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Forecasting Inflation under Globalization with Artificial Neural Network-Based Thin and Thick Models*

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Abstract—**We study globalization influences on forecasting inflation in an aggregate perspective using the Phillips curve for Hong Kong, Japan, Taiwan and the US by artificial neural network-based thin and thick models. Our empirical results support the hypothesis that globalization influences do generate the downward tendency in inflation through time in all cases with different levels. Moreover, the artificial neural network-based thin and thick models that have been developed upon the best linear model for each country have shown significant superiority over the naive model in the most cases and over the best linear model in some cases. Finding optimal values of all the parameters for so many artificial neural network models is a difficult task because of the large number of parameters involved. Thus we do not make any claim on the optimality of the artificial neural network models in this study. As a consequence, even though our empirical results are not overwhelmingly satisfactory, building the artificial neural network model based upon the best linear model is a good compromise between practicality and optimality.**

Keywords: ***artificial neural networks, nonlinearity, thick model***

1 Introduction

Inflation is widely taken as one of the main economic problems, because it involves in the allocation efficiency of the economy by means of changing the relative prices among commodities. A dramatic acceleration of inflation results in large costs to the public and business community. The mechanism of how the relative-price adjustments among commodities affect (or cost) the economy is very complicated and not yet well understood. Pursuing stable prices is the primary goal of a central bank while creating and maintaining an independent and efficient monetary system. However, the acceleration in the pace of international trade in good, service and financial assets relative to the growth rate of the domestic trade, broadly defined as globalization, has attracted a lot of attentions [1]. This is because globalization has broken some macro rules such as a decrease in the correlations between the labor cost and inflation and a decline in the elasticities between import prices and core inflation. During the past decade, the acceleration in the pace of the world trade growth is well above the acceleration in the pace of the world economic growth with a disparity from 2.99 percent in 1990 to 3.16 percent in 2006, specially in recent years, but the annual inflation in the advanced countries has been decreasing since 1990 and it is even well below the world economic growth rate. In other words, strong economic growth does not result in high inflation in the most advanced economies since 1990. Even for the developing countries, the annual inflation has started to decelerate since 1995. The global trade (exports and imports of goods and services) stood 38 percent of the total world GDP in 1990 and hit 61 percent in 2006. Hence, it is hard to consider the domestic factors only while conducting the monetary policy when the domestic commodity and financial markets becomes increasingly open (and integrated to the world markets). As a result, globalization seems to become more and more important to this issue.

Inflation is a major issue for the central bank when deciding the monetary policy, but forecasting inflation is intuitively not an easy task for any economy, in which there are many mechanisms operating simultaneously, especially as the influence of globalization becomes stronger. In economics, the Phillips curve theory conveys that there is a tradeoff relationship between inflation and unemployment rate. Empirically, it seems like the Phillips curve is nonlinear [2]. There is an increasing body of research [3, 4, 5, 6, 7] using artificial neural networks (ANNs) that provide evidence of the existence of nonlinear and complex relationships among (or within) economic time series. Consequently, an ANN can be used as an alternative approach to empirically analyze the Phillips curve theory. Atkeson and Ohanian [8] conclude that their linear models based on the non-accelerating inflation rate of

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unemployment (NAIRU) can not provide more accurate forecasts than the naive forecasts. Therefore, to a certain extent, the modern Phillips curve-based models are not as useful as expected. However, based on the study of McNelis and McAdam [6], the trimmed ANN-based thick model [9] outperforms the linear model for real-time and bootstrap forecasts in the Euro area as well as in some other countries considered in their study using the Phillips-Curve framework. Basically, they remove the 5 percent largest and smallest forecasts from several ANNs, and then use the average of the remaining forecasts as combined forecasts. It is practical to use a thick model on several neural networks in the first several forecasting periods, because there is no theoretical basis to select the best ANN among many ANNs that have different numbers of neurons in the hidden layer, or different network architectures, but have same input variables. Even after some periods of forecasting, the forecasting performances of different ANNs might be still too close to determine which one is the best. Therefore a thick model can be accordingly applied. However, the removals of the largest and smallest forecasts from several ANNs do not guarantee the best forecasting performance, insomuch as either the largest or the smallest forecast does not necessarily generate the largest forecasting error. To a certain extent, the range for forecasts should be known a priori when using the trimming method. Moreover, an ANN-based thick (ANN thick) model might not always be a better choice over an ANN-based thin (single ANN; ANN thin) model, so we should consider the ANN thin model as well. Besides, the globalization factor, an increasingly important factor, is absent in their study.

