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ON THE NONLINEAR CAUSALITY BETWEEN INFLATION AND INFLATION UNCERTAINTY IN THE G3 COUNTRIES

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This study examines the dynamic relationship between monthly inflation and inflation uncertainty in Japan, the US and the UK by employing linear and nonlinear Granger causality tests for the 1957:01-2006:10 period. Using a generalised autoregressive conditional heteroskedasticity (GARCH) model to generate a measure of inflation uncertainty, the empirical evidence from the linear and nonlinear Granger causality tests indicate a bi-directional causality between the series. The estimates from both the linear vector autoregressive (VAR) and nonparametric regression models show that higher inflation rates lead to greater inflation uncertainty for all countries as predicted by Friedman (1977). Although VAR estimates imply no significant impact, except for Japan, nonparametric estimates show that inflation uncertainty raises average inflation in all countries, as suggested by Cukierman and Meltzer (1986). Thus, inflation and inflation uncertainty have a positive predictive content for each other, supporting the Friedman and Cukierman-Meltzer hypotheses, respectively.

JEL classification codes: C22, E31.
Key words: inflation, inflation uncertainty, Granger-causality, nonlinear Granger-causality.

I. Introduction

The link between inflation and inflation uncertainty is an important indicator in determining monetary policy for the monetary authority. Researchers generally agree that the welfare cost of inflation is highest when the future inflation rate is unpredictable. Friedman's (1977) Nobel lecture outlined the most well known argument on inflation and its cost to welfare, suggesting that an increase in average inflation would raise nominal uncertainty about future inflation, which might cause an adverse output effect. Ball (1992) formally justifies Friedman's well-known insight by employing a game of asymmetric information. Contrary to Friedman (1977) and Ball (1992), Ungar and Zilberfarb (1993) establish that inflation gives rise to a lower level of uncertainty using a model in which agents invest more resources in forecasting inflation as inflation rises, leading to lower nominal uncertainty.

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These researchers do not present the only argument in the literature. Cukierman and Meltzer (1986) proposed a model to explain credibility, ambiguity, and inflation with asymmetric information. According to their argument, in the presence of higher inflation uncertainty, central banks tend to create inflation surprises to realise real economic gain. In other words, Cukierman and Meltzer conclude that inflation and inflation uncertainty had positive correlation, and the direction of causality was from inflation uncertainty to inflation. However, the opportunistic response of the central banks is not the only possible outcome, depending on their independency. Holland (1995) argues that more inflation uncertainty could lead to a lower average inflation rate if the central bank minimizes the welfare losses arising from more inflation uncertainty, which is the opposite of Cukierman and Meltzer's hypothesis. This would produce the stabilization motive of the monetary authority, the so-called "stabilizing Fed hypothesis". Holland claims that, as inflation uncertainty rises due to increasing inflation, the monetary authority responds by contracting money supply growth to eliminate inflation-uncertainty and the associated negative welfare effects. Therefore, a rise in inflation uncertainty will cause a fall in average inflation.

Though they differ in the direction of causality, both Friedman's and Cukierman and Meltzer's hypotheses suggest a positive relationship between inflation and inflation uncertainty. Ungar and Zilberfarb (1993) and Holland (1995), with different directions of causality, support instead a negative relationship.

There are contradictory results in the empirical literature. Engle (1982) introduced autoregressive conditional heteroskedasticity (ARCH), and Bollerslev (1986) created the generalized ARCH (GARCH) model. These models allow us to proxy uncertainty using the conditional variance of unpredictable shocks to inflation. Engle (1983) notes that a high rate of inflation did not necessarily imply a high variance in inflation, therefore, his findings do not support Friedman's hypothesis. Engle's study for the United States showed that high levels of inflation in the 1970s were predictable and not associated with higher inflation variability. Hwang (2001) provides support for Engle's claim with robust results for the high inflation period of the 1970s and the volatile period from 1929 to 1945. Conrad and Karanasos (2005), employing the ARFIMA-FIGARCH model for the period 1962-2001, provide supporting evidence for Friedman's theory for Japan, the United States and the United Kingdom, but only results from Japan support the Cukierman-Meltzer hypothesis. Berument and Dincer (2005), using the Full Information Maximum Likelihood Method for the 1957 to 2001 period, find evidence to support the Friedman-Ball hypothesis for all the G-7 countries. Grier and Perry (1998) offered evidence supporting the notion that inflation significantly raises inflation uncertainty for G-7 countries for 1948 to 1993 period, using Granger causality testing. However, they find weak evidence on the Cukierman-Meltzer hypothesis.

This article examines the causal links between inflation and inflation uncertainty using linear and nonlinear Granger causality tests for Japan, the United States and the United Kingdom during the 1957:01-2006:10 period. The sign of the predictability between the series is determined using the nonparametric average derivative estimates based on the additive model of Hastie and Tibshirani (1987, 1990). The study by Cecchetti and Krause (2001) reports that there is progress in the macroeconomic performances of the developed and developing countries after the mid-1980s and inflation and inflation uncertainty is more stable compared to the period before. This finding is also supported by Stock and Watson (2002). Besides the macroeconomic developments, the inflation series of these countries were higher around the 1973 oil crisis period than in the other periods. In examining the time trends of the inflation series in Japan, the US, and the UK, as shown in Figure 1, one might note more than one structural break. For instance, Ozdemir (2010) revealed two structural breaks in the inflation series of the UK, one corresponding to the mid-1980s and the other to the 1973 oil crisis.

[INSERT FIGURE 1]

When the underlying relationship between the series is nonlinear causality tests based on linear models are likely to show sensitivity to sample period and specification of the model. As noted by Koop and Potter (2001) apparent structural breaks may be a reflection of some form of nonlinearity. Under the light of conflicting evidence on the causal relationship between inflation and its uncertainty in Japan, the US, and the UK, one must take into account the possibility of a nonlinear relationship between the series. Recent studies that tested the arguments above relied on linear Granger causality tests. However, the problem with the linear approach to causality testing is that such tests generally have low power against nonlinear Granger causality tests (Baek and Brock 1992). Therefore, in addition to linear Granger causality tests, we use nonlinear causality tests based on the additive model approach of Bell et al. (1996) in order to determine the casual link between inflation and inflation. The nonlinear causality statistic we use is based on nonparametric estimation and can test any type of dependence between a set a random variables with known joint density. This approach we adopt does not assume any functional form and allows general dependence between inflation and inflation uncertainty series. The findings indicate the following results: Linear

VAR models imply that the Friedman hypothesis holds for all countries, but the Cukierman-Meltzer hypothesis holds only for Japan. The evidence obtained from the nonlinear additive models agree with the predictions from the VAR model, but additionally support the Cukierman-Meltzer hypothesis for the UK and the US.

The rest of the paper is organized as follows: the next section discusses the linear and nonlinear Granger causality tests. The third section presents the data and the empirical results. The last section presents the conclusions of the study.

II. Testing methodology

A. Linear Granger causality

Granger's (1969) causality definition is the source of causality tests between two stationary series. Formally, a time series Y_t Granger-causes another time series X_t if series X_t can be predicted better by using past values of Y_t than by using only the historical values of X_t. In other words, Y_t does not Granger-cause X_t if:

$$\Pr(X_{t+m} \mid \boldsymbol{X}_{t-k}) = \Pr(X_{t+m} \mid \boldsymbol{X}_{t-k}, \boldsymbol{Y}_{t-k}), \tag{1}$$

where, Pr(·) denotes conditional probability, $\boldsymbol{X}_{t-k} \equiv (X_t, X_{t-1},..., X_{t-k})$, and $\boldsymbol{Y}_{t-k} \equiv (Y_t, Y_{t-1},..., Y_{t-k})$. Suppose that X_t and Y_t are inflation and inflation uncertainty, respectively. Testing for causal relations between two series can be based on the following bivariate Vector Autoregression (VAR) model:

$$X_t = \alpha_0 + \sum_{k=1}^{n} \alpha_k X_{t-k} + \sum_{k=1}^{n} \beta_k Y_{t-k} + \varepsilon_{X,t}, \tag{2}$$

$$Y_t = \phi_0 + \sum_{k=1}^{n} \phi_k X_{t-k} + \sum_{k=1}^{n} \theta_k Y_{t-k} + \varepsilon_{Y,t}, \tag{3}$$

where α_0 and ϕ_0 are constants, α_k, β_k, ϕ_k, and θ_k are parameters, and $\varepsilon_{X,t}$ and $\varepsilon_{Y,t}$ are uncorrelated disturbance terms with zero means and finite variances. The null hypothesis that Y_t does not Granger-cause X_t is rejected if the β_k coefficients for k = 1,2,...,n in equation (2) are jointly significantly different from zero using a standard joint test (e.g., an F test). Similarly, in equation (3), if X_t Granger-causes Y_t, the ϕ_k coefficients for k = 1,2,...,n will jointly be different from zero. A bi-directional causality (or feedback) relation exists if both the β_k and ϕ_k coefficients are jointly different from zero. Using this test, within the framework of a VAR model, we will examine the causality of inflation and its uncertainty. For each case, the null hypothesis of no Granger causality is rejected if the exclusion restriction is rejected. If the elements ϕ_k (β_k) for k = 1,…,n are jointly different from zero, there exists bi-directional feedback between inflation and inflation uncertainty.

B. Sign of predictability and nonlinear Granger causality with nonparametric additive model

The problem of a linear approach to causality testing is that such tests can have low power in detecting certain kinds of nonlinear causal relations (Baek and Brock 1992). In order to take into account the possible nonlinearities, one can use nonlinear causality tests such as the Hiemstra and Jones (1994) and Diks and Panchenko (2006). As pointed out by Panchenko (2006), the Hiemstra-Jones test fails to detect linear Granger causality or suggests more causality than under the null hypothesis. In our study, it is also important to determine the sign of the predictability between the series, which is not possible with Hiemstra-Jones and Diks-Panchenko tests. Therefore, we use nonparametric causality tests based on the additive model. Theoretically, using nonparametric estimation, it is possible to test any type of dependence between a set a random variables with known joint density (Diks and Panchenko 2006). Nonparametric regression does not assume any functional form and allows general dependence between the variables (Hardle 1990). Nonparametric regression also offers an advantage over the other nonlinear approaches by allowing us to ascertain the sign of the predictability between the series using average derivative estimates (Hardle and Stoker 1989; Stoker 1991). Several studies consider nonparametric and nonlinear regression models for causality testing.

