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Modeling and Forecasting Inflation in Japan

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Abstract

This paper estimates an inflation function and forecasts one-year ahead inflation for Japan. It finds that (i) markup relationships, excess money and the output gap are particularly relevant long-run determinants for an equilibrium correction model (EqCM) of inflation; (ii) with intercept corrections, one-year ahead inflation forecast performance of the EqCM is good; and (iii) forecast accuracy can be improved by combining forecasts of the EqCM with those made by rival models. The EqCM obtained would serve for structural model-based inflation forecasting. It also highlights the importance of adjustment to a pure model-based forecast by utilizing information of alternative models. The methodology employed is applicable to a wider range of countries including some emerging market economies.

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I. Introduction

The aim of this paper is forecasting one-year ahead inflation in Japan, relying on structural model-based forecasting.

Forecasting future inflation is essential for monetary policy because of the time lag of its economic effects. That is, it is often reported that it takes one to two years before a change in monetary policy achieves the maximum effect on the economy.[2] Given the long lag between monetary policy actions and their effects, the preemptive strike strategy seems a sensible choice for the monetary authorities. However, the strategy requires good forecasts of the economy, in particular, that of inflation.

This point is further emphasized by monetary economists who advocate inflation targeting. In fact, Svensson (1997) argues that inflation *forecast* targeting is preferable. This forecast should be based on a good structural model. Otherwise, as demonstrated by Bernanke and Woodford (1997), the inflation forecast targeting would lead to indeterminacy.[3] In fact, in the case of Japan, difficulty in forecasting inflation is often referred to as one of the obstacles facing the Bank of Japan in adopting inflation targeting (Higo, 1999).

At the same time, the recent years have observed a resurgence of interest in econometric forecasting. The paper relies on contributions made by Clements and Hendry (1998, 1999) and Stock and Watson (1999), including the role of cointegrating vectors for forecasts, intercept corrections and over-difference of the model, and combining of forecasts (or thick modeling of Granger (2000)). The paper also exploits the 'general-to-simple' approach, which is now a standard technique for applied researchers.

This paper is one attempt towards structural model-based inflation forecasting. To this end, in Section II, we first try to establish a structural inflation function as an equilibrium correction model (EqCM). The model is derived by a general-to-specific approach based on long-run cointegration analyses. The paper finds that markup relationships, excess money, and the output gap are long-run determinants of Japanese inflation process.

Then, in Section III, based on findings in the previous section, a one-year ahead inflation forecast model is constructed. Excess money and the output gap are found to be particularly important for forecast accuracy. Forecast performances of the model are examined together with inflation indicators recently proposed by Stock and Watson

[2]See Svensson (1997). For an empirical study of a Japanese case, see Honda, Kamioka and Horaguchi (1995).

[3]For example, if forecast is based on something representing market expectations, then inflation forecast targeting policy is determined by market expectations, which in turn are certainly affected by the policy response. Because of this circularity, there would be multiple equilibria. The argument is closely related to Woodford's criticism on using inflation indicators without due consideration to causal relationships (Woodford, 1994).

(1999). The role of over-difference and intercept corrections are discussed. Finally, the paper finds forecast performances are improved by combining forecasts between a structural model and a rival model. These forecast combinations can be thought as systematic adjustment to the pure structural model-based forecast to protect the forecast against possible mis-specification or structural changes.

II. Modeling Inflation

A main objective of this section is to find relevant long-run relationships which govern the Japanese inflation process and to examine whether we can come up with a reasonable inflation function by imposing these relationships as equilibrium correction terms.

Inflation is thought to be an outcome of various economic factors. These include the supply side factors that come from cost-push or markup relationships; the demand side factors that may cause demand pull inflation; monetary factors; and foreign factors including exchange rate effects. One may further lengthen the list by adding inflation expectations. In fact, casual observation of data suggests a role for all of these factors in inflation determination (see figures in Data Appendix). Specifically, the rapid monetary expansion before the first oil crisis was said to fuel inflation even before the oil crisis hit Japan (Komiya, 1976). The first and second oil crises are obvious examples of the supply side and foreign factors. The fact that inflation is cyclical may reveal that inflation is demand driven.

In order to capture these multi-factors, or multi-causal relationships in the inflation process, we will follow the method developed by Juselius (1992), Metin (1995) and Hendry (1999). They first find various long-run relationships through the Johansen procedures and then construct multi-causal single equations of inflation by imposing restrictions on these long-run relationships.

A. Long-run relationships

We will find long-run relationships by segmenting variables a priori based on some sense of economic theory. That is, variables, which may represent four conditions (supply, demand, money and foreign) are investigated individually through segmented data sets. From a general-to-specific point of view, econometric theory suggests, instead of segmenting, estimating one large unrestricted vector autoregressive (VAR) model would be a more suitable vehicle with which to begin. However, in practice, such a large VAR is often difficult to handle. It is often the case that in the context of the analysis of the multivariate cointegration model, difficulties of interpreting the cointegration space grow when more variables are added to a VAR. For this reason, following Juselius (1992) and Metin (1995), we derive some long-run relationships from sector VARs. Also segmented

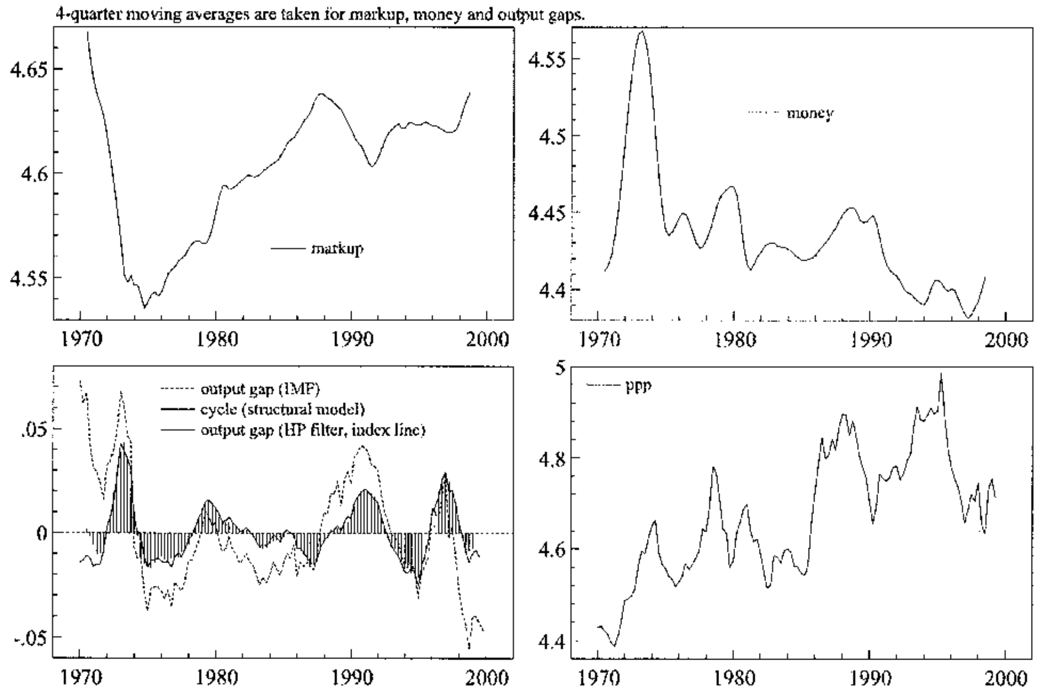

Figure 1: Japanese Inflation Model: Long-run Relationships

sector analysis gives us flexibility to use the Hodrick-Prescott (HP) filter or 'structural' time series technique. Figure 1 presents long-run relationships we will examine below.

Markup

First, we investigate a markup relationship, which is found significant by de Brouwer and Ericsson (1998) for Australian inflation, and Tanaka and Kimura (1998) for Japanese inflation. Following the argument of de Brouwer and Ericsson, a simple markup over total unit costs can be expressed as:

$$P = \theta \cdot (ULC)^{\gamma} \cdot (P^{in})^{1-\gamma}, \tag{1}$$

where P is output price (CPI less fresh food[4]), ULC is the unit labor cost, P^{in} is price of input such as intermediate goods and energy. $\theta - 1$ corresponds to a markup. The equation assumes that linear homogeneity holds in the long run.

[4]Impacts of changes in consumption tax rate are adjusted. See Data Appendix.

Table 1: System Analysis of Cointegration (1)

(A) Properties of VAR residuals				
	p	ulc	p^{fwpi}	Vector
AR	3.08*	3.26*	2.14	2.42**
$Normality$	0.95	1.53	5.73	11.30
$ARCH$	1.65	0.40	0.25	–
X_i^2	1.26	0.69	0.84	0.79
(B) Tests for the number of cointegrating vectors				
Eigenvalues	0.322	0.012	0.005	
Hypotheses	$r = 0$	$r \leq 1$	$r \leq 2$	
λ_{max}	42.8**	1.3	0.5	
λ_{trace}	44.6**	1.8	0.5	
(C) Standardized eigenvectors β'				
	p	ulc	p^{fwpi}	
	1.00	-0.90	-0.09	
	0.46	1.00	-0.05	
	0.93	-0.82	1.00	
(D) Standardized adjustment coefficients α				
p	-0.11	-0.00	-0.00	
ulc	0.03	0.01	0.01	
p^{fwpi}	-0.22	0.00	0.00	

Notes

1. The vector autoregression model includes eight lags on each variable (p, ulc, p^{fwpi}); a constant; the first and the second oil crises dummies ID_{74Q1} and ID_{80Q2}; the high growth era dummy SD_{73Q4}^{70Q1}; and centered seasonal dummies. The estimation period is 1972Q1-1999Q1. The VAR model can be reexpressed as a vector equilibrium correction model:

$$\Delta X_t = \alpha\beta' X_{t-1} + \sum_i \Gamma_i \Delta X_{t-i} + \Phi d_t + e_t,$$

   where X_t is (p_t, ulc_t, p_t^{fwpi}), and d_t is deterministic components.

2. The statistics λ_{max} and λ_{trace} are Johansen's maximal eigenvalue and trace statistics for testing cointegration.

To estimate this relationship, a system cointegration analysis is conducted using a trivariate VAR model, which consists of (p, ulc, p^{fwpi}).[5] For ULC, employees income is divided by potential output[6] (both income and output are all industry basis). For P^{in}, wholesale price index of final goods, P^{fwpi}, is used.

Table 1 summarizes performance and cointegration analysis of the VAR.[7] There are indications of auto-correlated residuals, but since the residual autocorrelations disappear when the sample before 1975 is omitted, it seems plausible that this is related to the huge fluctuations after the first oil crisis.[8]

The Johansen test supports existence of one cointegrating vector. Both maximum eigenvalue and trace statistics reject the hypothesis of no cointegration, but do not reject that there is only one cointegrating vector.

