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Deflationary Dynamics in Hong Kong: Evidence from Linear andNeural Network Regime Switching Models

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Abstract

This paper examines deflationary dynamics in Hong Kong with a linear and a nonlinear neural-network regime-switching (NNRS) model. The NNRS model is superior to the linear model in terms of in-sample specification tests as well as out-of-sample forecasting accuracy. As befitting a small and highly open economy, the most important variables affecting inflation and deflation turn out to be the growth rates of import prices and wealth (captured by the rates of growth of residential property prices). The NNRS model indicates that the likelihood of moving out of deflation has been steadily increasing.

JEL Classification: E0, E3, E5

Keywords: deflation, neural networks, regime-switching models

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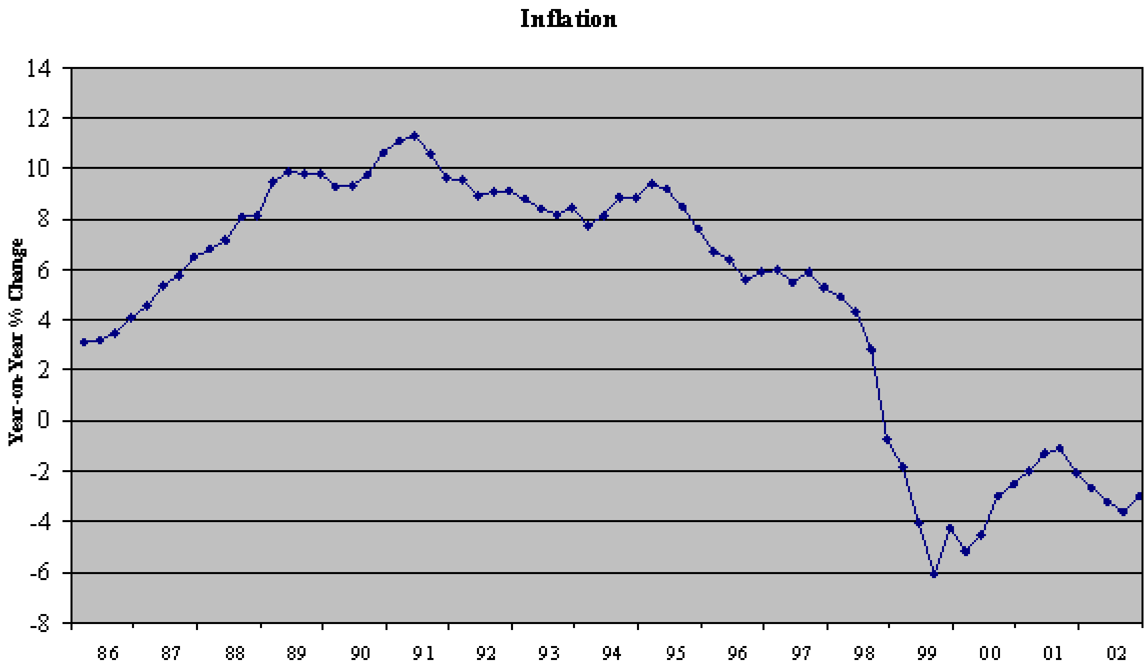
1 Introduction

Hong Kong has been in deflation for more than five years, as Figure 1 shows:

Figure 1



While much has been written (amid much controversy and debate) about deflation in Japan [see, for example, Krugman (1998), Yoshino and Sakahibara (2002) and McKibbin and Wilcoxen (1998)], Hong Kong is of special interest. First, the usual response of expansionary monetary policy is not an option for Hong Kong, since its currency board arrangement precludes active policy directed at inflation or deflation. Secondly, Hong Kong is a smaller but much more open economy than Japan, and is thus more susceptible to external factors. Finally, Hong Kong, as a "special administrative region", is in a process of increasing market integration with mainland China. However, there are some important similarities. Both Japan and Hong Kong have experienced significant asset-price deflation, especially in property prices, and more recently, negative output-gap measures.

Ha and Fan (2002) examined panel data for assessing price convergence between Hong Kong and mainland China. While convergence is far from complete, they showed that the pace has accelerated in recent years. However, comparing price dynamics between Hong Kong and Shenzhen, Schellekens (2003) argued that the role of price equalization as a source of deflation is minor, and contended that deflation is best explained by wealth effects.

Genberg and Pauwels (2003) found that both wages and import prices have "significant causal roles", in addition to property rental prices. These three outperform measures of excess capacity as "forcing variables" for deflation. Razzak (2003) also called attention to the role of unit labor costs as well as productivity dynamics for understanding deflation. However, making use of a vector autoregressive model (VAR), Genberg (2003) also reported that external factors account for more than fifty percent of "unexpected fluctuations" in the real GDP deflator at horizons of one to two years.