In this paper, we use the additive model approach of Bell et al. (1996) due to its robustness and known asymptotic properties (Hardle 1990). Assume that the relationship between the response variable y_t and a set of regressors $\mathbf{x}_t = (x_{1t}, x_{2t}, \ldots, x_{qt})'$ can be represented by the following nonparametric regression model

$$y_t = m(\mathbf{x}_t) + \varepsilon_t, t = 1,2,\ldots,T \tag{4}$$

where $E(y|\mathbf{x}) = m(\mathbf{x})$ is an unknown smooth regression function and ε_t is an error term with mean zero and constant variance σ^2. In our case, the covariates $\mathbf{x}_t$ includes p lags of inflation and inflation uncertainty series, i.e., $\mathbf{x}_t = (\pi_{t-1}, \pi_{t-2}, \ldots, \pi_{t-p}, h^2_{\pi,t-1}, h^2_{\pi,t-2}, \ldots, h^2_{\pi,t-p})'$ and y_t could be either the inflations series π_t or the inflation uncertainty series h_t^2. The q-dimensional regressor vector $\mathbf{x}_t$ is characterized by the density function $f(\mathbf{x})$ and a nonsingular covariance matrix Σ. The function $m(\cdot)$ is estimated by one of the several regression smoothing methods, such as the kernel smoothing, splines, local regression, etc. A variety of methods are also available for estimating the density function $f(\mathbf{x})$, kernel density estimation being the most popular one.

Our interest in estimating the nonparametric regression model in equation (4) is primarily to ascertain the sign of the impact of inflation on inflation uncertainty and *vice versa*. In order to so, we need to evaluate partial derivative of $m(\cdot)$ with respect to the variable of interest, say x_j, denoted $\delta_j = \partial m(\mathbf{x})/\partial x_j$. The partial derivative δ_j is a coefficient measuring the response of variable y with respect to a change in x_j. Collecting all partial derivatives in a vector δ we obtain $\delta = m'(\mathbf{x}) = (\partial m(\mathbf{x})/\partial x_1, \ldots, \partial m(\mathbf{x})/\partial x_q)'$. The partial derivate δ_j will not be a fixed number but vary with $\mathbf{x}$. Although this would be useful to characterize, say, the response of inflation to different levels of inflation uncertainty, we rather seek a response coefficient that measures the global curvature of the function $m(\cdot)$ with respect to $\mathbf{x}$. A natural measure of the global curvature is the average derivative (AD). The average derivative is defined as $\overline{\delta}_j = E[\overline{\beta}_j(x)] = \int_x \beta_j(x)dx$ for $j = 1,2,\ldots,q$. Then, the vector of average derivatives is given by $\overline{\delta} = E[m'(\mathbf{x})]$. Using integration by parts, it can be show that (see Hardle 1990):

$$\bar{\delta} = E[m'(\mathbf{x})] = -E\left[y \frac{f'(\mathbf{x})}{f(\mathbf{x})} \right]. \tag{5}$$

There are three alternative sample estimators of AD commonly used in practice. Powell et al. (1989) proposed an indirect estimator given by

$$\bar{\delta}_{\mathrm{p}} = -\frac{1}{T}\sum_{t=1}^{T} y_t \frac{\hat{f}'(\mathbf{x})}{\hat{f}(\mathbf{x})}, \tag{6}$$

where $\hat{f}(\mathbf{x})$ is the kernel density estimator of the density function $f(\mathbf{x})$ and $\hat{f}'(\mathbf{x})$ is the estimator of the first derivative of $f(\mathbf{x})$. Hardle and Stoker (1989) points out that the ratio $\hat{f}'(\mathbf{x}) / \hat{f}(\mathbf{x})$ will be ill-behaving when $\hat{f}(\mathbf{x})$ is small and proposes a trimmed estimator defined as

$$\bar{\delta}_{\mathrm{hs}} = -\frac{1}{T}\sum_{t=1}^{T} y_t \frac{\hat{f}'(\mathbf{x})}{\hat{f}(\mathbf{x})} \mathrm{I}[\hat{f}(\mathbf{x}) > b], \tag{7}$$

where b is a trimming parameter that converges to zero as T gets large and $\mathrm{I}[\cdot]$ is the indicator function taking a value of one when $\hat{f}(\mathbf{x}) > b$ and zero otherwise. A third estimator is the direct estimator of AD suggested by Stoker (1991). This estimator is defined as

$$\bar{\delta}_{\mathrm{s}} = \frac{1}{T}\sum_{t=1}^{T} [\hat{m}'(\mathbf{x})] \mathrm{I}[\hat{f}(\mathbf{x}) > b], \tag{8}$$

where $\hat{m}'(\mathbf{x})$ is the estimate of the first derivative of the regression function $m(\cdot)$ and $\mathrm{I}[\cdot]$ is as above.

Bell et al. (1996) consider nonparametric additive models for estimating the unknown function $m(\cdot)$ and report that this approach works well for detecting nonlinear causal links. They also find that the additive model is robust and loss of power is minimal when the true causal links are linear. An additive model representing the bi-variate causal links between inflation and inflation uncertainty can be written as follows:

$$\pi_t = \mu_\pi + \sum_{j=1}^{p} g_{\pi\pi}^{(j)}(\pi_{t-j}) + \sum_{j=1}^{p} g_{\pi h}^{(j)}(h_{\pi,t-j}^2) + \varepsilon_{\pi,t}, \qquad (9)$$

$$h_{\pi,t}^2 = \mu_h + \sum_{j=1}^{p} g_{h\pi}^{(j)}(\pi_{t-j}) + \sum_{j=1}^{p} g_{hh}^{(j)}(h_{\pi,t-j}^2) + \varepsilon_{\pi,t}, \qquad (10)$$

where the functions $\{g_{il}^{(j)}\}$, $i,l = \pi, h$, are unknown and will be estimated from the data using the nonparametric regression estimation. Unknown functions $\{g_{il}^{(j)}\}$ are univariate and can be estimated as one-dimensional nonparametric regressions, avoiding the curse of dimensionality problem (Hardle 1990).

Bell et al. (1996) proposed causality tests by imposing appropriate restrictions on equations (9) and (10). The hypothesis that inflation uncertainty does not Granger cause inflation can be tested by imposing the restriction

$$H_0 : g_{\pi h}^{(1)} = g_{\pi h}^{(2)} = \cdots = g_{\pi h}^{(p)} = 0 \qquad (11)$$

on equation (9) and estimating the restricted model

$$\pi_t = \mu_\pi^* + \sum_{j=1}^{p} g_{\pi\pi}^{*(j)}(\pi_{t-j}) + \varepsilon_{\pi,t}^* . \qquad (12)$$

Analogously, we can test the null hypothesis that inflation does not Granger inflation by imposing the restrictions

$$H_0 : g_{h\pi}^{(1)} = g_{h\pi}^{(2)} = \cdots = g_{h\pi}^{(p)} = 0 \qquad (13)$$

on equation (10) and estimating the restricted additive model

$$h_{\pi,t}^2 = \mu_h^* + \sum_{j=1}^{p} g_{hh}^{*(j)}(h_{\pi,t-j}^2) + \varepsilon_{\pi,t}^* . \tag{14}$$

Let RSS_R be the restricted residual sum of squares from equation (12) or (14) and RSS_U be the unrestricted sum of squares from equation (9) or (10). Then, the F-statistic to test the null hypotheses in the equations (11) and (13) is given by

$$\mathrm{F} = \frac{(RSS_R - RSS_U)/(d_U - d_R)}{RSS_U/(T - d_U)} \tag{15}$$

where d_U and d_R are the degrees of freedom of the unrestricted and restricted models, respectively. Hastie and Tibshirani (1990) argue that the test statistic in equation (15) is approximately distributed as $\mathrm{F}(d_U - d_R, T - d_u)$ and the null of no Granger causality is rejected, if the value obtained from the equation (12) is grater that the (1-α)th quantile of the standard F distribution.

III. Data and empirical results

We use monthly data on the Consumer Price Index (CPI) obtained from the International Financial Statistics (IFS) database as proxies for the price level. The data ranges from January 1957 to October 2006. The monthly CPI series used in this study have a monthly seasonal pattern. Hence, prior to calculating the inflation series, we deseasonalized the monthly CPI series. Then, the inflation series is measured by the monthly difference of the log CPI_t, that is $\pi_t = 100 \cdot \log(\mathrm{CPI}_t/\mathrm{CPI}_{t-1})$.

We first analyze the stationary properties of the inflation series. We use Phillips and Perron (1988), henceforth PP, unit root tests to determine whether the series are stationary or not. The unit root test results are given in Table 1. For the PP unit root test, we use the critical values computed by Sam Ouliaris and Peter C. B. Phillips (1990) in the GAUSS module COINT. In all cases, the results obtained from the PP test indicate that the null hypothesis that inflation rate series is non-stationary is rejected at 5% significance level. According to the results, all inflation series follow an I(0) process.

[INSERT TABLE 1]

This study extends the understanding of the relationship between inflation and inflation uncertainty in G3 countries, testing for nonlinear causalities in addition to linear linkages. We use the ARMA(p,q)-GARCH(r,s) model to generate inflation uncertainty. In the ARMA(p,q)-GARCH(r,s) model, the mean equation is defined as follows:

$$\pi_t = \mu + \sum_{i=1}^{p} \phi_i \pi_{t-i} + \sum_{j=1}^{q} \theta_j u_{t-j} + u_t \, , \qquad (16)$$

where π_t denotes the inflation, and u_t is conditionally normal with mean zero and variance $h^2_{\pi t}$. In other words, $u_t \mid \Omega_{t-1} \sim N(0, h^2_{\pi t})$, where Ω_{t-1} is the information set up to time t-1. The structure of the conditional variance is given by

$$h^2_{\pi t} = c + \sum_{i=1}^{r} \alpha_i u^2_{t-i} + \sum_{i=1}^{s} \delta_j h^2_{\pi, t-j} \, , \qquad (17)$$

where c is a positive constant and $(\sum_{i=1}^{r} \alpha_i + \sum_{j=1}^{s} \delta_j) < 1$. As Bollerslev (1986) showed, $c > 0$ and $\alpha_i \geq 0$ (for i = 1,…,r), and $\delta_i \geq 0$ (for i = 1,…,s) is sufficient for the conditional variance to be positive. The parameters of an ARMA(p,q)-GARCH(r,s) model can be estimated by a quasi-maximum likelihood estimator (QMLE) obtained using analogous methods described in Baillie et al. (1996).