The contribution of this paper is two-fold. First, we consider globalization influences while forecasting inflation in an aggregate perspective using the Phillips curve by artificial neural network-based thin and thick models for Hong Kong, Japan, Taiwan and the US that have data available for the globalization factor. Second, we compare the forecasting performances of ANN thin and thick models with the forecasting performances of a simple naive and the best linear models. The paper is organized as follows. Section 2 describes the theoretical underpinnings and methodology. In Section 3, we discuss and compare the empirical results. The paper ends with some concluding remarks.

2 Methodology

2.1 Theoretical Underpinnings of Artificial Neural Networks

Artificial Neural Networks (ANNs) are one of the most frequently used techniques in the field of machine learning. The field of machine learning focuses on the study of algorithms that improve their performance at some task automatically through experience [10].

Suppose we are given training data as a set of n observations. Each observation is a pair $(\mathbf{x}_i, y_i)$ where $\mathbf{x}_i \in \Re^d$ and $y_i \in \Re$. Assume that the training data has been drawn independently from some unknown cumulative probability distribution $P(\mathbf{x}, y)$. The goal is to find a function $f : \Re^d \mapsto \Re$ that implements the optimal mapping. In order to make learning feasible, we have to specify a function space $\mathcal{F}$ from which the function is to be chosen. In particular, a set of n pairs of training data, denoted by $\{(\mathbf{x}_i, y_i)\}_1^n$, are given for the purpose of a binary classification task, where $\mathbf{x}_i \in \Re^d$ and $y_i \in \{1, -1\}$ is the class label. Assume that the data is linearly separable and let $\mathcal{F}$ be the set of linear decision boundaries of the form

$$f(\mathbf{x}) = \operatorname{sign}(\mathbf{w} \cdot \mathbf{x} + b)$$

where $\mathbf{w} \in \Re^d$ and $b \in \Re$ are the adjustable parameters. Thus, choosing particular values for $\mathbf{w}$ and b results in a trained classifier. For any trained classifier, the hyperplane corresponding to $\mathbf{w} \cdot \mathbf{x} + b = 0$ is the decision boundary. A linear decision boundary is a simple classifier that can be learned very efficiently. However, due to its small complexity it can correctly classify data that is linearly separable only.

In general, one way to measure the performance of a trained classifier $f \in \mathcal{F}$ is to look at the mean error computed from the training data. This is known as the empirical risk (or training error). Minimizing the empirical risk is one of the most commonly used optimization procedures. However, even when there is no error on the training data, the classifier may not generate correct classifications on unseen data (See Figure 1). This problem is known as overfitting. The ability of a classifier to correctly classify new data that is not in the training set is known as generalization. Having a classifier with good generalization is, of course, a much harder problem. There is a competition of terms. As the complexity of the classifier increases, the empirical risk tends to decrease. However, the generalization error usually increases with increasing complexity. Thus, for such models with broad approximation abilities and few specific assumptions (e.g., ANNs), the distinction between memorization and generalization becomes important [11]. A validation set (disjoint from the training set) is commonly used to assess generalization performance. Cross-validation is a technique that reduces overfitting. For instance, in a κ-fold cross-validation, the collected data is divided into κ partitions. Each partition in turn is left out and the remaining $\kappa - 1$ partitions are used for training. The left out partition is then used to test generalization performance. The value reported is then the average of the κ tests.

