FINANCIAL INNOVATION AND DIVISIA MONEY IN TAIWAN: COMPARATIVE EVIDENCE FROM NEURAL NETWORK AND VECTOR ERROR-CORRECTION FORECASTING MODELS

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In this article a Divisia monetary index is constructed for the Taiwan economy, and its inflation forecasting potential is compared with that of its traditional simple sum counterpart. The Divisia index is adjusted in two ways to allow for the financial liberalization that Taiwan has experienced since the 1970s. The powerful artificial intelligence technique of neural networks is used and is found to beat the conventional econometric techniques in a simple inflation forecasting experiment. The preferred inflation forecasting model is achieved using networks 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. The explanatory power of the two innovation-adjusted Divisia aggregates dominates that of the simple sum counterpart in the majority of cases. (*JEL* C4, E4, E5)

I. INTRODUCTION

A standard result of most textbook macroeconomic models that 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. Friedman and Schwartz (1982) present a simple analysis of the correlation between U.S. money and prices over a span of more than 100 years, and Hallman et al. (1991) provide evidence of a long-run link between M2 and the price level using the P-star model based on the long-run quantity theory of money. It appears that the long-run causal chain is just as Friedman said it should be—inflation is a monetary phenomenon.

In the United States, the favored monetary aggregate among monetarists, particularly Milton Friedman, during the early to mid-1970s was simple sum M2. Barnett (1997) paints a very clear picture of the monetarist stance in the United States in the early 1980s in his description of the "broken road." Forecasts showed that the rise in growth of M2 from under 10% to over 30% between late 1982 and early 1983 was bound to result in renewed stagflation, that is, recession accompanied by high interest rates and rising inflation. Friedman's very visible forecast failure, according to Barnett (1997), delivered a very "serious blow to 'monetarism' and to advocates of stable simple sum money demand equations."

ABBREVIATIONS

GDP: Gross Domestic Product
VECM: Vector Error-Correction Model

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Central banks around the world became convinced of the importance of money as a policy control variable and confident in the use of monetary aggregates as intermediate monetary targets just at a time when everything started to go embarrassingly wrong. During the mid- to late 1970s, evidence of the deterioration in the formerly stable demand for money function was beginning to emerge, making the monetarist reign a short one. It was becoming apparent throughout the developed economies in the mid-1980s that increased competition within the banking sector and the computer revolution in the financial world was beginning to have substantial effects on the relative user-costs of bank liabilities and the ever increasing array of substitutes for them. It is now well established that monetary targeting failed in the major macroeconomies because the chosen target aggregates did not remain stably related to other key macroeconomic variables, such as nominal income. Some countries (such as the United States and Germany) moved from narrow to broader money targeting in the mid-1980s before officially abandoning targeting altogether in the late 1980s (e.g., United States and Canada). The Bundesbank kept its monetary goal until the formation of the European Central Bank, although Svensson (2000) claims that the Bundesbank has been an inflation targeter in deeds and a monetary targeter in words only. The consensus of opinion at the end of the 1980s was that it was not possible to reestablish the former apparently stable demand for money functions, even though broad monetary aggregates had been redefined and extended to include higher-interest-bearing building society deposits (see Hall et al., 1989).

Recent research into the construction of monetary aggregates (see the Barnett 2nd Serletis collected volume for the United States) attributes the breakdown in demand for money functions during the 1980s to the use of conventional official simple sum aggregates. Simply summing the constituent component assets to form the aggregate creates flawed index numbers because aggregating any set of commodities with equal weights implies that each good is a perfect substitute for every other good in the group. The simple sum aggregation method will lead to the mismeasurement of the monetary services provided, particularly during periods of significant financial development, when interest rate yields on the various components of broad money are changing over time. The use of equal weights for the user costs of the constituent component assets is wholly inappropriate during periods of high financial innovation because the introduction of new instruments and the technological progress that occurred in making transactions almost certainly have diverse effects on the productivity and liquidity of monetary assets.

