Deciphering Hong Kong's Deflation Dynamics

Paul D. McNelis* and Cynthia K.Y. Leung†

July 2003

Abstract

This paper deciphers with linear and neural network estimation the message in Hong Kong's deflation dynamics. The neural network estimates show significantly greater out-of-sample accuracy than linear methods. The empirical results show that while the deflation process is closely linked to monetary/fiscal variables, it is also more strongly tied to rental property rates. Labor cost and gdp growth rates have little to do with the deflationary process.

JEL Classification: E0, E3, E5

Keywords: deflation, neural networks

1 Introduction

Hong has been in a deflationary process since the end of 1997, as Figure 1 shows:

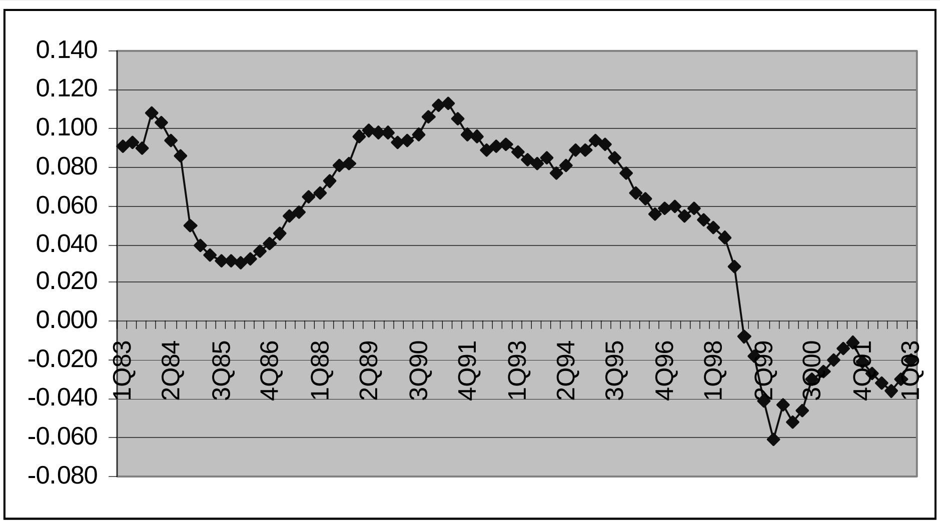

Figure 1: Inflation

There are several factors which may explain the switch in price dynamics from inflation to deflation after 1997. One is the sharp collapse in residential property prices. The other factor is the the influx of imported goods from China after the integration of Hong Kong after 1997. We see in Figure 2 that both of these variables have inflation rates which are either zero or negative since 1997. What is interesting to note, however, is the recurrence of "bubbles" in residential property rates, with bursts of inflation taking place in 1991, 1994, and 1996, before the collapse of property values in 1997.

*Department of Economics, Georgetown University, Washington, D.C. Email: McNelisp@georgetown.edu