Basically, ANNs are a class of non-linear, non-parametric models that can be trained to approximate general non-linear, multivariate functions. They are massively parallel systems comprised of many interconnected processing

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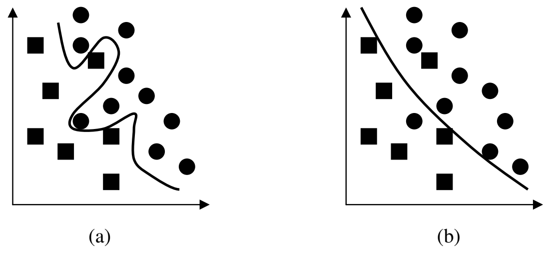

Figure 1: Generalization performance: a) an overly complex classifier that results in zero error on the training data, but may not generalize well to unseen data; b) a classifier that might represent the optimal tradeoff between error in the classification of training data and complexity of the classifier, thus capable of generalizing well on unseen data.

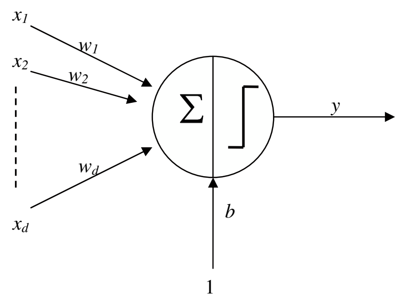

Figure 2: One neuron single-layer d-input perceptron with threshold activation function. The output $y = \text{sign}(\mathbf{w} \cdot \mathbf{x} + b) = \text{sign}(\sum w_i x_i + b)$

elements (known as nodes or neurons) based on neurobiological models of the brain. One of their main advantages in comparison to other models is that they have very few domain-specific assumptions and are highly adaptable (e.g., they learn from experience). Thus, they need no a priori assumption of a model and are capable of inferring complex non-linear input-output transformations. In addition to their typical use in (nonlinear) regression, they are commonly used in pattern recognition, where the ANNs assign a set of input features to one or more classes.

In the late 1950s, Rosenblatt [12] introduced the perceptron learning rule, the first iterative algorithm for training a simple ANN: the perceptron (see Figure 2), which is a linear classifier. After initializing $\mathbf{w}$ and b randomly, each training point $\mathbf{x}_i$ is presented and the output value of y is compared against y_i. If y and y_i are different (i.e., $\mathbf{x}_i$ is misclassified) the values of $\mathbf{w}$ and b are adapted by moving them either towards or away from $\mathbf{x}_i$. Rosenblatt proved that, assuming the classes are linearly separable, the algorithm will always converge and find values for $\mathbf{w}$ and b that solve the classification problem. That is, the algorithm finds a hyperplane that divides the d-dimensional space into two decision regions. A linear decision boundary (e.g., a single-layer perceptron) is a simple classifier that can be learned very efficiently. However, due to its small complexity it can correctly classify data that is linearly separable only. On the other hand, a more complex decision boundary can correctly classify general data that may not be linearly separable.

The key idea responsible for the power, potential, and popularity of ANNs is the insertion of one or more layers of nonlinear hidden units (between the inputs and output) [11]. These kinds of nonlinearity allow for interactions between the inputs (e.g., products between input variables). As a result, the network can fit more complicated functions [11]. A multilayer perceptron consists of an input layer, at least one middle or hidden layer, and an output layer of computational neurons (see Figure 3). The input signals are propagated in a forward direction on a layer-by-layer basis.

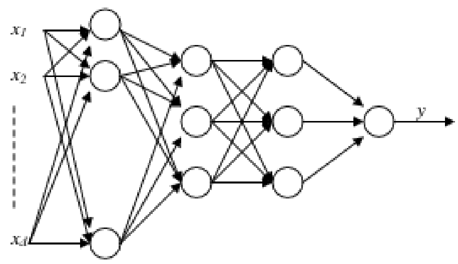

Figure 3: Multilayer d-input perceptron with two hidden layers.