Most of these studies 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.

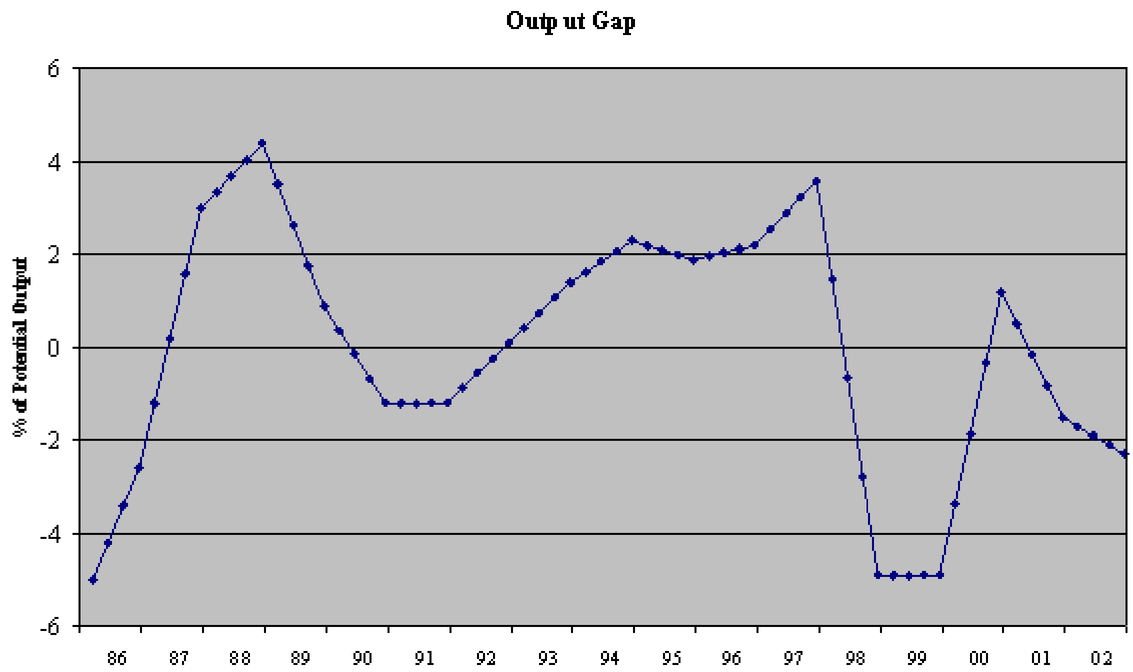
The next section dicusses the key variables we use to analyze the dynamics of inflation and deflation. Section 3 contains our model specification while Section 4 discusses the estimation method. Section 5 is analysis of our key empirical results and the last section concludes.

2 Key Variables for Assessing Inflation

In this section we examine the 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 price gap between Hong Kong and mainland China.

The output gap, which measures either "excess demand" or "slack" in the economy, comes from the World Economic Outlook of the IMF. This variable was interpolated from annual to quarterly frequency. Figure 2 pictures the evolution of this variable. We see that measures of the output gap show that the economy has been well "below potential" for most of the time since late 1998.

Figure 2



The behavior of import prices and unit labor costs, both important for understanding the supply-side or costs factors of inflationary movements, shows considerably different patterns of volatility. Figure 3 pictures the rate of growth of import prices while Figure 4 shows the corresponding movement in labor costs. The collapse of import prices in the year 2001 is mainly due to the world economic downturn following the burst of the bubble in the high technology sectors.

