Deciphering The Message in Japanese Deflation Dynamics

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Abstract

This paper attempts to "decipher", with linear and nonlinear neural network regime switching (NNRS) models , the message in Japanese deflation dynamics. The NNRS model is superior to the linear model in terms of in-sample specification tests as well as out-of-sample forecasting accuracy. The most important variables affecting inflation are interest rates and the output gap. Given the zero lower bound on interest rates, our analysis suggests that policies aimed the reversing the output gap through stimulating investment are the most important escape channels from the deflationary spiral.

JEL Classification: E0, E3, E5

Keywords: deflation, neural networks, regime-switching models

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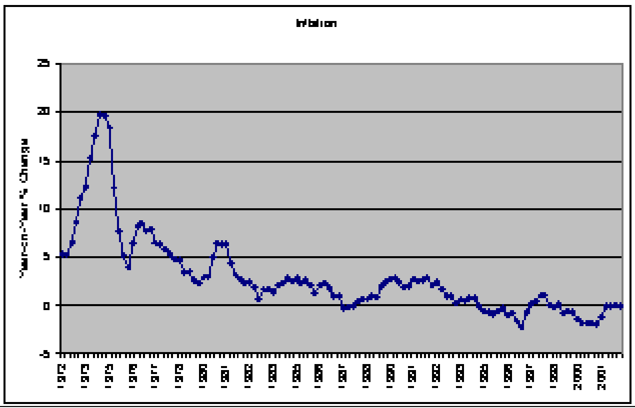
1 Introduction

Japan has been in deflation for over a decade, as Figure 1 shows:

Figure 1



Krugman (1998) comments on this experience of Japan:

> Sixty years after Keynes, a great nation - a country with a stable and effective government, a massive net creditor, subject to none of the constraints that lesser economies face - is operating far below its productive capacity, simply because its consumers and investors do not spend enough. That should not happen; in allowing it to happen, and to continue year after year, Japan's economic officials have subtracted value from their nation and the world as a whole on a truly heroic scale. [Krugman (1998): Introduction].

Krugman recommends expansionary monetary and fiscal policy to create inflation. However, Yoshino and Sakakibara have taken issue with Krugman's remedies. They counter Krugman in the following way:

> Japan has reached the limits of conventional macroeconomic policies. Lowering interest rates will not stimulate the economy, because widespread excess capacity has made private investment insensitive to interest rate changes. Increasing government expenditure in the usual way will have small effects because it will take the form of unproductive investment in the rural areas. Cutting taxes will not increase consumption because workers are concerned about job security and future pension and medical benefits [Yoshino and Sakakibara (2002): p.110].

Besides telling us what will not work, Yoshino and Sakakibara offer alternative longer-term policy prescriptions, involving financial reform, competition policy, and the reallocation of public investment:

> In order for sustained economic recovery to occur in Japan, the government must change the makeup and regional allocation of public investment, resolve the problem of nonperforming loans in the banking system, improve the corporate governance and operations of the banks, and strengthen the international competitiveness of domestically oriented companies in the agriculture, construction and service industries [Yoshino and Sakakibara (2002): p.110].

Both Krugman and Yoshino and Skakibara base their analysis and policy recommendations on analytically simple models, with reference to key stylized facts observed in macro-economic data.

Of course, there is no scarcity of proposed "remedies" for the Japanese deflation problem within academic discussion and policy analysis. . Svensson (2003) has recently reviewed many of these and has put forward his own "foolproof" way. His "foolproof" remedy has three key ingredients: first, a upward-sloping price level target path set by the central bank, secondly, an initial depreciation followed by a "crawling peg", and third, an exit strategy with abandonment of the peg in favor or inflation or price-level targeting when the price-level target path has been reached [Svensson (2003): p. 15]. Other remedies include a tax on money holding, proposed by Goodfriend (2002) and Buiter and Panigirtzoglou (1999) as well as targeting the interest rate on long-term government bonds, proposed by Clouse et al (2003), and Meltzer (2001).

The growth of low-priced imports from China has also been proposed as a possible cause of deflation in Japan (as in Hong Kong). McKibbin (2002) has argued that monetary policy would be effective in Japan through yen depreciation. He argues for a combination of a fiscal contraction with a monetary expansion based on depreciation:

> Combining a credible fiscal contraction that is phased in over three years with an inflation target would be likely to provide a powerful macroeconomic stimulus to the Japanese economy, through a weaker exchange rate and lower long term real interest rates, and would sustain higher growth in Japan for a decade [McKibbin (2002), p. 133].

In contrast to Krugman and Yoshino and Skakibara, McKibbin based his analysis and policy recommendations on simulation of the calibrated "G-Cubed" (Asia Pacific) dynamic general equilibrium model, outlined in McKibbin and Wilcoxen (1998).

Sorting out the relative importance of monetary policy, stimulus packages which affect overall demand (measured by the output gap), as well as the contributions of unit labor costs, falling imported goods prices, and financial-sector factors coming from the collapse of bank lending and asset-price deflation (measured by the negative growth rates of share price and land price indices) is no easy task. These variables display considerable volatility and the response of inflation to these variables is likely to be asymmetric.

Most studies of inflation have relied on linear extensions and econometric implementation of the Phillips curve or New Keynesian Phillips curve. While such linear applications are commonly used and have been successful for many economies, we show in this paper that a nonlinear smooth-transition neural network regime-switching method outperforms the linear model on the basis of in-sample diagnostics and out-of-sample forecasting accuracy.

Regime switching models have been widely applied to macroeconomic analysis of business cycles, initially with "linear" regimes switching between periods of recession and recovery [see Hamilton (1989, 1990)]. Similarly, there have been many studies examining nonlinearities in business cycles, which focus on the well-observed asymmetric adjustments in times of recession and recovery [see Teräsvirta, and Anderson (1992)]. This paper follows in this tradition by applying a nonlinear regime switching model to the inflationary/deflationary experience of Hong Kong.