†Manager (Economic Research), Hong Kong Monetary Authority Research Department

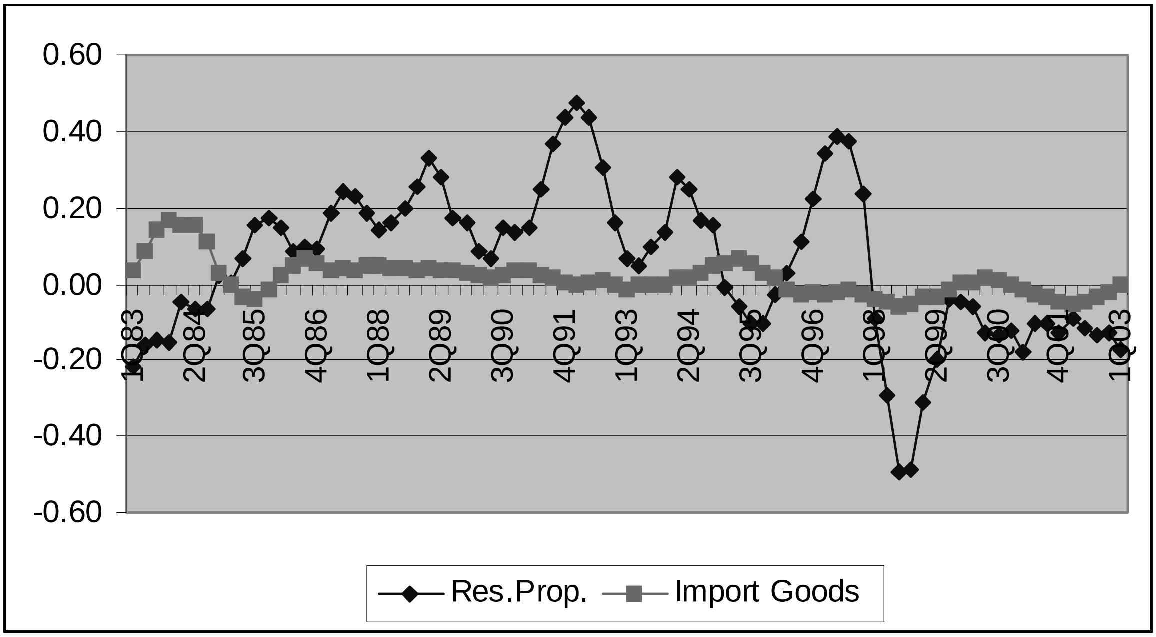

Figure 2

Several questions stand out. Do residential property rates have asymmetric effects on the overall inflation rate? The bubbles in the 90's did not appear to generate sharp changes in the overall inflation, but the collapse in 1997 appears to be highly correlated with the overal deflation. Similary for the price of imported goods: with integration with China, have these price changes become more important? Finally, is there is anything which the government can do, to reverse the deflation process?

In Hong Kong, the currency board arrangement means that the interest rate and domestic credit are exogenous. However, government spending can affect aggregate demand and the inflation process. Figure 3 pictures the annualized rate of growth of growth of government spending and overall gdp. We see that since 2000 there have been at lease some attempts to reverse deflation with increases in the rate of growth of government spending.