Figure 3

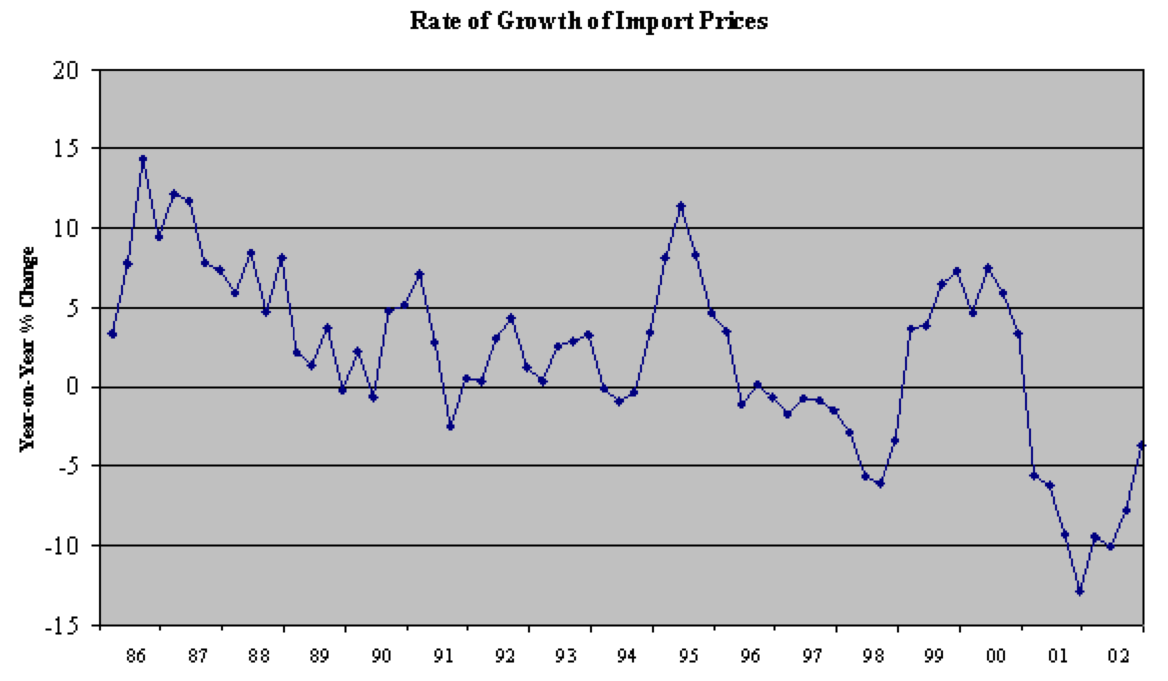


Figure 4