Assuming one cointegrating vector and a linear homogeneity, the derived long-run markup relationship becomes:

$$markup = p - 0.90ulc - 0.10p^{fwpi}. \tag{2}$$

The linear homogeneity restriction is accepted $(0.81 \sim \chi^2(1))$. The corresponding α vector is[9]

$$\begin{array}{ll} p & \cdots \\ ulc & \cdots \\ p^{fwpi} & \cdots \end{array} \begin{pmatrix} -0.11^{**} \\ 0.02 \\ -0.22^{**} \end{pmatrix}.$$

A share of the ULC in the total unit cost (γ), 0.90, appears high compared with 0.43 estimated by de Brouwer and Ericsson for an Australian case. This might reflect relatively labor intensive retail-service sector in Japan. If we replace p^{fwpi} with import price, p^{iwpi}, or commodity price, p^{como}, which is more closely corresponding to their estimated markup relationship, the share of ULC becomes even larger. With the same homogeneity restriction on each trivariate VAR, the cointegrating vectors are:

$$markup' = p - 0.96ulc - 0.04p^{iwpi}, \tag{3}$$

[5]Lower case letters denote logarithm of corresponding variables.

[6]The potential output estimated by the HP filter. The result is robust to choice of denominators used for calculating ULC. Two other potential outputs discussed below give very similar cointegrating vectors. Also, the result does not alter, even if actual output is used in place of potential output.

[7]All the estimations in this paper, unless otherwise noted, are conducted by PcGive 9.21 (Hendry and Doornik, 1996), PcFiml 9.21 (Doornik and Hendry, 1997), and Ox 2.20 (Doornik, 1997).

[8]AR is a Lagrange-Multiplier test for the fifth order of residual autocorrelation; *Normality* is the Doornik-Hansen normality test; $ARCH$ is a test for the fourth order conditional heteroscedasticity; and X_i^2 is the White heteroscedasticity test. * and ** denote significance at the 5% and 1% levels, respectively.

[9] A feedback coefficient to p^{fwpi} (-0.22) is significant. This implies that a single equation of inflation violates a weak-exogeneity condition.

$$markup'' = p - 0.94ulc - 0.06p^{como}. \tag{4}$$

However, these additional markup relationships are not included in the equations below, as a long-run homogeneity assumption is rejected, and they tend to show wrong signs when they are included with *markup*.

The observed *markup* declined substantially around 1973 (Figure 1). This reflects large wage increases around the first oil crisis, which might be due to then strong labor unions and high inflation expectations arising from accommodative monetary policy. After that, as labor unions gradually lost their bargaining power in wage negotiation and inflation expectations were subdued, *markup* recovered its level until the latter half of 1980s, and then became largely flat.

Excess money

The next long-run relationship is monetary conditions. Beginning with Friedman and Schwartz (1963), many researchers have examined whether inflation is a monetary phenomenon. For instance, advocates of the 'p star' approach (Hallman, Porter and Small, 1991) examine inflationary effects of excess money in terms of difference between actual money velocity and its long-run value (together with the output gap). Also, Juselius (1992) finds excess money in terms of a cointegrating vector, which represents the long-run money demand, as one source of inflation.

Following Juselius, we estimate a six-variate VAR, which consists of M2+CDs, m; the price, p; real GDP, y; real price of land, rp^{land}; the own rate of money, Rm; and the interest rate on rival assets, Rr. The VAR roughly corresponds to that in Sekine (1998), which finds the long-run money demand as a cointegrating vector of the above six variables, but the more comprehensive measure of real wealth is used in place of land price.[10]

Table 2 summarizes residual properties and a system cointegrating analysis of the VAR. Again, there are indications of auto-regressive residuals possibly associated with the first oil crisis, but otherwise the VAR seems satisfactory. The Johansen tests (both maximum eigenvalue and trace statistics) support existence of three cointegrating relationships.

Assuming three cointegrating vectors, the following restrictions are tested and accepted ($1.81 \sim \chi^2(3)$): (i) on the first cointegrating vector, the coefficients on (m, p, y) are $(1, -1, -0.5)$ and the coefficient on Rm is equal to, but the opposite sign of the coefficient on Rr; (ii) on the second cointegrating vector, the coefficient on m is equal to,

[10]Ideally this paper has to use the same wealth variable, but it is only available with a considerable lag (as of May 2000, only end-1998 wealth stock is available). Since this paper puts weight on forecasting, such a lagged variable is not useful. For this reason, rp^{land} is included as a proxy of the wealth stock.

Table 2: System Analysis of Cointegration (2)

	(A) Properties of VAR residuals						
	m	p	y	rp^{land}	Rm	Rr	Vector
AR	2.24	7.19**	2.69*	1.88	2.00	2.39	1.38*
$Normality$	1.33	1.86	2.86	2.86	0.09	2.37	10.97
$ARCH$	0.54	0.36	0.21	0.59	1.99	0.11	–
	(B) Tests for the number of cointegrating vectors						
Eigenvalues	0.412	0.385	0.330	0.160	0.09	0.05	
Hypotheses	$r = 0$	$r \leq 1$	$r \leq 2$	$r \leq 3$	$r \leq 4$	$r \leq 5$	
λ_{max}	57.8**	53.0**	43.7**	19.0	10.0	5.4	
λ_{trace}	188.9**	131.1**	78.1**	34.4	15.4	5.4	
	(C) Standardized eigenvectors β'						
	m	p	y	rp^{land}	Rm	Rr	trend
	1.00	-1.32	-0.95	-0.08	-3.02	3.98	-0.003
	-1.11	1.00	0.46	0.16	1.52	-1.77	0.009
	-0.14	-0.03	1.00	-0.03	-0.12	-1.03	-0.006
	-25.18	3.45	50.42	1.00	-247.2	366.7	0.21
	-0.02	-0.12	0.15	-0.05	1.00	-0.30	0.00
	0.79	-0.99	0.08	-0.02	-0.05	1.00	-0.008
	(D) Standardized adjustment coefficients α						
m	0.15	0.25	0.12	-0.00	0.01	-0.00	
p	0.10	-0.14	0.04	0.00	0.18	-0.00	
y	0.21	-0.02	-0.12	-0.00	-0.31	-0.03	
rp^{land}	0.20	0.07	-0.06	-0.00	-0.83	0.09	
Rm	0.02	-0.04	0.14	0.00	-0.11	-0.01	
Rr	0.03	-0.10	0.25	-0.00	0.03	0.00	

Notes

1. The vector autoregression model includes eight lags on each variable $(m, p, y, rp^{land}, Rm, Rr)$; a trend; a constant; the first and the second oil crises dummies ID_{74Q1} and ID_{80Q2}; the high growth era dummy SD^{70Q1}_{73Q4}; the 1995 supplementary budget dummy ID_{96Q1}; and centered seasonal dummies. The estimation period is 1972Q1-1999Q1. The VAR model can be reexpressed as a vector equilibrium correction model:

$$\Delta X_t = \alpha\beta' X^*_{t-1} + \sum_i \Gamma_i \Delta X_{t-i} + \Phi d_t + e_t,$$

where X_t is $(m_t, p_t, y_t, rp^{land}_t, Rm_t, Rr_t)$, X^*_t is $(X_t$, trend$)$ and d_t is deterministic components other than the trend.

2. The statistics λ_{max} and λ_{trace} are Johansen's maximal eigenvalue and trace statistics for testing cointegration.

but the opposite sign of the coefficient on p (i.e., linear homogeneity[11]); and (iii) on the adjustment coefficients, α_{22} and α_{23} are zero (i.e., no feedback from the second and the third cointegrating vectors to the inflation process). Then, the cointegrating vectors are:

$$\begin{array}{ccccccc} m & p & y & rp^{land} & Rm & Rr & \text{trend} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \end{array}$$
$$\begin{pmatrix} 1.00 & -1.00 & -0.50 & -0.12 & -2.15 & 2.15 & -0.008 \\ -0.23 & 0.23 & 0.55 & 0.00 & 0.56 & -1.13 & -0.002 \\ -0.14 & 0.03 & 0.70 & -0.01 & -0.04 & -0.81 & -0.004 \end{pmatrix},$$

and corresponding α matrix becomes:

$$\begin{array}{cc} m & \cdots \\ p & \cdots \\ y & \cdots \\ rp^{land} & \cdots \\ Rm & \cdots \\ Rr & \cdots \end{array} \begin{pmatrix} -0.30^{**} & -1.22^{**} & 0.89^{**} \\ 0.23^{**} & 0.00 & 0.00 \\ 0.11 & -0.96^{**} & 0.31 \\ -0.03 & -1.25 & 0.60 \\ 0.07 & 0.00 & 0.18^{**} \\ 0.17^{**} & 0.13 & 0.26^{**} \end{pmatrix}.$$

Only the first cointegrating vector is relevant for the inflation process, which can be written as:[12]

$$money = m - p - 0.5y - 0.12rp^{land} - 2.15(Rm - Rr) - 0.008\text{trend}. \tag{5}$$

The excess money defined by equation (5) shows a sharp spike around 1973, which corresponds to "excess liquidity" of Komiya (1976) (Figure 1). Compared with this, the peak around 1980 is more modest, which reflects tougher position of the Bank of Japan at the time of the second oil crisis. During the latter half of 1980s, there is another peak associated with the bubble. However, partly because the rapid increase in asset prices reduced the excessiveness of money as money demand increased through the wealth effect (see equation (5)), the peak during the bubble period is lower than that around 1980.

Excess demand

Excess demand is expressed as an output gap, $gap = y_t - \bar{y}_t$, where y_t is actual output (GDP) and $\bar{y}_t$ is potential output. In this paper, potential outputs are obtained by two popular approaches: the HP filter (*hpgap*) and a production function (*imfgap*).

[11] The same linear homogeneity restriction on the third cointegrating vector is rejected.

[12] Again, since -0.30 and 0.17 in the first column of the α matrix are significant, a weak-exogeneity condition does not hold for a single equation of inflation.

Augumented Dicky-Fuller (ADF) tests confirm that *hpgap* is I(0), but *imfgap* may not be.[13]

The validity of the HP filter can be checked by a 'structural' time series model.[14] In comparison with a structural time series model, Harvey and Jaeger (1993) show that the HP filter has a drawback in that it may create spurious cycles. However, in this case, a basic structural time series model yields a very similar cyclical component (see the bottom left of Figure 1).[15]

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[13]The Dickey-Fuller t-value of *hpgap* is $t_{adf} = -3.58^{**}$, whereas for *imfgap*, $t_{adf} = -1.75$, for the sample period from 1971Q3 to 1999Q1 with the null hypothesis of a unit root. A constant and seasonals (only for *hpgap*) are included in the regression.

[14]The Harvey's 'structural' time series model discussed here put more emphasis on decomposition of the series to a trend, a cycle, a seasonal pattern and irregularity. This might not necessarily coincide with a *structural* model discussed above, which is used as a model with 'deep' parameters in contrast to a reduced form equation.

[15]A basic structural time series model comprises the following equation:

$$y_t = \mu_t + \gamma_t + \psi_t + \epsilon_t, \quad \epsilon_t \sim \text{NID}(0, \sigma_\epsilon^2),$$

where μ_t is a trend, γ_t is a seasonal pattern and ψ_t is a cycle. Each component is modeled as stochastic.