Learning in a multilayer network is similar to learning with a perceptron. That is, each training point $\mathbf{x}_i$ is presented to the network as input. The network computes the corresponding output y. If y and y_i are different, the network weights are adjusted to reduce this error. In a perceptron, there is only one weight for each of the d inputs and only one output. However, in a multilayer network, how can we update the weights to the hidden units that do not have a target value? The revolutionary (and somewhat obvious) idea that solved this problem is the chain rule of differentiation [11]. This idea of error backpropagation was first proposed in 1969 [13] but was ignored due to its computational requirements. The backpropagation algorithm was rediscovered in 1986 [14] at a time when computers were powerful enough to allow for its successful implementation. In the backpropagation algorithm, the error (i.e., the difference between the network output and the desired output) is calculated and then propagated backwards through the network from the output to the input layer. The weights are modified as the error is propagated. The sum of squared errors (over all training data) is the performance measure that the backpropagation algorithm attempts to minimize. When the value of this measure in an entire pass through all training data is sufficiently small, it is considered that the network has converged. The following section is going to present the ANN models, inflation function, and data.

2.2 ANN thin and thick Models, Inflation Function, and Data

In contrast to traditional models that are "theory-rich" and "data-poor", ANNs are "data-rich" and "theory-poor" in a way that little or no a priori knowledge of the problem is present [11]. Thus, they need no a priori assumption of a model and are capable of inferring complex non-linear input-output transformations. In spite of its easy application, there is no theoretical basis to select the best ANN among several ANNs that have different parameter values such as the numbers of neurons in the hidden layer (different network architectures) at the beginning of forecasting periods, although they may have same input variables. Moreover, the following situation could also possibly occur: ANNs have no significant difference in their out-of-sample forecasting performances after a period of time. Usually there is a method, called thick model, that could be used under these circumstances. A thick model combines several forecasts from different ANNs. In the combination of several forecasts, the weights for the forecasts can be equal or different. Alternatively, we can trim the outliers from the forecasts if we have prior information about the reasonable range of forecasts. Therefore, it is reasonable to use a thick model on several neural networks in the first several periods of forecasting or when it is still hard to decide which ANN is the best after some periods.

In our study, ANN thin and ANN thick models are both considered. For the ANN thick model, we implement two different kinds. One is ANN thick with equal weight (i.e., average value) model, and the other one is ANN thick with unequal weight model that gives greater weight to the relatively better ANNs and less weight to the relatively worse ANNs by nonlinearly optimizing (minimizing) the forecast error statistics from the first several out-of-sample test periods. In this study, we repeatedly estimate and update both the linear and several ANN models to obtain a one-step-ahead forecast (the real time forecast) while the sample period rolls forward a quarter at a time. For the purpose of avoiding obsolete information, we keep the sample size fixed by getting rid of the oldest data while the estimation is rolling over to the next period.

The Phillips curve framework with a globalization factor can be described as the following function for both the linear and ANN models.

$$\begin{aligned}\pi^4_{t+1} - \pi^4_t &= f(\Delta\pi^4_t, ..., \Delta\pi^4_{t-i}, \Delta\pi_t, ..., \Delta\pi_{t-j}, \\ &\quad \Delta u_t, ..., \Delta u_{t-m}, \Delta g_t, ..., \Delta g_{t-n})\end{aligned}$$