The next section dicusses the key variables we use to analyze the dynamics of inflation and deflation. Section 3 contains our model specification while Section 4 discusses the estimation method. Section 5 is analysis of our key empirical results and the last section concludes.

2 Key Variables for Assessing Inflation

In this section we examine the interest rate, the output gap, the rates of growth of import prices and unit labor costs, two financial sector indicators, the rates of growth of the Hang Seng index and residential property prices, and the growth of bank lending.

The interest rate, of course, represents the key channel of monetary policy. We use the current-period short-term Gensaki rate as a measure or "indicator" of the stance of monetary policy. The output gap, which measures the "slack" in the economy, is defined as the difference between the logarithm of actual output less the logarithm of "potential" output, y^p, while potential output is given by the Hodrick-Prescott filter. Figures 2 and 3 picture these variables. We see that the interest rate effectively reached its positive "lower bound" by 1995, while measures of the output gap show that the economy has been well "below potential" (as Krugman point out) by factors of three or four percent in recent years.

Figure 2

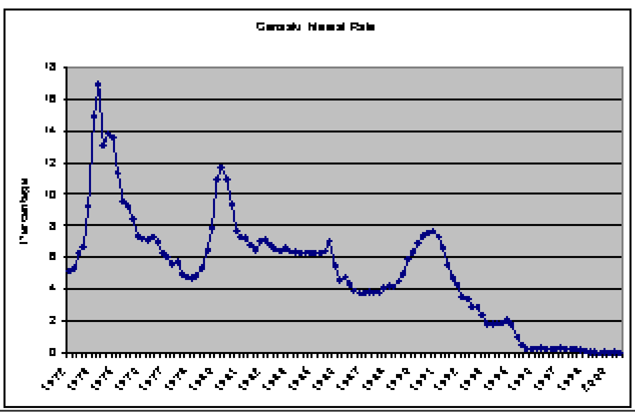
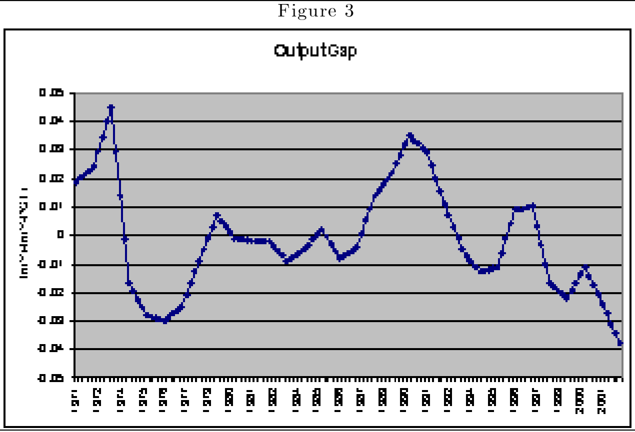


Figure 3



The behavior of imported goods prices and unit labor costs, both important for understanding the supply-side or costs factors of inflationary movements, show considerably different patterns of volatility. Figure 4 pictures the rate of growth of imported goods prices while Figure 5 shows the corresponding movement in labor costs.

Figure 4

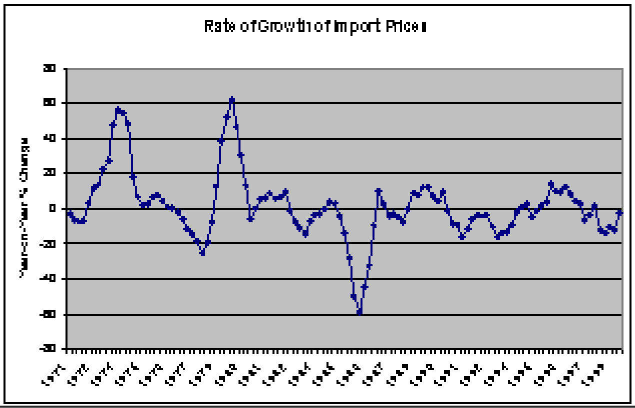


Figure 5

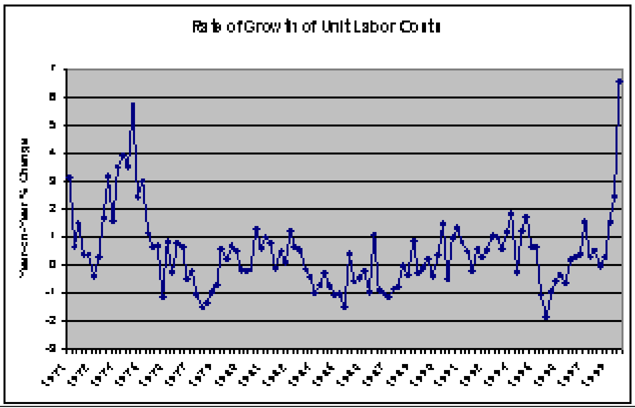


Figure 6 pictures the financial sector variables , the rates of growth of bank lending, the share price index (the Nikkei index), and the land price index. Bank lending of often cited as the "credit channel" of monetary policy, while asset price "inflation" or "deflation" factors are used as financial sector "pressures" affective overall demand and inflation. Not surprisingly, the share price index shows much more volatility than the growth of bank lending and the land price index.