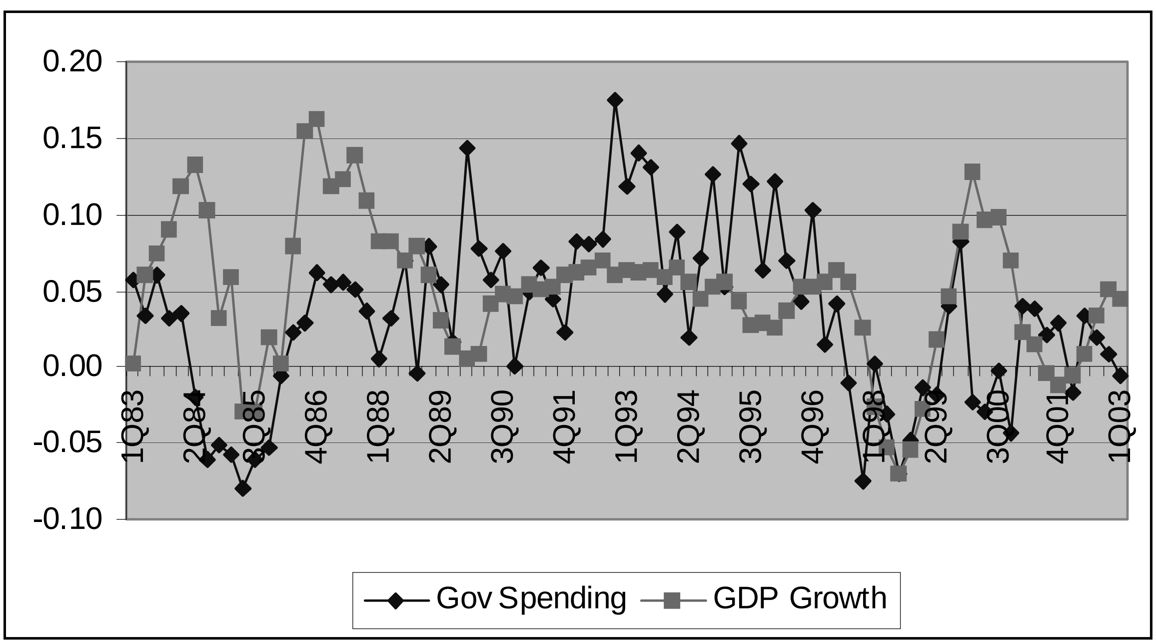

Figure 3

Since Hong Kong is a highly open economy with a currency board, it is natural to ask how closely Hong Kong price developments are synchronoized with those of its major trading partners. Genberg and Pauwles (2003) found that no single country CPI can be used to "represent adequately" the external influences on inflation in Hong Kong [Genberg and Pauwles (2003): p.7]. The same authors argue that nominal wages and import prices have "significant influence" on the more general price indices.

Gerlach and Peng (2003) have examined the interaction between banking credit and property prices in Hong Kong. They found that property prices are "weakly exogeneous" 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. Rather, 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 lead to price swings, and with rising demand for loans, "bank lending naturally responded" [[Gerlach and Peng (2003): p. 11].

The above studies made us of vector autoregressive (VAR) models and linear cointegration methods. Given the asymmetric response of the inflation rate to residential property prices, and the very sharp change from steady inflation to deflation, nonlinear approaches make sense as alternative, complimentary methods for modelling and understanding the Hong Kong inflation/deflation dynamics. In the next section, we present a simple nonlinear model based on neural network methods as an alternative to linear approaches. Section III compares the results of this estimation method with that of linear models. The last section concludes.

2 Specification

2.1 Firm Markup Behavior

We draw upon the framework for inflation similar to that put forward by Gali and Gertler (1999), and assume that each firm sets its price for the period h as a mark-up over marginal cost at time t :

$$P_{t+h} = (1 + \lambda_t) MC_t \tag{1}$$

where λ_t represents the markup coefficient, while marginal costs are given by MC_t. Taking logarithmic first differences, with $p = ln(P)$, the rate of change of the price level is a function of the expected change of the markup coefficient,Λ_t, and the corresponding rate of change of marginal costs,Γ_t,over the interval h:

$$\begin{aligned} p_{t+h} - p_t &= \Lambda_t + \Gamma_t && (2) \\ \Lambda_t &= \ln(1 + \lambda_{t+h}) - \ln(1 + \lambda_t) && (3) \\ \Gamma_t &= \ln(MC_{t+h}) - \ln(MC_t) && (4) \end{aligned}$$

With quarterly late, h = 4. We assume that the expected change in the markup coefficient is a function of changes in variables which affect overall demand and expectations, namely, the output gap, $\widetilde{y}$=ln(Y)−ln(Y^P), where Y and Y^p represent actual and potential output (obtained by the Hodrick-Prescott filtering method), the rate of growth of domestic credit, with d=ln(d), and the rate of growth of the residential propoerty price index, with $p^r = ln(P^r)$, the change in the domestic interest rate r, and the rate of growth of goverment spending, g,over the previous h periods:

$$\Lambda_t = \Lambda(\widetilde{y}_t, d_t - d_{t-h}, p_t^r - p_{t-h}^r, r_t - r_{t-h}, g_t - g_{t-h}) \tag{5}$$

The expected rate of growth of marginal costs is a function of the rate change in imported input prices, P^m as well as corresponding change in labor costs, ULC, with $p^m = \ln(P^m)$ and $ulc = ln(ULC)$:

$$\Gamma_t = \Gamma(p_t^m - p_{t-h}^m, ulc_t - ulc_{t-h}) \tag{6}$$

2.2 Inertial Component of Inflation

In addition to markups over marginal costs, we assume that price changes have an inertial or backward-looking compentent:

$$p_{t+h} - p_t = \Lambda_t + \Gamma_t + \phi_1[p_t - p_{t-h}] \tag{7}$$

2.3 Linear and Neural Network Specification

To make the model operational for estimation, we specify the following linear and neural network alternatives for the functions $\Lambda(y_t - y_{t-h}, b_t - b_{t-h}, s_t - s_{t-h}), \Gamma(p_t^m - p_{t-h}^m, ulc_t - ulc_{t-h})$, given respectively by $L(\Lambda), L(\Gamma)$for the linear specification, and $N(\Lambda), N(\Gamma)$ for the neural network specifications:

$$\begin{aligned}
L(\Lambda_t) &= \lambda_0 + \lambda_1\widetilde{y}_t + \lambda_2(d_t - d_{t-h}) + \lambda_3(p_t^r - p_{t-h}^r) + \lambda_4(r_t - r_{t-h}) + \lambda_4(g_t - g_{t-h}) && (8)\\
N(\Lambda_t) &= \frac{1}{1+\exp[-L(\Lambda_t)]} && (9)\\
L(\Gamma_t) &= \gamma_0 + \gamma_1(p_t^m - p_{t-h}^m) + \gamma_2(ulc_t - ulc_{t-h}) && (10)\\
N(\Gamma_t) &= \frac{1}{1+\exp[-L(\Gamma_t)]} && (11)
\end{aligned}$$

Letting $\Pi_{t+h} = p_{t+h} - p_t$, $\Delta_h d_t = d_t - d_{t-h}$, $\Delta_h g_t = g_t - g_{t-h}$, $\Delta_h p_t^m = p_t^m - p_{t-h}^m$, $\Delta_h p_t^r = p_t^r - p_{t-h}^r$, $\Delta_h ulc_t = ulc_t - ulc_{t-h}$, $\Delta_h r_t = r_t - r_{t-h}, \Delta_h g_t = g_t - g_{t-h}$,the linear estimation model is given by the following equation:

$$\begin{aligned}
\Pi_{t+h} &= \phi_1\Pi_{t-1} + \lambda_1\widetilde{y}_t + \lambda_2\Delta_h b_t + \lambda_3\Delta_h p_t^r + \gamma_1\Delta_h p_t^m + \gamma_2\Delta_h ulc_t + \pi_1\Delta_h r_t + \pi_2\Delta_h g_t + \phi_0 + \xi_t && (12)\\
\xi_t &= \epsilon_t + \sum_{i=1}^{p}\alpha_i\epsilon_{t-i} && (13)
\end{aligned}$$

where the constant terms λ_0, γ_0,a are captured by the term ϕ_0.[1]The disburbance term ξ_t follows a moving average (MA) process of order p, with innovations ϵ_t with having an identical and independent distribution, of mean zero and variance σ^2.

The moving average process for the model is due to the overlapping price dynamics. At time t, for example, the dependent variable is is $ln(p_{t+4}) - \ln(p_t)$, whereas at time $(t-1)$, the dependent variable is $ln(p_{t+3}) - \ln(p_{t-1})$. Thus, part of the innovation at time t-1 will carry over to time t, since innovations which affect $ln(p_{t+3})$ at time $(t-1)$ will also affect $ln(p_{t+4})$ at time t.

The neural network model is given by the following specification:

$$\begin{aligned}
\Pi_{t+h} &= \phi_1\Pi_{t-1} + N(\Lambda_t) + N(\Gamma_t) + \phi_0 + \xi_t^* && (14)\\
\xi_t^* &= \epsilon_t^* + \sum_{i=1}^{p}\alpha_i\epsilon_{t-i}^* && (15)
\end{aligned}$$

A diagram of the network "architecture" is given in Figure 4. In neural network language, the model is a NARMAX structure, a non-linear autoregressive moving-average model with exogeneous variables.

[1]The inflation variables are first-differenced to remove autocorrelation, and we use quarterly data with h = 4. Lagged instruments are used for variables y, b, s, p^m, ulc.

