Co-Evolving Neural Networks with Evolutionary Strategies : A New Application to Divisia Money

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Abstract

This work applies state-of-the-art artificial intelligence forecasting methods to provide new evidence of the comparative performance of statistically weighted Divisia indices vis a vis their simple sum counterparts in a simple inflation forecasting experiment. We develop a new approach that uses co-evolution (using neural networks and evolutionary strategies) as a predictive tool. This approach is simple to implement yet produces results that outperform stand-alone neural network predictions. Results suggest that superior tracking of inflation is possible for models that employ a Divisia M2 measure of money that has been adjusted to incorporate a learning mechanism to allow individuals to gradually alter their perceptions of the increased productivity of money. Divisia measures of money outperform their simple sum counterparts as macroeconomic indicators.

Keywords: Evolutionary Strategy, Divisia, Inflation Forecasting, Neural Networks, Co-evolution

1. Introduction

A standard result of most textbook macroeconomic models which include money and prices is that changes in the money supply lead, eventually, to proportional changes in the price level, or alternatively, long-run rates of money growth are linked to inflation. Money has traditionally been constructed by simply summing all the component assets of the money stock with an equal weighting; this is known as the 'simple sum' measure of money. Although this approach is now recognised as being demonstrably wrong, it continues to be the official approach adopted by the Central Banks and hence is used to guide monetary policy decisions across the world.

We offer an exploratory study of the relevance of the Divisia monetary aggregate for Taiwan over the period 1978 to date. In this way, we begin with a banking system that was heavily regulated by the Central Bank and the Ministry of Finance until 1989, which saw the introduction of the revised Banking Law in July. At the beginning of the 1980s, drastic economic, social and political changes took place creating a long-term macroeconomic imbalance. Rising oil prices caused consumer prices to rise by 16.3 per cent in 1981, followed by a period of near zero inflation in the mid eighties. From the nineties onwards, inflation has been fluctuating around the 5 per cent mark and hence the control of inflation has not been the mainstay of recent economic policy in Taiwan, unlike the experience of the western world. Rather, policy has focused on achieving balanced economic and social development.

There have been major financial innovations in Taiwan as transactions technology has progressed and new financial instruments have been introduced, such as interest-bearing retail sight deposits. Although it is difficult to make a distinction between the various types of financial innovation, the effects on the productivity and liquidity of monetary assets are almost certainly different. The question we ask, in keeping with Ford et al [1] is do the Divisia aggregates adequately capture all the financial innovations?

We explore the econometric performance of a new generation of Divisia indices that have been reformulated to take account of recent financial innovations in Taiwan,

extending the work of Ford in 1997 [2]. Two innovation adjusted Divisia series are therefore analysed, the data having kindly been provided to us by Ford. Both Divisia series have been modified to allow for a learning process by individuals as they adapt to changes in the productivity of monetary assets and adjust their holdings.

One adjusted series, namely Innovation1 Divisia (INN1), assumes that individuals, who had been adjusting well to cosmetic changes in interest rates, were slow to react to the increased productivity of money, initially underestimating the effect of financial innovation. In keeping with Ford [2, p21] we adopt the approach proposed in Baba et al [3], which imposes a learning adjustment process on the user cost of interest-bearing sight deposits in the construction of monetary indices.

The second series, namely Innovation2 Divisia (INN2), assumes a period of gradual and continuous learning throughout the whole period as individuals adjust to the increased productivity of money. The approach adopted in [2 ,p4] is used, whereby an estimate of the degree of productivity improvements is obtained by using an index number of bank branches of all kinds.

The novelty of this paper lies in the use of co-evolution, using neural networks and evolutionary strategies, to examine Taiwan's recent experience of inflation. This is a unique tool in this context and its use in this research is highly exploratory although results presented here give us confidence to believe that significant advances in macroeconomic forecasting and policymaking are possible using advanced Artificial Intelligence (AI) methods such as this. We build on the linear ES model reported in [4] and compare our results to those already produced for Taiwan using the AI technique of neural networks [5] as a means of evaluating the explanatory power of both Divisia and simple sum measures of broad money as indicators of inflation.