Figure 6

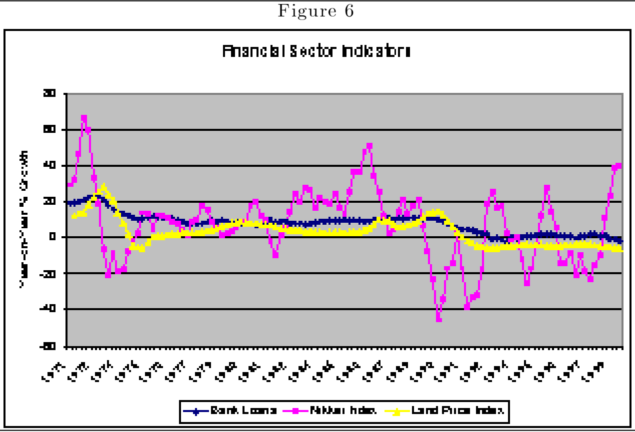


Table I contains a statistical summary of the data we use in our analysis We use quarterly observations from 1970.1 until 2001.1. Table I lists the means, standard deviations, and contemporaneous correlations of annualized rates of inflation, the Gensaki rate, the output gap, and changes in import prices, unit labor costs, the land price index, the share price index, and overall bank lending.

Table I

Statistical Summary of Data

	Inflation	Gensaki	y-gap	imp-growth	ulc-growth	lpi-growth	spi-growth	loan-growth
Mean	0.034	0.052	0.000	0.016	0.004	0.035	0.068	0.077
Std.Dev.	0.043	0.036	0.017	0.193	0.014	0.074	0.202	0.054
Correlation Matrix								
	Inflation	Gensaki	y-gap	imp-growth	ulc-growth	lpi-growth	spi-growth	loan-growth
Inflation	1.000							
Gensaki	0.607	1.000						
y-gap	-0.211	0.309	1.000					
imp-growth	0.339	0.550	0.225	1.000				
ulc-growth	0.492	0.198	-0.052	0.328	1.000			
lpi-growth	0.185	0.777	0.591	0.345	-0.057	1.000		
spi-growth	-0.069	-0.011	-0.286	-0.349	-0.176	0.081	1.000	
loan-growth	0.489	0.823	0.310	0.279	-0.016	0.848	0.245	1.000

The highest volatility rates (measured by the standard deviations of the annualized quarterly data) are for the rates of growth of the share market and import price indices.

Table I further shows that the highest correlation of inflation is with the Gensaki rate, but that it is positive rather than negative. This is another example of the well known "price puzzle", recently analyzed by Giordani (2001). This "puzzle" is also a common finding of linear vector-autoregressive (VAR) models, which show that an increase in the interest rate has positive, rather than negative, effects on the price level in impulse-response analysis. Sims (1992) proposed that the "cause" of the prize puzzle may be "unobservable" contemporaneous supply shocks. The policy makers observe the shock and think it will have positive effects on inflation, so they raise the interest rates in anticipation of countering higher future inflation. Sims found that this puzzle disappears in US data when we include a commodity price index in a more extensive VAR model.

Table I also shows that the second and third highest correlations of inflation are with unit labor costs and bank lending, followed by import price growth. The correlations of inflation with the share-price growth rate and the output gap are negative but insignificant.

Finally, what is most interesting from the information given in Table I is the very high correlation between the growth rate of bank lending and the growth rate of the land price index, not with the growth rate of the share price index. It is not clear which way the causality runs: does the collapse of land prices lead to a fall in bank lending, or does the collapse of bank lending lead to a fall in land prices?

Gerlach and Peng (2003) have examined the interaction between banking credit and property prices in Hong Kong. They found that property prices are "weakly exogenous" and determine bank lending, while bank lending does not appear to influence property prices [Gerlach and Peng (2003): p. 11]. They argue that changes in bank lending rates cannot be regarded as the source of the boom and bust cycle in Hong Kong. They hypothesize that "changing beliefs about future economic prospects led to shifts in the demand for property and investments". With a higher inelastic supply schedule, this caused price swings, and with rising demand for loans, "bank lending naturally responded" [[Gerlach and Peng (2003): p. 11].

In Japan, the story is different: banking credit and land prices show bidirectional causality or feedback. The collapse of land prices reduces bank lending, but the collapse of bank lending also leads to a fall in land prices. Table II gives the joint-F statistics and the corresponding P-values for a Granger test of causality. We see that the results are somewhat stronger for a causal effect from land prices to loan growth. However, the p-value for causality from loan growth to land price growth is only very slightly above five percent. These results indicate that both variables have independent influences and should be included as financial factors for assessing the behavior of inflation.

Table II

Granger Test of Causality: LPI and Loan Growth

	Loan Growth does not cause LPI Growth	LPI Growth does not cause Loan Growth
F-Statistic	2.429	3.061
P-Value	0.053	0.020

We acknowledge that econometric estimation for policy analysis, of course, is subject to the Lucas (1976) critique. Key parameter values would could hardly be expected to remain constant when monetary policy "regimes" change, so we do not argue that policy prescriptions should be based on econometric model estimation alone. Clearly, good policy should come from a combination of clear analytical thinking, exemplified by the diagnoses of Krugman, and Yoshino and Sakahibara, from rigorously constructed and calibrated dynamic general equilibrium models, as well as econometric estimation. The role of econometrically-estimated models is to provide a "secondary model" for capturing in a more precise fashion the "stylized facts" which the analytical and dynamic general equilibrium models are attempting to account for or explain.

3 Specification

3.1 Phillips Curve Model

We draw upon the standard Phillips Curve framework used by Stock and Watson (1999) for forecasting inflation in the United States. They define the inflation as an h-period ahead forecast. For our quarterly data set, we set h=4 for an annual inflation forecast:

$$\pi_{t+h} = \ln(p_{t+h}) - \ln(p_t) \tag{1}$$

We thus forecast inflation as an annual forecast (over the next four quarters), rather than as a one-period forecast. We do so because policy makers are typically interested in the inflation prospects over a longer horizaon than one quarter. For the most part, inflation over the next quarter is already "in process" and changes in current variables will not have much effect at so short a horizon.