1. The stochastic trend is modeled as a local linear trend as:

$$\begin{aligned} \mu_t &= \mu_{t-1} + \beta_{t-1} + \eta_t, \quad \eta_t \sim \text{NID}(0, \sigma_\eta^2) \\ \beta_t &= \beta_{t-1} + \zeta_t, \quad \zeta_t \sim \text{NID}(0, \sigma_\zeta^2). \end{aligned}$$

   where μ_t is the level and β_t is the slope.

2. The trigonometric seasonal pattern is the sum of cyclical component, $\gamma_{j,t}$ (i.e., $\gamma_t = \sum_{j=1}^{s/2} \gamma_{j,t}$), where a seasonal cyclical component evolve:

$$\begin{aligned} \gamma_{j,t} &= \cos\lambda_j \gamma_{j,t-1} + \sin\lambda_j \gamma_{j,t-1}^* + \omega_{j,t}, \quad \text{for } j = 1, ..., (s/2) - 1, \\ \gamma_{j,t}^* &= -\sin\lambda_j \gamma_{j,t-1} + \cos\lambda_j \gamma_{j,t-1}^* + \omega_{j,t}^*, \quad \text{for } j = 1, ..., (s/2) - 1, \end{aligned}$$

   and

$$\gamma_{j,t} = \cos\lambda_j \gamma_{j,t-1} + \omega_{j,t}, \quad \text{for } j = s/2.$$

   s is the number of seasons in the year and $\lambda_j = 2\pi j$. Both $\omega_{j,t}$ and $\omega_{j,t}^*$ are $\text{NID}(0, \sigma_\omega^2)$.

3. The stochastic cycle is defined as another trigonometric function:

$$\begin{aligned} \psi_t &= \rho\cos\lambda_c \psi_{t-1} + \rho\sin\lambda_c \psi_{t-1}^* + \kappa_t, \\ \psi_t^* &= -\rho\sin\lambda_c \psi_{t-1} + \rho\cos\lambda_c \psi_{t-1}^* + \kappa_t^*, \end{aligned}$$

   where ρ is a damping factor such that $0 \leq \rho \leq 1$, λ_c is the frequency of the cycle in radians, and both κ_t and κ_t^* are $\text{NID}(0, \sigma_\kappa^2)$.

Algorithm of STAMP 6.0 (Koopman, Harvey, Doornik and Shephard, 1999) yields very small σ_η^2 ($= 3.25 \times 10^{-8}$), which implies that the restriction implied by the HP filter, $\sigma_\eta^2 = 0$, may be acceptable. Presumably for this reason, the HP filter yields the very similar cyclical component to the structural time series model.

On the other hand, a production function approach yields somewhat different output gap. The Fund estimated output gap (International Monetary Fund, 1999), which is based on a production function approach (Bayoumi, 1999), tends to suggest that the size of output gaps is larger than estimates of the time series techniques (i.e., the HP filter and the structural time series model).

The difference between these two approaches is particularly large after 1998. Negative gaps estimated by the time series techniques are much smaller than the Fund estimates. On the one hand, as Hayakawa and Maeda (2000) point out, a production function approach may end up with overstating the situation since it may not fully take into account an increase in the ratio of obsolete capital stock under the rapid structural change. However, on the other hand, the time series techniques may underestimate the situation, because of overfit of the model. For instance, around 1996, output gaps estimated by the time series techniques exceed those at the peak of the bubble (around 1990) because potential growth is estimated as low as 1.5 percent from 1994 owing to the low growth in the 1990s—the estimated potential growth further declines to less than one percent from the latter half of 1997. Certainly, no one can deny the possibility that such low growth is *true* potential, but this looks on the low side.

Since all of the above estimates of output gaps contain some sort of smoothing, it is always difficult to see what is the *true* gap toward the end of the sample period. For this reason, although exposition below is mainly based on output gaps estimated by the HP filter, performances of the Fund estimates are also examined.

Purchasing power parity

Whether or not the purchasing power parity (PPP) holds in the long run has been a contentious issue among empirical economists. It is often found difficult to reject the hypothesis that real (effective) exchange rates follow a random walk even in the long-run horizon (Rogoff, 1986). In fact, an ADF test does not reject a unit root of the CPI-based real effective exchange rate of the yen.[16] PPP simply might not hold owing to various frictions such as transportation costs, trade restrictions, or mark-to-market pricing behavior. The combination of the high productivity growth in the tradable sector and the relatively lower productivity growth of the non-tradable sector in Japan may prevent the CPI-based real effective exchange rate from reverting to its mean (the Balassa-Samuelson effect). However, the lack of power of a simple unit root test may render test results in favor of I(1). As reviewed by Rogoff (1986), many researchers reject the random walk hypothesis by increasing power of unit root tests. These include looking at longer time-series, pooling cross-country data, or adding other macro variables.[17]

[16] See Table 7 in Data Appendix. Also, I could not find any meaningful cointegrating vector by the Johansen test of a trivariate VAR consisting of p_t, p_t^* and e_t.

[17] Kasuya and Ueda (2000) show that PPP might hold in terms of fractional cointegration for the bilateral yen-US dollar rate.

With a caveat that the real effective exchange rate of the yen may not be mean-reverting, given that Juselius (1992) and Hendry (1999) find diversion from PPP as one determinant of their inflation functions, we will examine its relevance below. The PPP relationship is defined as $ppp = p - p^* + e$, where p^* is foreign price (mainly CPI) and e is the nominal effective exchange rate of the yen.

B. Inflation Function

Using the above found long-run relationships, a single equation of inflation process is derived below. The procedure followed is a general-to-simple approach.

First, we estimate a very general model that regresses Δp_t on the above four long-run relationships, $markup_{t-1}$, $money_{t-1}$, $hpgap_{t-1}$, ppp_{t-1}; and short-run dynamics, Δp_{t-i}, Δy_{t-i}, Δm_{t-i}, Δp^{fwpi}_{t-i}, Δp^{como}_{t-i}, Δulc_{t-i}, Δrp^{land}_{t-i} and Rs_{t-i}, where i takes 1 to 4 for Δp_{t-i}, and nil to 4 for the rest of short-run dynamics variables.[18] In addition, to capture backward looking inflation expectations or some inertia of inflation, sum of the past 3 years' inflation rates, $\Delta_{12}p_{t-1}(=\sum_{i=1}^{12}\Delta p_{t-i})$, is included as an additional explanatory variable. Also, the first and the second oil crisis dummies, ID_{74Q1}, ID_{80Q2}, a constant and centered seasonal dummies are added. For the sample period from 1971Q2 to 1997Q4, this unrestricted general model yields $\hat{\sigma} = 0.22\%$ for 55 variables and 107 observations ($SC = -10.53$).[19]

Then, by sequentially eliminating insignificant terms or uninterpretable signs, the following model was derived:[20]

$$
\begin{aligned}
\Delta p_t = & -\underset{(0.01)}{0.04}markup_{t-1} + \underset{(0.01)}{0.03}money_{t-1} + \underset{(0.02)}{0.04}hpgap_{t-4} - \underset{(0.002)}{0.0003}ppp_{t-1} \\
& + \underset{(0.005)}{0.008}\Delta_{12}p_{t-1} + \underset{(0.05)}{0.23}\Delta p_{t-1} + \underset{(0.01)}{0.02}\Delta p^{como}_{t-1} + \underset{(0.01)}{0.04}\Delta p^{como}_{t-4} + \underset{(0.03)}{0.25}\Delta^2 p^{fwpi}_{t-3} \\
& + \underset{(0.01)}{0.08}\Delta_4 ulc_t - \underset{(0.02)}{0.11}\Delta_2 Rs_{t-2} + \underset{(0.02)}{0.06}\Delta^2 rp^{land}_{t-3} + \underset{(0.003)}{0.04}ID_{74Q1} + \underset{(0.003)}{0.02}ID_{80Q2} \\
& - \underset{(0.004)}{0.008}CS_1 + \underset{(0.003)}{0.014}CS_2 - \underset{(0.002)}{0.005}CS_3 + \underset{(0.08)}{0.03},
\end{aligned}
\tag{6}
$$

$T = 1971Q2 - 1997Q4$, $R^2 = 0.97$, $\hat{\sigma} = 0.24\%$, $DW = 2.26$, $SC = -11.48$
$AR: F(5,84) = 1.87$, $ARCH: F(4,81) = 0.80$, $Normality: \chi^2(2) = 2.18$,
$X_i^2: F(29,59) = 1.06$, $RESET: F(1,88) = 3.37$.

[18] Δ_d denotes the d-th difference operator.

[19] SC denotes the Schwarz Criterion. The larger minus means a better model in terms of this criterion.

[20] $RESET$ is the Ramsey's regression specification test.

The very small coefficient on the PPP term implies an extremely slow adjustment process, which is consistent with the literature. If we drop the PPP term, which might be I(1) and insignificant, then the model becomes:

$$
\begin{aligned}
\Delta p_t \;=\; & \underset{(0.01)}{-0.04 markup_{t-1}} + \underset{(0.01)}{0.03 money_{t-1}} + \underset{(0.02)}{0.04 hpgap_{t-4}} \\
& + \underset{(0.005)}{0.008\Delta_{12}p_{t-1}} + \underset{(0.05)}{0.22\Delta p_{t-1}} + \underset{(0.01)}{0.02\Delta p^{como}_{t-1}} + \underset{(0.01)}{0.04\Delta p^{como}_{t-4}} + \underset{(0.03)}{0.25\Delta^2 p^{fwpi}_{t-3}} \\
& + \underset{(0.01)}{0.08\Delta_4 ulc_t} - \underset{(0.02)}{0.11\Delta_2 Rs_{t-2}} + \underset{(0.02)}{0.06\Delta^2 rp^{land}_{t-3}} + \underset{(0.003)}{0.04 ID_{74Q1}} + \underset{(0.003)}{0.02 ID_{80Q2}} \\
& - \underset{(0.004)}{0.008 CS_1} + \underset{(0.003)}{0.014 CS_2} - \underset{(0.002)}{0.005 CS_3} + \underset{(0.07)}{0.03}, \qquad (7)
\end{aligned}
$$

$T = 1971Q2 - 1997Q4$, $R^2 = 0.97$, $\hat{\sigma} = 0.24\%$, $DW = 2.26$, $SC = -11.52$
$AR : F(5, 85) = 1.89$, $ARCH : F(4, 82) = 0.80$, $Normality : \chi^2(2) = 2.09$,
$X_i^2 : F(27, 62) = 1.18$, $RESET : F(1, 89) = 2.71$.

Little change is observed in estimated coefficients.[21] The model proves its congruency in terms of various diagnostic tests, and it encompasses the general model ($1.29 \sim F(38, 52)$ with the null hypothesis of encompassing). The model succeeds in forecasting 1998Q1 to 1999Q1 as indicated by insignificant Forecast Chow test, $1.54 \sim F(5, 90)$. Figure 2 visually shows how well the model tracks and forecasts actual outcomes. For instance, the right bottom panel indicates actual outcomes are within the approximately 95% error bands of the forecasts.[22]

Figures 3 and 4 summarize results of recursive estimates. First, in Figure 3, both recursive 1-step forecasts and various types of Chow tests confirm stability of the model. Figure 4 shows recursively estimated coefficients. Although some coefficients shift around 1989, which corresponds to the height of the bubble, these are broadly within the band of ±2 standard errors, and thus we may conclude the model is reasonably stable.