Based on evidence obtained from the unit root test results of the inflation series, we estimate the ARMA(p,q) model in Equation (16) for the first moment of the series. Thus, in the subsequent analysis, we first estimate the optimum number of lags of the ARMA(p,q) models with p,q = {0,1,2,…,24} for equation (16). Therefore, we estimate 625 parametric models for the inflation rates for each country included in the sample, and the selection of the best ARMA model is based on the Akaike information criterion (AIC). For estimation, we used Laurent and Peters's (2002) GARCH module in the Ox package. The results indicate that the best ARMA model for the first moment of the inflation series of Japan, the US and the UK is AR(17), AR(10), and AR(6), respectively. The summary statistics of the inflation series are in Table 2. The summary statistics of the inflation rates of three countries indicated that the distributions of the inflation series skewed to the right. The distributions of the British and Japanese inflation rates had fat tails. The large values of the Jarque–Bera (JB) statistic implies a deviation from normality, and the significant Q-statistics of the squared deviations of the inflation rate from its sample mean indicated the existence of ARCH effects. Highly significant LM statistics for ARCH supported the evidence.

[INSERT TABLE 2]

In order to gauge inflation uncertainty, following the determination of the Data Generating Process (DGP) for the first moment of inflation, we determine the best GARCH (r,s) model for the second moment of the inflation series. Hence, we estimate GARCH (r,s) models with $r,s = \{1,2\}$ for equation (14) by using Laurent and Peters's (2002) GARCH module in the Ox package. To identify the best GARCH model, we consider model selection criteria, such as AIC, the significant test of parameters and positive variance condition. Based on these criteria, we choose the GARCH (1,1) model for the inflation series of each country. Table 3 summaries the AR(17)-GARCH(1,1), AR(10)-GARCH(1,1) and AR(6)-GARCH(1,1) models for Japan, the US, and the UK, respectively. The values of the Ljung-Box test statistics (Q) of the residual series indicate that there is no serial correlation in the residual series in neither 6th nor 12th order, except for the US series in the 12th order. Before analyzing the causal link between inflation and inflation uncertainty, we also analyse the stationarity property of inflation uncertainty of each country. Table 1 reports the results of the PP unit roots test applied to the inflation uncertainty series. The PP unit root test applied to the inflation uncertainty series indicates that the null hypothesis that inflation uncertainty series is non-stationary is rejected at 5% significance level for each country This implies that inflation uncertainty for each country is an I(0) process.

[INSERT TABLE 3]

A. Linear Granger-causality test results

We examine the linear Granger causality, which requires that all data series involved are stationary; otherwise, the inference from the F-statistic might be spurious because the test statistics would have non-standard distributions (Granger 1988). We estimate the bivariate VAR models given in the equations (2) and (3). The pairwise Granger causality test results, given in Table 4, showed inflation has positive predictive power for inflation uncertainty for 4 and 8 lags, at a 5 percent significance level for all three series, which supports Friedman's hypothesis. On the other hand, inflation uncertainty has no predictive power for inflation in the US and the UK, while inflation uncertainty has positive predictive content for inflation in Japan. These results indicated that the Cukierman and Meltzer hypothesis holds for Japan, but does not for the UK and the US. Conrad and Karanasos (2005) have mixed results for the causation of inflation uncertainty on inflation that favored our results. In their study, the UK series provides evidence that uncertainty about inflation had a positive impact on inflation at 8 lags, as predicted by Cukierman-Meltzer; however, they provided evidence that inflation uncertainty had a negative impact on inflation at 12 lags as predicted by Holland's hypothesis.

[INSERT TABLE 4]

The mixed findings of the studies in the literature might be the result of uncovered nonlinear causalities. Considering the macroeconomic stability now compared to before the mid-1980s period and the 1973 oil crisis lead us to identify the time trends of inflation and its uncertainty for the sampled three countries. We observe at least two possible structural breaks. We consider whether inflation have a nonlinear predictive power for inflation uncertainty or *vice-versa*. Moreover, to detect both linear and nonlinear dynamic relationships between inflation and inflation uncertainty of these countries, we create scatter plot diagrams of the inflation versus inflation uncertainty series, given in Figure 2. Each scatter plot displayed an unclear relationship between the series, especially in the lower left corner. The scatter plots implied nonlinear dynamic links between the series but do not show clear linear dynamics.

[INSERT FIGURE 2]

After removing the linear dependencies, using the VAR system in the series, we tested for the serial correlation in the residuals with the Ljung-Box Q-test. The test results are given in panel A of Table 5. The null hypothesis of no serial correlation in the residuals of VAR(4) and VAR(8) for Japan was retained at a 5 percent significance level at the 6th and 12th order with the exception of $\varepsilon_{\pi_t,h_{\pi,t}}$. For the UK, the null hypothesis that the residuals, obtained from the VAR(4) and VAR(8) models, have no serial correlation is retained at the 5 percent significance level at the 6th and 12th order with an exception of $\varepsilon_{\pi_t,h_{\pi,t}}$ at the 12th order in the VAR(4) model. For the US, the null hypothesis of no serial correlation for $\varepsilon_{\pi_t,h_{\pi,t}}$ derived from VAR(4) model at the 6th and 12th lag order is rejected at the 5 percent significance level, as is the null hypothesis that $\varepsilon_{\pi_t,h_{\pi,t}}$ obtained from VAR(8) model have no serial correlation. Generally, these results show no serial correlation in the residual series of interest under consideration.

Next, we examine nonlinear dependencies in the residuals with McLeod and Li's (1983) Q^2-test. The results in Panel B of Table 5 show that the null hypothesis that no serial correlation in squared residuals obtained from VAR(4) and VAR(8) model is rejected at the 5 percent significance level at the 6th and 12th order for residual series ($\varepsilon_{\pi_t,h_{\pi,t}}$), which is obtained from equation (2) for the three countries. This evidence suggests that all squared residual series ($\varepsilon_{\pi_t,h_{\pi,t}}$) from equation (2) had significant nonlinear dependencies. However, the Q^2-test statistics failed to reject the null hypothesis that the squared residuals series ($\varepsilon_{h_{\pi,t},\pi_t}$) obtained from equation (3) of VAR(4) and VAR(8) models have no serial correlation for the three countries, suggesting there are significant nonlinear dependencies.

[INSERT TABLE 5]

B. Nonparametric Granger causality tests and average derivative estimates

As we discussed above, the plots in Figure 2 indicated a nonlinear relationship between the inflation and inflation uncertainty series for all three countries. Therefore, we use the nonparametric Granger causality tests based on the additive models to investigate the nonlinear causal links between the series. Moreover, in order to determine the sign of the effect between the series, we estimate the ADs of the nonparametric additive models described in part B of Section II. The additive models are also estimated with lag orders $p = 4$ and $p = 8$.

The additive models in equations (8) and (9) fit separate nonparametric regressions to each regressor and a variety of estimation methods are available, each requiring several choices and control parameters. A commonly used algorithm for fitting the additive models is the local scoring algorithm of Hastie and Tibshirani (1987, 1990). The back fitting algorithm (Hardle 1990) is the core of local scoring algorithm. In this paper, we use the back fitting algorithm to estimate the two additive models in equations (8) and (9). There are also several choices for estimating the nonlinear functions $\{g_{il}^{(j)}\}$, $i, l = \pi, h$, commonly known as "smoothing" methods. Here, we use the Nadaraya-Watson kernel regression estimator, also called "kernel smoothing". In order to determine the appropriate kernel used for smoothing we examined all commonly used kernels and found that the Gaussian kernel of order 2 worked the best in terms of the highest R-squared values and smallest mean square error (MSE). Indeed, the choice of the kernel type is not crucial in terms of the MSE criterion as emphasized by Hardle (1990). Hardle (1990) points out that the choice of bandwidth (*h*) is the most important parameter having significant impact on the estimates. The bandwidth controls the span of the data used in smoothing. A too-small bandwidth may result in interpolation of data by joining points and yield ultra-rough estimates. On the other hand, a too-large bandwidth may fit a function close to a linear one, resulting in ultra-smooth estimates. At least as a starting point, using one of the automatic bandwidth selection procedures may be quite useful. For each component of the additive model we use the cross-validation (CV), or leave-one-out, method to select the bandwidth parameter, which is optimal in terms of the prediction ability across different subsamples (Stone 1977). We check the robustness of nonlinear causality tests and AD estimates by repeating the estimates with three other bandwidth choices.

We first report the nonlinear Granger causality tests based on the nonparametric additive model estimates. All tests are performed for four different bandwidth choices. The bandwidth *h* should be chosen such that $h \to 0$ as $T \to \infty$. We have moderately large sample size for each series and the range for each series is small. The automatic bandwidths chosen by the CV method are all less than 0.05. Therefore, we check robustness of additive model causality tests and AD estimates for bandwidths $h = 0.05$, $h = 0.10$ and $h = 0.15$. In order to compute the F-statistic in equation (15), we need to obtain the model degrees of freedoms d_U and d_R. Denote additive models in equations (8) or (9) compactly as $y = m(\mathbf{x}) + \varepsilon$, then the Nadaraya-Watson kernel regression estimate of the function m can be written as $\hat{m} = \mathbf{P}y$, where $\mathbf{P}$ is a matrix that contains the weights used for smoothing. Although there are alternative definitions of model degrees of freedom, we use one of the definitions proposed by Hastie et al. (1989) and obtain the degrees of freedom used to compute the F-statistic as $d = 2\,\mathrm{trace}(\mathbf{P}) - \mathrm{trace}(\mathbf{P}'\mathbf{P})$.