In this model, inflation depends on a set of current variables $\mathbf{x}_t$, including current inflation π_t, and lags of inflation, and a disturbance term η_t. This term incorporates a moving average process with innovations ϵ_t, normally distributed with mean zero and variance σ^2 :

$$\pi_{t+h} = f(\mathbf{x}_t) + \eta_t \tag{2}$$

$$\pi_t = \ln(p_t) - \ln(p_{t-h}) \tag{3}$$

$$\eta_t = \epsilon_t + \gamma(\mathbf{L})\epsilon_{t-1} \tag{4}$$

$$\epsilon_t \sim N(0, \sigma^2) \tag{5}$$

where $\gamma(\mathbf{L})$ are lag operators. Besides current and lagged values of inflation, $\pi_t, ...\pi_{t-k}$, the variables contained in $\mathbf{x}_t$ include measures of the interest rate, i_t ,the output gap, y_t^{gap}, defined as the difference between actual output y_t and potential output y_t^{pot}, the (logarithmic) price gap with mainland China p_t^{gap},the rate of growth of unit labor costs (ulc) and the rate of growth of import prices (imp). The vector $\mathbf{x}_t$ also includes two financial-sector variables: changes in the share price index (spi), the residential property price index (rpi), and bank lending, (b) :

$$\begin{aligned} \mathbf{x}_t &= [\pi_t,\ \pi_{t-1}, \pi_{t-2}, ..., \pi_{t-k}, i_t, y_t^{gap}, ... \\ &\quad \Delta_h ulc_t, \Delta_h imp_t, \Delta_h spi_t, \Delta_h rpi_t, \Delta_h b_t] \end{aligned} \tag{6}$$

The operator Δ_h for a variable z_t represents simply the difference over h periods. Hence $\Delta_h\ z_t = z_t - z_{t-h}$. The rates of growth of unit labor costs, the import price index, the share price index, and the residential property price index thus represent annualized rates of growth for $h = 4$ in our analysis. We do this for consistency with our inflation forecast, which is a forecast over four quarters. In addition, taking log differences over four quarters helps to reduce the influence of seasonal factors in the inflation process.

The disturbance term η_t consists of a current period shock ϵ_t in addition to lagged values of this shock. We explicitly model serial dependence, since it is well known that when the "forecasting interval" h exceeds the sampling interval (in this case we are forecasting for one year but we sample with quarterly observations), temporal dependence is induced in the disturbance term.

3.2 Linear and Neural Network Regime Switching Specification

To make the model operational for estimation, we specify the following linear and neural network regime-switching (NNRS) alternatives.

The linear model has the following specification:

$$\pi_{t+h} = \alpha \mathbf{x}_t + \eta_t \tag{7}$$

$$\eta_t = \epsilon_t + \gamma(\mathbf{L})\epsilon_{t-1} \tag{8}$$

$$\epsilon_t \sim N(0, \sigma^2) \tag{9}$$

We nest this linear specification within a more general NNRS model:

$$\begin{aligned}\pi_{t+h} &= \alpha\mathbf{x}_t + \beta\{[\Psi(\pi_{t-1};\theta,c)]G(\mathbf{x}_t;\kappa) + \\ &\quad [1-\Psi(\pi_{t-1};\theta,c)]H(\mathbf{x}_t;\lambda)\} + \eta_t \qquad (10)\\ \eta_t &= \epsilon_t + \gamma(\mathbf{L})\epsilon_{t-1} \qquad (11)\\ \epsilon_t &\sim N(0,\sigma^2) \qquad (12)\end{aligned}$$

The NNRS model is similar to the smooth-transition autoregressive model discussed in Frances and van Dijk (2000), originally developed by Teräsvirta (1994), and more generally discussed in van Dijk, Teräsvirta, and Franses (2000). The function $\Psi(\pi_{t-1};\theta,c)$ is the transition function for two alternative nonlinear approximating functions $G(\mathbf{x}_t;\kappa)$ and $H(\mathbf{x}_t;\lambda)$.

The transition function depends on the value of lagged inflation π_{t-1} as well as the parameter vector θ and threshold c. We use a logistic or logsigmod specification for $\Psi(\pi_{t-1};\theta,c)$:

$$\Psi(\pi_{t-1};\theta,c) = \frac{1}{1+\exp[-\theta(\pi_{t-1}-c)]} \qquad (13)$$

For simplicity we set the threshold parameter $c = 0$, so that the regimes divide into periods of inflation and deflation. As Frances and van Dyck (2000) point out, the parameter θ determines the smoothness of the change in the value of this function, and thus the transition from the inflation to deflation regime.

The functions $G(\mathbf{x}_t;\kappa)$ and $H(\mathbf{x}_t;\lambda)$ are also logsigmoid and have the following representations:

$$\begin{aligned}G(\mathbf{x}_t;\kappa) &= \frac{1}{1+\exp[-\kappa\mathbf{x}_t]} \qquad (14)\\ H(\mathbf{x}_t;\lambda) &= \frac{1}{1+\exp[-\lambda\mathbf{x}_t]} \qquad (15)\end{aligned}$$

The inflation model in equation (11) has a "core" linear component, including autoregressive terms, a moving average component, and a nonlinear component incorporating "switching regime" effects, which is weighted by the parameter β.

For values of $\Psi(\pi_{t-1};\theta,c)$ strictly less than 1 and strictly greater than zero, the nonlinear regime-switching component resembles a familiar "feedforward" or multiperceptron neural network of two neurons with a jump connection in one hidden layer. Figure 7 pictures the "architecture" of such our NNRS model as a "neural network" architecture.