[21] If we substitute *imfgap* to *hpgap* in equation (7), its coefficient becomes 0.03 with t-value of 2.1.

[22] These forecasts assume that future values of explanatory variables are known.

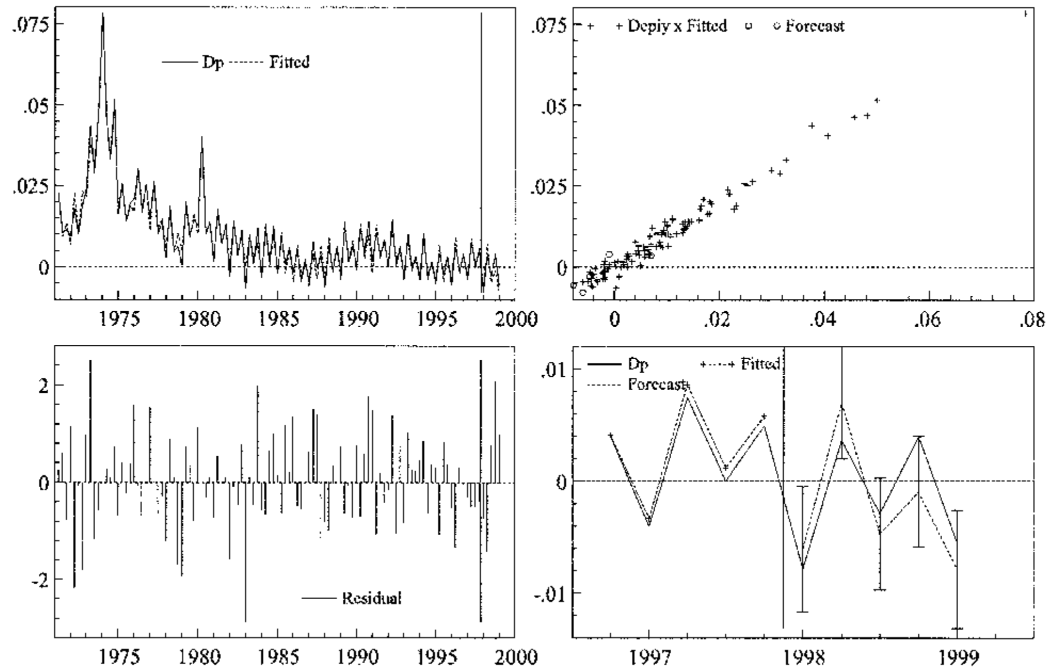

Figure 2: Japanese Inflation Model: Fit and 1-step Forecasts

III. Forecasting Inflation

Although the above estimated model appears sufficiently congruent with the data generation process of Japanese inflation, it cannot be used to forecast the future course of inflation by itself. Forecast performance examined above is within-sample forecast tests: they assume future values of explanatory variables are known, which is not a case in reality.

One way out might be estimating a vector equilibrium correction model (VEqCM) or a more restricted system of simultaneous equations, in which explanatory variables are endogenized. However, preliminary investigation of 4-quarter ahead dynamic simulation of a VEqCM results in rather poor forecast performance.[23]

[23]The following VEqCM is estimated from the sample beginning in 1974Q2

$$\Delta X_t = \alpha\beta' X^*_{t-4} + \sum_i \Gamma_i \Delta X_{t-i} + \Phi d_t + e_t,$$

where ΔX_t is $(\Delta p_t, \Delta m_t, \Delta y_t, \Delta p_t^{fwpi}, \Delta ulc_t, Rs_t, \Delta rp_t^{land})$, $\beta' X^*_{t-4}$ is $(markup_{t-4}, money_{t-4}, hpgap_{t-4}, ppp_{t-4})$ and d_t is a deterministic component consisting of ID_{80Q1}, ID_{80Q2}, ID_{96Q1}, a constant and centered seasonal dummies. 4-quarter ahead dynamic simulation is iterated to obtain $\Delta_4 p_t$ forecasts for

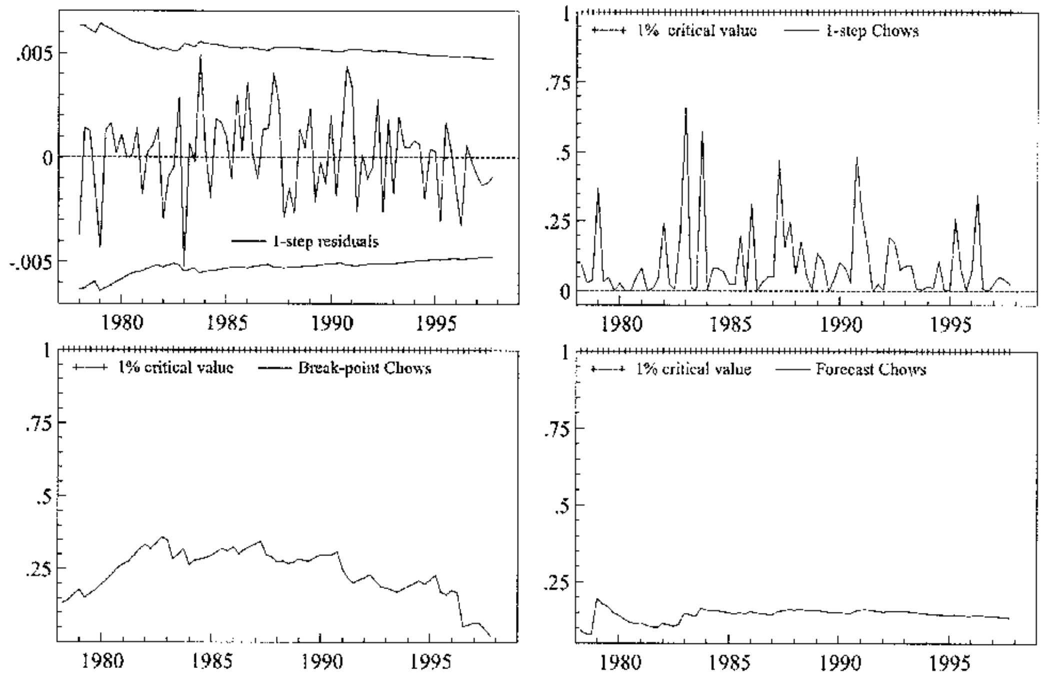

Figure 3: Japanese Inflation Model: Recursive Statistics

Instead, in this paper, a 4-quarter ahead inflation function is directly estimated by exploiting the knowledge of the above found long-run relationships. The importance of retaining cointegrating vectors for forecast is first pointed out by Engle and Yoo (1987) and subsequently elaborated by Clements and Hendry (1998, paper 6). Alternatively, information contents of inflation indicators are examined by an approach suggested by Stock and Watson (1999). Finally, forecast encompassing tests are conducted to see whether there is a gain from combining forecasts.

A. 4-quarter ahead inflation function

As the first step, we estimate the general model again. The four-quarter ahead annual inflation rate,[24] $\Delta_4 p_{t+4}$ is regressed on (i) four long-run solutions, $hpgap_t$; $markup_t$; $money_t$; and ppp_t, and (ii) short-run dynamics, $\Delta_{12} p_t$; Δp_{t-i}; Δy_{t-i}; Δm_{t-i}; Δp^{como}_{t-i};

1989Q1 to 1999Q1. Obtained MSFE is 1.50, which is significantly worse than those obtained by single equation analysis (Table 3). In the meantime, Kameda, Kyoso and Yoshida (1998) estimate a small simultaneous equations model for Japan, but do not report outcomes of dynamic simulation.

[24] In order to remove seasonal fluctuation, core inflation is often represented by annual growth. For example, the US Federal Reserve Board reports its inflation (the chain-type price index for personal consumption expenditures (PCE)) forecast to the Congress as annual growth at the fourth quarter ("Monetary Policy Report to the Congress Pursuant to the Full Employment and Balanced Growth

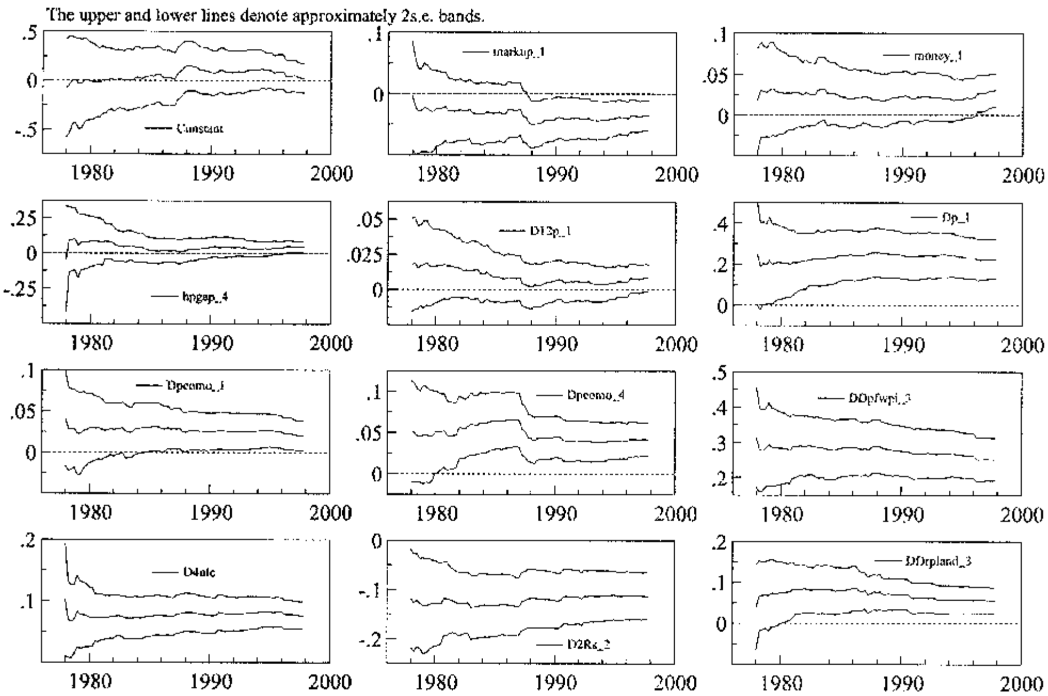

Figure 4: Japanese Inflation Model: Recursive Coefficients

Δp_{t-i}^{fwpi}; Δulc_{t-i}; Δrp_{t-i}^{land}; Rs_{t-i}; where $i = 0, ..., 3$. Together with the first and the second oil crisis dummies, SD_{74Q4}^{74Q1}, SD_{81Q1}^{80Q2}, a constant and centered seasonal dummies, for the period 1972Q1 to 1987Q1, the estimated model yields $\hat{\sigma}^2 = 0.53\%$ ($SC = -8.80$) for 47 variables and 61 observations.

From this general and overfitted model, the following simplified model is obtained by a sequential reduction:

Act 1978"). Similarly, the Bank of England publishes the annual growth of the retail price index less mortgage interest payments (PRIX) in its quarterly *Inflation Report*. Since annual growth is sum of the past four quarterly growth ($\Delta_4 p_t = \sum_{i=0}^{3} \Delta p_{t-i}$), it also has an advantage that it pools the past observations so that it smoothes out disturbances. This is a sensible choice for policy makers who are more interested in a trend of inflation.