2. Data and Model Specification

The level of monetary aggregation selected for this study was M2, as this is the measure currently monitored by the monetary authorities in Taiwan. Four different M2 measures were used independently to predict future movements in the inflation rate. Monetary data thus consisted of three Divisia series provided by [2], one conventional Divisia, (DIVM2), Innovation1 (INN1) and Innovation2 (INN2), together with a simple sum series (M2), constructed from component assets obtained from the Aremos-Financial Services database in Taiwan. The Divisia M2 (DIVM2) aggregate is constructed by weighting each individual component by its own interest rate whilst Innovation1 (INN1) and Innovation2 (INN2) seek to improve upon the weighting system by capturing the true monetary services flow provided by each component asset more accurately. Thus INN1 is a development of DIVM2 and it should be noted that it does not diverge from the conventional Divisia measure until the late 1980s. The second modified Divisia series, INN2 assumes a period of gradual and continuous learning by agents as they adapt to the increased productivity of money throughout the period and corrects, at least partially, for the distortion arising from technological progress. Individuals are thus assumed to adjust their holdings of financial assets until the diffusion of financial liberalisation is complete.

Inflation was constructed for each quarter as year-on-year growth rates of prices. Quarterly data over the sample period 1970Q1 to 1995Q3 was used as illustrated in Figure 1. Our preferred price series, the Consumer Price Index (CPI), was obtained from DataStream. The four monetary series were subjected to a smoothing process by taking three quarter averages to reduce noise. Finally, to avoid the swamping of mean percent error by huge values during a period of very low inflation from 1983 to 1986, the entire series was translated upwards by 5 percent and results are presented on this basis. Of the total quarterly data points available, after loss of data points due to the smoothing process and the time lag implicit in the model of up to four quarters, 96 quarters remained, of which the first 85 were used for training and the last 7 for were used as a validation set. The first 4 items were only used as a basis for the first prediction.

The aim of the co-evolutionary model is to evolve a neural network that represents the predictive function. In previous work [4] an evolutionary strategy was using a linear

function. One of the criticisms of the previous work is the use of a linear model. In this work, due to the activation function used within the neural network, it has the ability to evolve a non-linear function.

3. Co-evolution Model

Co-evolution is based on the idea that a population of agents compete against one another and the fittest survive. At the start of this evolutionary process the agents are created randomly and, of course, these agents act in a random way. However, some will be slightly better than others and these will survive (and evolve), whilst the lesser agents die off.

In this work we evolve a population of neural networks which are evaluated by considering how well the network can predict the test cases in the data (in sample). Once evolution has completed the best individual (i.e evolved neural network) is tested to see how well it can predict the data that it has not seen before (out of sample). The input supplied to the neural network is the four previous quarters from the money supply currently being tested (i.e. M2, DIVM2, INN1, INN2) and an autoregressive term in the form of the previous months inflation figure. The network has one output, a prediction of the next quarters inflation rate.

A population of 20 networks were randomly created and, after evaluating them, the top 10 are retained and evolved using an evolutionary strategy (see [6,7,8,9] for good introductions). In addition to evolving the weights in the network, the sigma value (that is, the standard deviation value used in the mutation operator) is also evolved. Sigma is initially set to 0.05.

Various experiments were conducted. The number of hidden neurons was varied between 3 and 5 and sigmoid and tanh activation functions were used in the hidden layer (an identify function was used for the input and output layer). Each test consisted of 1,000,000 iterations so as to be comparable with the results reported in [4].

In summary, the various parameters we used are as follows

- Measures: {M2, DIVM2, INN1, INN2)
- Population Size of Networks: 20
- Iterations: 1,000,000
- Networks Retained and Mutated: 10
- Input Neurons: 5
- Hidden Neurons: {3,4,5}
- Activation fn (hidden): {sigmoid, tanh}
- Activation fn (input/output): identity
- All results averaged over 6 runs

Therefore, we conducted 120 (|Measures| x |Hidden Neurons| x |Activations fn (hidden)| x Averaged over six runs) runs, each of 1,000,000 iterations.