Figure 7

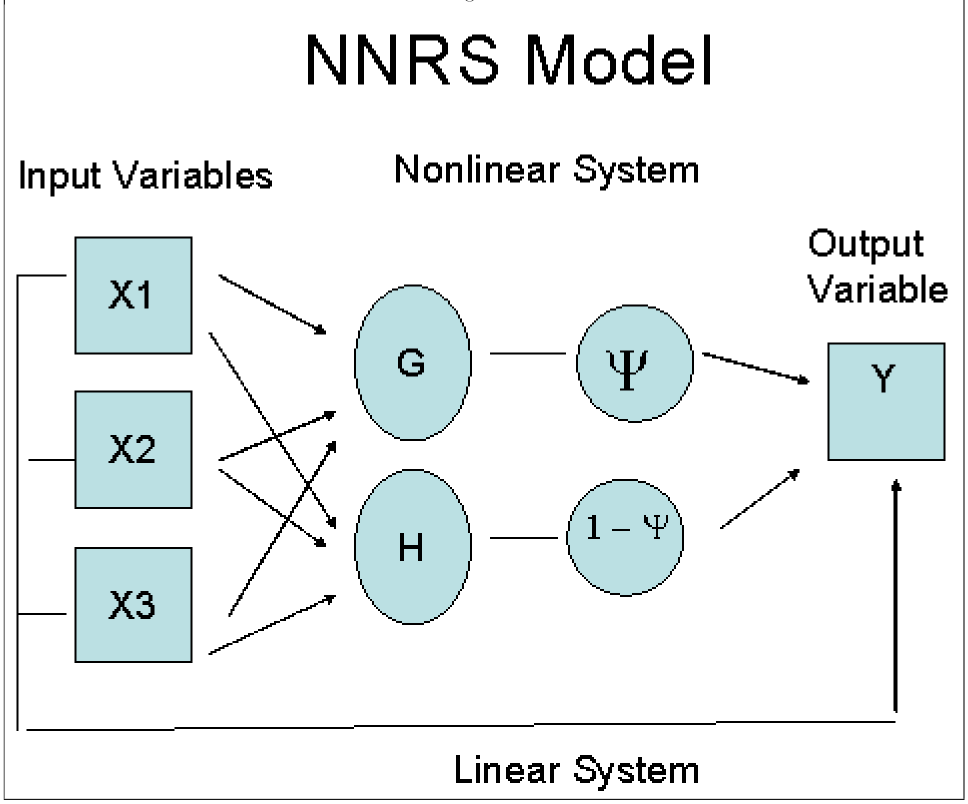


Figure 7 shows that components of input vector **x** $[x1, x2, x3]$, directly affect the "output" $[y]$ via a linear direct connectors, pictured by the "straight line" at the bottom of the chart. However, the nonlinear system works through the new "neurons", G and H, in the single hidden layer. This neurons transform the input variables $[x1, x2, x3]$. The functions G and H in turn affect the final output variable Y through the weighting function Ψ.

As van Dijk, Teräsvirta, and Franses (2000) point out, the advantage of incorporating a neural network comes from the fact that such a network, with a finite number of hidden units, can "approximate any continuous function to any desired degree of accuracy" [see Hornik, Stinchcombe, and White (1989, 1990)].

4 Estimation Method

We estimate the models given by equations by maximum likelihood methods. We initially set the autoregressive lag structure and moving average order to four, given our quarterly observations. Since we are interested in both in-sample explanatory power, out-of-sample forecast accuracy (as well as economic insight), and wish to avoid "data snooping", we fix the lag structure for the AR or MA components at a reasonably liberal length of four for both.[1]

The linear model is rather straightforward. For the NNRS model, we have two problems: a larger

[1] For a forecast horizon of four quarters, with quarterly data, we expect at a minimum a third-order moving average error process.

number of parameters to estimate, and the very high possibility, given the nonlinear functional forms, that we will obtain coefficients which are local, rather than global, optima. This is a well-known problem in nonlinear optimization in general, and there is no "silver bullet" to overcome it.

To increase our chances of finding coefficients close to a global optima, we first estimate the coefficients of the model with a "evolutionary stochastic" search, called the genetic algorithm. The algorithm starts with a population of p initial guesses, $[\Omega_{01}, \Omega_{02} ... \ \Omega_{0p}]$, for the coefficient set $\{\alpha, \beta, \gamma, \theta, \kappa, \lambda\}$. It then updates the population of guesses by genetic selection, breeding and mutation, for many generations, until the best coefficient vector is found among the last-generation "population", which maximizes the likelihood function.

The genetic algorithm does not involve taking gradients or second derivatives, and thus avoids the problem of "blowing up" or "crashing" during an estimation process. It is a *global* and *evolutionary* search process. We "score" the variously randomly-generated coefficient vectors by the objective maximum likelihood function, which does not have to be smooth and continuous with respect to the coefficient set Ω. De Falco (1998) applied the genetic algorithm to nonlinear neural network estimation, and found that his results "proved the effectiveness" of such algorithms for neural network estimation.

The main drawback of the genetic algorithm is that it is slow. For even a reasonable size or dimension of the coefficient vector Ω, the various combinations and permutations of elements of Ω which the genetic search may find "optimal" or close to optimal, at various generations, may become very large. This is another example of the well-known "curse of dimensionality" in non-linear optimization. Thus, one needs to let the genetic algorithm "run" over a large number of generations—perhaps several hundred—in order to arrive at results which approximate unique and global optima.

Since most nonlinear estimation methods rely on an arbitrary initialization of Ω, we follow-up the genetic global search with a Quasi-Newton gradient estimation. This estimation is known as a *hybrid approach.* We run the genetic algorithm for a reasonable number of generations, and then use the final weight vector Ω as the initialization vector for the gradient-descent or simulated annealing optimization. We repeat this process several times, and choose the coefficient estimates from the final set of estimates which optimize the likelihood function.