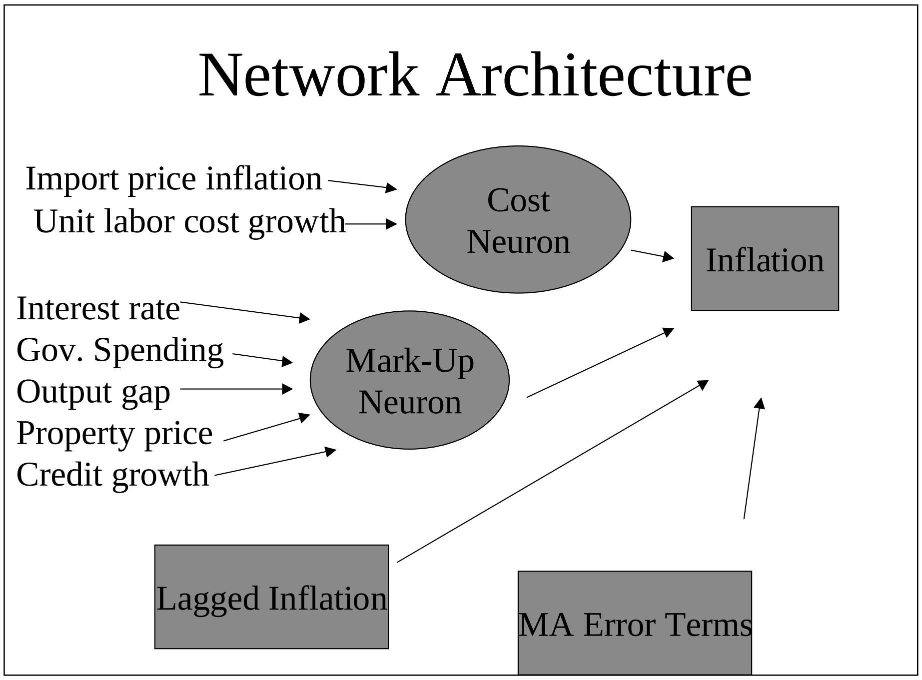

Figure 3

We use the neural network alternative to the linear specification since these methods have been shown to "approximate almost any nonlinear function arbitrarily close"[Frances and van Dijk (2002): p. 206]. At the same time, we are parsimonious in our parameterization of the network in order to avoid overfitting. We use two neurons for grouping or clusing the exogeneous variables, one a "marginal cost" neuron, the other a "demand" or "markup" neuron.

The appeal of the log-sigmoid transform function for the mark-up and demand "neurons" comes from its "threshold behavior" which characterizes many types of economic responses to changes in fundamental variables. For example, if interest rates are already very low or very high, small changes in this rate will have very little effect on demand, for example. However within critical ranges between these two extremes, small changes may signal significant upward or downward movements and therefore create a pronounced impact on demand.

Furthermore, the shape of the logsigmoid function reflects a kind of learning behavior. Often used to characterize "learning by doing", the function becomes increasingly steep until some inflection point. Thereafter the function becomes increasingly flat up and its slope moves exponentially to zero. Following the same example, as interest rates begin to increase from low levels, consumers will judge the probability of a sharp uptick or downtick in the interest rate based on the currently advertised financing packages. The more experience they have, up to some level, the more apt they are to interpret this signal as the time to take advantage of the current interest rate, or the time to postpone a purchase. The results are markedly different than those experienced at other points on the temporal history of interest rates. Thus, the nonlinear logsigmoid function captures a threshold response characterizing "bounded rationality" or a "learning process" in the formation of expectations.

Kuan and White (1994) describe this threshold feature as the "fundamental" characteristic of nonlinear response in the neural network paradigm. They describe it as the "tendency of certain types of neurons to be quiescent of modest levels of input activity, and to become active only after the input activity passes a certain threshold, while beyond this, increases in input activity have little further effect [Kuan and White (1994) : p.2].