Many attempts have been made to improve the measurement of money. The most well-known attempt is that of Friedman and Schwartz (1970). They suggested applying some form of weighting of the components in the aggregate depending on their relative "moneyness." The pioneering work of Barnett (1978, 1980) has provided a consistent method to perform this weighting. Economic aggregation theory provides methods for choosing which assets to include in a monetary aggregate and how to construct aggregator functions, whereas index number theory provides parameter- and estimation-free methods to perform the aggregation. One index that has particularly good properties for the purpose of constructing monetary quantity indices is the Divisia index, derived from the class of superlative index numbers discussed by Diewert (1976). Much attention has also been devoted to the viability of alternative weighting schemes, such as weighting by bid-ask spreads, turnover rates, price variations, and denomination size. The preference for a Divisia monetary index was founded on neoclassical microeconomic theory, approximation theory, and revealed preference theory. When applying these theories to the construction of monetary aggregates, it becomes apparent that the components included should be weighted depending on the monetary services they provide. It can be shown that traditional simple sum aggregation is only justified when all asset components are perfect substitutes (Barnett, 1984).

Indeed, many economists concede that in principle, reported simple sum aggregates are flawed and based on untenable assumptions (see, for example, Belongia, 1996). In this study using U.S. data, Belongia reestimated empirical models by replacing simple sum money with Divisia and thereby significantly altered the conclusions that should have been reached by several influential studies. Similarly, Barnett (1980) showed that an apparent decline in velocity was removed when Divisia measures replaced simple sum. Central banks continue to publish simple sum measures of the money stock and draw policy inferences from their behavior, even though it has been demonstrated conclusively that such data violate basic principles of economic and index number theory. Barnett et al. (1992) provide a survey of the relevant literature; Drake and Mullineux (1997) review the construction of Divisia indices and associated problems.

The hypothesis developed over a series of studies (summarized in Gazely and Binner, 2000) is that measures of money constructed using the Divisia index number formulation are superior indicators of monetary conditions when compared to simple sum counterparts. This hypothesis is reinforced by a growing body of evidence from empirical studies around the world that demonstrate that broad Divisia-weighted index number measures may be able to overcome the drawbacks of the simple sum, provided the underlying economic weak separability and linear homogeneity assumptions are satisfied. Whenever new assets are included in Divisia monetary aggregates, the issue of separability must be addressed. Economic theory provides several methods, both parametric and nonparametric, for choosing which assets are admissible for inclusion. The nonparametric (nonpar) approach to demand analysis developed by Varian (1982, 1983) is particularly interesting because there is no need to be specific on the functional form of the utility function. Studies by Swofford and Whitney (1988) on U.S. data and by Belongia (2000) using data from the United States, Germany, and Japan have applied the nonpar procedure. Varian's nonparametric approach has, however, been heavily criticized in the literature. The test is nonstochastic, and hence a single rejection suggests rejection of the tested hypothesis as a whole. It may well be the case that the rejection was caused by, for example, a shift in demand or some form of measurement error. Second, it has been shown by Barnett and Choi (1989) (using Monte Carlo simulations) that the test results are biased toward rejection. A stochastic extension to the nonpar procedure has been suggested and is the subject of ongoing research (see, for example, de Peretti, 2000 and Binner et al., 2001). In the current work it is assumed that the Divisia monetary aggregates under investigation satisfy the separability assumption.

This article aims to provide further support for the use of Divisia indices by policy makers and academic economists. The potential of a new generation of Divisia monetary aggregates is explored and adjusted to take account of the recent developments in the financial sector in Taiwan over the period 1970 to the present. Ultimately, such evidence could reinstate monetary targeting as an acceptable method of macroeconomic control, including price regulation.

The inflation forecasting potential of the standard Divisia and simple sum indices are compared with that of two new Divisia indices designed to capture the true user costs of the component assets during times of high financial innovation. Hence, the first new Divisia index, inspired initially by Hendry and Ericsson (1990) and used subsequently by Ford et al. (1992), uses a learning adjustment of the retail sight-deposit interest rate to reflect the adaption of agents to the introduction of interest-bearing sight deposits in 1984. The second modified Divisia series assumes a period of gradual and continuous learning by agents as they adapt to the changes in the financial system throughout the period. Standard econometric evidence from cointegration analysis is compared with results generated by the artificial intelligence technique of neural networks in a standardized forecasting experiment.

