Economics Letters 75 (2002) 293–301

economics letters

www.elsevier.com/locate/econbase

Inflation and output growth uncertainty and their relationship with inflation and output growth

Stilianos Fountas[a], Menelaos Karanasos[b,*], Jinki Kim[b]

[a]Department of Economics, National University of Ireland, Galway, Ireland
[b]Department of Economics and Related Studies, University of York, Heslington, York YO10 5DD, UK

Received 20 May 2001; accepted 12 September 2001

Abstract

Using a bivariate GARCH model of inflation and output growth we find evidence that higher inflation and more inflation uncertainty lead to lower output growth in the Japanese economy. These results support the argument of a price stability objective for the monetary authority.

Keywords: Inflation; Output growth; Uncertainty; Granger-causality; Bivariate GARCH

JEL classification: C22; E0

1. Introduction

Inflation uncertainty represents an important determinant of the real costs of inflation. According to Friedman (1977), a rise in the average rate of inflation leads to more uncertainty about the rate of inflation, economic inefficiency, and a lower output. Given the destabilising effect on output caused by high average inflation, the monetary authority might have an incentive to respond to more inflation uncertainty by contractionary monetary policy. This is the 'stabilising Fed' hypothesis advanced by Holland (1995). The more independent a Central Bank is, the more likely to observe evidence in favour of the 'stabilising Fed' hypothesis. Therefore, Central Banks whose overriding objective is price stability and which are independent from the political process, would be expected to tighten if evidence of a rise in average inflation is available.

In this paper, the above issues are analysed empirically for Japan with the use of a bivariate Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model that includes output

*Corresponding author. Tel.: +44-1904-433-799; fax: +44-1904-433-759.
E-mail address: mk16@york.ac.uk (M. Karanasos).

0165-1765/02/$ – see front matter
PII: S0165-1765(02)00009-5

growth and inflation. Our estimated model is used to generate the conditional variances of inflation and output growth as proxies of inflation and output growth uncertainty, respectively, and perform Granger-causality tests.[1] This model allows us to examine the causal relationships between inflation and output growth, on the one hand, and uncertainty about inflation and output growth, on the other hand. The choice of Japan is based on several grounds. First, this country represents the second largest economy in the world. Second, the Japanese economy during the 1990s was plagued by a deflationary episode associated with low or zero rates of inflation and low output growth rates. It would be interesting to find out whether the low output growth rates can be associated with the rate of inflation and the corresponding inflation uncertainty as predicted by Friedman (1977).

Our methodology allows us to test for evidence on all the bidirectional causality relationships between inflation and output growth, on the one hand, and uncertainty about inflation and output growth, on the other hand. Macroeconomic theory provides us with the predicted effects for these relationships which are discussed in Section 2. Section 3 presents our econometric model and Section 4 reports and discusses our results. Finally, Section 5 summarises our main conclusions and draws some policy implications.

2. Theory

Economic theory supplies the economic interpretation for the predicted relationships between nominal (inflation) uncertainty, real (output growth) uncertainty, output growth, and inflation. The total number of testable hypotheses regarding bidirectional causality among these four variables is 12.

The most well known hypotheses are the ones that relate inflation to inflation uncertainty and output growth. Friedman (1977) provided an intuitive argument that higher inflation leads to more uncertainty about inflation. Ball (1992), using an asymmetric information game, offers a formal derivation of Friedman's hypothesis that higher inflation causes more inflation uncertainty.

The causal effect of inflation uncertainty on inflation has been analysed in the theoretical macro literature by Cukierman and Meltzer (1986). Using the well-known Barro–Gordon model, Cukierman and Meltzer (1986) show that an increase in uncertainty about money growth and inflation will raise the optimal average inflation rate because it provides an incentive to the policymaker to create an inflation surprise in order to stimulate output growth. Therefore, the prediction of the Cukierman–Meltzer analysis is that higher inflation uncertainty leads to more inflation. Holland (1995) claims that, in the presence of a stabilisation motive on the part of the policymaker, an increase in inflation uncertainty will invite a tight monetary policy response and a lower average inflation rate in order to minimise the real costs of inflation uncertainty. This is more likely to happen under Central Bank independence and a commitment to long-run price stability. Hence, the prediction of the stabilisation hypothesis runs opposite to that of the Cukierman–Meltzer theory, i.e., a negative causal effect of inflation uncertainty on inflation.