where π^4_t is the the 4-quarter change consumer price index (CPI) between quarters t and $t-4$ in an aggregate perspective at an annualized value as measured by $100[\ln(P_t) - \ln(P_{t-4})]$, π_t is quarterly inflation as measured by $400[\ln(P_t) - \ln(P_{t-1})]$, u_t is the quarterly employment rate in quarter t, g_t is the quarterly globalization factor (the ratio of exports plus imports to the overall GDP for a country) in quarter t, and i, m, and n are the lag lengths. The left side term is the difference between the 4-quarter change inflation in the current quarter and the next quarter. We have to avoid forecasting long horizons such as the difference between the inflation over the next 4 quarters and inflation over the previous 4 quarters, although some research does not avoid forecasting long horizons [8, 6]. The reason is that a long forecasting horizon does not cohere with the Phillips curve theory that only exists in the short or medium run. In other words, there is no permanent tradeoff between inflation and unemployment in the long run, because the long-run inflation is determined by the central bank, i.e., the relationship in the Phillips cure does not exist in the long run. In addition, we also try different forms of information from the past such as the 4-quarter change employment rate and 4-quarter change globalization factor to check if they also generate significant influences on $\Delta\pi^4_t$ in each country. As a result, only the 4-quarter change globalization factor is more significant than the quarterly globalization factor in the case of the US.

In the inflation function, we focus on the influences running from the growth paces of the input variables to the growth pace of the output variable. Usually, the central bank is more concerned with 12-month change in CPI so that the comfort zone of the CPI changes can be observed easily. Due to the unavailability of monthly data for the globalization factor, we can only investigate four countries, which are Hong Kong, Japan, Taiwan and the United States in this study with quarterly data. It will still mean the same for the central bank if we use the 4-quarter change in CPI. The whole sample period runs from the fourth quarter of 1982 to the third quarter of 2006, and the dataset is obtained from the database of the International Monetary Fund (IMF). For each sample country, around three fourths of each dataset is used to estimate or train the forecasting models. Afterward, the remaining one fourth dataset (i.e., 20 periods as test periods starting from the first quarter of 2002 till the third quarter of 2006) is used to evaluate real time forecast performances among different forecasting approaches.

3 Empirical Results and Analysis

As mentioned previously, we repeatedly estimate and update both the linear and several neural network models to get a one-step-ahead forecast (the real time forecast) from these different forecasting models. Since the economy evolves through time, it is not appropriate to keep obsolete information in our forecasting models, so we get rid of the earliest period while the estimation is rolling over to the next period. Thus, the sample size is fixed. The derived benefit to do so is that we can examine the model's evolution (model stability) through time, insomuch as it is not quite appropriate to use the same model while repeatedly estimating the forecasting models for a growing economy. As a result, the explainable variables in each period might be different through time, and we can also obtain the time-varying coefficients for every input in the linear model and their relative importance through time. The linear model is a multivariate time series model. To ensure that the residuals from the linear models are white noise, we perform the Breusch-Godfrey Lagrange multiplier test, Ljung-Box Q-statistics and correlogram of squared residuals while building the linear model in each period. Selecting the variables for the ANN models is based on the best linear model. The reason is that it is a very time-consuming and complex process to obtain all the optimal parameters (e.g., learning rate, number of neurons in each layer, number of training cycles, etc.) for so many candidate ANN models. Note that this is only a compromise between practicality and optimality. Nevertheless, our previous work does indicate great advantages when applying this method [7, 15].

The inverse relationship between unemployment rate and inflation (Phillips curve) exists in all cases, and the historical inflation significantly affects the current inflation as well in all cases. It is not surprising that the globalization factor is very significant in the linear model for each sample country, and it does generate the downward tendency in inflation through time with different levels. Table 1 presents all the summary forecast error statistics, root-mean-squared error (RMSE) and mean absolute error (MAE), for each sample country. As previously discussed, in the first few out-of-sample test periods, we might be able to decide which ANN performs best, but some ANNs still have similar performances after some test periods. If this situation happens, thick models (ANN thick with equal weight and ANN thick with unequal weight models) can be accordingly applied. Except for the linear, ANN thin and thick models, a simple naive model producing the benchmark forecast is also included. Basically, there are five different forecasting models, which are naive, linear, ANN thin, ANN thick with equal weight (ANN-Thick-W_E), and ANN thick with unequal weight (ANN-Thick-W_O) models.