4. Testing and Results

The four money measures (M2, DIVM2, INN1 and INN2) were tested independently and these results compared against previous results obtained on the same data using a neural network (see [5] for a full description of the neural network procedure employed). The results reported here are the arithmetic means calculated over six individual trials of the co-evolutionary approach and are divided between within sample (the training set) and out-of-sample (the validation set). Within these two categories, three standard forecasting evaluation measures were used to compare the predicted inflation rate with the actual inflation rate, namely, Root Mean Squared Error (RMS), Mean Absolute Difference (MAD) and Mean Percent Error (MPE). The in-sample and out-of-sample results produced by the co-evolutionary approach averaged over six trials are shown in table 1. These six trials represent varying the number of hidden neurons (3) and the hidden layer activation function (2). These two parameters are used when testing all the Divisia measures (M2, DIVM2, INN1, INN2). The best fitting model is shown in table 2. This trial represents 3 hidden neurons and using the tanh activation function. Previous results [5] using neural networks are shown in table 3. Results for trial 6 only are presented for reasons of brevity, although the pattern of findings is consistent across all six trials performed.

A comparison of tables 1 and 3 reveals that co-evolution clearly compete favourably with the neural network, on average, in terms of forecasting capabilities across all forecasting evaluation methods both in- and

out-of sample. When the results of the best-fitting co-evolutionary model are considered, however, using trial 6 presented here in table 2, the co-evolutionary method produces forecasts equal to or superior to the neural network in 8 out of 12 out-of-sample cases analysed. This result is representative of all six co-evolutionary trials performed. The best inflation forecast is achieved using the INN1 monetary aggregate, where the co-evolutionary approach RMS error is 14% lower than that achieved for Divisia M2 and 34% lower using forecasts from the simple sum M2 model. Figures 1 and 2 illustrate the best fitting (INN1) and worst fitting (M2) forecasts for the co-evolutionary technique. On average, evidence presented in table 1 clearly indicates that both INN1 and standard Divisia M2 outperform the simple sum M2 counterpart in all cases out-of-sample. INN2 is undoubtedly the worst performing aggregate, producing out-of-sample RMS errors some 7.5 times greater than INN1 on average.

5. Concluding Remarks

This research provides a significant improvement upon [4] in terms of comparative predictive performance of co-evolution and have been found to compete very favourably with neural networks and have the potential to beat neural networks in terms of superior predictive performance when co-evolution is used to evolve neural networks. Artificial Intelligence techniques in general and co-evolution in particular are highly effective tools for predicting future movements in inflation; there is tremendous scope for further research into the development of these methods as new macroeconomic forecasting models.

Evidence provides overwhelming support for the view that Divisia indices are superior to their simple sum counterparts as macroeconomic indicators. It may be concluded that a money stock mismeasurement problem exists and that the technique of simply summing assets in the formation of monetary aggregates is inherently flawed. The role of monetary aggregates in the major economies today has largely been relegated to one of a leading indicator of economic activity, along with a range of other macroeconomic variables. However, further empirical work on Divisia money and, in particular, close monitoring of Divisia constructs that have been adjusted to accommodate financial innovation, may serve to restore confidence in former well established money-inflation links. Ultimately, it is hoped that money may be re-established as an effective macroeconomic policy tool in its own right. This application of evolutionary strategies to explore the money - inflation link is highly experimental in nature and the overriding feature of this research is very much one of simplicity. It is virtually certain in this context that more accurate inflation forecasting models could be achieved with the inclusion of additional explanatory variables, particularly those currently used by monetary authorities around the world as leading indicator components of inflation.