Friedman (1977) argued that higher inflation uncertainty distorts the effectiveness of the price mechanism in allocating resources efficiently and, hence, causes a negative output effect, i.e., a negative causal effect of inflation uncertainty on real growth. It would be expected that the effect of

[1] For an alternative empirical methodology focusing on a smaller number of testable hypotheses and US data, see Grier and Perry (2000).

output growth on inflation uncertainty would be positive. As higher output growth leads to more inflation (the short-run Phillips curve), the uncertainty about inflation would also increase, according to the Friedman hypothesis.

We now focus our attention on the bidirectional causality between output growth uncertainty, on the one hand, and inflation and output growth, on the other hand. According to Deveraux (1989), real uncertainty increases the average rate of inflation. Using the Barro–Gordon model, Deveraux (1989) shows that more real uncertainty reduces the optimal amount of wage indexation and induces the policymaker to engineer more inflation surprises in order to obtain favourable real effects.

According to Black (1987), more output uncertainty should lead to higher output growth. His argument is that investment in a more risky technology would be followed by higher average output growth. The reverse causality effects (from inflation and output growth to real uncertainty) are expected to be as follows: an increase in the average inflation rate should lead to more inflation uncertainty, according to Friedman. Furthermore, more inflation uncertainty would be accompanied by less output growth uncertainty according to Taylor's (1979) result of a trade off between inflation uncertainty and output growth uncertainty (the so-called Taylor curve). In summary, more inflation leads to lower output uncertainty.

One would expect a positive causal effect of output growth on output growth uncertainty. As output growth rises and an inflationary pressure is created, the monetary authority responds by a monetary contraction which reduces the average rate of inflation and inflation uncertainty and, hence, increases real uncertainty.

3. A bivariate GARCH model of inflation and output growth

We use a bivariate GARCH model to simultaneously estimate the conditional means, variances, and covariances of inflation and output growth. Estimates of the inflation rate and the real output growth are based upon the following bivariate VAR(4) model:

$$\pi_t = \phi_{\pi 0} + \sum_{i=1}^{4} \phi_{\pi\pi,i}\pi_{t-i} + \sum_{i=1}^{4} \phi_{\pi y,i} y_{t-i} + \varepsilon_{\pi t}, \tag{1a}$$

$$y_t = \phi_{y0} + \sum_{i=1}^{4} \phi_{y\pi,i}\pi_{t-i} + \sum_{i=1}^{4} \phi_{yy,i} y_{t-i} + \varepsilon_{yt}, \tag{1b}$$

where π_t and y_t denote the inflation rate and real output growth, respectively. Define the residual vector ε_t as $\varepsilon_t = (\varepsilon_{\pi t}, \varepsilon_{yt})'$. We assume that ε_t is conditionally normal with mean vector 0 and covariance matrix H_t. That is $(\varepsilon_t \mid \Omega_{t-1}) \sim N(0, H_t)$, where Ω_{t-1} is the information set up to time $t-1$. Following Bollerslev (1990), we impose the constant correlation GARCH(1,1) structure on the conditional covariance matrix H_t:

$$h_{\pi t} = \omega_\pi + \beta_\pi h_{\pi,t-1} + a_\pi \varepsilon^2_{\pi,t-1}, \tag{2a}$$

$$h_{yt} = \omega_y + \beta_y h_{y,t-1} + a_y \varepsilon^2_{y,t-1}, \tag{2b}$$

$$h_{\pi y,t} = \rho\sqrt{h_{\pi t}}\,\sqrt{h_{yt}}, \tag{2c}$$

where $h_{\pi t}$, h_{yt} denote the conditional variances of the inflation rate and output growth, respectively, and $h_{\pi y,t}$ is the conditional covariance between $\varepsilon_{\pi t}$ and ε_{yt}. It is assumed that ω_i, $a_i > 0$, $\beta_i \geq 0$, for $i = \pi, y$, and $-1 \leq \rho \leq 1$.

Bollerslev (1990) states that the constant correlation model is computationally attractive. His argument is that the correlation matrix can be concentrated out from the log-likelihood function, resulting in a reduction in the number of parameters to be optimized. Moreover, it is relatively easy to control the parameters of the conditional variance equations during the optimization so that h_{it} is always positive.

