Measuring the Connection Strengths between Markets Using Artificial Neural Networks

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Abstract

In this paper a hybrid model combining neural networks and genetic training is designed to measure the connection strengths between five international equity markets. Using weekly data for the period 1990-2003, sensitivity coefficients are estimated to measure the pulse that is being transmitted and to answer questions related to strength, duration, and symmetry of transmission.

1. INTRODUCTION

As evidence of contagion between international equity markets mounts, accurate assessment of the degree of interdependence between them becomes increasingly important to: investors, who aim at diversifying their portfolio; speculators, who seek to profiteer from accurate forecasts of market movements; and policy makers, who want to insure stability in the international financial markets.

This paper aims to explore the degree and nature of interdependence between five international equity markets: Tokyo (Nikkei 225), Hong Kong (Hang Seng), Frankfurt (DAX), London (FTSE100), and New York (DJIA) by estimating sensitivity coefficients that measure the strengths of the connections between them. The results reported are used to answer the following questions:

- Have connection strengths between the markets increased over time?
- Do connections strengthen during periods of crises i.e. are linkages transitory or are they permanent?
- Is the strength of the pulse transmitted between markets symmetric?

The paper is divided into four sections. Section 2 describes the basic neural network architecture and introduces genetic training as an optimizing technique. Data description and methodology is presented in Section 3 and in the last section, the results are reported and discussed.

2. MODEL DESIGN

In this paper a hybrid system that combines neural networks with genetic training is designed to evaluate the connection strength between five international equity markets. The basic network architecture is developed using the Brainmaker Software by California Scientific, and is that of the multi-layer perceptron (MLP) which is the most commonly used. The network consists of three layers: the input, hidden, and output layers. The input layer is passive; it receives data, which it transmits to the hidden or intermediate layer. The hidden layer is what connects the input layer with the output layer. The output layer is what produces the network's results.

The neural network architecture design relies on supervised learning. Under this class of learning, the network's output target is known during training. The difference between the desired target and the actual output, which is the error, is fed back to the network to improve its performance and from hence the name backpropagation is derived [1].

The training process is initiated when the input layer transmits facts to the hidden nodes in the second layer, which through a transfer function calculates a weighted sum of inputs. The hidden nodes then broadcast the results to the output node that then calculates a weighted sum and passes it through the same transfer function to compute actual results. The results generated are then compared to the desired output or pattern, and an output error is calculated. Lastly, the errors are propagated back to the hidden layer so that the weighted sum of error derivative is computed in order to determine its contribution to the output. Weights are then adjusted according to a pre-specified rule such as minimizing the model's sum squared errors. The process continues until the desired accuracy level is achieved [2].

Once the network is trained, tested and identified as being "good", its performance is further enhanced by subjecting it to a genetic algorithm (GA). GAs offer a number of attractive features. Other than being adaptive, flexible, robust and simple, GAs are capable of optimizing solutions.

Genetic algorithms are a class of random search techniques based on biological evolution [3], [4], [5]. Their search is based on computationally simulated version of survival of the fittest. In search for the optimal solution, the algorithm mimics the process of natural selection by testing the fitness of the individuals (networks) to determine if they will be allowed to reproduce. The genes of the " good" or "fit" network are mutated to create another "parent" network. The two networks are then crossed over to create to create a new "child" network. If the child network outperforms one or both parents, it is saved and used for reproducing even better generations of future networks [6].

The process of genetic evolution is initiated by randomly selecting a population and evaluating each of its members. Three operators are then applied to all candid solutions: reproduction, crossover and mutation evolution. Reproduction allows relatively fit networks to survive and procreate. The process is asexual with the hopes that it could improve on the fitness levels. Crossover represents a way of moving through the space of possible solutions based on information gained from existing solutions. As an operator, crossover is described in terms of exploitation of information in good individuals, and is similar to "artificial mating" and requires taking neurons from each parent to produce the child network. Mutation is the random adjustment of the individual's genetic structure. As an operator, mutation is described as the exploration of the search space, it requires one parent, and is conducted by a random modification of the neuron weights [6].

Unlike traditional techniques, GAs seek to identify optimal solutions by searching entire populations of candid solutions in parallel. The advantage to this approach is that it is more likely to estimate the true global optimum, and much less likely to get stuck at a local optimum. Another appealing feature of GAs is that their performance is largely unaffected by initial conditions. Furthermore, they are capable of finding relationships between inputs and outputs even when patterns are ill defined.