Some significant observations emerge from our empirical results in Table 1. First, there are two (Hong Kong and the US) out of four cases, in which either ANN thin or thick models outperforms the naive and best linear models. This result is very encouraging because we do not make any claim on the optimality of the ANN models that are merely based upon these repeatedly-updated and well-specified linear models. As previously mentioned, although the ANNs have the same inputs as the best linear model, the variations on learning rates, number of neurons in each layer, and number of training cycles could generate a lot of different ANN models that might lead to different forecasting performances. Nevertheless, obtaining optimal values for so many ANN models is rather time-consuming and complex. In the case of Hong Kong (and all other cases indeed), we use the average of all forecasts from the different ANNs in the first 10 out-of-sample test periods, because we could not determine which ANN is the best without any performance history. Afterward, we use the forecasting performances from the first 10 test periods to obtain the weights in order to combine weighted forecasts for the next test period, and we update the weights before each test period. Actually, the weights vary just a little each time as the new information rolls in. This indicates that weights could become stable after some test periods in the case of Hong Kong if we have more data available. However, due to the constraint of data availability, we do not expect to get the optimal weights within some test periods, which could be possibly improved by using longer test periods with more experiences. Hong Kong is the only case in which the ANN thick with unequal weight (ANN-Thick-W_O) model outperforms all other models in this study with substantially lower RMSE and MAE. In the case of the US, the ANN thin model outperforms all other models. Thirdly, in the cases of Taiwan, the ANN thin model performs as well as the best linear model, and it significantly outperforms the naive model. Fourthly, in the case of Japan, the linear model has the best forecasting performance, and neither the ANN thin nor the ANN thick model can outperform the naive model. Lastly, the ANN thick with unequal weight model in all cases do outperform the ANN thick with equal weight model despite the fact that they are not the best in some cases.

Table 1: Forecast Accuracy for Inflation of Sample Countries

Model	Hong Kong		Japan		Taiwan		US	
	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
Navie	0.746	0.595	0.331	0.279	0.771	0.607	0.572	0.445
Linear-Thin	0.813	0.541	0.265	0.204	0.702	0.601	0.482	0.406
ANN-Thin	0.730	0.620	0.360	0.284	0.745	0.570	0.464	0.397
ANN-Thick-W_E	0.667	0.521	0.428	0.341	0.818	0.608	0.494	0.426
ANN-Thick-W_O	0.655	0.516	0.390	0.327	0.791	0.592	0.486	0.421

In short, our empirical results are not the most satisfactory but due to the application flexibility of ANNs, it

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is very hard to obtain all the optimal parameters (e.g., learning rate, number of neurons in each layer, number of training cycles, etc.) for so many ANN candidate models through a very time-consuming and complex process. The focus of this study was on a real time forecasting with many repeated estimations and sample countries, so selecting the variables for the ANN based upon the best linear model is only a compromise between practicality and optimality. However, our results are very encouraging.

4 Conclusions

In this paper, we study the globalization influences on forecasting inflation in an aggregate perspective using the Phillips curve for Hong Kong, Japan, Taiwan and the US by artificial neural network-based thin and thick models. Our empirical results support that globalization influences do generate the downward tendency in inflation through time in all cases. Either the ANN thin or the ANN thick model that has been developed upon the best linear model for each country in this study has shown significant superiority over the naive model in most cases and over the best linear model in some cases. In fact, finding optimal values for the large number of parameters involved in the ANN models is rather difficult, and thus we do not make any claim on the optimality of our ANN models. Even though our empirical results are not overwhelmingly satisfactory, building the ANN model based upon the best linear model is a good compromise between practicality and optimality, which sheds strong light for future work such as cross-validations and sensitivity analysis for selecting variables to enhance the ANN's performances. In addition, whether or not obtaining the optimal parameter values (time-consuming and unpractical task) is essential to conspicuously enhance the ANN's performances to a very satisfactory level could be an issue to study as well.

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