4.1 In-Sample Evaluation

We estimate the model initially for the entire data set. We use the following diagnostics: the sum-of squared errors $[SSE]$, the multiple correlation coefficient $[R^2]$, the Hannan-Quinn (1979) information criterion $[HQIF]$, the marginal significance of the Ljung-Box (1978) $[LB]$ Q-statistic for serial dependence in the residuals, as well as that of the MacLeod-Li (1983) $[ML]$ Q-statistic for serial dependence in the squared residuals, the Engle-Ng (1993) $[EN]$ test for symmetry of residuals, the Jarque-Bera (1980) $[JB]$ test of normality of residuals and the Brock-Deckert-Scheinkman (1987) $[BDS]$ test of nonlinearity in the residuals Finally, the Lee-White-Granger (1992) $[LWG]$ test gives the number of significant regressions of the residuals against 1000 randomly generated nonlinear combinations of regressors.[2]

4.2 Forecasting Accuracy

For evaluating the out-of-sample forecasting performance of the two competing models, we use the "real time" forecasting approach of Stock and Watson (1999). We first estimate the model from 1980.1 until 1990.1. We forecast the dependent variable (year-on-year inflation) for the second quarter of 1990, and obtain the first "forecast error" of our exercise. Then we incorporate this observation, and estimate the model from 1980.1 until 1990.3, and forecast the dependent variable for the fourth quarter of 1990, and obtain the second forecast error of our exercise. We continue this method of rolling one period forecasting until we exhaust our sample.

Needless to say, with nonlinear estimation, this method takes time. However, the advantage of this method of evaluating out-of-sample performance of two competing models (the linear and the NNRS models), is that it reflects how economists *de facto* do their forecasting. Economists are always updating coefficients as new data and new information become available.

For comparing the forecasting performance, we use the root mean squared error $[RMSQ]$ value and the Diebold-Mariano (1995) $[DM]$ test of relative out-of-sample performance.[3]

4.3 Evaluation and Significance

To assess the relative importance and statistical significance of the estimation results, we first have to obtain the partial derivatives implied by the neural network coefficient estimates.

Since we use logsigmoid functional forms for the two regimes, we can calculate the partial derivatives rather easily. The derivative of the logsigmod function G is simply $G\ (1-G)$. Thus, for the linear model, the partial derivatives of the inflation forecast with respect to $x_{j,t}$ is simply α_j, for all observations t. The corresponding neural network partial derivative is given by the following expression:

$$\frac{\partial \pi_{t+h}}{\partial x_{j,t}} = \alpha_j + \beta[\Psi_t G_t(1-G_t)\kappa_j + (1-\Psi_t)H_t(1-H_t)\lambda_j] \tag{16}$$

Equation (17) comes from applying the familiar "chain rule" method for taking the partial derivative of equation (11) with respect to argument $x_{j,t}$.

Since the nonlinear partial derivatives are "state-dependent", we compute the partial derivatives of the neural network for three different states: at the beginning of the sample, at the sample mid-point, and at the end of the sample.[4]

Of course, any discussion of the relative importance of the determinants of inflation and deflation has to consider their "statistical significance". The difficulty of obtaining tests of significance of nonlinear

[2] All of these statistical tests are clearly summarized in Franses and van Dijk (2000).
[3] These tests are also summarized in Franses and van Dijk (2000).
[4] Stefan Gerlach made this suggestion at a seminar at the Hong Kong Institute of Monetary Research.

parameter estimates or state-dependnet partial derivative estimates should not be underestimated. All too often, asymptotic t-statistics based on the inverted Hessian matrices of coefficient estimates simply "blow up" or fail to invert.

As an alternative we use the "bootstrapping" method, due to Efron (1979) and Efron and Tibshirani (1993). Bootstrapping consists of sampling the original set of "residuals" from the network model, with replacement. Then we re-set the dependent variable equal to the original forecast plus the "resampled" residual vector, re-estimate the model, and obtain new coefficients and partial derivatives. We repeat this process 1000 times, and we find a distribution of the partial derivatives, from which we calculate probability values indicating if the initially estimated partial derivatives are significantly different from zero.[5]

5 Analysis of Results

5.1 In-Sample Evaluation

Table III shows that the NNRS model clearly dominates the linear model on virtually all criteria for model specification. In terms of explanatory power, even when we adjust for the increased complexity of the NNRS model relative to the linear model by the Hannan-Quinn criterion, the results strongly favor the selection of the NNRS model. The Q-statistics for serial independence in the regression residuals and squared-regression residuals lead to rejection for the linear model. For the NNRS model, the Q-statistic for serial independence in the residuals cannot be rejected, barely, at the five percent level of significance, though it can be rejected at the ten percent level. However, the tests for serial independence in the squared residuals cannot be rejected.

The in-sample diagnostics indicate that the linear model, with four lags of the dependent variables and a MA(4) error process, is not a well-specified model. However, for the same lag structure of the dependent variable and the same MA(4) error process, the NNRS model appears to be well-specified. Since we value parsimony in specification of the lag structure and error process, we proceed with this specification.

[5] Mark Taylor suggested this approach for an earlier version of this paper.