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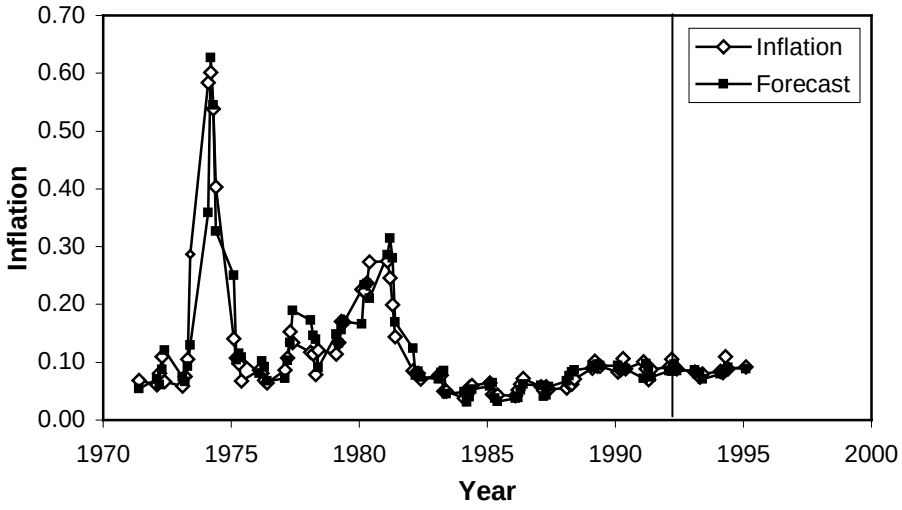

Figure 1: Inflation and predicated inflation using Innovation 1

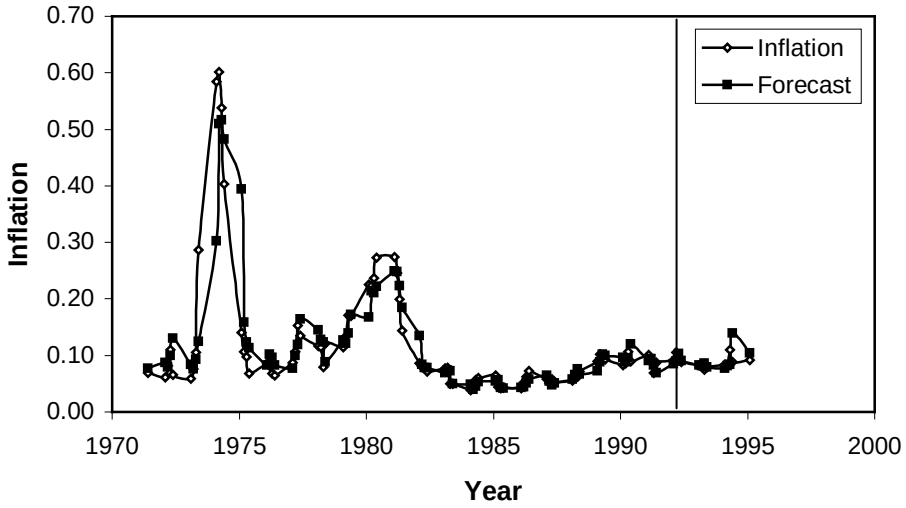

Figure 2: Inflation and predicated inflation using Simple Sum M2.

Table 1. Co-evolutionary Results Average Errors Over 6 Trials

Within Sample	**M2**	**DIVM2**	**INN1**	**INN2**
RMS	0.050759	0.038414	0.039012	0.044366
MAD	0.024788	0.023520	0.023335	0.024782
MPE	20%	22%	21%	21%
Out-of-Sample	**M2**	**DIVM2**	**INN1**	**INN2**
RMS	0.035561	0.014817	0.020179	0.151284
MAD	0.031064	0.012219	0.017148	0.128701
MPE	34%	14%	19%	145%

Table 2. Co-evolutionary Results for Best-Fit Model (Trial 6)

Within Sample	**M2**	**DIVM2**	**INN1**	**INN2**
RMS	0.050696	0.040938	0.041234	0.048419
MAD	0.024900	0.024000	0.023000	0.026300
MPE	20%	22%	20%	23%
Out-of-Sample	**M2**	**DIVM2**	**INN1**	**INN2**
RMS	0.017289	0.013175	0.011312	0.080092
MAD	0.013800	0.012000	0.008300	0.078500
MPE	15%	14%	9%	89%

Table 3. Comparison with Neural Network Results

Within Sample	**M2**	**DIVM2**	**INN1**	**INN2**
RMS	0.032106	0.022578	0.018764	0.026806
MAD	0.024700	0.017500	0.013900	0.018200
MPE	30%	22%	16%	21%
Out-of-Sample	**M2**	**DIVM2**	**INN1**	**INN2**
RMS	0.014801	0.016043	0.010715	0.011575
MAD	0.013800	0.015000	0.00800	0.009000
MPE	16%	17%	9%	10%

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