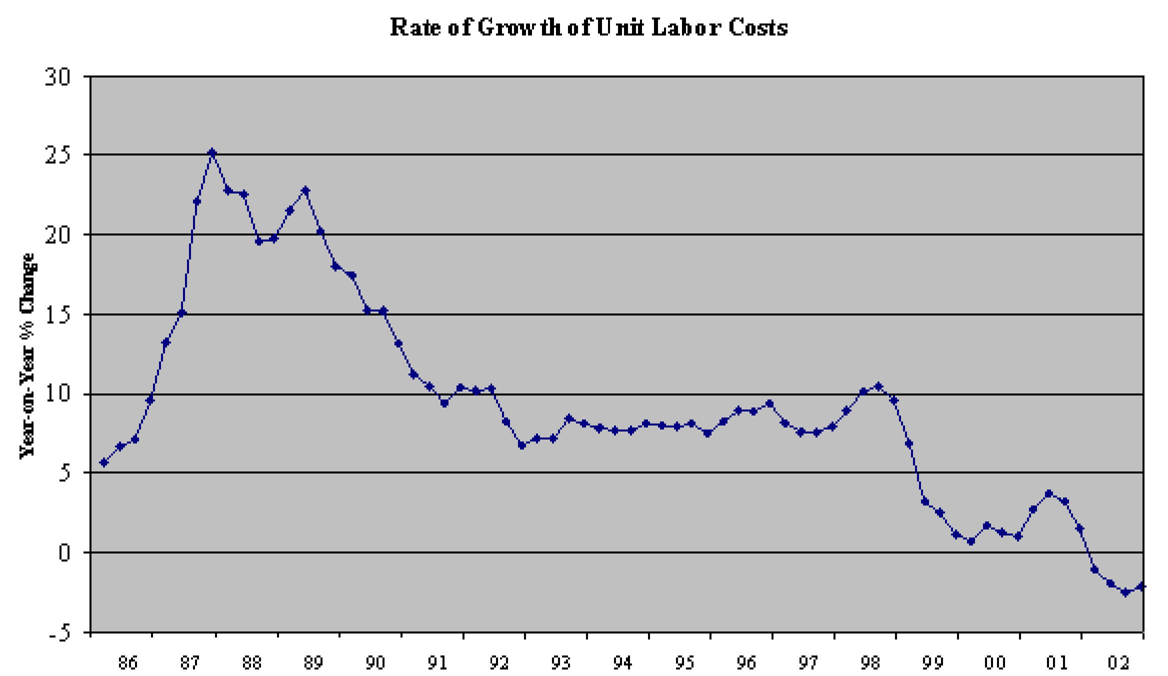
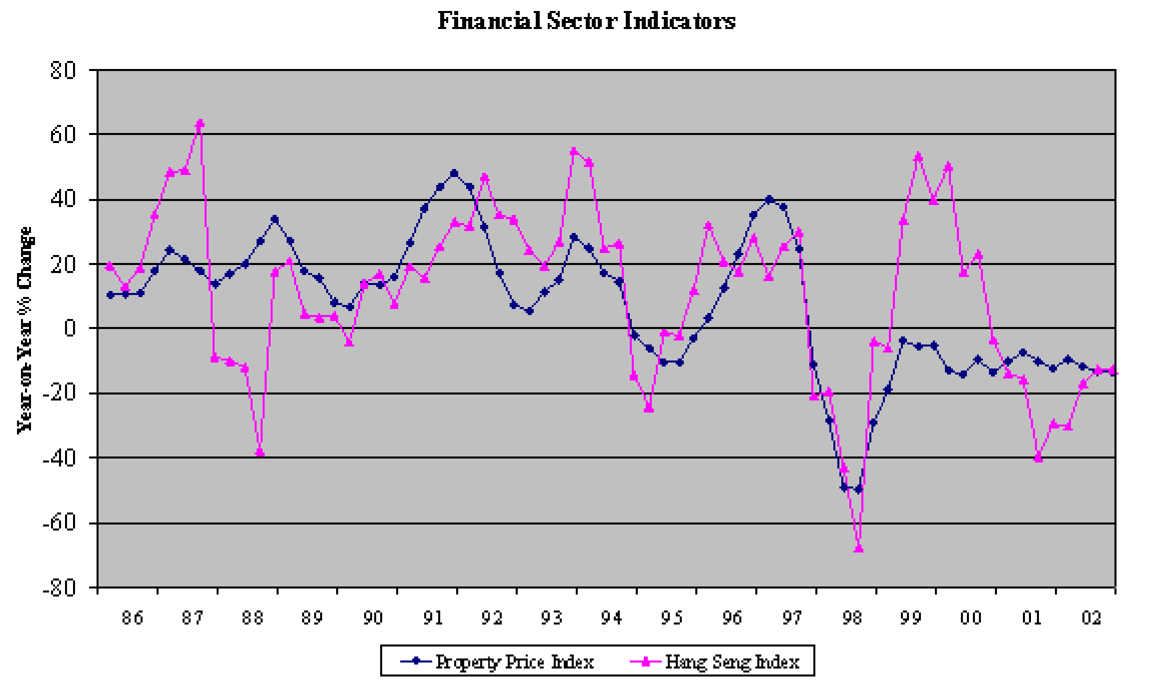