We estimate the system of Eqs. (1) and (2) using the Berndt et al. (1974) numerical optimization algorithm (BHHH) to obtain the maximum likelihood estimates of the parameters. Bollerslev (1990) shows that under the assumptions of our model, the BHHH estimate of the asymptotic covariance matrix of the coefficients will be consistent. Given our relatively large sample size (more than 450 observations), our estimated asymptotic t-statistics should be sufficiently accurate. For completeness, we have also estimated our bivariate VAR(4)-constant correlation GARCH(1,1) model assuming conditionally t-distributed errors. Results from this model (not reported) are quite similar to those reported in the text using the normal distribution.

Note that a general bivariate VAR(p) model can be written as

$$x_t = \Phi_0 + \sum_{i=1}^{p} \Phi_i x_{t-i} + \varepsilon_t,$$

with

$$\Phi_0 = \begin{bmatrix} \phi_{\pi 0} \\ \phi_{y0} \end{bmatrix}, \text{and } \Phi_i = \begin{bmatrix} \phi_{\pi\pi,i} & \phi_{\pi y,i} \\ \phi_{y\pi,i} & \phi_{yy,i} \end{bmatrix},$$

where x_t is a 2×1 column vector given by $x_t = (\pi_t \;\; y_t)'$, Φ_0 is the 2×1 vector of constants and Φ_i, $i = 1, \ldots, p$, is the 2×2 matrix of parameters.

In our empirical work, we estimate several bivariate VAR specifications for inflation and output growth. We used the optimal lag-length algorithm of the Akaike (AIC) and Bayesian (BIC) information criteria to determine the order of the VAR process. We estimated VAR models of order up to 8. We also estimated VAR models where the Φ_i matrix was either lower triangular ($\phi_{\pi y,i} = 0$), or upper triangular ($\phi_{y\pi,i} = 0$) or diagonal ($\phi_{y\pi,i} = \phi_{\pi y,i} = 0$). Both criteria chose the specifications given by (1). Similarly, the chosen GARCH(1,1) model corresponds to the smallest estimated value of both the AIC and BIC.

We measure inflation and output uncertainty by the estimated conditional variances of inflation and output growth, respectively. We then perform Granger causality tests to examine the bidirectional causal relationships between the four variables. We have chosen the Granger causality approach (see also Grier and Perry, 1998) over the simultaneous-estimation approach for three reasons. (1) It allows us to capture the lagged effects between the variables of interest. (2) The simultaneous approach is subject to the criticism of the potential negativity of the variance. (3) The Granger causality approach minimises the number of estimated parameters.

4. Results and discussion

In our empirical analysis we use the Producer Price Index (PPI) and the Industrial Production Index (IPI) for Japan as proxies for the price level and output, respectively. The data have monthly frequency and range from 1961:1 to 1999:12. Allowing for differencing implies 463 usable observations. Inflation is measured by the monthly difference of the log PPI:

$$\pi_t = \log\left(\frac{\mathrm{PPI}_t}{\mathrm{PPI}_{t-1}}\right).$$

Real output growth is measured by the monthly difference in the log of the IPI:

$$y_t = \log\left(\frac{\mathrm{IPI}_t}{\mathrm{IPI}_{t-1}}\right).$$

We test for the stationarity properties of our data using the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests. The results of these tests, reported in Table 1, imply that we can treat the inflation rate and the growth rate of industrial production as stationary processes. We check the sensitivity of our results to the order of augmentation of the unit root tests by including both a 'small' and a 'large' number of lagged differenced terms in the ADF regressions. Likewise, we use both a 'low' and a 'high' truncation lag for the Bartlett kernel in the PP tests.

Table 2 reports estimates of the VAR-GARCH model of Section 3. The conditional mean and variance equations for inflation are reported in Eqs. (1) and (2) of Table 2. The sum of lagged output coefficients is 0.05. The ARCH and GARCH parameters are significant at the 0.01 level. Eqs. (3) and (4) in Table 2 report estimates of the conditional mean and variance of output growth. The sum of lagged inflation coefficients is −0.21. The GARCH parameter is highly significant whereas the ARCH parameter is significant at the 0.09 level. The sum of the ARCH and GARCH parameters is 0.704 and 0.987 for inflation and output growth, respectively. That is, for the output growth, current information remains important for the forecasts of the conditional variances for long horizons.