Table 6 reports the F-tests performed on additive model estimates. The degrees of freedom estimates are also given in parentheses. These vary across models and bandwidths, since the weights used in smoothing vary in each case. According to the F-test results reported in Table 6, a bi-directional nonlinear causal link exists between inflation and inflation uncertainty in all countries. Moreover, the results are robust to the various bandwidths used. First, consider the tests with automatic bandwidth selection reported under column named *h*-CV. In this case, the null hypotheses of no Granger causality from inflation to inflation uncertainty and no Granger causality from inflation uncertainty to inflation are both rejected at 1 percent significance level for all countries. Therefore, there is strong evidence of bi-directional nonlinear causality with optimal bandwidth choice. When other bandwidths are considered, we observe that the results obtained with the *h*-CV are preserved, except one case where the null hypothesis of no causality from inflation uncertainty to inflation in the UK is not rejected when $h = 0.15$. Considering that all the CV bandwidths are less than 0.05, large bandwidth results should be less reliable.

[INSERT TABLE 6]

Additive model nonlinear causality tests established strong evidence in favor of the bi-directional nonlinear causality between inflation and inflation uncertainty in all countries. It is also interesting to establish the sign of the predictability between the series to see which ones of the hypotheses proposed by Friedman (1977), Ungar and Zilberfarb (1993), Cukierman and Meltzer (1986) and Holland (1995) are supported by the evidence. When the relationship between the pairs of variables is a nonlinear unknown functional form, the derivative of the function is not constant and the sign of the predictability between the series depends on the values taken by the predictor. In such a case, the standard econometric procedure for testing the predictions of the economic theory using the estimates of derivatives is not directly applicable. For the nonparametric regression models, Stoker (1986, 1991) and Hardle and Stoker (1989) show that nonparametric analysis can be successfully applied, using the AD estimates, in the same mode to test the predictions of economic theory. They also establish the relevant asymptotic theory for statistical testing using AD estimates and show that AD estimates have normal limiting distribution. Yanga et al. (2003) show that same approach is valid for AD estimation in additive models (additive models lend themselves to easy calculation of average derivatives, since no matter the dimension of the regressors $\boldsymbol{x}$, the surface $m(\mathbf{x})$ can be perceived by drawing each $g_{il}^{(j)}(\cdot)$, $i, l = \pi, h, j = 1,2,\ldots, p$, separately). Hence, in order to test the above four hypotheses about the sign of the effect of inflation on inflation uncertainty and *vice versa* we estimate ADs using the additive model estimates with the same choice parameters. As Hardle (1990) points out, arguably the derivatives of optimal kernels may not be optimal for estimating ADs. Observe that the derivative of the kernel function is used as the density kernel for estimating the ADs in equations (6) and (7). The kernel function used as the smoother for obtaining first derivatives should be an odd function. The first derivative of the Gaussian kernel of order 2 is used as the smoother in AD estimators defined in equations (6) and (7) satisfies this requirement.[1]

The three alternative AD estimates for the sign of predictability from inflation to inflation uncertainty as well as from inflation uncertainty to inflation based on the definitions in equations (6)-(8) are given in Table 7. All AD estimates are repeated for lag orders of 4 and 8. In order to check the robustness of the estimates to bandwidth choice we report estimates for bandwidth choices $h = 0.05$, $h = 0.10$ and $h = 0.15$ in addition to the optimal bandwidth *h*-CV.[2] We set the trimming parameter b in equations (7) and (8) such that at least 5 percent of the estimates are trimmed.

Since more than one lagged value of each series enter into equations (8) and (9), Table 7 report the sum of the average derivative estimates relating to the lagged inflation uncertainty variables in the inflation equation (8) as a measure of total impact of inflation uncertainty on inflation. Analogously, the sum of the average derivative estimates corresponding to the lagged inflation variables in equation (9) are reported as a measure of total impact of inflation on inflation uncertainty. Table 7 also reports the standard errors of these total impact derivatives in parentheses, which are calculated using the delta method from the estimate of the covariance matrix of AD estimates.

[1] We restrict our choices to low order kernels since a side effect of higher order kernels is that, by construction, they have negative side lobes and they may yield negative derivative estimates even though the response is positive (Bierens, 1987).
[2] Hardle (1990) points out that the bandwidth choice is more crucial than the kernel choice. Sufficiently smooth kernel weights with well tuned bandwidth will guarantee that all three AD estimators we used will converge to derivatives of $m(\boldsymbol{x})$.

[INSERT TABLE 7]

First, we note that all total impact estimates are positive, irrespective of the bandwidth choice and the type of estimator used. This is the most noteworthy observation in Table 7. Therefore, that the sign of predictability between the series are positive in both directions is uniformly established for all three countries.

In terms of the lag orders, all AD estimates are quite close across all bandwidths and countries for lag orders 4 and 8 we considered, except a few cases, particularly the $\bar{\delta}_{\mathrm{hs}}$ estimator for the impact of inflation on inflation uncertainty for the UK. Thus, the models we have estimated sufficiently capture the dynamic links between the series and are robust in terms of the lag orders used in the study. Among the three alternative AD estimators we used, two trimmed estimators $\bar{\delta}_{\mathrm{hs}}$ and $\bar{\delta}_{\mathrm{s}}$ yield quite close estimates across all bandwidths. However, the untrimmed estimator gave much higher total impact estimates in some cases, mainly for the impact of inflation uncertainty on inflation in all three countries. As we pointed out above the estimator $\bar{\delta}_{\mathrm{p}}$ is ill-behaved for values of the density function estimate $\hat{f}(\mathbf{x})$ that are close to zero. As $\hat{f}(\mathbf{x})$ gets closer to zero, it inflates the average derivative estimate $\bar{\delta}_{\mathrm{p}}$, yielding overestimate of the response. To overcome this inefficiency Hardle and Stoker (1989) proposed the trimmed estimator $\bar{\delta}_{\mathrm{hs}}$. Our results show that the untrimmed estimator behaves well in most cases, but resulted in likely inflated estimates for the response of inflation uncertainty to inflation.

The bandwidth choice used in estimating ADs seems to have significant impact on the size of the estimates in most cases. Particularly, larger total impact estimates are more sensitive to the bandwidth. In most cases, larger bandwidths yield smaller total impact estimates for both the effect of inflation on inflation uncertainty and inflation on inflation uncertainty. Noticeably, in cases where the total impact estimates are sensitive to the bandwidth, the total impact estimates fall as the bandwidth increases. This tendency is likely due to the over-smoothing with high bandwidths. Although we get smaller total impact estimates with higher bandwidths, the sign of the predictability between the series is always positive in both directions. All these observations about the bandwidths hold commonly for Japan, the UK, and the US.

Comparing at the optimal bandwidths chosen by the cross-validation, *h*-CV, the estimates of the total impact of inflation uncertainty on inflation at lag 8 with the $\bar{\delta}_{\mathrm{hs}}$ estimator are 0.952, 0.900, and 0.722 for Japan, the UK, and the US. The responses with lag 4 are very close to these estimates. Analogous to the $\bar{\delta}_{\mathrm{hs}}$ estimator, we obtained quite close total impact estimates at lag 4 and lag 8 with the estimators $\bar{\delta}_{\mathrm{s}}$ and $\bar{\delta}_{\mathrm{p}}$ for all countries. With the direct estimator $\bar{\delta}_{\mathrm{s}}$ the responses of inflation to inflation uncertainty are 1.294, 0.996, and 0.791 for Japan, the UK, and the US. The untrimmed estimator $\bar{\delta}_{\mathrm{p}}$ estimates these responses to be twice as large, but as we discussed above this estimator is most likely to overestimate the ADs.

Considering the response of inflation uncertainty to inflation at the optimal bandwidth choice *h*-CV, all three estimators yielded close total impact estimates for all countries. Moreover, the response of inflation to inflation uncertainty at lags 4 and 8 match each other quite closely across all estimators and countries. The indirect estimator $\bar{\delta}_{\mathrm{hs}}$ estimates the impact of inflation on inflation uncertainty at lag 8 as 0.078, 0.008, and 0.060 for Japan, the UK and the US, while the estimates obtained from the direct estimator $\bar{\delta}_{\mathrm{s}}$ are 0.095, 0.005 and 0.045, and those from the untrimmed indirect estimator $\bar{\delta}_{\mathrm{p}}$ are 0.126, 0.038 and 0.047.

In terms of the sign of the predictability between inflation and inflation uncertainty, in both directions all three countries we examined have the same signs. The responses of inflation and inflation uncertainty to each other are positive in all countries. Furthermore, the total impact of each series on each other estimated by the ADs did not differ significantly across countries, except the impact of inflation on inflation uncertainty in the UK, which is smaller compared to the estimates for Japan and the US. Taking into account that some of the estimates are insignificant at the 5 percent level, it can be argued that the response of inflation uncertainty to inflation in the UK is weaker compared to Japan and the US. In summary, the evidence obtained from the AD estimates for all countries supports the Friedman hypothesis that inflation raises inflation uncertainty and the Cukierman-Meltzer hypothesis that inflation uncertainty has a positive impact on inflation, although the evidence in favor of the Cukierman-Meltzer hypothesis for the UK is somewhat weaker.

The nonparametric AD estimates for all countries agree with the linear VAR estimates in terms of sign. Both models estimate a positive predictive content between the series. The significance of the estimates from both models supports the Friedman hypothesis in all countries. However, the linear model supports the Cukierman-Meltzer hypothesis only for Japan, while the nonlinear estimates support it for all countries, though the evidence for the UK is somewhat weaker.

Our study differs from previous studies on two major points. First, the sample period we cover is much longer, since previous studies mostly concentrate on the post-1980s, while our sample starts in the 1950s. Second, the nonparametric causality tests used in our study are robust to model misspecification and allow general dependence between the series. Causality tests based on linear models will suffer from model specification and hence display low power. Linear causality tests will also display sample period sensitivity due to misspecification when the underlying relationship is nonlinear. Empirical findings of the some of the previous studies will therefore differ from ours while others might be complementary.

In this study, for all three countries we find that inflation significantly raises inflation uncertainty as predicted by Friedman. Our findings agree with the conclusions of Conrad and Karanasos (2005) in terms of the sign of the predictability between the inflation and inflation uncertainty series for all three countries. Our findings are also complementary to the findings in Grier and Perry (1998), where inflation uncertainty significantly raises inflation in the G-7 countries. Our results do not match the evidence for the US obtained in Hwang (2001), who obtained weakly supporting evidence for the Ungar-Zilberfarb hypothesis, while he found no significant impact from inflation uncertainty to inflation.