The article proceeds as follows. It begins by motivating the study with a review of recent financial innovations in Taiwan before comparing the artificial intelligence technique of neural networks with the more traditional econometric methodology in sections III and IV. Results of a simple inflation forecasting experiment designed to evaluate the empirical performance of the innovation-adjusted Divisia indices compared with the traditional Divisia and simple sum counterparts are presented in section V, and section VI concludes and offers suggestions for further development of this research.

II. FINANCIAL INNOVATION AND THE DIVISIA MONEY IN TAIWAN

At the beginning of the 1980s, drastic economic, social, and political changes took place in Taiwan, creating a long-term macroeconomic imbalance. Rising oil prices caused consumer prices to rise by 16.3% in 1981, followed by a period of near zero inflation in the mid-1980s. From the 1990s onward, inflation has been fluctuating around the 5% mark, and hence the control of inflation has not been the mainstay of recent economic policy in Taiwan, in contrast to the experience of the Western world. Rather, policy in Taiwan has focused more on achieving balanced economic and social development.

The revolution in the financial and monetary sectors of Taiwan over the past two decades has resulted in the implementation of major financial liberalization policies. In July 1987, trade-related foreign exchange controls were abolished and capital flow–related foreign exchange controls were relaxed. The entry of new securities firms was permitted in January 1988, increasing their number from 60 to 150 within the first year. The banking system in Taiwan was heavily regulated by the Central Bank and the Ministry of Finance until September 1989, which saw the introduction of the revised Banking Law. As a result, bank interest rates on deposits and loans were completely liberalized, and new private commercial banks became established. Deregulations of financial price variables and market entry resulted in the rapid expansion of local financial markets, and interest rates, exchange rates, and stock prices became increasingly sensitive to market forces. As outlined by Shih (2000), in her pioneering work on the performance of Divisia money aggregates in Taiwan, such financial liberalization had significant impact on the stability of the monetary aggregates. Concerns were expressed as to whether the technique of simply summing the balances of component assets with equal weights can adequately capture the increased productivity of the monetary assets. This question was taken one step further by Ford et al. (1992, p. 87) who asked, "Do the Divisia aggregates adequately capture the effects of all these financial innovations?" Caves et al. (1982) demonstrate that the Divisia index adjusts automatically to taste or technological change where the economic entities exhibit constant returns to scale, and Barnett (1986) also shows that if the technological innovation in the financial industry is neutral, the Divisia index can successfully measure that technological progress. However, in this article the approach used initially by Koenig and Fomby (1990) and subsequently by Ford et al. (1992) is followed by adopting the philosophy that most financial innovations are nonneutral with regard to their effects on the liquidity and productivity of different assets, and thus the Divisia monetary aggregates do not adequately adjust for the effects of financial innovations, especially those related to technological progress and the introduction of new monetary asset types. Hence the assumption of linear homogeneity of the function is retained, but nonneutral technological progress implies that progress in transactions technology has different effects of different financial assets and thus changes the liquidity of some assets relative to that of others. In the terminology of Ford et al. (1992, p. 89), this creates a wedge between the true monetary services and the Divisia measure. It is difficult to make a clear distinction between the diverse range of financial innovations; the introduction of new instruments and the increased sophistication associated with transactions technology have almost certainly had a considerable influence on the liquidity and monetary services provided by the component assets of money. Under conditions of rapid financial innovation, the impact will be on the productivity of the monetary services of retail sight deposits or checking accounts, although Koenig and Fomby (1990) assume that cash is also subject to the technological revolution as they include it in the checking deposits on their data set. By incorporating the impact of technological progress on the expenditure shares of each component, the associated user cost is effectively adjusted by multiplying by its productivity factor.