We calculate Ljung–Box Q statistics at four and 12 lags for the levels, squares, and cross-equation products of the standardized residuals for the estimated bivariate GARCH system. The results, reported in Table 3, show that the time series models for the conditional means and the GARCH(1,1) models for the residual conditional variance–covariance adequately capture the joint distribution of the disturbances. The conditional correlation coefficient is close to zero, suggesting that the residual covariance between equations is not statistically significant.

Table 1
Unit root tests

	Augmented Dickey–Fuller test statistic	Phillips–Perron test statistic	Critical value[a]
Inflation	−4.88	−8.31	−3.45
Output growth	−5.00	−25.83	−3.45

A constant and six lagged difference terms are used for the augmented Dickey–Fuller test.
[a] Denotes MacKinnon critical value for rejection of the hypothesis of a unit root at the 1% significance level.

Table 2
Estimates of the VAR-GARCH model of Section 3

Bivariate AR(4)-constant conditional correlation GARCH(1,1) model

(1) $$\pi_t = -\underset{(0.84)}{0.0002} + \underset{(6.59)}{0.453}\pi_{t-1} + \underset{(0.2)}{0.014}\pi_{t-2} + \underset{(2.52)}{0.117}\pi_{t-3} = +\underset{(1.09)}{0.051}\pi_{t-4} +$$
$$+\underset{(3.65)}{0.025}y_{t-1} + \underset{(1.68)}{0.02}y_{t-2} + \underset{(1.11)}{0.011}y_{t-3} - \underset{(0.64)}{0.007}y_{t-4} + \varepsilon_{\pi t}$$

(2) $$h_{\pi t} = \underset{(10.08)}{0.000005} + \underset{(7.91)}{0.548}\varepsilon^2_{\pi,t-1} + \underset{(2.49)}{0.156}h_{\pi,t-1}$$

(3) $$y_t = \underset{(3.87)}{0.003} - \underset{(5.37)}{0.278}y_{t-1} + \underset{(3.64)}{0.157}y_{t-2} + \underset{(10.36)}{0.477}y_{t-3} + \underset{(2.50)}{0.128}y_{t-4} +$$
$$+\underset{(1.78)}{0.227}\pi_{t-1} - \underset{(0.66)}{0.145}\pi_{t-2} - \underset{(0.61)}{0.119}\pi_{t-3} - \underset{(1.31)}{0.17}\pi_{t-4} + \varepsilon_{yt}$$

(4) $$h_{yt} = \underset{(0.56)}{0.000003} + \underset{(1.72)}{0.032}\varepsilon^2_{y,t-1} + \underset{(22.98)}{0.955}h_{y,t-1}$$

(5) $$h_{\pi y,t} = \underset{(0.21)}{0.015}\sqrt{h_{\pi t}}\,\sqrt{h_{yt}}$$

Notes: the table reports parameter estimates for the Bivariate AR(4)-ccc-GARCH(1,1) model. π_t is the inflation rate calculated from the Producer Price Index. y_t is the growth rate calculated from the Industrial Production Index. $h_{\pi t}$ is the inflation uncertainty. h_{yt} is the output growth uncertainty. The numbers in parentheses are the absolute values of the *t*-statistics.

We have also estimated our bivariate GARCH(1,1) system using two alternative models of the conditional covariance matrix. First, the diagonal-vec model, introduced by Bollerslev et al. (1988), where the conditional covariance follows a GARCH(1,1) process:

$$h_{\pi y,t} = \omega_{\pi y} + a_{\pi y}\varepsilon_{\pi,t-1}\varepsilon_{y,t-1} + \beta_{\pi y}h_{\pi y,t-1}.$$

Second, a model where the conditional correlation is equal to zero. According to the AIC and the maximum likelihood criterion, our preferred model is the constant correlation model (see Table 4).

Next we report the results of Granger-causality tests to provide some statistical evidence on the nature of the relationship between average inflation, output growth, nominal uncertainty, and real

Table 3
Residual diagnostics

	Inflation equation	Output equation	Cross-equation	Critical value (at 5% significance level)
$Q(4)$	6.05	3.00	2.93	9.48
$Q(12)$	18.64	18.84	6.8	21.02
$Q^2(4)$	0.40	2.72	–	9.48
$Q^2(12)$	1.62	13.22	–	21.02

Notes: $Q(4)$ and $Q(12)$ are the Ljung–Box statistics for fourth- and 12th-order serial correlation in the residuals. $Q^2(4)$ and $Q^2(12)$ are the Ljung–Box statistics for fourth- and 12th-order serial correlation in the squared residuals.

