_{22} is relative to 0.5.

Table 2: Estimation Results of Equation (6)–1985:03-2009:08

Parameter	**Estimate**	**Standard Error**
ϕ_{01}	0.001***	0.000
β_{11}	0.021	0.070
β_{21}	0.328***	0.053
β_{31}	0.257***	0.059
ϕ_{02}	0.000	0.002
β_{12}	0.277**	0.130
β_{22}	0.051	0.153
β_{32}	0.053	0.157
σ_{01}	0.004***	0.000
σ_{02}	0.011***	0.001
P_{11}	0.947***	0.023
P_{22}	0.808**	0.093
Log-likelihood	1324.364	

Notes: *, **, *** denote significance at the 10%, 5% and 1% levels.

Table 3: Estimation Results of Equation (5)–1985:03-2009:08

Parameter	**Estimate**	**Standard Error**
ϕ_{01}	0.002***	0.001
β_{11}	-0.001	0.066
β_{21}	0.294***	0.057
β_{31}	0.202***	0.054
φ_{11}	-0.135	0.110
δ_{01}	-0.087*	0.053
ϕ_{02}	0.003	0.002
β_{12}	-0.121	0.182
β_{22}	-0.242	0.220
β_{32}	-0.282	0.265
φ_{12}	0.699*	0.424
δ_{02}	-0.383***	0.129
σ_{01}	0.004***	0.000
σ_{02}	0.010***	0.002
P_{11}	0.948***	0.025
P_{22}	0.664***	0.118
Log-likelihood	1117.299	

Notes: *, **, *** denote significance at the 10%, 5% and 1% levels.

Table 4: NBER Dates of Expansions and Contractions

Business Cycles Reference Dates		**Duration in Months**	
Peak	Trough	Contraction	Expansion
July 1990(III)	March 1991(I)	8	92
March 2001(I)	November 2001 (IV)	8	120
December 2007 (IV)	June 2009 (II)	18	73

Source: National Bureau of Economic Research (NBER),
Quarterly dates are in parentheses.

Table 5: Estimation Results of Equation (5)–1985:QI-2009:QIV

Parameter	**Estimate**	**Standard Error**
ϕ_{01}	0.009***	0.001
β_{11}	-0.070	0.110
β_{21}	0.248***	0.097
β_{31}	-0.068	0.119
φ_{11}	0.031	0.093
δ_{01}	-0.152*	0.089
ϕ_{02}	0.008***	0.002
β_{12}	0.420***	0.095
β_{22}	0.127	0.093
β_{32}	-0.648***	0.083
φ_{12}	-0.023	0.055
δ_{02}	-0.603***	0.092
σ_{01}	0.004***	0.000
σ_{02}	0.002***	0.001
P_{11}	0.875*	0.066
P_{22}	0.592***	0.165
Log-likelihood	390.711	

Notes: *, **, *** denote significance at the 10%, 5% and 1% levels.

Table 6: ARCH LM Test for Squared Standardized Residuals

		Output Growth Equation	**Inflation Equation**
1985:01-2009:08	ARCH LM test	0.021	7.136
(monthly data)	(lag=4)	[0.999]	[0.129]
1985:QI-2009:QIV	ARCH LM test	0.422	
(quarterly data)	(lag=4)	[0.981]	

Notes: p values in square brackets.