Baillie et al. (1996), for three high-inflation countries and the United Kingdom, and Conrad and Karanasos (2005) for the United States, find strong evidence in favor of a positive bidirectional relationship in accordance with the predictions of economic theory. We find evidence for the Cukierman–Meltzer hypothesis in all three countries, namely, the US, the UK and Japan. The weaker evidence we obtained in favour of the Cukierman-Meltzer hypothesis for the UK is also the case in Conrad and Karanasos (2005). Grier and Perry (1998) also find a positive impact of inflation uncertainty on inflation in the G7 countries. Grier and Perry (1998) label the Cukierman–Meltzer hypothesis as the ‘opportunistic Fed’. Cukierman and Meltzer show that, in their model, increases in inflation uncertainty raise the optimal average inflation rate by promoting the incentive for the policy-maker to create inflation surprises. The results presented above bear noteworthy implications for macroeconomic modeling and policy-making. All three countries experienced wide variations in their conduct of monetary policy in the last forty years. The country-specific evidence on the Cukierman–Meltzer hypothesis is anticipated given that national central banks adjust their rate of money growth differently to nominal uncertainty depending on their relative preference towards inflation stabilization. Although the countries follow different monetary policies and dispose of different central banking institutions, we find no differences among countries.

IV. Summary and conclusion

The study investigates the relationship between inflation and inflation uncertainty in the G3 countries (Japan, the US, and the UK) for the period 1957-2006. GARCH models generated a measure of inflation uncertainty and linear and nonlinear tests for Granger causality between inflation and inflation uncertainty. The results from the linear Granger-causality approach indicates that inflation significantly raises inflation uncertainty for these countries, as predicted by Friedman (1977) and Ball (1992). However, for Japan, inflation uncertainty has positive predictive power for inflation, supporting the Cukierman and Meltzer (1986) hypothesis. On the other hand, inflation uncertainty has no predictive content for inflation for the US and the UK. The evidence obtained from nonlinear Granger causality tests indicates a bi-directional nonlinear predictive power between inflation and inflation uncertainty for the countries. The sign and size of the predictability between the series is estimated nonparametrically using alternative average derivative estimators. The sign of the predictability between the series is estimated to be positive in both directions. Thus, the evidence shows that the Friedman and Cukierman-Meltzer hypotheses apply in all three G3 countries. The results presented above bear noteworthy implications for macroeconomic modelling and policy-making. All three countries experienced wide variations in their conduct of monetary policy in the last forty years. The country-specific evidence on the Cukierman–Meltzer hypothesis is anticipated given that national central banks adjust their rate of money growth differently to nominal uncertainty depending on their relative preference towards inflation stabilization. Although the countries follow different monetary policies and dispose of different central banking institutions, we find no differences among countries. An increase in inflation that changes either the structure of inflation uncertainty dynamics or the long-run level of inflation has the potential to disrupt credibility and accountability. Berument (1999) observed that the change in the expected inflation rate was slower than actual inflation, when a stabilization program lacked credibility. Therefore, the results of this study are crucial in re-examining those hypotheses for future researchers.

In future work we seek to extend the sample of countries and investigate whether the robust relation between inflation and uncertainty we find in the G3 holds throughout the higher inflation developing countries. As central bank independence (CBI) index changes over time, the rankings of CBI might not be uniform over time. We also want to examine if central bank independence and inflation policy can be more formally tested in an expanded sample of countries through a longer time span.

References

Baek, Ehung, and William Brock (1992), A general test for non-linear Granger causality: Bivariate model, Working Paper, Iowa State University and University of Wisconsin.

Baillie, Richard T., Tim Bollerslev, and Hans O. Mikkelsen (1996), Fractionally integrated generalized autoregressive conditional heteroskedasticity, *Journal of Econometrics* **74**: 3-30.

Ball, Laurence (1992), Why does high inflation raise inflation uncertainty?, *Journal of Monetary Economic* **29**: 371-388.

Bell, David N. F., Jim Ray, and Jim Malley (1996), A nonparametric approach to nonlinear causality testing, *Economics Letters*, **51**: 7–18.

Berument, Hakan (1999), The impact of inflation uncertainty on interest rates in the UK, *Scottish Journal of Political Economy* **46**: 207-218.

Berument, Hakan, and Nergis Dincer (2005), Inflation and inflation uncertainty in the G-7 countries, *Physica A* **348**: 371-379.

Bierens, Herman J. (1987), *Kernel estimators of regression functions, Advances in econometrics*, Cambridge, Cambridge University Press.

Bollerslev, Tim (1986), Generalised autoregressive conditional heteroskedasticity, *Journal of Economics* **31**: 307-326.

Cecchetti, S.G. and Stefan Krause (2001), Financial structure, macroeconomic stability and monetary policy, Working Paper 8354, NBER.

Conrad, Christian, and Menelaos Karanasos (2005), On the inflation-uncertainty hypothesis in the USA, Japan and the UK: A dual long memory approach, *Japan and the World Economy* **17:** 327 - 343.

Cukierman, Alex, and Allan H. Meltzer (1986), A theory of ambiguity, credibility, and inflation under discretion and asymmetric information, *Econometrica* **54:** 1099-1128.

Diks, Cees, and Valentyn Panchenko (2006), A new statistic and practical guidelines for nonparametric Granger causality testing. *Journal of Economic Dynamics & Control* **30**:1647–1669.

Engle, Robert F. (1982),Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation, *Econometrica* **50**: 987-1007.

Engle, Robert F. (1983), Estimates of the variance of US inflation based upon the ARCH model, *Journal of Money, Credit and Banking* **15**: 286-301.

Friedman, Milton (1977), Nobel lecture: Inflation and unemployment, *Journal of Political Economy* **85:** 451-472.

Granger, Clive W. J. (1969), Investigating causal relations by econometrics models and cross spectral methods, *Econometrica* **37:** 424-438.

Granger, Clive W. J. (1988), Some recent developments in a concept of causality, *Journal of Econometrics* **39:** 199-211.

Grier, Kevin B., and Mark J. Perry (1998), On inflation and inflation uncertainty in the G7 countries, *Journal of International Money and Finance* **17:** 671-689.

Hardle, Wolfgang (1990), *Applied nonparametric regression,* NewYork, Cambridge University Press.

Hardle, Wolfgang, and Thomas M. Stoker (1989), Investigating smooth multiple regression by the method of average derivatives, *Journal of the American Statistical Association* **84**: 986-995.

Hastie, Trevor, and Robert Tibshirani, (1987), Generalized additive models: Some applications, *Journal of the American Statistical Association* **82:** 371–386.

Hastie, Trevor, and Robert Tibshirani (1990), *Generalized additive models*, Chapman and Hall, London.

Hastie, Trevor, Robert Tibshirani, and Buja Andreas (1989), Linear smoothers and additive models, *Annals of Statistics* **17**: 453–555.

Hiemstra, Craig and Jonathan D. Jones (1994), Testing for linear and non-linear Granger causality in the stock price–volume relation, *Journal of Finance* **5:** 1639–1664.

Holland, Steven (1995), Inflation and uncertainty: Tests for temporal ordering, *Journal of Money, Credit, and Banking* **27:** 827-837.

Hwang, Yung (2001), Relationship between inflation rate and inflation uncertainty, *Economics Letters* **73**:179-186.

Koop, Gary and Simon M. Potter (2001), Are apparent findings of nonlinearity due to structural instability in economic time series?, *Econometrics Journal* **4**: 37–55.

Laurent, S. and J. P. Peters, (2002), G@RCH 2.2: an Ox package for estimating and forecasting various ARCH models, *Journal of Economic Surveys* **3:** 447-485.

McLeod, Allan I., and William K. Li (1983), Diagnostic checking ARMA time series models using squared residual autocorrelations, *Journal Time Series Analysis* **4**: 269–73.

Ozdemir, Zeynel A. (2010), Dynamics of inflation, output growth and their uncertainty in the UK: An empirical analysis, *Manchester School* **78**: 511–537.

Panchenko, Valentyn (2006), *Nonparametric methods in economics and finance: Dependence, causality and prediction,* Amsterdam, Rozenberg.

Phillips, Peter C. and Pierre Perron (1988), Testing for a unit root in time series regression, *Biometrica* **75:** 335-346.

Phillips, Peter C. and Ouliaris, S. (1990), Asymptotic properties of residual based tests for cointegration, *Econometrica*, **58**: 165–93.

Powell, James L., James H. Stock, and Thomas M. Stoker (1989), Semiparametric estimation of index coefficients, *Econometrica* **57**: 1403-1430.

Stock, James, and Mark Watson (2002), Has the business cycle changed and why?, Working Paper 9127. NBER.

Stoker, Thomas M. (1986), Consistent estimation of scaled coefficients, *Econometrica* **54**:1461–1481.

Stoker, Thomas M. (1991), *Equivalence of direct, indirect, and slope estimators of average derivatives*, in W. Barnett, J. Powell, and G. Tauchen, eds., *Nonparametric and semiparametric methods in econometrics and statistics*, Cambridge, Cambridge University Press.

Stone, M. (1977), Asymptotics for and against cross-validation, *Biometrika* **64:** 29-35.

Ungar, Meyer and Ben_Zion Zilberfarb, (1993) Inflation and its unpredictability - theory and empirical evidence, *Journal of Money, Credit, and Banking* **25**: 709-720.

Yanga, Lijian, Stefan Sperlichb, and Wolfgang Hardle (2003), Derivative estimation and testing in generalized additive models, *Journal of Statistical Planning and Inference* **115**: 521-542.