When the optimal networks are identified, sensitivity analysis is performed to determine the strength of the connections between the inputs and output. As a tool, sensitivity analysis is used to ascertain the strength of the relationship between the model's output and the inputs. Although numerous approaches have been developed for performing sensitivity tests, they all require elaborate computations that have rendered them prohibitively costly. Using trained artificial neural networks to explore the sensitivity analysis a fast and approximated alternative is offered.

3. DATA AND METHODOLOGY

The network consists of weekly closing values for five international stock market indices. Weekly averages are used, as daily market trading dates may not be aligned and would present a problem. Moreover, by using weekly averages we do not have to identify markets that lead and those that follow.

The raw data set was compiled and obtained from Yahoofinance.com, covering the period November 1990- September 2003. The selection of the markets was made to include major markets in Asia (Tokyo and Hong Kong), Europe (Germany and Britain), and North America (USA). The test period covers thirteen years and captures periods of crises, which include the Japanese market crash of the 1990's, the Asian crises of 1997, and the technology bubble burst of 2000. During that same period episodes of market booms were also experienced.

The input data set consists of 670 observations, which is consistent with the general guidelines recommended for such analysis [7]. The input layer consists of four nodes, each representing closing values of the four stock indexes. The output layer has one node, the pattern, which is the closing value of the fifth market.

The network is initially trained using a train/test approach with pre-specified tolerance levels. The Brainmaker software randomly reserves ten percent of the fact for testing the other ninety percent are used for training the network. During training, the model is interrupted periodically, and tested until the measured system performance meets the defined parameters. Once the trained network is identified, it is then subjected to a process of genetic evolution, to further enhance its performance. The statistical evaluation parameter specified as the measure of the best network is R 2. The sensitivity coefficients of the best-trained networks is evaluated to determine the linkage between the markets and to answer the questions posed in the paper.

4. RESULTS AND FINDINGS

The networks' genetically trained results are reported in Tables 1-5 for the five markets. The first row reports estimates of spillover from the indices listed in the columns for the complete data set 1990-2003.

The second and third row estimates correspond to market downturns for the subset periods: 07:1997-08:1998, and 10:1999-09:2001. The last three rows in the table for market booms of: 11:1990-06:1997, 02:1998- 08:1999 and 01:2002-08:2003.

The reported coefficients are those generated by the genetic child networks that were trained at a 10% tolerance level. Stubborn networks that would not train at the 10% level were subject to a gradual easing in their training tolerance. Networks that trained at the 11-15% tolerance level are indicated by *, while those at lower tolerance level of 16-20% by ** and 21-30% by ***. The values reported in the tables are the absolute mean sensitivity coefficients.

To determine if connection strengths between markets has increased over time, a comparison of the sensitivity estimates for the market boom periods reported in the last three rows of Tables 1-5 are examined. As indicated by the values of the coefficients, we find that while the connections were stronger between the first boom market of 11:1990-06:1997 and the second boom market of 02:1998-08:1999, the strength could not be sustained during the third boom market of 01:2002-08:2003. The weakening of the connections for the third boom may be explained in part by the dampening of investor sentiment following the burst of the technology bubble. This restrained participation does not provide support to the premise that connections between equity markets increased continually over time.

To determine if market linkages are stronger during periods of crisis, the long-run coefficients reported in the first row of the tables are compared to the two crisis periods. Estimates for the entire test period 11:1990- 08:2003 when compared to those of the Asian financial crisis of 07:1997-08:1998 indicate that spillover from both NIKKEI and Hang Seng to the FTSE, DAX and DJIA were significantly larger. This suggests that markets experiencing turbulence do indeed transmit a stronger pulse during periods of crisis. Moreover, transmission was found to be stronger for those markets within the geographic proximity of the Asian markets experiencing turmoil and turbulence.

While location proved to be an important determinant affecting the strength of the transmission mechanism for the crisis period 11:1990- 08:2003, sector weights and composition of the indices are shown to be key determinants in the strength of transmission for the second crisis period 10:1999-09:2001. Results in the third row in the tables show that the indices that have a significant technology weight in their composition show increased spillover compared to their long- term values reported in the first row. The DAX having a large and significant technology sector (20.54%) transmitted a stronger pulse to all four markets over that period. Moreover, because the DAX is a performance index rather than a price index, transmission to it from all other markets during that period was stronger.