Table III

In-Sample Diagnostic Tests of Alternative Models
Sample Period: 1971.4:2001.1
Specification: 4 Inflation Lags, MA(4) Error Process

	Models:	
	Linear	Network
Diagnostics:		
SSE	0.034	0.002
RSQ	0.876	0.972
HQIF	-346.735	-609.474
LB*	0.000	0.050
ML*	0.000	0.332
JB*	0.085	0.802
EN*	0.000	0.321
BDS*	0.000	0.485
LWG	34	1

*: Prob Value

SSE: Sum of Squared Residuals
RSQ: R-Squared
HQIF: Hannan-Quinn Information Criterion
LB: Ljung-Box Q-Statistic on Residuals
ML: McLeod-Li Q-Statistic on Squared Residuals
JB: Jarque-Bera Test of Normality
EN: Engle-Ng Test of Symmetry
BDS: Brock-Deckert-Schenkman Test of Nonlinearity
LWG: Lee-White-Granger Test of Nonlinearity

5.2 Forecasting Accuracy

The linear model, though failing in-sample specification tests relative to the NNRS model, may still be used for purposes of forecasting, and compared with the corresponding performance of the NNRS model. The relative performance of the two models for the sequence of 56 one-period forecast errors appears in Figure 8. We see that the NNRS model does either better or equally as well as the linear model. We note in particular that during sharp up-turns or sharp downturns, the NNRS forecast error is usually lower than that of the linear model.

Figure 8

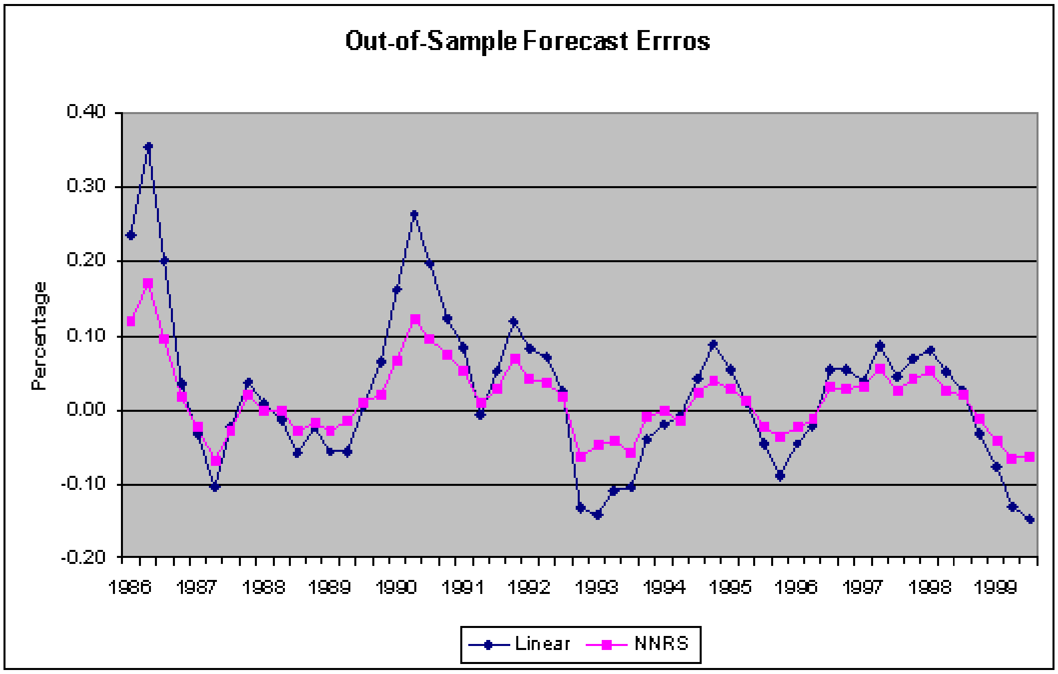


Table IV summarizes the out-of-sample forecasting performance of the two models. We see that the NNRS model reduces the root mean squared error by a factor of more than 50 percent. The Diebold-Mariano statistics show that we can reject at a high degree of confidence the null hypothesis of zero differences in the out-of-sample forecast errors.

Table IV

Out-of-Sample Forecasting Accuracy Statistics

	Linear	NNRS
RMSQ	0.104555	0.051577
DM-1*		2.19E-07
DM-2*		6.33E-07
DM-3*		2.25E-07
DM-4*		5.21E-08
DM-5*		6.93E-09

*: Prob Value

RMSQ: Root Mean Squared Error
DM: Diebold-Mariano Test of Forecasting Performance
Between NNRS and Linear Models
Correction for Serial Correlation of Forecast Errors
for orders 1 thorugh 5

5.3 Evaluation and Significance

Table V contains the partial derivative estimates of the NNRS models, as well as the bootstrapped p-values (marginal significance values) at three periods, 1981.1, 1992.1 and 2002.1 The first period, 1981.1, is a time of steady inflation, the period of 2002.1 is a time of continued deflation, whilte the mid-point period, 1992.1, representing a time of inflation volatility, at the end of the first Gulf War. Since the diagnostics indicate that the linear model is suspect on grounds of specification errors, given the parsimonious lag structure and MA(4) error process, we evaluate only NNRS model for assessing deflationary dynamics in Japan.

Table V

Partial Derivative Estimates of NNRS Model

	Estimate			P-Value		
Evaluation Date of Partial Derivatives	1981.1	1992.1	2002.1	1981.1	1992.1	2002.1
Argument:						
Inflation	0.360	0.498	0.334	0.487	0.467	0.524
Gensaki	**-0.161**	**-0.023**	**-0.187**	0.000	0.000	0.000
Imp Price Growth	0.064	0.202	0.038	0.704	0.700	0.764
Bank Lending Growth	0.209	0.347	**0.183**	0.509	0.516	0.587
Nikkei Index Growth	0.255	0.393	0.228	0.541	0.511	0.619
Property Price Growth	-0.142	-0.004	-0.168	0.347	0.353	0.423
Output Gap	**0.325**	**0.463**	**0.299**	0.029	0.050	0.097
Unit Labor Cost Growth	-0.012	0.126	-0.038	0.337	0.301	0.426
Inflation(-1)	0.411	0.549	0.385	0.394	0.407	0.499
Inflation(-2)	**0.338**	**0.476**	**0.312**	0.041	0.079	0.103
Inflation(-3)	0.050	0.188	0.024	0.203	0.171	0.229

Table V shows that the Gensaki rate, the output gap, and the inflation rate at a two period lag are the only significant variables. We see that the Gensaki rate is significant and negative in all three periods. The NNRS model thus evades the familiar "price paradox" problem obtained by estimation of linear models. We also see that the magnitude of the interest rate effect is about the same in 2002 as in 1981. Of course, the problem for the Bank of Japan is not the potential effects of interest rate cuts on inflation but the feasibility of making cuts, since the interest rate is bounded below by zero.