Table 1. Unit root test results for the inflation series

	Level	
Series	$Z(t_{\mu})^{a}$	$Z(t_{\tau})^{b}$
Inflation of Japan	-17.109*	-18.745*
Inflation uncertainty of Japan	-4.607*	-5.518*
Inflation of the UK	-11.199*	-11.364*
Inflation uncertainty of the UK	-9.692*	-10.331*
Inflation of the US	-10.199*	-10.232*
Inflation uncertainty of the US	-5.532*	-5.623*

Notes: *, **, *** indicate significance at the 1%, 5%, and 10% levels, respectively. [a] Test allows for a constant; one-sided test of the null hypothesis that the variable is nonstationary; 1%, 5%, and 10% critical values equal -3.458, -2.871, and -2.593, respectively.
[b] Test allows for a constant and a linear trend; one-sided test of the null hypothesis that the variable is nonstationary; 1%, 5%, and 10% critical values equal -3.997, -3.431, and -3.161, respectively.

Table 2. Summary statistics for inflation series

Countries	μ	σ	*S*	*K*	JB	Q_6	Q_{12}	Q_6^2	Q_{12}^2	ARCH-LM(6)	ARCH-LM(12)
Japan	0.126	0.239	1.70* (0.00)	5.71* (0.00)	1101.2* (0.00)	369.3* (0.00)	719.3* (0.00)	313.8* (0.00)	460.4* (0.00)	189.4* (0.00)	213.8* (0.00)
UK	0.206	0.221	2.23* (0.00)	11.28* (0.00)	3666.1* (0.00)	1095.2* (0.00)	1848.2* (0.00)	129.8* (0.00)	156.6* (0.00)	157.4* (0.00)	160.5* (0.00)
USA	0.144	0.128	1.01* (0.00)	2.37* (0.00)	241.1* (0.00)	1127.8* (0.00)	2090.9* (0.00)	514.3* (0.00)	849.1* (0.00)	297.7* (0.00)	310.6* (0.00)

Notes: μ denotes the average inflation rate over the February 1957–October 2006 period, and σ its standard deviation. *S* and *K* are the estimated skewness and kurtosis. JB is the Jarque–Bera statistic for normality. $Q_{(m)}$ and $Q^2_{(m)}$ give the Ljung-Box test statistics for inflation and the squared deviations of the inflation rate from its sample mean up to *m*th order serial correlation. ARCH-LM(*m*) gives the ARCH-LM test statistics for the series up to *m*th order of ARCH effects. Numbers in parentheses are p-values. * indicates significance at the 0.05 level.

Table 3. Estimation results of AR(*k*)-GARCH(1,1) model for the inflation rate series

Panel A: The estimated AR(17)-GARCH(1,1) model for Japanese inflation rate

$$\pi_t = \underset{(1.62)}{0.06} - \underset{(-0.49)}{0.02}\,\pi_{t-1} + \underset{(0.04)}{0.01}\,\pi_{t-2} + \underset{(2.59)}{0.11}\,\pi_{t-3} + \underset{(0.87)}{0.04}\,\pi_{t-4} + \underset{(3.92)}{0.16}\,\pi_{t-5} + \underset{(1.43)}{0.07}\,\pi_{t-6} + \underset{(1.22)}{0.06}\,\pi_{t-7} + \underset{(2.565)}{0.11}\,\pi_{t-8} + \underset{(2.77)}{0.13}\,\pi_{t-9}$$

$$+ \underset{(2.99)}{0.19}\,\pi_{t-10} + \underset{(1.59)}{0.07}\,\pi_{t-11} - \underset{(-2.89)}{0.12}\,\pi_{t-12} - \underset{(-0.63)}{0.03}\,\pi_{t-13} - \underset{(-0.98)}{0.04}\,\pi_{t-14} + \underset{(1.55)}{0.07}\,\pi_{t-15} + \underset{(0.46)}{0.02}\,\pi_{t-16} + \underset{(1.45)}{0.06}\,\pi_{t-17} + u_t$$

$$h_{\pi t} = \underset{(2.73)}{0.002} + \underset{(2.73)}{0.22}\,u_{t-1}^2 + \underset{(10.11)}{0.74}\,h_{\pi,t-1}$$

Q(6)= 11.417 [0.076], Q(12)= 18.235 [0.108]

Panel B: The estimated AR(10)-GARCH(1,1) model for the US inflation rate

$$\pi_t = \underset{(1.89)}{0.11} + \underset{(5.80)}{0.32}\,\pi_{t-1} + \underset{(1.99)}{0.12}\,\pi_{t-2} - \underset{(-0.63)}{0.04}\,\pi_{t-3} + \underset{(0.99)}{0.06}\,\pi_{t-4} + \underset{(1.73)}{0.11}\,\pi_{t-5} + \underset{(1.15)}{0.04}\,\pi_{t-6} + \underset{(1.14)}{0.05}\,\pi_{t-7} + \underset{(0.72)}{0.03}\,\pi_{t-8} + \underset{(1.34)}{0.05}\,\pi_{t-9} + \underset{(3.25)}{0.13}\,\pi_{t-10} + u_t$$

$$h_{\pi t} = \underset{(2.31)}{0.0004} + \underset{(2.32)}{0.25}\,u_{t-1}^2 + \underset{(8.43)}{0.73}\,h_{\pi,t-1}$$

Q(6)= 5.345 [0.500], Q(12)= 25.828 [0.011]

Panel C: The estimated AR(6)-GARCH(1,1) model for the UK inflation rate

$$\pi_t = \underset{(2.49)}{0.16} + \underset{(6.51)}{0.31}\,\pi_{t-1} + \underset{(4.31)}{0.23}\,\pi_{t-2} + \underset{(1.32)}{0.06}\,\pi_{t-3} - \underset{(-0.19)}{0.02}\,\pi_{t-4} + \underset{(2.98)}{0.14}\,\pi_{t-5} + \underset{(2.02)}{0.11}\,\pi_{t-6} + u_t$$

$$h_{\pi t} = \underset{(0.98)}{0.004} + \underset{(1.92)}{0.50}\,u_{t-1}^2 + \underset{(1.28)}{0.43}\,h_{\pi,t-1}$$

Q(6)= 6.087 [0.413], Q(12)= 14.140 [0.291]

Notes: t-statistics for each coefficient is given in parenthesis. The Q-test is the Ljung-Box test and its F statistics is given in parenthesis.

Table 4. Linear Granger-causality test results between inflation and inflation uncertainty

	Japan	UK	US
Panel A	H_0:Inflation does not Granger-cause inflation uncertainty		
Four lags	35.730* [0.000] (+)	41.644* [0.000] (+)	2.583* [0.036] (+)
Eight lags	18.726* [0.000] (+)	20.862* [0.000] (+)	2.064* [0.037] (+)
Panel B	H_0:Inflation uncertainty does not Granger-cause inflation		
Four lags	10.613* [0.000] (+)	2.185 [0.069] (+)	1.045 [0.383] (+)
Eight lags	2.198* [0.026] (+)	1.458 [0.169] (+)	0.705 [0.686] (+)

Notes: †,*,** denote rejections of the null hypothesis at 10%, 5%, and 1% significance levels, respectively; the numbers in brackets are the p-values. In panel A and B, (+) shows that the sum of the lagged coefficients is positive.

Table 5. Residual diagnostics of VAR(*k*) model residuals

		Panel A: Ljung-Box Q test		Panel B: McLeod and Li Q^2 test	
K	Series	Q(6)	Q(12)	$Q^2(6)$	$Q^2(12)$
Panel 1: Results for Japan					
Four lags	$\varepsilon_{\pi_t, h_{\pi,t}}$	4.096 (0.663)	34.345 (0.000)	156.2 (0.000)	242.9 (0.000)
Four lags	$\varepsilon_{h_{\pi,t}, \pi_t}$	6.308 (0.389)	12.758 (0.386)	3.670 (0.721)	16.43 (0.172)
Eight lags	$\varepsilon_{\pi_t, h_{\pi,t}}$	0.281 (0.999)	27.822 (0.005)	154.9 (0.000)	265.7 (0.000)
Eight lags	$\varepsilon_{h_{\pi,t}, \pi_t}$	0.099 (0.999)	5.172 (0.951)	3.701 (0.717)	13.72 (0.318)
Panel 2: Results for the UK					
Four lags	$\varepsilon_{\pi_t, h_{\pi,t}}$	11.890 (0.064)	23.206 (0.026)	29.56 (0.000)	31.43 (0.001)
Four lags	$\varepsilon_{h_{\pi,t}, \pi_t}$	3.397 (0.757)	17.401 (0.135)	1.617 (0.951)	3.519 (0.990)
Eight lags	$\varepsilon_{\pi_t, h_{\pi,t}}$	0.201 (0.999)	13.084 (0.362)	21.14 (0.001)	25.45 (0.012)
Eight lags	$\varepsilon_{h_{\pi,t}, \pi_t}$	0.096 (0.999)	12.644 (0.395)	1.222 (0.975)	3.829 (0.986)
Panel 3: Results for US					
Four lags	$\varepsilon_{\pi_t, h_{\pi,t}}$	13.053 (0.042)	63.431 (0.000)	49.80 (0.000)	79.75 (0.000)
Four lags	$\varepsilon_{h_{\pi,t}, \pi_t}$	7.904 (0.245)	20.382 (0.060)	2.386 (0.881)	4.402 (0.975)
Eight lags	$\varepsilon_{\pi_t, h_{\pi,t}}$	1.363 (0.968)	44.151 (0.000)	44.65 (0.000)	65.54 (0.000)
Eight lags	$\varepsilon_{h_{\pi,t}, \pi_t}$	0.148 (0.999)	9.612 (0.649)	5.320 (0.503)	7.688 (0.809)

Notes: This table provides the diagnostics tests for error terms obtained from VAR model. The Q-test is the Ljung-Box test and the Q^2-test is the McLeod-Li test, at 6 and 12 lags. p-values for statistical significance are given in parentheses.