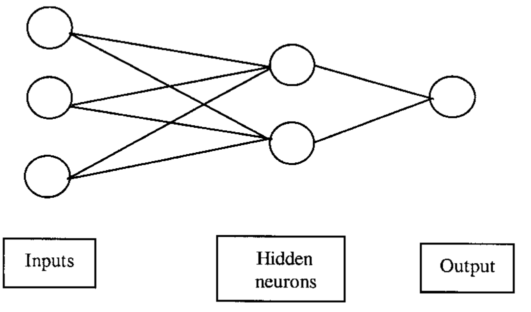
The question asked by Ford et al. (1992, p. 87) is revisited, and the econometric performance of a new generation of Divisia indices (reformulated as outlined) are explored to take account of recent financial innovations in Taiwan. Thus, two innovation-adjusted Divisia series are analyzed, using data provided by Ford, that 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, Innovation1 Divisia, 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 (1997, p. 21) the approach proposed in Baba et al. (1985) is adopted, which imposes a learning adjustment process on the user cost of interest-bearing sight deposits in the construction of monetary indices. The second series, Innovation2 Divisia, assumes gradual and continuous learning throughout the whole period as individuals adjust to the increased productivity of money. The approach adopted in Ford (1997, p. 4) is used, whereby an approximate estimate of the degree of productivity improvements is obtained by using an index number of bank branches of all kinds (excluding medium-sized business banks). In the case of Taiwan, financial innovation accelerated around the end of 1989, and the changes are assumed to occur gradually and continuously throughout the years and be assimilated by individuals as they occurred, Innovation2; or a period of learning occurs before individuals adapt to the change of regime, Innovation1.

III. NEURAL NETWORK METHODOLOGY AND DATA

The use of artificial neural network technology to examine Taiwan's recent experience of inflation is an unusual tool in this context, although the application of neural networks in the field of economics is growing in popularity, as indicated by the diverse range of applications surveyed in Li et al. (1998). Neural networks allow approximation of highly nonlinear functions and so offer more promise in the context of econometric modeling than standard linear models, especially because there is no requirement to specify regression parameters and assumptions about data distribution are less rigorous. It is recognized that the neural networks in the current study are limited by the shortage of data points on which to train the network. However, promising results achieved in Gazely and Binner (2000) have encouraged the authors to believe that the technique holds great potential and that exploratory studies such as this one are worthwhile.

Originally inspired by studies of the human brain, neural networks are made up of many relatively simple, interconnected "neurons." The outer layers of neurons deal with input and output, and the hidden layers carry out the main processing tasks. There are many different types of neural networks, but this description will focus on the commonly used back-propagation type. Figure 1 shows a simple three-layer network. Each input neuron conveys the value of its input datum to each neuron in the hidden layer, without processing, although inputs are normally first scaled to a

FIGURE 1
A Three-Layer Back-Propagation Neural Network



range between zero and one. Outputs from neurons in the hidden layer and the output layer are not simply the sum of inputs; a nonlinear activation function, such as a sigmoid function, is applied. In addition, weights are present for each connection between neurons, and it is the adjustment of these weights that constitutes learning. During the training phase, both the inputs and the outputs for the training examples are presented many times over. The network repeatedly compares the output from the previous iteration with the desired output and adjusts the weights on the connections between neurons to minimize error on the whole training set. This error may never disappear altogether even if the training examples are absolutely consistent, making neural networks unsuitable for problems in which a precise answer is obtainable in some other way. On the other hand, a network can deal with missing or noisy data in both the training and test examples.

Establishing the architecture for the neural network is analogous to curve fitting (Refenes and Azema-Barac, 1994) in that choosing the number of hidden layers and hidden neurons is like choosing the order of a polynomial. Choosing a lower order of polynomial than required leads to a poor fit with the data (the network fails to converge for the training data, and prediction for new data is poor). Choosing a higher order than required leads to a good or perfect fit to the data (overfitting to the training data) but poor prediction for new data (poor generalization).

The advantage of neural network methodology for this investigation, however, is that neural networks are inductive. Thus, even when there is no exact knowledge of the rules determining the features of a given phenomenon, knowledge of empirical regularities can still allow the phenomenon to be modeled. The process of training allows the network to ignore excess input variables, and hence the technique seems ideal for economic phenomena where the central task is to model a system of immense complexity without losing predictive power. It also seems that the potential of nontraditional techniques such as the neural network has not been exploited.