3 Estimation Results

3.1 In-Sample Diagnostics

Table I gives the in-sample diagnostics for the two specifications, with estimation based on quarterly data from 1983 to 2003, with a moving-average specification of 8 lagged disturbance terms.. The diagnostics are the multiple correlation coefficient (R^2), the Hannan-Quinn information criterion, the marginal significance of the Leung-Box Q statistic (LB), as well as that of the MacLeod-Li Q statistic of the squared residuals (ML), the Engle-Ng test of symmetry (EN), the Jarque-Bera test of normality, and the Brock-Deckert-Scheinkman test of nonlinearity. Finally, the Lee-White-Granger (LWG) test gives the number of signifiant regressions of the residuals against 1000 randomly generated nonlinear combinations of regressors.[2] This table shows that the neural network clearly dominates on the basis of overall explanatory power, model selection criteria, and regression residuals representing white noise.

Table I

	Linear	Neural Net
Diagnostic:		
R^2	.95	.95
HQIF	-415	-421
LB*	.17	.17
ML*	.006	.03
EN*	.004	.005
JB*	.10	.004
BDS*	.01	.18
LWG**	999	620

* marginal significance levels

**number of significant regressions per 1000

3.2 Forecasting Accuracy

Table II gives the forecasting accuracy statistics for "real time" rolling one quarter forecasting for each period beginning in 1995.1. The statistics are the root mean squared error (RMSQ) value, the Diebold-Mariano test of relative out-of-sample performance, and the Pesaran-Timmerman "success ratio" (SR) for correct sign predictions.[3] The neural network dominates the linear model by these accuracy criteria.

Table II

Out-of-Sample Accuracy

Statistic:	Linear	Neural Network
RMSQ	.724	.0099
DM*	–	.0007
SR	1	1

* marginal significance levels

4 Determinants of Inflation

Table III shows the linear regression coefficients and the partial derivatives of the explanatory variables in the network estimation. Values in bold are statistically significant at the five-percent level. Since both the linear MA and the network models involve recursive nonlinear estimation, we evalulated the significance of each of the regressors by likelihood ratio tests. While both models show that government spending variables are significant and positive, the network model shows that the effect is lower. Similarly, changes in wages and residential property rents taken together outweight the effect of government spending growth. These results are similar with recent arguments of Yoshino and Sakakibara (2002) regarding the limits fiscal policy in Japan.

[2] These statistical tests are clearly summarized in Franses and van Dijk (2000).

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

Linear and Network Determinants of Inflation								
Argument:	Π_{t-1}	$\Delta_h r$	$\Delta_h g$	$\Delta_h p^m$	$\Delta_h d$	$\Delta_h p^r$	$\widetilde{y}$	$_\Delta ulc$
Linear	.306	**.037**	**.079**	**-.087**	**.341**	**.143**	**-.001**	**.074**
Network	**.397**	**-.031**	**.049**	.025	**.001**	**.041**	**.002**	**.067**

5 Conclusion

The results indicate that fighting deflation is not simply a matter of fiscal policy. A reversal in residental property prices is also necessary to push the economy out of the deflation trap, even with expansionary policies in place.

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, as well as for accurate out-of-sample forecasting.

References

[1] Franses, Philip Hans and Dick van Dijk (2000), *Non-linear Time Series Models in Empirical Finance.* Cambridge: Cambridge University Press.

[2] Gali, Jordi and Mark Gertler (1999), "Inflation Dynamics: A Structural Econometric Analysis". *Journal of Monetary Economics* 44, 195-222.

[3] Genberg, Hans and Laurent Pauwels (2003), "Inflation in Hong Kong, SAR: In Search of a Transmission Mechanism". Hong Kong Institute of Economic Research, Working Paper 1/2003.

[4] Gerlach, Stefan and Wensheng Peng (2003), "Bank Lending and Property Prices in Hong Kong". Hong Kong Institute of Economic Research, Working Paper 12/2003.

[5] Kuan, Chung-Ming and Halbert White (1991), "Artifical Neural Networks: An Econometric Perspective". Working Paper, Departmet of Economics, University of California, San Diego.

[6] Krugman, Paul (1998), "Special Page on Japan: Introduction". Web: web.mit.edu /krugman /www/jpage.html.

[7] Yoshino, Naoyuki and Eisuke Sakakibara (2002), "The Current State of the Japanese Economy and Remedies", Asian Economic Papers, 1:2, 110-126.