Table 4
Model selection criteria

	AIC	ML
(*A*)		
ccc-GARCH(1,1)	**−6723.21**	3385.61
Univariate GARCH(1,1)	−6723.13	3385.57
Dvec-GARCH(1,1)	−6712.76	3383.38
(*B*)		
ccc-GARCH(1,1)	−6719.94	3379.97
Univariate GARCH(1,1)	−6719.72	3379.86
Dvec-GARCH(1,1)	−6716.30	3381.15

Notes: AIC and ML stand for the Akaike Information Criterion and the maximum likelihood value, respectively, for the constant conditional correlation (ccc)-GARCH(1,1) model, the univariate GARCH(1,1) model, and the diagonal-vec (Dvec)-GARCH(1,1) model.
In Panel A, the conditional mean equations are estimated using a bivariate VAR(4) model (see Eq. (1) in the text).
In Panel B, we set $\phi_{\pi y,i}$, $i = 1, \dots, 4$, equal to zero. That is, lagged output growth is not included in the inflation equation.
The bold number indicates the minimum value of the AIC.

uncertainty. Table 5 provides the F statistics of Granger-causality tests using four, eight, and 12 lags, as well as the signs of the sums of the lagged coefficients in case of statistical significance. Panel A considers Granger causality from inflation and output growth to uncertainty about inflation and output growth. We find strong evidence that increased inflation raises inflation uncertainty, confirming the

Table 5
Bivariate Granger-causality tests between inflation, output growth, inflation uncertainty and output growth uncertainty

(A)	$H_0: \pi_t \to h_{\pi t}$	$H_0: \pi_t \to h_{yt}$	$H_0: y_t \to h_{yt}$	$H_0: y_t \to h_{\pi t}$
4 lags	122.85*** (+)	0.72	4.37*** (+)	0.39
8 lags	60.64*** (+)	0.64	2.26** (+)	0.48
12 lags	42.60*** (+)	0.61	2.36*** (+)	0.61
(B)	$H_0: h_{\pi t} \to \pi_t$	$H_0: h_{\pi t} \to y_t$	$H_0: h_{yt} \to y_t$	$H_0: h_{yt} \to \pi_t$
4 lags	15.90*** (−)	3.19** (−)	0.42	0.59
8 lags	8.18*** (−)	2.21** (−)	0.47	0.43
12 lags	5.91*** (−)	2.45*** (−)	0.66	0.73
(C)	$H_0: \pi_t \to y_t$	$H_0: y_t \to \pi_t$	$H_0: h_{\pi t} \to h_{yt}$	$H_0: h_{yt} \to h_{\pi t}$
4 lags	2.88** (−)	2.22	0.12	0.15
8 lags	2.48** (−)	1.44	0.09	0.17
12 lags	2.90*** (−)	1.51	0.19	0.27

Notes: $\pi_t \to h_{\pi t}$: inflation does not Granger-cause inflation uncertainty; $\pi_t \to h_{yt}$: inflation does not Granger-cause output growth uncertainty; $y_t \to h_{yt}$: output growth does not Granger-cause output growth uncertainty; $y_t \to h_{\pi t}$: output growth does not Granger-cause inflation uncertainty.
F statistics are reported. *** and ** denote significance at the 0.01 and 0.05 levels.
In panel A, a (+) indicates that the sum of the coefficients on lagged inflation (first column) or on lagged output growth (third column) is positive.
In panel B, a (−) indicates that the sum of the coefficients on lagged inflation uncertainty is negative.
In panel C, a (−) indicates the sum of the coefficients on lagged inflation (first column) is negative.

theoretical predictions of Friedman and Ball. Further, the null hypothesis of no Granger causality from output growth to output growth uncertainty is rejected at the 5% level of significance or better. The association between the two variables is positive, in agreement with the predictions of our theory in Section 2. Panel B provides evidence that the null hypotheses that inflation uncertainty does not Granger-cause inflation and output growth are rejected at the 5% level of significance or better. The sum of the coefficients on lagged inflation uncertainty in the inflation and growth of output equations is negative. Hence, our key result is that inflation uncertainty significantly lowers real output growth and average inflation. We thus provide strong empirical support of Friedman's and Holland's hypotheses, respectively. In contrast, we fail to find any effect of output growth uncertainty on either average inflation or output growth. In other words, we find no evidence in support of Black's and Deveraux's hypotheses. Combining our results from Panels A and B, we derive two important conclusions. First, the 'stabilizing Fed' notion discussed in Section 2 is supported by our evidence. Increased inflation first raises uncertainty, which creates real welfare losses and then leads to monetary tightening to lower inflation and thus also inflation uncertainty. Second, it is unlikely that the claim that inflation uncertainty lowers output growth is subject to the possibility of reverse causation, as suggested by Brunner (1993). Our Granger-causality tests indicate clearly that causation runs uniquely from inflation uncertainty to output growth.[2]