Dorsey (2000) used a genetic algorithm technique to explore the potential of the neural network approach to forecasting U.S. inflation. The standard back-propagation network has been chosen because this is a simpler algorithm, although it should be recognized that results are sensitive to the choice of algorithm. However, Dorsey's lead is followed to emphasize the usefulness of the neural network as a tool for function approximation, without laying much emphasis on the prediction of values at the end of the time series. A simple model of the relationship between money and inflation taken from Dorsey (2000, p. 34) and depicted here in equation (1) has also been used. This model takes inflation in the current period to be a function of money measures in the four preceding periods. An autoregressive term is also included to represent inflation for the preceding period, and a final variable to represent time (here taking the values 1 to 96) that allows for the possibility that external factors, not catered for by the autoregressive variable, might affect the inflation rate. This model is the preferred specification in the authors' earlier studies because it consistently outperforms the even simpler model constructs, although of course in the same vein, it is recognized that a more complex model design will almost certainly yield superior results. In a similar spirit, a neural architecture of five hidden units in a standard back-propagation network and a policy of deliberate extended training was used rather than risk the unreliability of premature stopping techniques because this policy had proved successful in earlier studies.

$$(1)\quad \Pi_t = F(M_{t-1}, M_{t-2}, M_{t-3}, M_{t-4}, \Pi_{t-1}).$$

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 2. The

FIGURE 2
Taiwan: Inflation 1971 to 1995

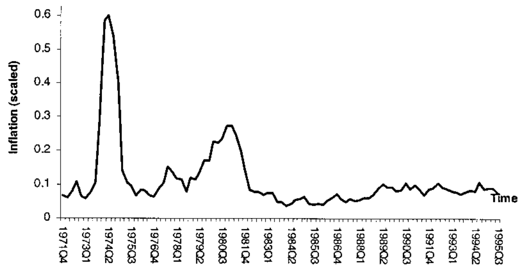
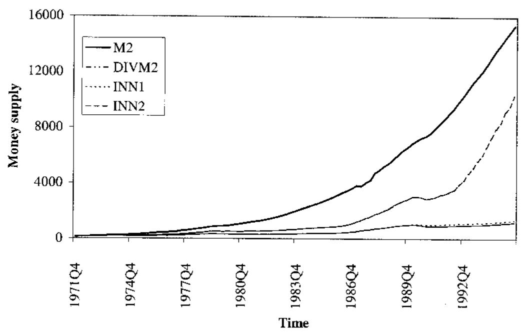


FIGURE 3
Innovation-Adjusted Monetary Indices



preferred price series, the Consumer Price Index, was obtained from DataStream. Four series of monetary data were used and are illustrated in Figure 3. Three Divisia series provided by Ford (1997) consisted of one conventional Divisia M2 series currently monitored by the monetary authorities in Taiwan and the new series Innovation1 and Innovation2. A simple sum M2 series was constructed from component assets obtained from the Aremos–Financial Services database in Taiwan. Note: The Innovation1 series, representing the index incorporating a period of gradual learning, does not diverge from the conventional Divisia measure until the late 1980s. 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 upward by 5% 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 4 quarters, 96 quarters remained, of which the first 89 were used for training and the last 7 for testing (forecasting). This proportion of training to testing is higher than that conventionally used for neural networks, but at this exploratory stage the primary interest is in the ability of the network to model the data as a precursor to predictive ability, rather than focusing exclusively on predictive accuracy per se.

IV. VECTOR ERROR-CORRECTION MODELING

The econometric performance of the monetary assets is evaluated with a system approach. The simple neural network model described in equation (1) was extended to incorporate additional variables widely accepted as having explanatory power for predicting future movements in inflation in traditional macroeconomic forecasting models, such as the one currently in operation at the Bank of England. Thus, the alongside the three alternative measures of Divisia money described, gross domestic product (GDP) and an interest rate were introduced into the model. Three-month time deposits with banks and the dual Divisia price index were interchanged according to whether money was measured as a simple sum or more sophisticated Divisia variant respectively. GDP and the standard three-month interest rate measure were obtained from the Aremos-Financial Services database in Taiwan, as were the constituent components of the Divisia price dual index. Three dummy variables were constructed to take explicit account of the high peaks in inflation evident in Figure 2 during the early part of the period under investigation. Hence *Dummy*1, *Dummy*2, and *Dummy*3 were constructed as one during the three periods of high inflation, 1972Q1 to 1975Q3, 1977Q1, to 1978Q2, and 1978Q4 to 1983Q2, and zero otherwise, respectively.