Moreover, for forecasting tests, non-seasonally adjusted series are often preferred (Meese and Rogoff, 1983). This is because forecasts based on seasonally adjusted data with two-sided filter such as Census X11 or X12ARIMA implicitly makes use of information which would not have been available at the time of a given forecast. Also, in case of X12ARIMA, there is a certain circular argument. Reliability of seasonal adjustment made around the end of a sample period depends crucially on accuracy of forecast made by a chosen ARIMA model. However, if that ARIMA model really produces accurate forecasts, then there is no need to explore an issue of how to forecast inflation.

$$
\begin{aligned}
\Delta_4 p_{t+4} = & -\underset{(0.06)}{0.06} markup_{t-2} + \underset{(0.04)}{0.58} money_t + \underset{(0.12)}{0.21} hpgap_t \\
& + \underset{(0.02)}{0.08} \Delta_{12} p_t + \underset{(0.03)}{0.07} \Delta p^{como}_{t-2} + \underset{(0.13)}{0.80} \Delta p^{fwpi}_t + \underset{(0.04)}{0.11} \Delta_4 ulc_t \\
& - \underset{(0.10)}{0.53} \Delta_2 Rs_t + \underset{(0.06)}{0.11} \Delta_3 \Delta rp^{land}_t + \underset{(0.01)}{0.05} SD^{74Q1}_{74Q4} + \underset{(0.004)}{0.02} SD^{80Q2}_{81Q1} \\
& - \underset{(0.018)}{0.018} CS_1 - \underset{(0.019)}{0.026} CS_2 - \underset{(0.016)}{0.008} CS_3 - \underset{(0.30)}{2.29}, \qquad (8)
\end{aligned}
$$

$T = 1972Q1 - 1987Q1$, $R^2 = 0.99$, $\hat{\sigma} = 0.69\%$, $DW = 1.35$, $SC = -9.23$
$AR : F(5, 44) = 2.73^*$, $ARCH : F(4, 38) = 1.08$, $Normality : \chi^2(2) = 2.52$,
$X_i^2 : F(23, 22) = 0.76$, $RESET : F(1, 45) = 1.92$.

markup is hardly significant, which might suggest that the adjustment through this relationship has rather short-run impacts. Dropping this term, the model becomes:

$$
\begin{aligned}
\Delta_4 p_{t+4} = & \underset{(0.04)}{0.57} money_t + \underset{(0.11)}{0.18} hpgap_t \\
& + \underset{(0.02)}{0.10} \Delta_{12} p_t + \underset{(0.03)}{0.07} \Delta p^{como}_{t-2} + \underset{(0.13)}{0.77} \Delta p^{fwpi}_t + \underset{(0.04)}{0.10} \Delta_4 ulc_t \\
& - \underset{(0.10)}{0.49} \Delta_2 Rs_t + \underset{(0.05)}{0.09} \Delta_3 \Delta rp^{land}_t + \underset{(0.01)}{0.05} SD^{74Q1}_{74Q4} + \underset{(0.004)}{0.02} SD^{80Q2}_{81Q1} \\
& - \underset{(0.017)}{0.021} CS_1 - \underset{(0.017)}{0.018} CS_2 - \underset{(0.012)}{0.018} CS_3 - \underset{(0.18)}{2.54}, \qquad (9)
\end{aligned}
$$

$T = 1972Q1 - 1987Q1$, $R^2 = 0.99$, $\hat{\sigma} = 0.69\%$, $DW = 1.33$, $SC = -9.28$
$AR : F(5, 42) = 2.87^*$, $ARCH : F(4, 39) = 1.05$, $Normality : \chi^2(2) = 3.87$,
$X_i^2 : F(21, 25) = 0.83$, $RESET : F(1, 46) = 2.07$.

It is rather surprising to see that the model satisfies all diagnostic tests other than marginal failure of the AR test, even though it misses $t+1$ to $t+3$ variables. Also, the model outperforms the general model in terms of an encompassing test ($2.00 \sim F(33, 14)$).[25]

Forecasts are made from 1989Q1 to 1999Q1 by recursively estimating equation (9) up to two years before each forecast point. For example, in order to forecast 1989Q1, (i) the

[25]If we substitute *imfgap* to *hpgap* in equation (9), its coefficient becomes 0.12 with t-value of 1.2.

equation is estimated from the data of 1974Q1 to 1987Q1 (i.e., up to 1988Q1 inflation is regressed on up to 1987Q1 explanatory variables); and (ii) the 1989Q1 inflation forecast is made by replacing the explanatory variables with those up to 1988Q1. The same procedure is repeated for 1989Q2 onward.

Forecast performance of the above model is compared with three benchmark models:

- A pure random walk, which simply predicts that the four-quarter ahead inflation is same as the last observation, which implies:

  $$\Delta_4 p_{t+4} = \Delta_4 p_t + \varepsilon_{t+4}.$$

  For the exchange rate forecast, Meese and Rogoff (1983) find that a random walk model performs at least as well as any models they considered, including various structural models and uni/multivariate time series models. It is interesting to see whether the similar story holds or not for inflation forecast. Since the random walk model can be expressed as:

  $$\Delta_4 \Delta_4 p_{t+4} = \varepsilon_{t+4},$$

  the model can be thought as a univariate equivalence to the second differenced VAR (DDV in terminology of Clements and Hendry (1998, 1999)).

- A univariate model, which regresses $\Delta_4 p_{t+4}$ on its own lags:

  $$\Delta_4 p_{t+4} = \sum_{i=0}^{3} \beta_i \Delta_4 p_{t-i} + c + \varepsilon_{t+4},$$

  where c is a constant. This is a univariate equivalence to the first differenced VAR (DV in Clements and Hendry).

- A model which drops the long-run relationships from equation (9). Also examined are models which incorporate only one of the above three long-run relationships.

Clements and Hendry (1998, 1999) show in the presence of a structural break, the DDV has usually smaller forecast biases at the cost of forecast standard-error losses. When a gain in forecast biases is large enough, mean squared forecast errors (MSFEs) become smaller since MSFE is sum of a squared forecast bias and a forecast standard error.[26]

The role of intercept correction is examined with the above models by adding dummies for the last four observations and the corresponding forecast period. Intercept corrections also correct errors caused by a possible structural change or mils-specification. Again, Clements and Hendry show that intercept corrections can improve forecast accuracy

[26] $E[\mathbf{e}_{T+h}\mathbf{e}'_{T+h}] = E[\mathbf{e}_{T+h}]E[\mathbf{e}'_{T+h}] + V[\mathbf{e}_{T+h}]$, where $\mathbf{e}_{T+h}$ is forecast errors.

Table 3: Forecast Performances of Quarterly Models

	no intercept correct.			intercept correct.			
	Bias	SE	MSFE	Bias		SE	MSFE
Random walk	-0.06	0.79	0.63	...	...	...	...
Univariate	-0.46	0.78	0.82	-0.04	(-0.46)	0.84	0.71
EqCMs where long-run relationships are:							
money, hpgap	0.61	0.62	0.75	0.21	(0.48)	0.65	0.47
money, imfgap	0.50	0.58	0.59	0.29	(0.28)	0.57	0.41
markup	-0.22	1.01	1.06	-0.09	(-0.13)	1.00	1.00
money	0.76	0.75	1.15	0.33	(0.50)	0.82	0.79
hpgap	-0.47	1.18	1.62	-0.48	(0.01)	1.16	1.57
imfgap	-0.96	1.02	1.96	-0.43	(-0.69)	1.19	1.60
no long-run relationship	-0.20	1.09	1.23	-0.12	(-0.07)	1.04	1.10

Notes

1. In annual percentage points. 4-quarter ahead inflation forecasts based on equation (9).
2. Forecast period is 1989Q1–1999Q1. Estimation is 1973Q1 to two-year before for each forecast point.
3. Figures in parentheses are the average sizes of intercept corrections. Intercept corrections are conducted by adding dummies for the last four observations and the corresponding forecast period.

on bias measures at some cost of forecast standard-errors. Thus, MSFEs are smaller if intercept corrections reduce biases sufficiently. For instance, Hayakawa and Maeda (2000) indicate that the markup relationships might shift recently, owing to more aggressive pricing behaviors of firms after the 1997 financial system shock. Even if this is the case, it is very difficult to capture such a recent change by the above Johansen procedure, which tries to estimate the long-run relationship. In this case, either over-difference (DDV) or intercept correction may pay.

Table 3 summarizes test results:

- Without intercept correction, the random walk model performs at least as well as any models. The EqCM with (*money*, *imfgap*) yields the smaller MSFE (0.59) than the random walk model (0.63), but the gain is almost negligible.
- With intercept corrections, on the other hand, the EqCM with (*money*, *hpgap*) or (*money*, *imfgap*) outperforms all of the benchmark models. For instance, the EqCM with (*money*, *imfgap*) yields 0.41 of MSFE, which is smaller than those obtained by the random walk model (0.63) and the univariate model (0.71).
- Intercept corrections tend to pay. As the theory predicts, MSFEs improve through

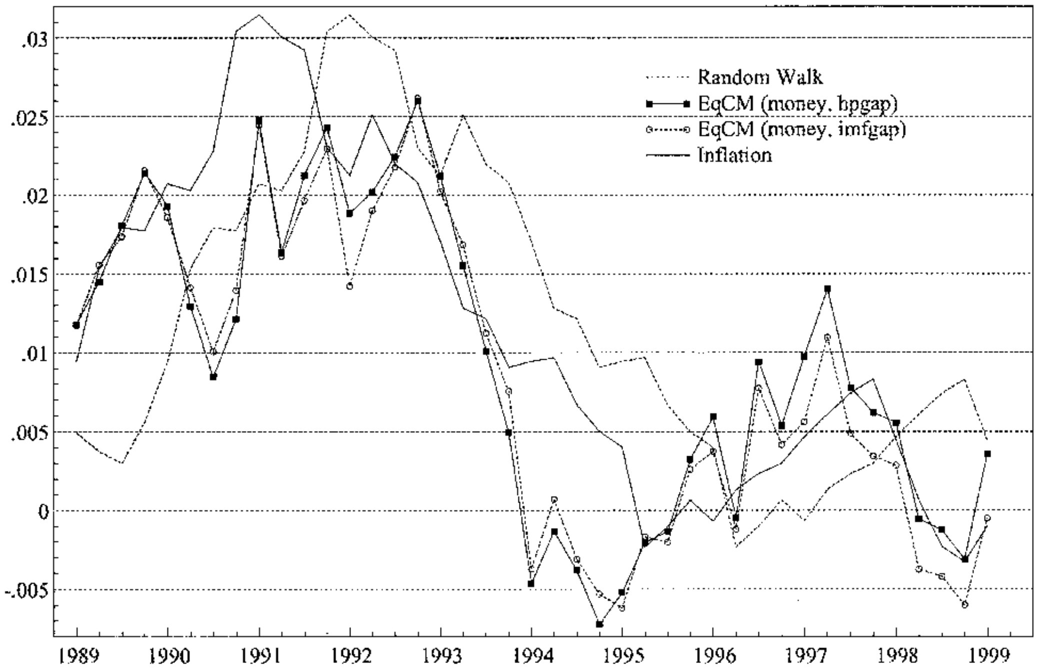

Figure 5: Forecast Performances of Quarterly Model

reduction in forecast biases (but not necessarily increasing standard-errors.)