Figure 5 pictures the financial sector variables , the rates of growth of the share price index (the Hang Seng index), and the residential property price index. Not surprisingly, the growth rate of the share price index shows much more volatility than the corresponding growth rate of the property price index.

Figure 5



Finally, as a measure of structural market integration and price convergence with mainland China, we picture the evolution of a "price gap" . The gap is defined as the logarithmic difference between the Hong Kong CPI and mainland China CPI. The latter is converted to the Hong Kong dollar basis using the market exchange rate. If there is significant convergence taking place, we expect a negative relationship between the price gap and inflation. If there is a unexpected and large price differential between Hong Kong and China, *ceteris paribus*, the inflation rate in Hong Kong should fall over time to close the gap. This variable appears in Figure 6:

Figure 6

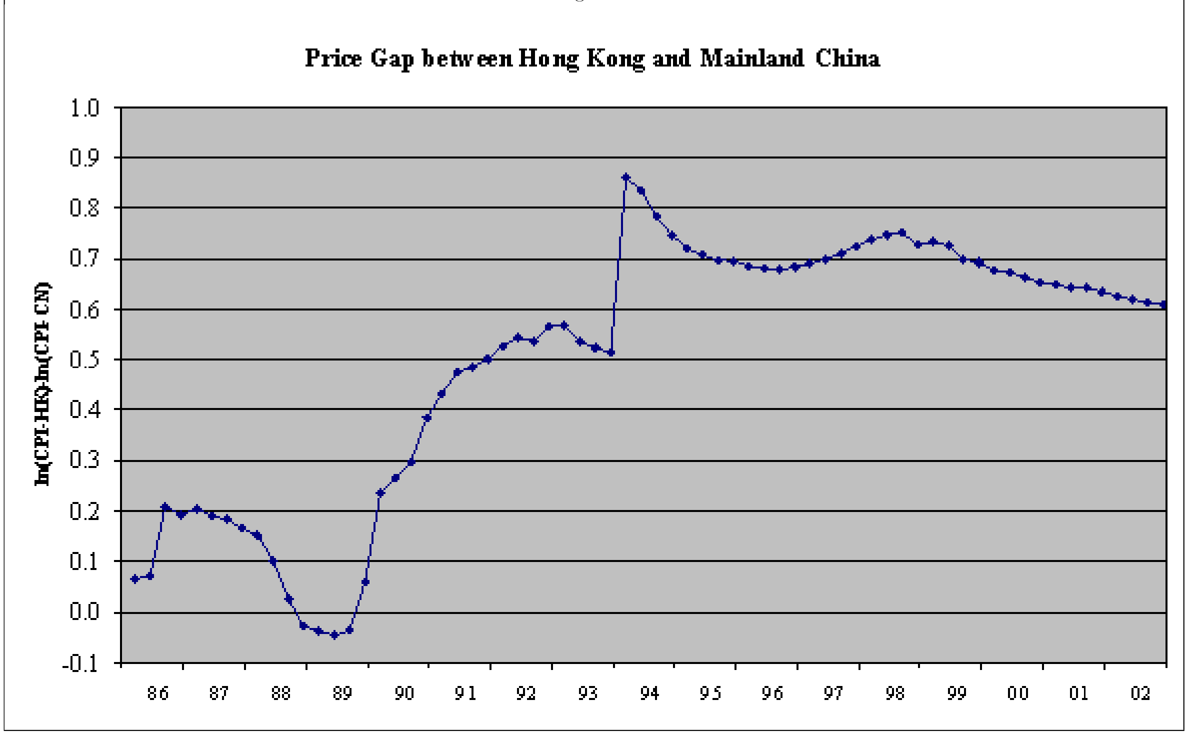


Figure 6 shows that the price gap after 1998 is slowly but steadily falling. The jump in 1994 is due to the devaluation of the Chinese Renminbi against the U.S. dollar.

Table I contains a statistical summary of the data we use in our analysis We use quarterly observations from 1985 until 2002. Table I lists the means, standard deviations, and contemporaneous correlations of annualized rates of inflation, the price and output gap measures, and the rates of growth of import prices, the property price index, the share price index, and unit labor costs.

Table I

Statistical Summary of Data

Hong Kong Quarterly Data, 1985-2002

	Inflation	Price Gap	Output Gap	Imp Price Growth	Property Price Growth	HSI Growth	ULC Growth
Mean	0.055	0.511	0.004	0.023	0.088	0.127	0.102
Std.Dev.	0.049	0.258	0.024	0.051	0.215	0.272	0.062

Correlation Matrix

	Inflation	Price Gap	Output Gap	Imp Price Growth	Property Price Growth	HSI Growth	ULC Growth
Inflation	1.00						
Price Gap	-0.39	1.00					
Output Gap	0.56	-0.29	1.00				
Imp Price Growth	0.15	-0.37	0.05	1.00			
Property Price Growth	0.57	-0.42	0.36	0.23	1.00		
HSI Growth	0.06	-0.04	-0.15	0.43	0.56	1.00	
ULC Growth	0.59	-0.84	0.48	0.29	0.38	-0.09	1.00

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 residential property price indices, as well as the price gap. However, the price gap volatility is due in large part to the once-over Renminbi devaluation in 1994.

Table I also shows that highest correlations of inflation are with rates of growth of unit labor costs and property prices, followed closely by the output gap.

Finally, Table I shows a strong correlation between the growth rates of the share price and the residential property price indices.

In many studies relating to monetary policy and overall economic activity, bank lending appears as an important "credit channel" for assessing inflationary or deflationary impulses. 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 argued that changes in bank lending cannot be regarded as the source of the boom and bust cycle in Hong Kong. They hypothesized 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]. For this reason, we leave out the growth rate of bank lending as a possible determinant of inflation or deflation in Hong Kong. [1] [2]

Clearly, good economic insight should come from a combination of clear analytical thinking, 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-quarter ahead forecast. We do so because policy makers are typically interested in the inflation prospects over a

[1] 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. Hoffman(2003) also points out, with a sample of 20 industrialized countries, that "long run causality runs from property prices to bank lending" but short run bidirectional causality cannot be ruled out.

[2] Goodhard and Hofman (2003) support the finding of Gerlach and Peng with results from a wider sample of 12 countries.

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 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):

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

$$p_t^{gap} = p_t^{HK} - p_t^{CHINA} \tag{7}$$

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. For forecasting four quarters ahead with quarterly data, the error process is a third-order moving average process.

We specify four lags for the dependent variable. For quarterly data, this is equivalent to a twelve-month lag for monthly data, used by Stock and Watson (1999) for forecasting inflation.

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:

$$\begin{aligned} \pi_{t+h} &= \alpha \mathbf{x}_t + \eta_t & (8) \\ \eta_t &= \epsilon_t + \gamma(\mathbf{L})\epsilon_{t-1} & (9) \\ \epsilon_t &\sim N(0, \sigma^2) & (10) \end{aligned}$$

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

$$\begin{aligned} \pi_{t+h} &= \alpha \mathbf{x}_t + \beta\{[\Psi(\pi_{t-1}; \theta, c)]G(\mathbf{x}_t; \kappa) + \\ &\quad [1 - \Psi(\pi_{t-1}; \theta, c)]H(\mathbf{x}_t; \lambda)\} + \eta_t & (11) \\ \eta_t &= \epsilon_t + \gamma(\mathbf{L})\epsilon_{t-1} & (12) \\ \epsilon_t &\sim N(0, \sigma^2) & (13) \end{aligned}$$