Prior to undertaking cointegration analysis, variance stabilizing log transformations were performed and unit root tests were conducted using the Dickey-Fuller and augmented Dickey-Fuller (1979) procedures to determine the orders of integration of each variable. All variables were categorized as $I(1)$, or integrated of order one, with the exception of the Divisia price dual, which required second-order differencing to render it stationary. The now-familiar Johansen and Juselius (1990) maximum likelihood method was employed to determine the number of long-run equilibrium relationships existing between money, output, interest rates, and inflation. The three dummy variables representing periods of high inflation were incorporated into the vector autoregressive model as $I(0)$ variables. A linear deterministic trend was assumed in the data and an intercept with no trend assumed in the cointegrating equations.

Several criteria are available for the purpose of testing how many lags should be included in the cointegration analysis. The multivariate Akaike information criteria suggested that a lag length of four should be used in all cases without ambiguity. This result is confirmed by inspection of the residuals from the vector error-correction model (VECM) based on the same lag length and corresponds to the lag length used in the neural network analysis described. In the Johansen and Juselius framework, the number of cointegrating vectors (if any) is estimated by studying the rank of π. Maximum eigenvalue and trace statistics identified two cointegrating vectors for the models incorporating the simple sum and Divisia monetary indices, whereas three and one cointegrating vectors were detected in the Innovation1 and Innovation2 variants.

Short-run error-correction models were constructed for each of the four systems and parameters insignificant at the 5% level of confidence were deleted from the model to obtain a more parsimonious specification, thereby reducing the standard errors of the models considerably and increasing forecasting potential. Standard diagnostic tests, readily available in the Microfit software, were performed on the residuals from the error-correction models to ensure model adequacy and correct functional form. Detailed results of the VECM construction are not presented here for reasons of brevity but are available from the authors on request. Both neural network and VECM model performances are compared to that of a simple random walk model.

V. RESULTS AND DISCUSSION

Taking the neural network models first, Table 1 (top) shows the mean absolute difference for each of the four monetary series, together with the mean percent error and the root mean squared errors for the neural networks. Equivalent results produced from the VECM models are presented in Table 2 and

TABLE 1
Within-Sample and Out-of-Sample Forecast Errors

	Simple Sum	Divisia	Innovation1	Innovation2
Neural networks—levels data				
In-sample				
RMS error	0.032106	0.022578	0.018764	0.026806
Mean absolute error (%)	0.025	0.018	0.014	0.018
Mean percent error (%)	30	22	16	21
Out-of-sample				
RMS error	0.014801	0.016043	0.010715	0.011575
Mean absolute error (%)	0.014	0.015	0.008	0.009
Mean percent error (%)	16	17	9	10
Neural networks—log-differenced data				
In-sample				
RMS error	0.253926	0.219826	0.227102	0.255866
Mean absolute error (%)	0.188	0.163	0.166	0.192
Mean percent error (%)	321	302	289	352
Out-of-sample				
RMS error	0.160749	0.192385	0.178166	0.189129
Mean absolute error (%)	0.121	0.154	0.139	0.147
Mean percent error (%)	117	198	183	214

TABLE 2
Within-Sample and Out-of-Sample Forecast Errors VECMs Including Dummy Variables

Assumption	Criterion	In-Sample		Postsample	
Simple Sum, TD3 interest rate, real GDP					
Linear deterministic trend in the data	RMSE	0.195743	(0.0428365)	5.486611	(0.013972)
(intercept no trend in CE)	MAE (%)	0.139	(2.12)	4.90	(1.02)
	MAPE (%)	319	(63.24)	44,826	(26.79)
Divisia, Divisia interest rate, real GDP					
Linear deterministic trend in the data	RMSE	0.195334	(0.0428365)	2.393770	(0.013972)
(intercept no trend in CE)	MAE (%)	0.136	(2.12)	2.001	(1.02)
	MAPE (%)	277	(63.24)	4784	(26.79)
Innovation1, Divisia interest rate, real GDP					
Linear deterministic trend in the data	RMSE	0.197398	(0.0428365)	2.121423	(0.013972)
(intercept no trend in CE)	MAE (%)	0.138	(2.12)	1.798	(1.02)
	MAPE (%)	279	(63.24)	7080	(26.79)
Innovation2, Divisia interest rate, real GDP					
Linear deterministic trend in the data	RMSE	0.195846	(0.042837)	2.014970	(0.013972)
(intercept no trend in CE)	MAE (%)	0.131	(2.12)	1.561	(1.02)
	MAPE (%)	263	(63.24)	6540	(26.79)