Superiority of the EqCM is more obvious in Figure 5.[27] A simple chart would provide more precise comparison, since as argued by Clements and Hendry (1998, Chapter 6), MSFE might be a poor measure of forecast accuracy. By definition, forecasts of the random walk model always lag behind the actual outcome (and this is more or less the case for the univariate model as well). Although volatile, two EqCMs (using either *hpgap* or *imfgap*) succeed in tracking more closely actual development. The EqCMs fail to predict the peak around 1991, but this is probably due to the effect of the unforeseeable supply shock arising from the gulf war.

[27]For the sake of visibility, forecasts of the univariate model are dropped from figures hereafter, which tend to show slightly more volatility and longer lags than the random walk model.

B. Alternative approach: inflation indicators

As an alternative approach to the above EqCM, this section extends an analytical framework of Stock and Watson (1999), who examine forecast performances of monthly inflation indicators in terms of 12-month ahead inflation of the United States.

A basic formula to forecast 12-month ahead core inflations by inflation indicators is as follows:

$$\pi_{t+12} = \delta(L)g_t + \gamma(L)\Delta p_t + \theta\Delta p_{t+11}^{iwpi} + \mathbf{d}_t + \varepsilon_{t+12}, \tag{10}$$

where π_t is 12-month change in CPI less fresh food ($= \Delta_{12}p_t$); g_t is an inflation indicator; Δp_t^{iwpi} is added for controlling a supply shock; $\mathbf{d}_t$ is a vector of determinants including a constant and centered seasonal dummies; and $\delta(L)$ and $\gamma(L)$ are polynomial in the lag operator L.[28]

Stock and Watson constructs inflation indicators as the first principal components of various sets of monthly economic indicators. In particular, they find an inflation indicator derived from 60 real economic indicators provides the good basis of the US inflation forecast.

We derive principal components from 39 monthly economic indicators (see Data Appendix). These indicators are broadly categorized as real sector indicators (further these can be divided into labor market indicators and goods market indicators); financial market indicators (various exchange rates and interest rates); money and credit quantity indicators; and other price indicators (commodity prices etc.) They are transformed to I(0) by taking first difference.

Forecast performances of the above indicator models are compared with two benchmark models: a pure random walk model:

$$\pi_{t+12} = \pi_t + \varepsilon_{t+12},$$

and a univariate model, which drops $\delta(L)g_t$ term from equation (10):

$$\pi_{t+12} = \gamma(L)\Delta p_t + \theta z_{t+11} + \mathbf{d}_t + \varepsilon_{t+12}.$$

In order to simulate the real environment of forecasting, we will use the following algorithm for out of sample forecasting exercise. At time t,

1. calculate the principal component, g_t, from various indicators;

[28]In fact, assuming Δp_t is I(1), Stock and Watson estimate something equivalent to:

$$\pi_{t+h} - \Delta p_t = \delta(L)g_t + \gamma(L)\Delta^2 p_t + \theta\Delta p_{t+h-1}^{iwpi} + \mathbf{d}_t + \varepsilon_{t+h}.$$

However, the ADF test suggests Δp_t in Japan is I(0), which supports equation (10) (see Table 7).

Table 4: Forecast Performances of Monthly Indicator

	no intercept correct.			intercept correct.			
	Bias	SE	MSFE	Bias		SE	MSFE
Random walk	-0.06	0.80	0.64	...	...	...	...
Univariate	-0.06	0.82	0.68	-0.09	(0.01)	0.77	0.59
Principal (All)	0.06	0.79	0.62	-0.04	(0.08)	0.75	0.57
Principal (Real)	-0.05	0.81	0.67	-0.08	(0.02)	0.77	0.59
Principal (Financial)	-0.10	0.82	0.68	-0.10	(-0.03)	0.75	0.57
Principal (Money)	-0.02	0.81	0.65	-0.09	(0.05)	0.78	0.61
Principal (Price)	-0.10	0.78	0.62	-0.08	(-0.07)	0.74	0.56

Notes

1. In annual percentage points. 12-quarter ahead inflation forecasts based on equation (10).
2. Forecast period is 1989M1–1999M5. Estimation is 1981M1 to two-year before for each forecast point.
3. Figures in parentheses are the average sizes of intercept corrections. Intercept corrections are conducted by adding dummies for the last 12 observations and the corresponding forecast period.

2. determine the lag length of $\delta(L)$ and $\gamma(L)$ in equation (10) within 12 months according to the Schwartz Information Criterion. In order to ease computational burden, we make a restriction that the lag lengths of both polynomials are same;
3. estimate equation (10) and have the 12-month ahead inflation forecast, $\hat{\pi}_{t+12}$;
4. in case of the intercept correction, shift dummies are added for the last 12 observations and the forecast period.

Then go to $t+1$ and repeat the same routine.

Table 4 compares forecast performances in terms of MSFEs. There are three observations:

- Without intercept correction, principal component indicators do not quite outperform the two benchmark models. MSFE of the first principal component of all indicators (and price indicators) is 0.62, which is just marginally smaller than those of the random walk model and the univariate model.
- Intercept corrections seem to reduce MSFEs by about 0.05 to 0.1 percentage points. Contrary to the theory, this is achieved through reduction in the forecast standard errors.

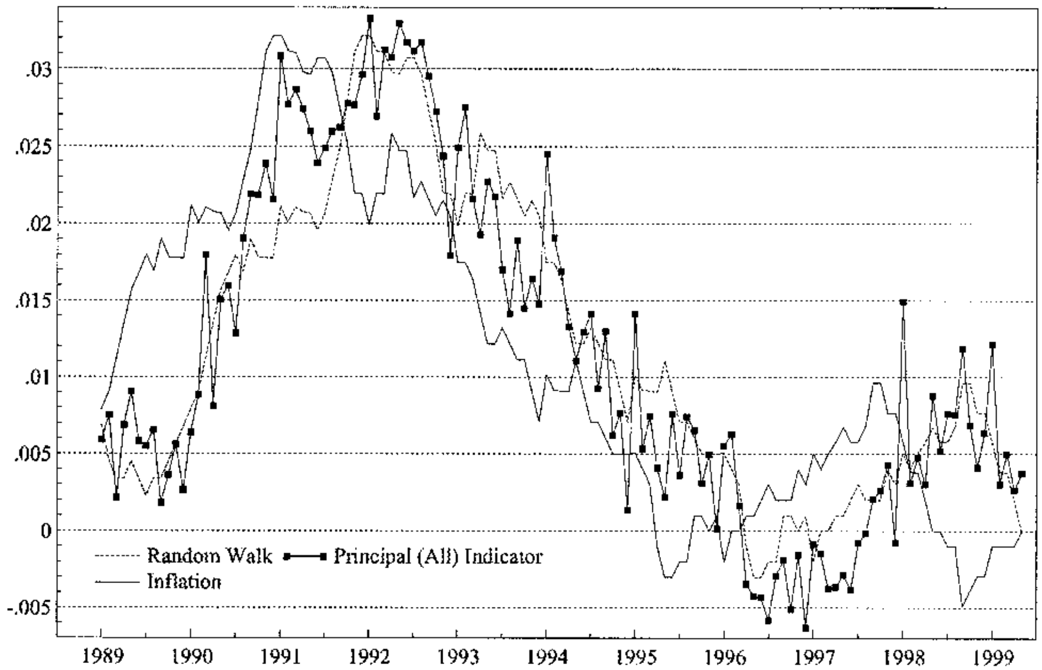

Figure 6: Forecast Performances of Monthly Indicator

- With intercept corrections, again, principal component indicators barely outperform the univariate model (with intercept corrections) nor the random walk model.

The finding that principal component indicators little add forecast accuracy over the random walk model can be easily confirmed by Figure 6. The figure shows principal (all) component indicator (with intercept corrections) more closely tracks the random walk model than the actual outcome of inflation. Rather disappointing performance of the Stock-Watson type indicators could be due to the restriction on the lag length (the second item of the employed algorithm). Or given the limited success of the indicator approach so far in general, one may cast doubt on robustness of this approach, which neglects any causal relationships including those represented by the cointegrating relationships (Clements and Hendry (1998, Chapter 9)).

C. Combined forecasts

Finally, we will try to examine whether there may be gains from combining forecasts. To investigate into this, forecast encompassing tests are conducted by regressing the

Table 5: Forecast Encompassing Tests

$\widetilde{\Delta_4 p_t}$ \ $\widehat{\Delta_4 p_t}$	EqCM	Principal	Random Walk	Univariate
EqCM	...	0.46 (0.08)	0.42 (0.08)	0.39 (0.08)
Principal	0.54 (0.08)	...	-0.09 (0.41)	-0.45 (0.34)
Random Walk	0.58 (0.08)	1.09 (0.41)	...	0.12 (0.36)
Univariate	0.61 (0.08)	1.45 (0.34)	0.88 (0.36)	...

Notes

1. $\hat{\gamma}$ in equation (11).
2. Sample period is 1989Q1–1999Q1. Figures in parentheses are heteroscedastic-consistent standard errors.
3. EqCM with *money* and *hpgap*. EqCM with *money* and *imfgap* does not change the qualitative results.

following equation in the quarterly frequency.[29]

$$\Delta_4 p_{t+4} = \gamma \cdot \widehat{\Delta_4 p_{t+4}} + (1-\gamma) \cdot \widetilde{\Delta_4 p_{t+4}} + \eta_{t+4}, \tag{11}$$

where $\widehat{\Delta_4 p_{t+4}}$ is forecasts made by one model and $\widetilde{\Delta_4 p_{t+4}}$ is those made by the competing model. If the former model dominates the other in forecast, estimated $\hat{\gamma}$ should be close to 1. If neither model encompasses each other, then there is a case for combining these two forecasts.

Indeed, there is a case for combining forecasts of the EqCM with those of the others. From Table 5, we can see

1. The univariate model is encompassed by the random walk model and the principal component indicator;
2. The random walk model is encompassed by the principal component indicator – this is probably owing to volatile movement of the principal component indicator's forecasts;
3. The EqCM and the other models do not encompass each other.

From them, there is a strong case for combining forecasts of the EqCM with those of the principal component indicator, which encompasses both the random walk model and the univariate model. However, since the EqCM does not encompass the remaining two models either, there are also cases for combining forecasts of each of them.

Table 6: Combined Forecasts

		Bias	SE	MSFE
EqCM (*money*, *hpgap*)				
with	Principal	0.03	0.56	0.31
	Random Walk	0.06	0.56	0.32
	Univariate	0.07	0.60	0.36
EqCM (*money*, *imfgap*)				
with	Principal	0.09	0.53	0.28
	Random Walk	0.13	0.52	0.29
	Univariate	0.13	0.55	0.32

Notes

1. In annual percentage points. 4-quarter ahead inflation forecasts based on equation (11).
2. Forecast period is 1990Q4–1999Q1. $\hat{\gamma}$ is obtained by recursive OLS from the sample 1989Q1 to one-year before for each forecast point.