For completeness, Panel C reports the results of causality tests between (i) inflation and output growth and (ii) nominal and real uncertainty. We find no support for both the short-run Phillips curve effect and Taylor's hypothesis on the negative association between real and nominal uncertainty. The results of Panel C are consistent with most of our findings in Panels A and B. First, the lack of a causal effect of output growth on inflation (the short-run Phillips curve effect) can explain the lack of causal effect from output growth on nominal uncertainty (Panel A), as such an effect hinges on the short-run Phillips curve relationship. Second, the lack of evidence on Taylor's hypothesis that is necessary to explain the negative causal effect of inflation on real uncertainty can explain the lack of evidence on this latter effect. Third, the lack of evidence for both the short-run Phillips curve and Taylor's hypothesis cannot justify our evidence in Panel A in favour of a positive effect of output growth on real uncertainty. Hence, our suggested interpretation on this last causal relationship given at the end of Section 2 is not supported by the data. Some other mechanism might be at work.

In summary, our results that higher inflation uncertainty and more inflation lead to lower output growth have important implications for the Japanese economy. They indicate that, in the absence of the low and stable inflation of the 1990s, output growth in Japan might have been even lower. They also provide an argument for a price stability objective on the part of the monetary authority.

5. Conclusion

We have used a GARCH model to obtain estimates of nominal and real uncertainty and examine the bidirectional causal relationships between average inflation and real growth, on the one hand, and

[2] The results (not reported) from the alternative parameterizations discussed above are qualitatively similar to those reported in the text using the constant correlation parameterization. Inflation uncertainty is still a negative and significant determinant of both output growth and average inflation, increased inflation raises inflation uncertainty, and increased output growth raises output uncertainty.

nominal and real uncertainty on the other hand. Our evidence for the Japanese economy supports, among others, the conclusion that a higher rate of inflation, and the associated inflation uncertainty, causes a reduction in the rate of output growth. This finding provides some support to the proponents of price stability as a fundamental objective of the monetary authority.

References

Ball, L., 1992. Why does high inflation raise inflation uncertainty? Journal of Monetary Economics 29, 371–388.

Berndt, E., Hall, B., Hall, R., Hausman, J., 1974. Estimation and inference in nonlinear structural models. Annals of Economic and Social Measurement 3, 653–665.

Black, F., 1987. Business Cycles and Equilibrium. Basil Blackwell, New York.

Bollerslev, T., 1990. Modelling the coherence in short-run nominal exchange rates: a multivariate generalized ARCH model. Review of Economics and Statistics 72, 498–505.

Bollerslev, T., Engle, R., Wooldridge, M., 1988. A capital asset pricing model with time-varying covariances. Journal of Political Economy 96, 116–131.

Brunner, A., 1993. Comment on inflation regimes and the sources of inflation uncertainty. Journal of Money, Credit, and Banking 25, 512–514.

Cukierman, A., Meltzer, A., 1986. A theory of ambiguity, credibility, and inflation under discretion and asymmetric information. Econometrica 54, 1099–1128.

Deveraux, M., 1989. A positive theory of inflation and inflation variance. Economic Inquiry 27, 105–116.

Friedman, M., 1977. Nobel lecture: Inflation and Unemployment. Journal of Political Economy 85, 451–472.

Grier, K., Perry, M., 1998. On inflation and inflation uncertainty in the G7 countries. Journal of International Money and Finance 17, 671–689.

Grier, K., Perry, M., 2000. The effects of real and nominal uncertainty on inflation and output growth: some GARCH-M evidence. Journal of Applied Econometrics 15, 45–58.

Holland, S., 1995. Inflation and uncertainty: tests for temporal ordering. Journal of Money, Credit, and Banking 27, 827–837.

Taylor, J., 1979. Estimation and control of a macroeconomic model with rational expectations. Econometrica 47, 1267–1286.