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 $\Psi(\pi_{t-1}; \theta, c)$:

$$\Psi(\pi_{t-1}; \theta, c) = \frac{1}{1 + \exp[-\theta(\pi_{t-1} - c)]} \qquad (14)$$

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:

$$\begin{aligned} G(\mathbf{x}_t; \kappa) &= \frac{1}{1 + \exp[-\kappa \mathbf{x}_t]} & (15) \\ H(\mathbf{x}_t; \lambda) &= \frac{1}{1 + \exp[-\lambda \mathbf{x}_t]} & (16) \end{aligned}$$

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

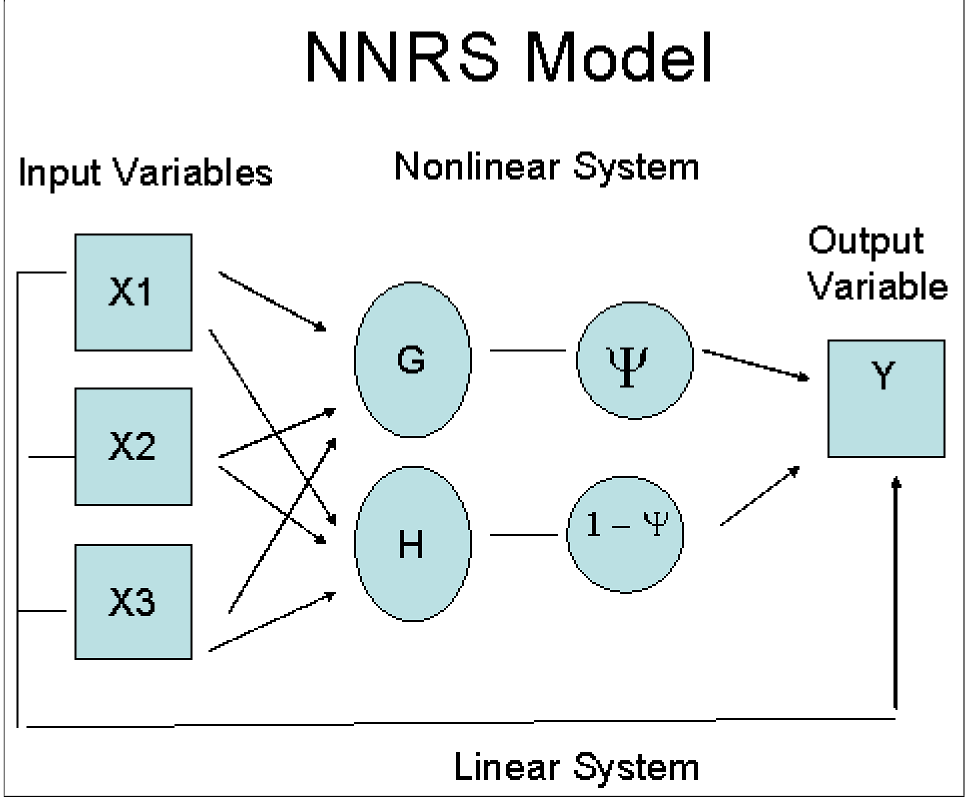


Figure 7 shows that components of input vector $\mathbf{x}$ $[x1, x2, x3]$, directly affect the "output" $[y]$ via a linear direct connectors, pictured by the "straight line" at the bottom of the chart. However, the nonlinear system works through the new "neurons", G and H, in the single hidden layer. 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.[3]

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

[3] 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.[4]

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 1986.1 until 1994.2. We forecast the dependent variable (year-on-year inflation) for the third quarter of 1994 (for the next four year interval), and obtain the first "forecast " of our exercise. Then we incorporate this observation, and estimate the model from 1986.1 until 1994.3, and forecast the dependent variable, the one-year ahead inflation rate, for the fourth quarter of 1994, and obtain the second forecast of our exercise. We continue this method of rolling one period forecasting until we exhaust our sample. At the end we evaluate the set of out-of-sample forecasting errors.

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.[5]

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:

$$\frac{\partial \pi_{t+h}}{\partial x_{j,t}} = \alpha_j + \beta[\Psi_t G_t(1 - G_t)\kappa_j + (1 - \Psi_t)H_t(1 - H_t)\lambda_j] \tag{17}$$

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.[6]

[4] All of these statistical tests are clearly summarized in Franses and van Dijk (2000).

[5] These tests are also summarized in Franses and van Dijk (2000).

[6] Stefan Gerlach made this suggestion at a seminar at the Hong Kong Institute of Monetary Research.

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 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.[7]

5 Analysis of Results

5.1 In-Sample Evaluation

Table II 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 residuals and squared 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 ten percent level of significance. 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 variable and a MA(3) error process, is not a well-specified model, on the basis of the Q-statistics and the BDS tests for neglected nonlinearity.