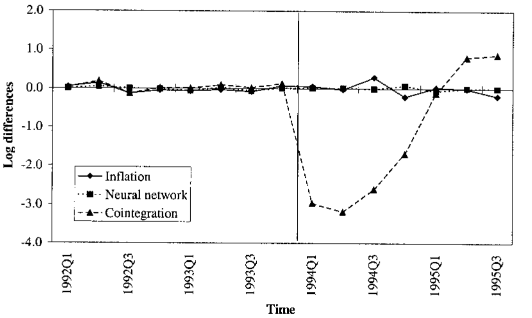
Note: Forecasts from random walk shown in parentheses.

provide a strong contrast to those of the neural network models. Root mean squared forecasting errors and mean absolute errors are on average seven times higher for the VECMs within sample and three times higher out of sample. Divergences are still wider when mean percent errors are considered. Moreover, the random walk forecast errors presented in parentheses in Table 2 testify to the fact that single equation univariate models may well provide more accurate forecasting models as they outperform the VECM forecasts in all cases out of sample. In contrast, the neural network models have superior forecasting capabilities when compared to the random walk models for inflation in six out of the eight cases studied.

To compare the two model types on an equal footing, the neural network forecast errors were transformed into log differences and results are presented in Table 1 (bottom). Interestingly, VECM models are found to provide superior within-sample forecasts across the board when predicted values are compared in log differences. This result must be interpreted with caution, however, bearing in mind that the neural network has at no stage been trained and tested on log-transformed first-differenced data. It is entirely possible that the network could indeed be trained to recognize the patterns of changes in inflation rates over time and thus could provide superior forecasts of short-run movements in inflation under truer modeling conditions. The main advantage of the neural network model emerging from this latter analysis is the power to forecast more accurately than standard, widely accepted econometric models out of sample. Certainly, the performance of the neural networks postsample in Table 1 is considerably superior to the corresponding VECM results in Table 2. The log-transformed first-differenced root mean squared forecasting errors reported in Table 1 for the neural network models are on average 16 times lower than their VECM counterparts, whereas mean percent errors are beyond comparison as the VECM out-of-sample forecasts clearly perform extremely badly using this criterion. Figure 4 provides a visual representation of the out-of-sample forecast errors of the VECM and neural network techniques.

The comparative inflation forecasting performance of the four measures of money now becomes the focus. The results support the general hypothesis that Divisia measures are superior to simple sum in modeling inflation. Considering traditional cointegration methods first, in keeping with the 1997 analysis of Ford, the two innovation adjusted Divisia systems provide the best forecasts out of sample. However in contrast to the earlier study, Innovation2 is preferred to Innovation1 within sample. The benchmark simple sum system provides the worst fitting model both within and out of sample, providing further evidence that Divisia indices do indeed outperform the traditional simple sum counterparts using standard econometric techniques.

FIGURE 4
Neural Network versus Cointegration Out-of-Sample Forecast Errors



The neural network results support the results of Ford (1997) in that Innovation1 is a superior form of Divisia than either conventional Divisia or Innovation2. For all three measures of error and both within sample and out of sample, Innovation1 shows smaller error. Looking at mean absolute error for example, within-sample error is found to be 21% lower for Innovation1 Divisia compared to the next best alternative. Likewise, out-of-sample forecast errors are found to produce an 11% reduction in error compared with Innovation2 Divisia and a 42% reduction when compared with the traditional simple sum measures of money. Figure 5 illustrates the actual versus forecast series for the neural networks worst fit (simple sum) and best fit (Innovation1), respectively. Figure 6 shows output error for each monetary series, defined simply as inflation for the quarter subtracted from the neural network model output. It can be seen that for much of the period a simple sum measure overestimates inflation, and Innovation2 produces several noticeable underestimates. In summary, results presented here clearly demonstrate that a money stock mismeasurement problem does exist and that the technique of simply summing assets in the formation of monetary aggregates is inherently flawed.