Table 6. **Pairwise nonlinear-Granger causality tests between the inflation and inflation uncertainty**

Countries	Null Hypothesis	*Ly*=*Lx*	*h*-CV	*h* = 0.05	*h* = 0.10	*h* = 0.15
Japan	$\pi_t \neq> h_{\pi t}$	4	F(15.536,575.732)=3.275**	F(5.682,573.836)=3.325**	F(4.209,576.34)=3.503**	F(3.501,577.637)=3.600**
	$h_{\pi t} \neq> \pi_t$	4	F(27.223,575.4)=34.511**	F(8.634,576.788)=78.687**	F(6.48,578.611)=94.285**	F(5.37,579.507)=103.963**
	$\pi_t \neq> h_{\pi t}$	8	F(7.255,536.408)=8.412**	F(9.361,552.543)=3.527**	F(6.881,557.431)=3.537**	F(5.694,559.952)=3.502**
	$h_{\pi t} \neq> \pi_t$	8	F(37.979,549.012)=34.195**	F(15.761,558.943)=47.327**	F(11.77,562.32)=55.484**	F(9.708,563.966)=60.667**
UK	$\pi_t \neq> h_{\pi t}$	4	F(12.69,572.698)=3.046**	F(5.666,573.772)=2.577*	F(4.347,576.343)=2.064†	F(3.704,577.683)=1.769
	$h_{\pi t} \neq> \pi_t$	4	F(16.49,566.652)=76.114**	F(8.35,576.456)=114.985**	F(6.216,578.212)=133.132**	F(5.135,579.113)=144.102**
	$\pi_t \neq> h_{\pi t}$	8	F(12.349,553.563)=4.800**	F(9.846,552.338)=3.712**	F(7.606,557.358)=3.820**	F(6.516,559.967)=3.778**
	$h_{\pi t} \neq> \pi_t$	8	F(32.93,560.892)=43.666**	F(15.017,557.509)=68.406**	F(11.13,560.883)=78.009**	F(9.17,562.621)=83.468**
US	$\pi_t \neq> h_{\pi t}$	4	F(3.172,571.278)=4.311**	F(5.378,570.9)=3.074**	F(4.07,573.864)=3.425**	F(3.42,575.431)=3.557*
	$h_{\pi t} \neq> \pi_t$	4	F(7.651,573.667)=85.250**	F(11.979,577.5)=50.021**	F(9.338,579.132)=57.460**	F(7.941,579.953)=62.033**
	$\pi_t \neq> h_{\pi t}$	8	F(10.341,547.495)=4.297**	F(9.353,546.805)=2.950**	F(7.082,552.56)=3.190**	F(5.961,555.605)=3.315**
	$h_{\pi t} \neq> \pi_t$	8	F(37.898,562.53)=23.484**	F(22.287,559.739)=29.728**	F(17.388,562.865)=33.062**	F(14.786,564.431)=34.988**

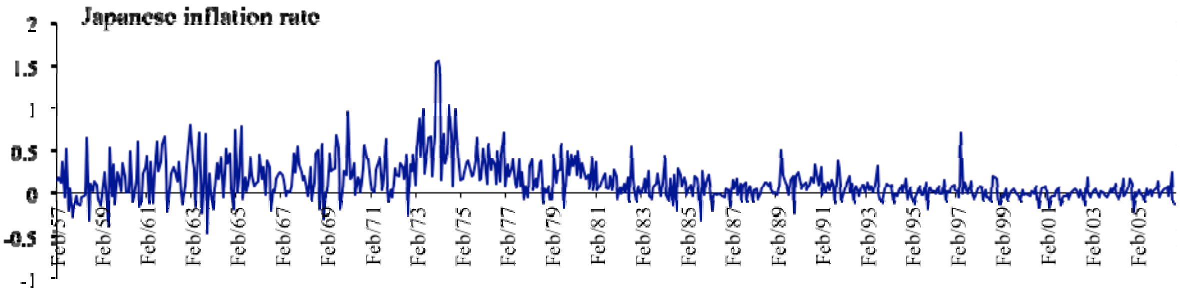
Notes: This table provides the results of the nonlinear causality tests based on the additive models, applied for the inflation and its uncertainty. F(v_1,v_2) is the F-statistic defined in equation (15), with v_1 denoting the numerator degrees of freedom (d_U- d_R) and v_1 denoting the denominator degrees of freedom (T- d_U). h is the bandwidth used for the kernel estimator such that observation falling in the range [x-k(h),x+k(h)] are used the obtain smoothed estimate at x. h-CV refers to the estimates where the bandwidth is automatically selected for each smooth component of the additive model using cross-validation. For other bandwidths reported, the same bandwidth is used for all smooth components.
†,*,** denote rejections of the null hypothesis at 10%, 5%, and 1% significance levels, respectively; and the symbol "≠>" implies does not nonlinear-Granger cause. The test statistic is approximately distributed as F and the critical values can be obtained from the standard F-distribution tables.

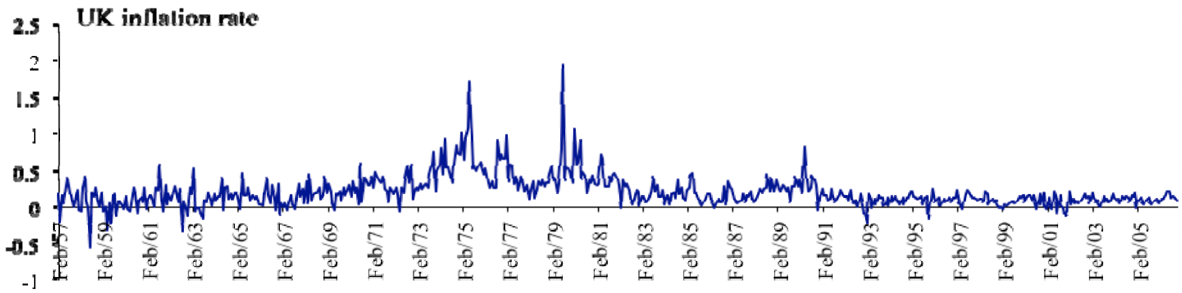
Table 7. Average derivative estimates for the sign of the predictability

	Null Hypothesis	*Ly*=*Lx*	*h*-CV	*h* = 0.05	*h* = 0.10	*h* = 0.15
Japan	$\bar{\delta}_{\mathrm{hs}}: h_{\pi t} \Rightarrow \pi_t$	4	0.929^{**} (0.244)	0.800^{**} (0.106)	0.712^{**} (0.208)	0.441^{**} (0.007)
	$\bar{\delta}_{\mathrm{hs}}: h_{\pi t} \Rightarrow \pi_t$	8	0.952^{**} (0.262)	0.848^{**} (0.117)	0.829^{*} (0.404)	0.498^{**} (0.021)
	$\bar{\delta}_{\mathrm{hs}}: \pi_t \Rightarrow h_{\pi t}$	4	0.080^{*} (0.038)	0.103^{**} (0.026)	0.094^{**} (0.030)	0.125^{**} (0.022)
	$\bar{\delta}_{\mathrm{hs}}: \pi_t \Rightarrow h_{\pi t}$	8	0.078 (0.059)	0.094^{**} (0.032)	0.082^{*} (0.039)	0.105^{**} (0.038)
	$\bar{\delta}_{\mathrm{s}}: h_{\pi t} \Rightarrow \pi_t$	4	1.328^{*} (0.570)	1.297^{**} (0.382)	1.292^{**} (0.296)	0.873^{**} (0.057)
	$\bar{\delta}_{\mathrm{s}}: h_{\pi t} \Rightarrow \pi_t$	8	1.294^{*} (0.618)	1.290^{**} (0.421)	1.262^{**} (0.274)	0.848^{**} (0.072)
	$\bar{\delta}_{\mathrm{s}}: \pi_t \Rightarrow h_{\pi t}$	4	0.083 (0.059)	0.089^{*} (0.044)	0.087^{*} (0.051)	0.109^{*} (0.048)
	$\bar{\delta}_{\mathrm{s}}: \pi_t \Rightarrow h_{\pi t}$	8	0.095 (0.094)	0.085 (0.051)	0.080 (0.061)	0.092 (0.074)
	$\bar{\delta}_{\mathrm{p}}: h_{\pi t} \Rightarrow \pi_t$	4	2.102^{**} (0.407)	2.014^{**} (0.244)	1.956^{**} (0.252)	0.874^{**} (0.032)
	$\bar{\delta}_{\mathrm{p}}: h_{\pi t} \Rightarrow \pi_t$	8	2.105^{**} (0.440)	2.020^{**} (0.269)	1.961^{**} (0.339)	0.877^{**} (0.046)
	$\bar{\delta}_{\mathrm{p}}: \pi_t \Rightarrow h_{\pi t}$	4	0.124^{**} (0.048)	0.127^{**} (0.035)	0.125^{**} (0.04)	0.110^{**} (0.035)
	$\bar{\delta}_{\mathrm{p}}: \pi_t \Rightarrow h_{\pi t}$	8	0.126 (0.077)	0.128^{**} (0.041)	0.126 (0.050)	0.111^{**} (0.056)
UK	$\bar{\delta}_{\mathrm{hs}}: h_{\pi t} \Rightarrow \pi_t$	4	0.771^{**} (0.193)	0.736^{**} (0.166)	0.499^{**} (0.175)	0.310^{**} (0.029)
	$\bar{\delta}_{\mathrm{hs}}: h_{\pi t} \Rightarrow \pi_t$	8	0.900^{**} (0.251)	0.990^{**} (0.241)	0.645^{*} (0.325)	0.399^{**} (0.039)
	$\bar{\delta}_{\mathrm{hs}}: \pi_t \Rightarrow h_{\pi t}$	4	0.007 (0.059)	0.041 (0.039)	0.056 (0.038)	0.104^{**} (0.029)
	$\bar{\delta}_{\mathrm{hs}}: \pi_t \Rightarrow h_{\pi t}$	8	0.008 (0.060)	0.032 (0.044)	0.038 (0.045)	0.093^{*} (0.042)
	$\bar{\delta}_{\mathrm{s}}: h_{\pi t} \Rightarrow \pi_t$	4	0.970^{*} (0.387)	0.954^{**} (0.235)	0.865^{**} (0.165)	0.603^{**} (0.000)
	$\bar{\delta}_{\mathrm{s}}: h_{\pi t} \Rightarrow \pi_t$	8	0.996^{*} (0.417)	0.956^{**} (0.240)	0.898^{**} (0.145)	0.609^{**} (0.000)
	$\bar{\delta}_{\mathrm{s}}: \pi_t \Rightarrow h_{\pi t}$	4	0.005 (0.085)	0.031 (0.062)	0.045 (0.063)	0.078 (0.067)
	$\bar{\delta}_{\mathrm{s}}: \pi_t \Rightarrow h_{\pi t}$	8	0.005 (0.101)	0.028 (0.062)	0.035 (0.065)	0.063 (0.081)
	$\bar{\delta}_{\mathrm{p}}: h_{\pi t} \Rightarrow \pi_t$	4	2.356^{**} (0.29)	1.511^{**} (0.200)	1.123^{**} (0.170)	0.532^{**} (0.015)
	$\bar{\delta}_{\mathrm{p}}: h_{\pi t} \Rightarrow \pi_t$	8	2.428^{**} (0.334)	1.545^{**} (0.240)	1.144^{**} (0.235)	0.539^{**} (0.02)
	$\bar{\delta}_{\mathrm{p}}: \pi_t \Rightarrow h_{\pi t}$	4	0.037 (0.072)	0.055 (0.050)	0.061 (0.051)	0.064 (0.048)
	$\bar{\delta}_{\mathrm{p}}: \pi_t \Rightarrow h_{\pi t}$	8	$0.038^{\dagger}$ (0.081)	0.056 (0.053)	0.062 (0.055)	0.065 (0.061)
US	$\bar{\delta}_{\mathrm{hs}}: h_{\pi t} \Rightarrow \pi_t$	4	0.585^{**} (0.206)	0.416^{**} (0.070)	0.291^{**} (0.013)	0.146^{*} (0.067)
	$\bar{\delta}_{\mathrm{hs}}: h_{\pi t} \Rightarrow \pi_t$	8	0.722 (0.448)	0.578^{**} (0.205)	0.388^{**} (0.017)	0.308 (0.23)
	$\bar{\delta}_{\mathrm{hs}}: \pi_t \Rightarrow h_{\pi t}$	4	0.019 (0.022)	0.036^{**} (0.011)	0.043^{**} (0.01)	0.045^{**} (0.009)
	$\bar{\delta}_{\mathrm{hs}}: \pi_t \Rightarrow h_{\pi t}$	8	0.060^{**} (0.015)	0.036^{**} (0.013)	0.038^{**} (0.013)	0.041^{**} (0.015)
	$\bar{\delta}_{\mathrm{s}}: h_{\pi t} \Rightarrow \pi_t$	4	0.767^{**} (0.223)	0.717^{**} (0.088)	0.394^{**} (0.000)	0.778^{**} (0.000)
	$\bar{\delta}_{\mathrm{s}}: h_{\pi t} \Rightarrow \pi_t$	8	0.791^{**} (0.214)	0.763^{**} (0.140)	0.394^{**} (0.000)	0.778^{**} (0.000)
	$\bar{\delta}_{\mathrm{s}}: \pi_t \Rightarrow h_{\pi t}$	4	0.020 (0.034)	0.027 (0.022)	$0.037^{\dagger}$ (0.022)	0.037 (0.031)
	$\bar{\delta}_{\mathrm{s}}: \pi_t \Rightarrow h_{\pi t}$	8	$0.045^{\dagger}$ (0.025)	0.026 (0.024)	0.033 (0.025)	0.030 (0.037)
	$\bar{\delta}_{\mathrm{p}}: h_{\pi t} \Rightarrow \pi_t$	4	2.126^{**} (0.215)	0.998^{**} (0.079)	0.613^{**} (0.006)	0.216^{**} (0.033)
	$\bar{\delta}_{\mathrm{p}}: h_{\pi t} \Rightarrow \pi_t$	8	2.129^{**} (0.331)	1.000^{**} (0.172)	0.615^{**} (0.008)	0.217 (0.115)
	$\bar{\delta}_{\mathrm{p}}: \pi_t \Rightarrow h_{\pi t}$	4	0.044 (0.028)	0.045^{**} (0.017)	0.046^{**} (0.016)	0.041^{*} (0.020)
	$\bar{\delta}_{\mathrm{p}}: \pi_t \Rightarrow h_{\pi t}$	8	0.047^{*} (0.020)	0.048^{*} (0.019)	0.048^{*} (0.019)	0.042 (0.026)

