A Neural Network Analysis of Brazilian Stock Prices:
Tequila Effects vs. Pisco Sour Effects

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Abstract

This paper examines the reaction of Brazilian stock prices to "shocks" in the U.S. and in Latin American markets, with classical linear methods, as well as with non-linear neural network methods. The analysis makes use of the Gallant-Russel-Tauchen filter for daily stock price data, in order to correct for holiday effects across countries. The results show that shocks in the Chile stock market, in contrast to Mexico or the United States, are more important determinants of movements in the Brazilian stock index.

I. Introduction

Should "tequila effects"—movements in the Mexican market—be taken seriously, as important and statistically significant determinants of stock price movements in Brazil? This paper examines this question, with classical econometric methods (linear VAR's), with more recent generalized autoregressive heteroskedastic (GARCH) models, as well as neural network methods. The answer is that "pisco sour effects"—movements in the Chile market—are much more important—even more important than events in Mexico or the USA. Results from non-linear GARCH and neural network estimation indicate this result.

Since December 1994, there has been much discussion of the Mexican "tequila effect" on the Brazilian and other Latin American stock markets. Figures I through III picture the adjustment of the Brazilian, Chilean, and Argentine markets, along with the adjustment of the share price index in Mexico. All the share price data are the Morgan Stanley Capital Market indices, in dollar values. Thus, the decline in the Mexican index, in part, reflects the crash of the peso against the U.S. dollar. As Figures I through III show, with daily data since 1988, the fast upward movement of the Mexican market between 1989 and 1991 was highly correlated with upward movement in Argentina, Brazil and Chile. Similarly, as the shaded regions in each of these graphs show, the Mexican crash after December 1994 is
highly correlated with a fall in the markets in these three countries. Figure IV shows that only the US market escaped the downward pull of the Mexican crash.

Thus, an examination of the raw series gives some merit to the existence of a "tequila effect" on the Latin American markets. But why should one country have such a strong effect on movements in stock markets, particularly in markets so far apart? After all, does not a stock price index simply reflect the expected discounted present value of future earnings of firms in a particular country? A crash in Mexico hardly means that future earnings of Brazilian firms will fall.

One reason for a regional "contagion effect", from one stock market in Latin America to another, is the growth of large international investment funds, particularly pension funds. It is no secret that the ageing populations in the United States and Europe, and the fragility of the official social security funds, have made private-sector investment funds increasingly popular. The current generation of baby-boomers in the United States, those born after World War II, and in their prime working years, 45-55 years of age, cannot afford not to participate in such funds. Furthermore, the deregulation, liberalization and internationalization of financial markets, coupled with this growing pool of investment funds, have made diversification of investment across countries attractive.

The rationale for diversification lies in a low or even negative correlation between emerging market and US and developed-country stock returns. Because many of the funds going into emerging markets of Latin America represent diversified portfolios of large investor funds, there are strong spillover effects, in perceived risks, from one country to another, in a similar region. The decision to invest in a regional emerging market is made on the basis of expected risks and expected returns—not necessarily historical covariance and variances. If expected risk increases, due to events in other markets in a regional portfolio, investors can be expected to demand higher returns, or remove their funds to other markets.

To examine quantitatively how movements in Mexico may have affected stock prices in Brazil, of course, requires more formal statistical analysis. In the next section, we use classical statistical methods. Simple correlation analysis shows that Mexico matters more than any other Latin American market, and even more than the United States. However, when lagged adjustment is allowed, in a pure linear vector-autoregressive (VAR) model, the United States is the most important source of adjustment in Brazil. Thus, classical analysis—more precisely, linear classical analysis—
these three countries. Figure I shows the downward pull of the Mexican peso in 1994.

es some merit to the existence of markets. But why should one invest in stock markets, as does not a stock price index at value of future earnings of a company hardly means that future

correlation, from one stock market in one country to another, in a similar emerging market is made on a basis—not necessarily historical

5. or even negative correlation expected to demand higher returns in Mexico may have required more formal statistical methods. Simple regression analysis is more than any other Latin American index, linear classical analysis—
offers some support for a short-lived contemporaneous Tequila effect, but this gives way to a longer-term Wall-Street effect. When we incorporate non-linear processes in the model, either through a time-varying variance with generalized autoregressive conditional heteroskedasticity (GARCH) or a neural network model, the Chilean “pisco sour” effect dominates both the U.S. and Mexico effects. In rank orderings, the neural network model generates the lowest out-of-sample forecast errors, followed by the GARCH model, and then the linear VAR. Thus, our analysis shows that non-linear processes are important, and with this recognition comes the inescapable influence of Chile.

Section II is a discussion of the VAR and GARCH methodology, along with a discussion of the results from these models. Section III discusses neural network methodology, and compares the overall performance of this model as well the results relative to the linear and GARCH models. Section IV concludes.

II. Linear Econometric Analysis

To evaluate the possible effects of shocks in share-markets in other Latin American and U.S. markets “spilling over” into the Brazilian market, one would normally use a linear model, of share-price data, with daily data, allow liberal lag patterns to pick up delayed effects, and evaluate the significance of the coefficients of each country. This is what we do, with daily data from Jan. 1988 through March 24, 1995, for Argentina, Brazil, Chile, Mexico, and the United States.