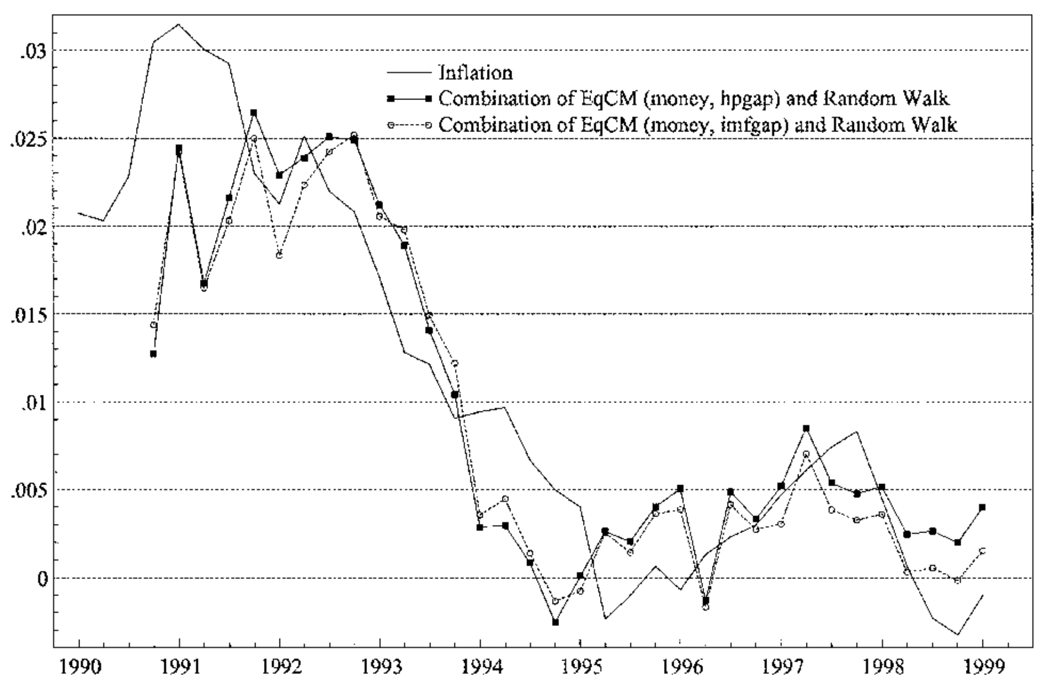

Figure 7: Performances of Combined Forecasts

These combinations certainly improve the forecast performance. The forecast combinations of EqCM-principal component indicator, EqCM-random walk model and EqCM-univariate model yield MSFEs in Table 6, which are considerably smaller than those attained in Tables 3 and 4.[30] Figure 7 also shows gains of the forecast combinations. Compared with Figure 5, the combined forecasts more closely track actual outcomes with less volatility. EqCM (*money*, *imfgap*) yields slightly better MSFEs than EqCM (*money*, *hpgap*) owing to the better forecast performances for the recent years. However, the difference between them is generally very small. These forecast combinations highlight the importance of adjustment on the pure structural model-based forecasts. Indeed, if the EqCM is prefect, there is no room for improvement by the forecast combination. However, in reality, to protect the forecast against possible mis-specification or structural changes, adjustment such as intercept corrections often pay (see paper 8 of Clements and Hendry (1998)). The above forecast combination can be regarded as one way of systematic adjustments on the pure structural model-based forecasts.[31]

IV. Conclusion

This paper estimates an inflation function and forecasts one-year ahead inflation in Japan. It finds:

1. markup, excess money and the output gap are particularly relevant long-run determinants for an EqCM of inflation.

[29] Monthly forecasts of the principal component (all) indicator are converted to quarterly forecasts by taking 3-month average of the corresponding periods.

[30] Forecast periods of Tables 3 and 4 are 1989Q1–1999Q1 and 1989M1–1999M5. For the 1990Q4–1999Q1 forecast interval, each model (with intercept correction except for Random Walk) yields the following MSFEs:

Random Walk	0.55
Univariate	0.64
EqCM (*money, hpgap*)	0.48
EqCM (*money, imfgap*)	0.43
Principal (All)	0.44

[31] In fact, combination with a random walk model can be thought as a variant of intercept corrections. Assume $\widehat{\Delta_4 p_{t+4}}$ is forecasts made by a random walk model and $\widetilde{\Delta_4 p_{t+4}}$ is the EqCM. From equation (11), the forecast combination, $\overline{\Delta_4 p_{t+4}}$, is

$$
\begin{aligned}
\overline{\Delta_4 p_{t+4}} &= \gamma(\widehat{\Delta_4 p_{t+4}} - \widetilde{\Delta_4 p_{t+4}}) + \widetilde{\Delta_4 p_{t+4}} \\
&= \gamma(\Delta_4 p_t - \widetilde{\Delta_4 p_{t+4}}) + \widetilde{\Delta_4 p_{t+4}},
\end{aligned}
$$

In case of $\gamma = 1$, $\overline{\Delta_4 p_{t+4}} = \Delta_4 p_t$, which is an example of full intercept correction. On the other hand, in case of $\gamma = 0$, there is no intercept correction. In case of $0 < \gamma < 1$, which is what we found above, is an intermediate case between the two cases (partial intercept correction).

2. with intercept corrections, one-year ahead inflation forecast performance of the EqCM is better than those of benchmark models. Among the three long-run relationships, combinations of excess money and the output gaps contribute most on explanatory power. Meanwhile, contrary to the U.S. experience, the Stock-Watson type of inflation indicators does not significantly outperform the benchmark models.

3. forecast accuracy can be improved by combining forecasts of an equilibrium correction model together with those made by rival models.

The obtained multi-causal EqCM conforms with a general belief "Inflation is, after all, determined by the interaction of many forces." (Bernanke, et.al., 1999), and would serve for structural model-based inflation forecasting. The paper also highlights the importance of adjustment to a pure structural model-based forecast by means of combining the forecast with those of other rival models.

Now that the Fund is trying to adopt inflation targeting as one of its conditionalities, how to forecast inflation will be a critical aspect of the policy design not only for central banks of advanced economies, but for those of a wider range of countries. The methodology employed in this paper may be applicable to some of these countries.

There are two caveats, which in turn suggest the possible extensions of this study: One relates to modeling. As footnotes 9 and 12 state, there are signs of violation of exogeneity conditions, which cast doubt on validity of a single equation model. Although the obtained single equation model behaves reasonably congruently in terms of various other diagnostic tests, it would be interesting to see whether findings based on the single equation approach in this paper can be confirmed by a system approach such as a simultaneous equations model.

The other relates to forecasting. Although the EqCM updates estimates using information available one year prior to each forecast point, it also imposes restrictions on the long-run relationships, which cannot be obtained at that time—for instance, the Johansen tests from the sample up to 1988 do not yield the same cointegrating vectors used in the above because of a small sample problem. Furthermore, in general, there is always danger of overfit as in- and post-sample is under the control of an investigator. Presumably the only genuine test of the forecast would be to revisit this model in the future to assess the accuracy of forecasts—only the future knows the answer.[32]

[32]This research was conducted based on information available as of May 2000. At that time, the 2000 CPI inflation was forecasted as 0.1 percent (combination of EqCM (*money*, *hpgap*) with random walk) and 0.0 percent (combination of EqCM (*money*, *imfgap*) with random walk) with 0.5 percent standard errors. In fact, CPI in 2000 turned out to be 0.4 percent lower than the previous year's level, which was within one standard error bands of the above forecasts.

Data Appendix

A. Data for equilibrium correction models

Consumer price index less fresh food (p): Adjustments are made at 1989 April (introduction of the then 3% consumption tax) and 1997 April (a rise in consumption tax rate to 5%). 1.1% and 1.4% are estimated as permanent shifts in the level of the price index respectively, based on level shift dummies of the X12ARIMA program. The almost identical impacts are also obtained by STAMP. In Figure 8, the series are plotted with the trimmed-mean CPI (Mio and Higo, 1999).

Wholesale price index of final goods (p^{fwpi}): Adjustments are also made at 1989 April and 1997 April by 1.1% and 2.1%, respectively, which are detected by both the X12ARIMA and STAMP.

Wholesale price index of import goods (p^{iwpi}).

Nikkei commodity index (p^{como}): The simple geometric average of major 42 commodities.

Unit labor cost (ulc): SNA-basis employees income divided by potential output.

M2+CDs (m).

GDP (y).

Short-term interest rate (Rs): CD 3-month rate. Spliced with the 3-month *Gensaki* (bonds with repurchase agreements) rate before 1984 April.

Own interest rate of money (Rm): See Sekine (1998) for details.

Interest rate on rival assets (Rr): See Sekine (1998) for details.

Real land price (rp^{land}): The biannual land price index (urban district, all purposes, six major cities) is interpolated to the quarterly series by means of linear interpolation of the land price to nominal GDP ratio. Deflated by p above.

Real effective exchange rate (ppp): CPI-based real effective exchange rate of the yen.

Impulse dummy (ID_{xxQy}): A dummy which takes one at 19xxQy, otherwise nil.

Step dummy (SD^{aaQb}_{xxQy}): A dummy which takes one from 19aaQb to 19xxQy, otherwise nil.

B. Data for principal component indicators

All indicators are detrended by taking first differences of the corresponding logarithms except for interest rates which do not take logarithms (but take first differences.)

Table 7: ADF Statistics for Testing Unit Roots

Variables	t_{adf}	Lag	Variables	t_{adf}	Lag
p	-2.55	1	Δp	-4.67**	0
p^{fwpi}	-2.36	1	Δp^{fwpi}	-5.33**	0
p^{iwpi}	-2.26	1	Δp^{iwpi}	-5.39**	0
p^{como}	-2.68	1	Δp^{como}	-5.24**	4
ulc	-2.80	5	Δulc	-2.50	5
m	-2.43	1	Δm	-3.36	1
y	-1.61	5	Δy	-15.81**	0
Rs	-4.11**	3	ΔRs	-8.23**	0
Rm	-2.54	1	ΔRm	-5.76**	0
Rr	-3.30	1	ΔRr	-7.33**	0
rp^{land}	-2.36	2	Δrp^{land}	-2.21	1
ppp	-3.20	1	Δppp	-7.80**	0

Notes

1. The estimation periods are 1971Q3 (or 1971Q4)-1999Q1. Constant, trend and seasonals are added as regressors.

- Real economic indicators
  - Labor market (9 indicators): Job Application to Offer Ratio, New Job Application to Offer Ratio, New Vacancy, Unemployment Ratio, Employees Cash Payroll (more than 30 employees), Employment, Regular Employment (more than 30 employees), Hours Works (more than 30 employees), Unit Labor Cost (manufacturing).
  - Goods market (12 indicators): Industrial Production, Shipment, Inventory, Inventory Ratio, Operating Ratio, New Machinery Order (private, less shipment and electricity), New Housing Starts, Public Works Contracts, Department Sales, New Passenger Car Registry, Consumption Level Index (all households), Consumption Level Index (employees).
- Financial market (8 indicators): Nominal Effective Exchange Rate, Real Effective Exchange Rate, Yen-US dollar Rate (Tokyo market at 17:00), Nikkei 225 Stock Price, Overnight Call Rate, CD 3-month Rate, TB 10-year (over the counter market), Bank Debenture 5-year (over the counter market).
- Money and Credit (4 indicators): Base Money, M2+CDs, M1, Bank Loan.
- Prices (3 indicators): Nikkei Commodity Index Wholesale Price Index (import goods), Wholesale Price Index (final goods).
- Economic Planning Agency Composite Index (3 indicators): Lead Index, Coincide Index, Lagged Index.