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

Table II

In-Sample Diagnostic Tests of Alternative Models

Sample Period: 1986.1:2002.4

Specification: 4 Inflation Lags, MA(3) Error Process

Models:

Diagnostics:	Linear	Network	
SSE	0.008	0.001	SSE: Sum of Squared Residuals
RSQ	0.934	0.979	RSQ: R-Squared
HQIF	-274.174	-373.144	HQIF: Hannan-Quinn Information Criterion
LB*	0.006	0.108	LB: Ljung-Box Q-Statistic on Residuals
ML*	0.005	0.480	ML: McLeod-Li Q-Statistic on Squared Residuals
JB*	0.792	0.360	JB: Jarque-Bera Test of Normality
EN*	0.243	0.295	EN: Engle-Ng Test of Symmetry
BDS*	0.015	0.218	BDS: Brock-Deckert-Schenkman Test of Nonlinear
LWG	22	0	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. We compare the linear forecasts with the corresponding performance of the NNRS model. The relative performance of the two models for the sequence of 55 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. It is also clear from Figure 8 that the forecast errors do not display serial independence. This should not be surprising. The errors are the forecast errors of inflation over a four-period horizon. There is a "built-in" serial dependence in the forecast error as there is in the dependent variable.

Figure 8

Table III summarizes the out-of-sample forecasting performance of the two models. We see that the NNRS model reduces the root mean squared error of the linear model 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 of the two models.

Table III

Out-of-Sample Forecasting Accuracy Statistics

	Linear	NNRS
RMSQ	0.154	0.072
DM-1*		8.8E-08
DM-2*		6.0E-06
DM-3*		2.2E-05
DM-4*		2.6E-05
DM-5*		1.5E-05

*: 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 IV contains the partial derivative estimates of the NNRS models, as well as the bootstrapped p-values (marginal significance values) at three periods, 1988.1, 1995.3 and 2002.1 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 Hong Kong.

Table IV

Partial Derivative Estimates of NNRS Model

	Estimate			P-Value		
Evaluation Date of Partial Derivatives	1988.1	1995.3	2002.1	1988.1	1995.3	2002.1
Argument:						
Inflation	0.778	0.773	0.888	0.097	0.128	0.107
Price Gap	-0.242	-0.247	-0.132	0.297	0.397	0.316
Output Gap	0.352	0.348	0.463	0.329	0.396	0.371
Imp Price Growth	0.566	0.562	0.676	0.074	0.101	0.074
Property Price Growth	0.696	0.692	0.807	0.094	0.157	0.120
HSI Growth	0.057	0.052	0.167	0.022	0.020	0.025
ULC Growth	0.083	0.079	0.194	0.108	0.141	0.120
Inflation(-1)	0.382	0.377	0.492	0.025	0.039	0.032
Inflation(-2)	-0.021	-0.025	0.089	0.497	0.556	0.515
Inflation(-3)	-0.308	-0.313	-0.198	0.539	0.611	0.555

First, we see that the NNRS shows a significant degree of "inflationary inertia", in that current inflation (annualized over the past year) has a positive effect (more than 70 percent) on the forecast of inflation for the next year, in all three periods Secondly, there are positive and significant effects of the rates of growth of import prices and the Hang Seng index. Furthermore, the residential property price effect is significant at the beginning of the period, it is only marginally less than significant (at the ten percent level) in 1995 and 2002. Its point estimate in all three periods is much more pronounced than the effects of the rates of growth of import prices and the Hang Seng index.

We also note that changes in the partial derivatives over the sample period. We see that the current inflation effect increases from .78 to .89, the import price effect from .57 to .68, the Hang Seng index effect from .06 to .17, and the residential property price effect from .70 to .81. .

Bootstrapping is a very demanding test for finding significance of coefficients or partial derivatives. While unit labor costs and the output and price gap measures are not significant by this test procedure, they do enter with the "correct" expected signs.

The insignificance of the price gap measure may be due in part to the overall import price effect. We do not separate in the import price index the effects of goods originating from mainland China. Thus, the overall import price index may be picking up both the convergence effects of the price index with China as well as the effects of foreign commodity prices.[8]