VI. CONCLUDING REMARKS

Results presented herein provide the first available evidence of the comparative

FIGURE 5
Neural Network Results (A) Actual versus Forecast. (B) Actual versus Forecast Innovation 1

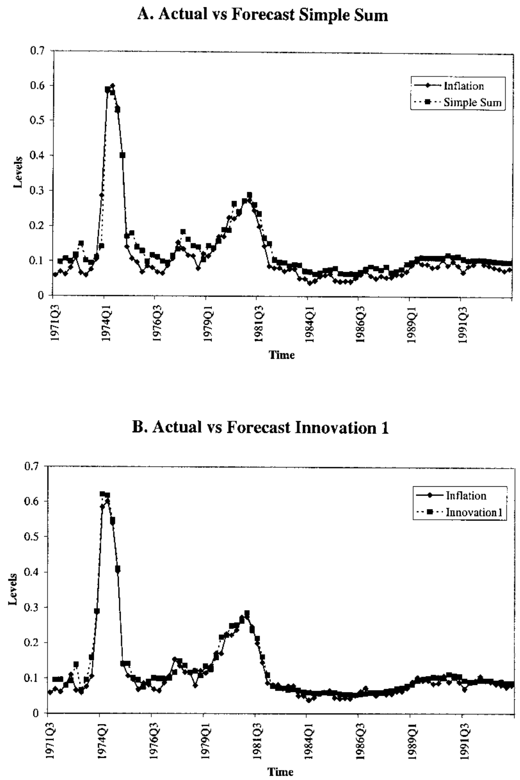
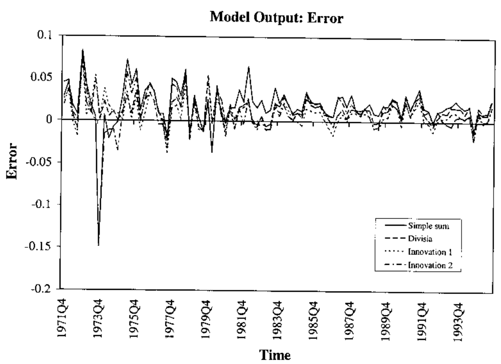


FIGURE 6
Neural Network Models: Output Error over Time



performance of neural network models with conventional econometric modeling methods in a simple inflation forecasting experiment. The power of the neural network lies in the greater flexibility of functional form and inductive pattern recognition capabilities. Neural network models have been shown to provide superior forecasting models for predicting long-run trends in data and are thus worthy of consideration for use by macroeconomic policy makers in the construction of composite leading indicators of GDP. A particularly important finding arising from this analysis is the capability of the network to provide relatively more accurate forecasts out of sample when compared to a VECM forecasting model.

The combination of Divisia measures of money with the artificial neural network offers a promising starting point for the development of an improved model of inflation. This application of the neural network methodology to examine the money–inflation link is highly experimental in nature and in keeping with the pioneering work conducted by the current authors for the United Kingdom, United States, and Italy, the overriding feature of this research is very much one of simplicity. It is virtually certain that improvements in the neural network models may 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.

The authors have stressed that particular advantages arise from the use of monetary constructs that have been adjusted to accommodate financial innovations, such as the introduction of new assets or the payment of interest on formerly noninterest-bearing accounts. The weights used to construct both standard Divisia aggregates and the new generation of innovation-adjusted monetary indices do accommodate financial innovation fully in the own rates of interest on the component assets of the index. It is evident in this research that the effects of financial innovation during the period under study are considerable, hence the weights used to construct the Divisia monetary index should indeed be modified to allow for the impact of the growth in monetary services provided. In conclusion, the adoption of monetary aggregates that are allowed to vary in response to innovations in the financial markets does appear to offer an improvement on the information content of money. Empirical results suggest that that the Divisia index that accommodates a learning mechanism to allow individuals to gradually alter their perceptions of the increased productivity of money enhances the explanatory power of the standard Divisia aggregate and dominates its simple sum counterpart.

Given the increased liquidity of many financial assets and the increased monetary services provided by broader assets not previously regarded as money, increased substitution between monetary and nonmonetary assets is taking place. Central banks run the risk that conventional broad monetary aggregates will become increasingly unstable unless such substitutions between official and unofficial monetary assets are internalized into the construction of money. As stated briefly in the introduction, research into the incorporation of such risk-adjusted assets into money is now well underway in the United States and also the United Kingdom. Such extensions are recommended for the Asian Pacific countries, such as Taiwan.

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