Unlike the DAX, the DJIA transmitted a weaker spillover during that second crisis than its long-run coefficient to all markets except for the DAX. This result is consistent with the view that it should not be used as a gauge of particular industry sector as it reflects the relative stability of the old economy, and does not follow movements of the more volatile technology stocks.

As to symmetry, the sensitivity coefficients reported for market downturns are larger than those for market upturns. This finding is consistent with that reached by Longin and Solnick [8] who refute the conventional wisdom argument that states that the correlation between international equity markets increases in volatile times. Instead, their results show that correlation does increase during large bear market moves, but surprisingly declines in large bull market moves. Asymmetry in spillover is supported by the results reported for the FTSE, Hang Seng, and DJIA. Whereas for the first market downturn transmission was significantly stronger to the FTSE compared to the three boom markets, the second market decline recorded a larger spillover to the Hang Seng compared to the three boom markets. The DJIA on the other hand shows spillover during the two downturns to be larger than the three upturns. This conclusion however cannot be surmised for the DAX and NIKKEI for which the findings are mixed.

Inferences drawn from the results of this paper albeit interesting are hard to generalize. While the findings provide weak support for the strengthening of connections between markets, stronger evidence is presented for the case of asymmetry. The larger sensitivity coefficients for crisis periods highlight the importance of identifying the source and nature of the crisis in determining the degree of spillover between markets. Moreover the resulting spillovers during crisis episodes appear to be transitory rather than permanent.

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Test Period	Hang Seng	DJIA	NIKKEI	DAX
11:1990 - 08:2003	0.0195	0.0543	0.0600	0.0590
07:1997 - 08:1998	0.2594	0.1404	0.3114	0.1105
10:1999 – 09:2001	0.0327	0.0136	0.0438	0.0630
11:1990 – 06:1997	0.0354	0.0884	0.0019	0.0537
02:1998 – 08:1999	0.0361	0.0916	0.0568	0.0426
01:2002 – 08:2003	0.0400	0.0529	0.0445	0.0186

Table. 1: Spillover Estimates to FTSE

Test Period	FTSE	DJIA	NIKKEI	DAX
11:1990 – 08:2003 *	0.1407	0.1916	0.0650	0.0589
07:1997 - 08:1998	0.0330	0.0287	0.1689	0.0583
10:1999 – 09:2001**	0.1794	0.0923	0.0906	0.1069
11:1990 – 06:1997	0.1633	0.0702	0.0380	0.0611
02:1998 – 08:1999	0.1187	0.0810	0.0732	0.0829
01:2002 – 08:2003*	0.0395	0.0230	0.1169	0.0548

Table. 2: Spillover Estimates to Hang Seng

Test Period	FTSE	Hang Seng	NIKKEI	DAX
11:1990 – 08:2003	0.0618	0.0562	0.0396	0.0985
07:1997 – 08:1998	0.1023	0.1532	0.0923	0.1667
10:1999 – 09:2001**	0.1751	0.0498	0.0185	0.0602
11:1990 – 06:1997	0.1026	0.0185	0.0126	0.126
02:1998 – 08:1999*	0.1008	0.1147	0.0450	0.0546
01:2002 – 08:2003*	0.1277	0.1338	0.0682	0.0430

Table 3: Spillover Estimates to DJIA

Test Period	Hang Seng	DJIA	FTSE	DAX
11:1990 – 08:2003***	0.0852	0.1592	0.0547	0.0657
07:1997 - 08:1998	0.1408	0.0413	0.0349	0.0602
10:1999 – 09:2001	0.0459	0.0285	0.1556	0.1618
11:1990 – 06:1997***	0.1542	0.1514	0.0510	0.0539
02:1998 – 08:1999**	0.1647	0.1938	0.1241	0.0205
10:2001 – 08:2003	0.1029	0.1888	0.1008	0.1161

Table 4: Spillover Estimates to NIKKEI

Test Period	Hang Seng	DJIA	NIKKEI	FTSE
11:1990 – 08:2003**	0.0763	0.0398	0.0390	0.0122
07:1997 - 08:1998*	0.1111	0.1158	0.1928	0.0909
10:1999 – 09:2001*	0.1324	0.0815	0.0824	0.0580
11:1990 – 06:1997	0.0466	0.0547	0.0170	0.0380
02:1998 – 08:1999	0.2182	0.1713	0.0570	0.2182
01:2002 – 08:2003	0.1240	0.0192	0.0350	0.1240

Table 5: Spillover Estimates to DAX