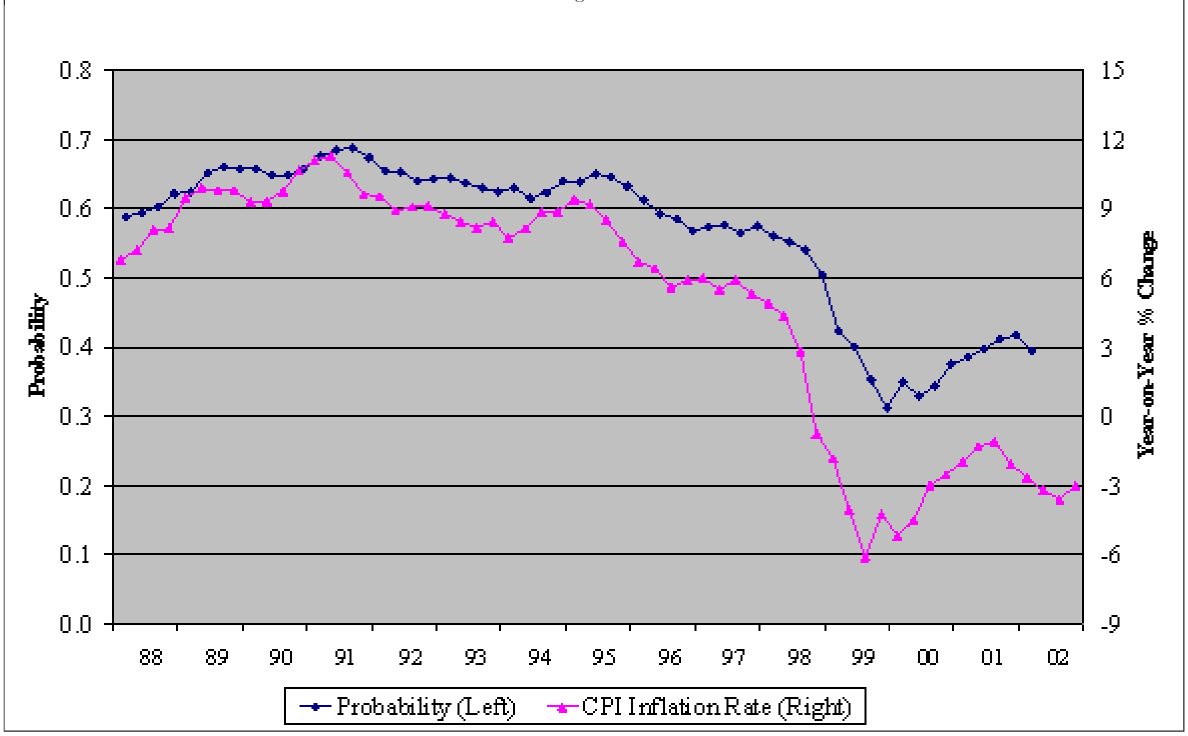
The insignificant output-price gap may be due to our definition, based on the World Economic Outlook indices. Alternative defintions of the output gap based on Kalman fitlering or Hodrick-Prescott filtering of quarterly GDP data may yield significant results.

How do the inflation/deflation regimes affect the dependent variable? Do the regimes "abruptly switch" or simply "blend together" over the course of the sample? Figure 9 pictures the NNRS transition probability along with the CPI inflation rate. We see that there is a "blending". During the positive inflation regime, the transition probability falls between .6 and .7, and during the deflation regime, the transition probability falls between .3 and .4.

[8] The import price index affects inflation through its rate of growth, while the price gap affects inflation via the logarithmic difference of the price levels in Hong Kong and mainland China. Therefore, the "overlap" of these two variables may not be very significant.

What does the movement of this smooth transition probability mean? After 1998, the probability of returning to a period of positive inflation is not trivial, but stays in a range of 30 to 40 percent. Even more to the point, the probability of moving from deflation to inflation is steadily rising from 30 to 40 percent since 2000. These results indicate Hong Kong need not despair. There is an increasing likelihood of "escape" from the current state of "deflationary dynamics".

Figure 9



6 Conclusion

The results of this paper indicate that nonlinear methods best describe the inflationary/deflationary dynamics in Hong Kong. A neural network version of the "smooth transition" regime-switching model outperforms the linear model on the basis of in-sample diagnostics as well as out-of-sample forecast accuracy. The partial derivatives of the NNRS model indicate that the fall in the rates of growth of the Hang Seng index, residential property prices and import prices are the most important and significant factors affecting deflation. One of the surprising results is that the price gap is not significant in this study. This result may be partly explained by the overall import index effect. Finally, the transition probability model indicates that there is a non-trivial and steadily rising likelihood of switching from a "deflation" regime to an inflation regime.

In this study, we have examined only one nonlinear alternative to the standard linear model of inflation. There are of course many more alternatives, such as the general autoregressive conditional heteroskedastic model (GARCH), or the smooth-transition autoregressive (STAR) model of Teräsvirta (1994).[9] We estimated

[9] In fact, our model is not very far away, theoretically, from the framework of Teräsvirta (1994), since our logistic functions

the model with maximum likelihood methods using a hybrid genetic search approach, but general method of moments (GMM) methods are also appropriate. We leave to further research and analyisis of the robustness of our results to alternative nonlinear models and alternative estimation methods.

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