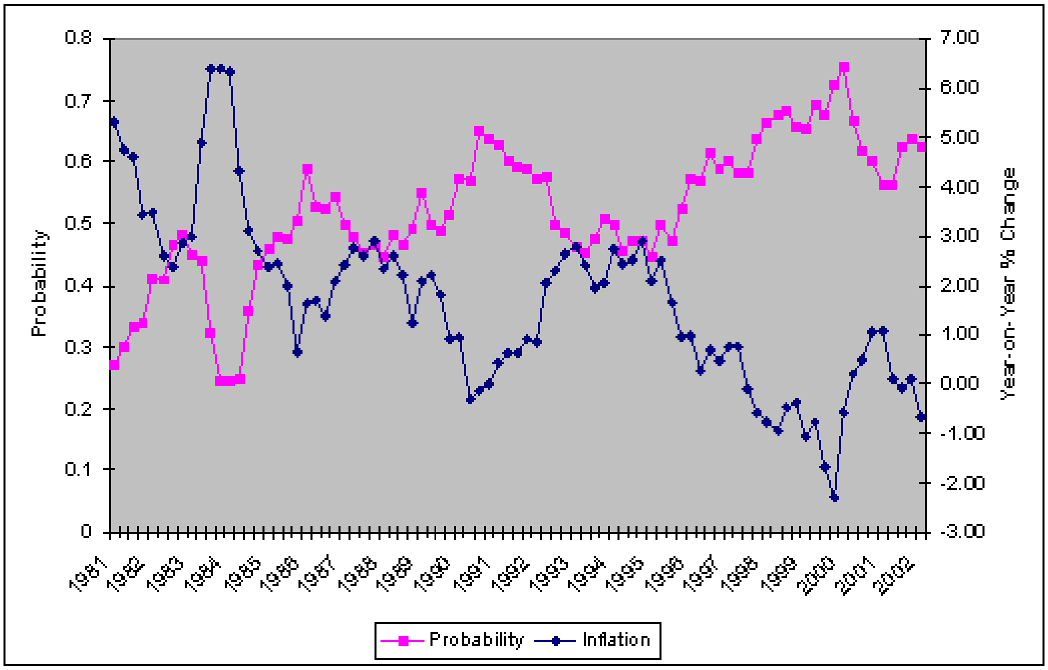
We also see that the output gap has the expected positive sign on inflation in all three periods, and that the effect in 2002 is only slightly below its value in 1981. The sharp fall in the output gap after 1997 cannot help but be the major factor driving deflation, given the partial deriviatives implied by the coefficient estimates of the model.

What is surprising in the model is that the rate of growth of property prices and unit labor costs not only are insignificant but also have the wrong signs. The rate of growth of import prices, bank lending, and the Nikkei index, while insignificant, have the expected positive signs.

The results of Table V indicate that interest rates and the output gap are the most important and significant determinants of price changes, both in the "inflation" regime and in the "deflation" regime.

What about the adjustment of the smooth transition probability? Figure 9 pictures this estimate (in this case, the probability of being in the deflation state), along with the annual inflation rates. This figure shows that the probability was between .3 and .4 in the early 1980's, around .5 in the early 90's and has been in the neighborhood of .7 since 2000. While it has falled slightly, it has remained well above .5 since 1997. More importantly, the figure does not show any noticeable downward trend in recent years, indicating the likelihood of an "escape" from deflationary dynamics.

Figure 9



Overall, the NNRS model points to the collapse of overall demand (through the output gap effect) as well as inability of interest rates to fall below zero, as the main factors behind Japanese deflationary dynamics. While the rate of growth of bank lending is not significant, this does not mean that it is unimportant. Table VI pictures the results of a Granger causality test between the output gap and the rate of growth of bank leanding in Japan. We see strong evidence, at the five percent level of significance, that the rate of growth of bank loans is a causal factor for changes in the output gap. There is also evidence of reverse causality, from the output gap to the rate of growth of bank lending, to be sure. These results indicate that a reversal in bank leanding will improve the output gap, and such an improvement will call forth more bank leanding, leading, in turn, in a virtuous cycle, to further output-gap improvement.

Table VI

Granger Test of Causality
Loan Growth and the Output Gap

Hypothesis:	Loan Growth Does Not Cause the Output Gap	Output Gap Does Not Cause Loan Growth
F-Statistic	2.5	2.4
P-Value	0.049	0.053

What our econometric analysis suggests is that policies aimed at restructuring the financial sector, which would stimulate both bank lending, would in turn generate new investment spending, reverse the negative output gap, and help break the deflationary spiral.

6 Conclusion

The results indicate that fighting Japanese deflation is not simply a matter of expansionary monetary policy. Expansion of bank lending and other financial restructuring policies aimed at improving investment and the overall growth in gdp are also necessary to push the economy out of the deflation trap, even with expansionary low interest-rate policies in place.

These results should not be so surprising. Unlike Hong Kong, Japan is a relatively more closed economy. Policies aimed at domestic demand are likely to be much more important factors for inflation than in a small, highly open economy such as Hong Kong. Inflation or deflation in asset prices and import prices do not play the same role in Japanese inflation and deflation cycles as they would in a very small but much more open economy.

The contrast between linear and very simple neural network specifications indicates that these approaches may be very useful for capturing or "deciphering" key stylized facts about deflation

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