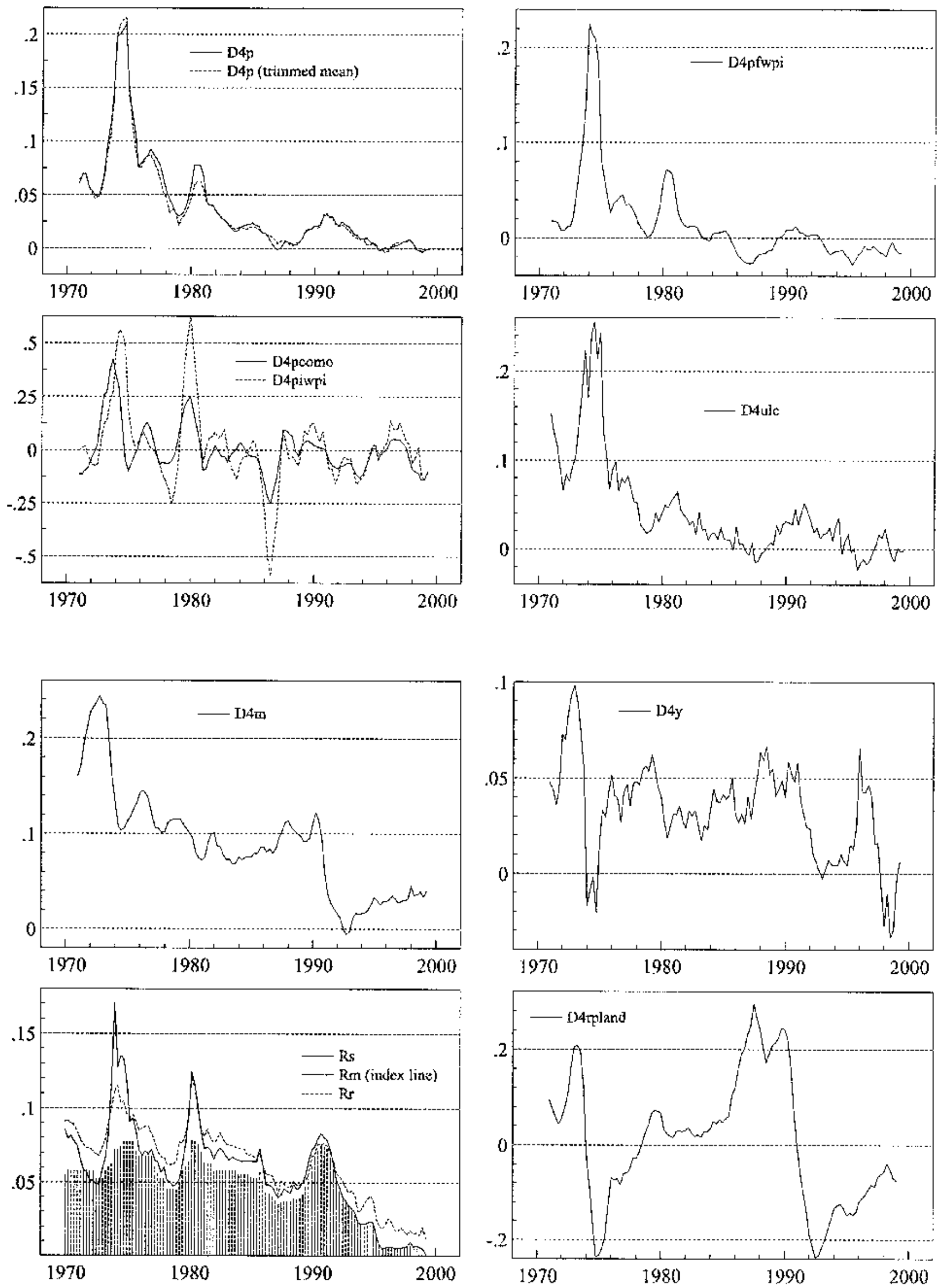

Figure 8: Japanese Inflation Model: Data

References

Bayoumi, Tamim (1999). "Where Are We Going? The Output Gap and Potential Growth" in Bayoumi, Tamim and Charles Collynes (eds.) *Post-Bubble Blues: How Japan Responded to Asset Price Collapse,* International Monetary Fund, Washington DC.

Bernanke, Ben S. and Michael Woodford (1997). "Inflation Forecasts and Monetary Policy," *Journal of Money, Credit and Banking*, Vol. 29, pp. 653–684.

Bernanke, Ben S., Thomas Laubach, Frederic S. Mishkin and Adam S. Posen (1999). *Inflation Targeting: Lessons from the International Experience*, Princeton University Press, Princeton.

Clements, Michael P. and David F. Hendry (1998). *Forecasting Economic Time Series*, Cambridge University Press, Cambridge.

Clements, Michael P. and David F. Hendry (1999). *Forecasting Non-stationary Economic Time Series*, The MIT Press, London.

de Brouwer, Gordon and Neil R. Ericsson (1998). "Modeling Inflation in Australia," *Journal of Business and Economic Statistics*, Vol. 15, pp. 433–449.

Doornik, Jurgen A. (1997). *Object-oriented Matrix Programming Using Ox,* Timberlake Consultants Press, London.

Doornik, Jurgen A. and David F. Hendry (1997). *Modelling Dynamic Systems Using Pc-Fiml 9 for Windows,* Timberlake Consultants Press, London.

Engle, Robert F. and Byung Sam Yoo (1987). "Forecasting and Testing in Co-integrated Systems," *Journal of Econometrics*, Vol. 35, pp. 143–159.

Friedman, Milton and Schwartz, Anna J. (1963). *A Monetary History of the United States, 1867–1960*, Princeton University Press, Princeton.

Granger, Clive (2000), "Thick Modeling," Unpublished paper.

Hallman, Jeffrey J., Richard D. Porter and David H. Small (1991). "Is the Price Level Tied to the M2 Monetary Aggregate in the Long Run?" *American Economic Review,* Vol. 81, pp. 841–858.

Harvey, Andrew C. and A. Jaeger (1993). "Detrending, Stylized Facts and the Business Cycle," *Journal of Applied Econometrics*, Vol. 8, pp. 231–247.

Hayakawa, Hideo, and Eiji Maeda (2000). "Understanding Japan's Financial and Economic Developments Since Autumn 1997," *Bank of Japan Research and Statistics Department Working Paper*, No. 00-1.

Hendry, David F. (1999). "Does Money Determine UK Inflation over the Long Run?" Unpublished paper.

Hendry, David F. and Jurgen A. Doornik (1996). *Empirical Econometric Modelling Using PcGive for Windows,* Timberlake Consultants Press, London.

Higo, Masahiro (1999). "What Can Inflation Expectations and Can Inflation Tell Us About Monetary Policy?" *Bank of Japan IMES Discussion Paper*, No. 99-E-22.

Honda, Yuzo, Kouichi Kamioka and Shinya Horaguchi (1995). "Kinyu Jouhou Hensu to Taimu Ragu (Financial Information Variables and Time Lag)" in Honda, Yuzo (ed.) *Nihon no Keiki (Business Conditions in Japan)*, Yūhikaku, Kyoto (in Japanese).

International Monetary Fund (1999). *World Economic Outlook, October 1999.* Washington DC.

Juselius, Katarina (1992). "Domestic and Foreign Effects on Prices in an Open Economy: The Case of Denmark," *Journal of Policy Modeling*, Vol. 14, pp. 401–428.

Kameda, Seisaku, Kinuyo Kyoso and Tomoo Yoshida (1998). "Searching for the Long-Run Relations between Monetary Aggregates and Other Macroeconomic Variables in Japan: A Vector Error Correction Approach," *Bank of Japan Research and Statistics Department Working Paper*, No. 98-2.

Kasuya, Munehisa, and Kozo Ueda (2000). "Testing Purchasing Power Parity Hypothesis: Re-examination by Additional Variables, Tests with Known Cointegrating Vectors, Monte Carlo Critical Values, and Fractional Cointegration," *Bank of Japan Research and Statistics Department Working Paper*, No. 00-3.

Komiya, Ryutaro (1976). "Syouwa Yonju Hachi, Kyu Nen Infureshon no Geinin [Causes of the 1973-74 Inflation,]" *Keizaigaku Ronsyu*, University of Tokyo, Vol. 42, No. 1, pp. 2–40 (in Japanese).

Koopman, Siem Jan, Andrew C. Harvey, Jurgen A. Doornik and Neil Shephard (1999). *Stamp: Structural Time Series Analyser, Modeller and Predictor*, Timberlake Consultants Press, London.

Meese, Richard A. and Kenneth Rogoff (1983). "Empirical Exchange Rate Models of the Seventies: Do they fit out of sample?" *Journal of International Economics*, Vol. 14, pp. 3–24.

Metin, Kivilcim (1995). "An Integrated Analysis of Turkish Inflation," *Oxford Bulletin of Economic and Statistics*, Vol. 57, pp. 513–531.

Mio, Hitoshi and Masahiro Higo (1999). "Underlying Inflation and the Distribution of Price Change: Evidence from the Japanese Trimmed-Mean CPI," *Bank of Japan Economic and Monetary Studies*, Vol. 17, No. 1, pp. 103–132.

Rogoff, Kenneth (1996). "The Purchasing Power Parity Puzzle," *Journal of Economic Literature*, Vol. 34, pp. 647–668.

Sekine, Toshitaka (1998). "Financial Liberalization, the Wealth Effect, and the Demand for Broad Money in Japan," *Bank of Japan Economic and Monetary Studies*, Vol. 16, No. 1, pp. 35–55.

Stock, James H. and Mark W. Watson (1999). "Forecasting Inflation," *Journal of Monetary Economics*, Vol. 44, pp. 293–335.

Svensson, Lars E. O. (1997). "Inflation Forecast Targeting: Implementing and Monitoring Inflation Targets," *European Economic Review*, Vol. 41, pp. 1111–1147.

Tanaka, Hidenori and Takeshi Kimura (1998). "Vector Error Correction Model wo Moci-ita Bukka no Kettei Mekanizum ni kansuru Jissyou Kenkyu [Empirical Analysis on Price Determination Using a Vector Error Correction Model]," *Bank of Japan Research and Statistics Department Working Paper*, No. 98-10 (in Japanese).

Woodford, Michael (1994). "Nonstandard Indicators for Monetary Policy," in Mankiw, N. Gregory (ed.) *Monetary Policy*, University Chicago Press, Chicago.