Notes: The estimates of the average derivatives (AD) are sums relating to lags of inflation in the inflation uncertainty equation ($\pi_t \Rightarrow h_{\pi t}$), and to lags of inflation uncertainty in the inflation equation ($h_{\pi t} \Rightarrow \pi_t$). *h* is bandwidth for kernel estimator. *h*-CV refers to the estimates where bandwidth is automatically selected for each smooth component of the AD using cross-validation. In the rest, the same bandwidth is used for all smooth components. Standard errors of the sum of the ADs in parentheses. †,*,** denote rejection of the null hypothesis at the 10%, 5%, and 1% significance levels. The tests are asymptotically normally distributed.

Figure 1. Monthly inflation rates for the period February 1957-October 2006





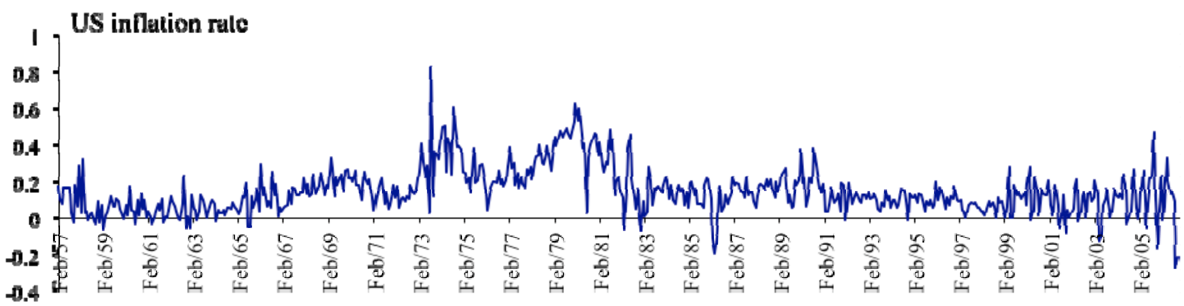
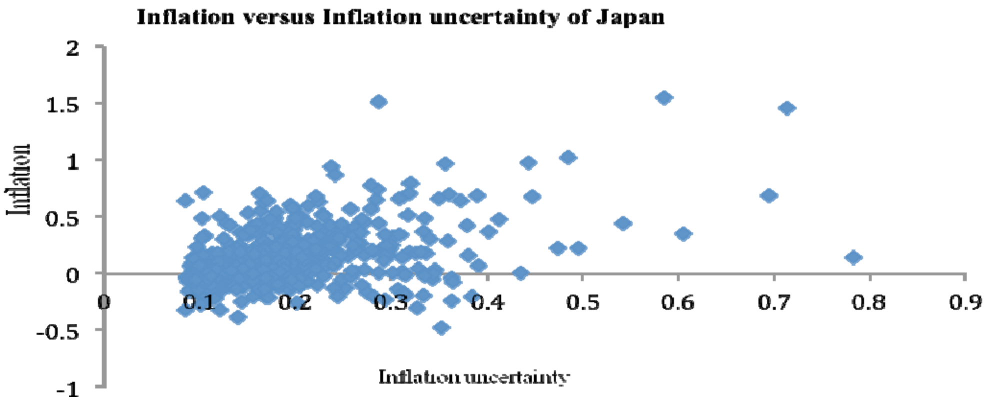
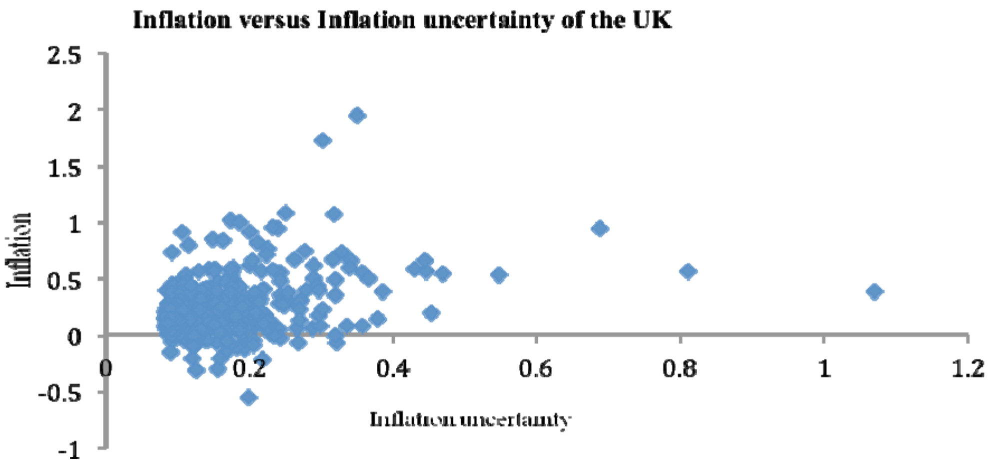
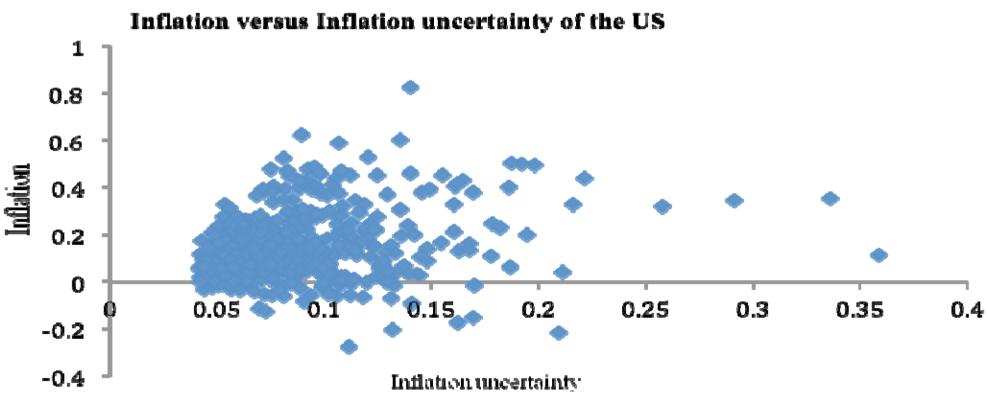


Figure 2. Inflation versus inflation uncertainty fort he period February 1957-October 2006


Inflation versus Inflation uncertainty of Japan
Inflation
Inflation uncertainty


Inflation versus Inflation uncertainty of the UK
Inflation
Inflation uncertainty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Inflation
Inflation uncertainty