However, multicountry analysis of share-market data requires special treatment for high-frequency (daily) data. Despite a relatively large number of observations, “holiday effects”, which differ across countries, can significantly distort the outcomes. Several combinations of days with no-trading in New York and much price movement in Brazil, or days with no trading in Brazil, during Carnival days, for example, when there may be movement in New York, can put a downward bias on the “true” effect of New York movements on Brazilian stock prices. Similarly there may be common calendar effects across countries: heated trading days during the middle of the business week, and diminished trading during holiday periods in December and January, which can put an upward bias on a statistical analysis of the interrelations. Thus, a careful prefiltering of the data is an important first step.
oraneous Tequila effect, but effect. When we incorporate through a time-varying variance heteroskedasticity (GARCH) sour effect dominates both s, the neural network models, followed by the GARCH analysis shows that non-linear tion comes the inescapable iARCH methodology, along models. Section III discusses the overall performance of linear and GARCH models.

analysis
s in share-markets in other r" into the Brazilian market, share-price data, with daily red effects, and evaluate the y. This is what we do, with 1995, for Argentina, Brazil, market data requires special ite a relatively large numberffer across countries, can binations of days with not- nt in Brazil, or days with no ample, when there may be bias on the “true” effect of es. Similarly there may be tided trading days during the ding during holiday periods upward bias on a statistical refiltering of the data is an
Gallant, Rossi, and Tauchen (1992) have offered a special filtering method. Each country series, in logarithmic first differences, is set in a regression with the following independent variables: dummy variables for each month of the year, from February through November, special dummies for each week in December and January, and daily dummy variables for Tuesday through Friday. Finally, there is a dummy set at the square root of the number of elapsed days since the last trading day. Normally, this implies each Monday is set at the square root of two, since the preceding Saturday and Sunday are non-trading days. For Brazil, the dependent variable, each holiday is deleted from the sample. Thus, Carnival days imply a calendar dummy set at the square root of five for the Thursday following Carnival. Following the regression, the original series is replaced by the residuals. Thus, the series is purged of the calendar day-of-the-week, month-of-the-year, and holiday effects.

The same method is applied to the four other countries, except that holidays in these countries that are not holidays in Brazil are not deleted from the sample. A non-trading day on Friday, July 4, for example, will simply imply in data filtering a holiday dummy of the square root of three for the following Monday. The reason why we choose not to delete the holidays for the other markets, which are not holidays in Brazil, is because the focus of the analysis is Brazil: we want to explain as much as possible of the movement in Brazil. Eliminating days of price movements in Brazil, due to a holiday in New York, but not in Mexico, would eliminate too much information from the sample. While leaving in holidays in New York, with trading days in Brazil, may downwardly bias any statistical relations, the use of a calendar variable in the New York data filtering may correct some of the bias.

Analysis of the data, after the Gallant-Rossi-Tauchen filtering, shows the following contemporaneous country correlations with Brazil:

*Argentina:* 0.0639; *Chile:* 0.1148; *Mexico:* 0.1494; *USA:* 0.0975.

Thus, a rigorous filtering of the data confirms what a cursory eye balling of the charts led us to believe: Mexico dominates all of the other regional markets, and the United States, in terms of contemporaneous correlation of disturbances.

The problem with contemporaneous correlation analysis, is that it does not get one very far for making predictions. The common method for forecasting is to use a vector autoregressive (VAR) model, in which one regresses the current filtered Brazilian stock-price variable on several lags of the filtered stock-price in Mexico, and the USA. How one can always improve parsimony in the number of Hannan-Quinn criteria are models, with corrections to VAR model with increasing variable, we found that the 0 With this linear model, we at the U.S lags were significant movements in the Brazilian

The following coefficients:

<table>
<thead>
<tr>
<th>Estimate</th>
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<tbody>
<tr>
<td>0.0108</td>
</tr>
<tr>
<td>0.1665</td>
</tr>
<tr>
<td>0.0084</td>
</tr>
<tr>
<td>0.0014</td>
</tr>
<tr>
<td>0.2575</td>
</tr>
</tbody>
</table>

The asterisk (*) indicate percent level.

The problem with the class of stock-price movements is data. Slow upward movements of a bubble, indicate processes than those implied variance. Furthermore, even significant coefficients for the not very large. Thus, it is used which might outperform it in about tequila effects.2

Generalized autoregres otherwise known as GARCH component in the stochastic p time-varying. The GARCH r due to Bollerslev (1986):
e offered a special filtering first differences, is set in a variables: dummy variables for November, special dummies daily dummy variables for every set at the square root of g day. Normally, this implies since the preceding Saturday the dependent variable, each interval days imply a calendar thursdays are replaced by the residuals. -of-the-week, month-of-the-

other countries, except that uys in Brazil are not deleted y, July 4, for example, will y of the square root of three we choose not to delete the holidays in Brazil, is because explain as much as possible price movements in Brazil, exico, would eliminate too initing in holidays in New York, bias any statistical relations, k data filtering may correct si-Tauchen filtering, shows relations with Brazil: ico: .1494; USA: .0975 what a cursory eye balling of es all of the other regional contemporaneous correlation ation analysis, is that it does

The common method for VAR model, in which one variable on several lags of the filtered stock-price movements in Argentina, Brazil itself, Chile, Mexico, and the USA. How many? With more and more lags, of course, one can always improve prediction. Classical econometrics also values parsimony in the number of regressors. Both the Akaiku, Schwartz, and Hannan-Quinn criteria are indices to discriminate between alternative models, with corrections for the number of regressors. Using the same VAR model with increasingly longer lags, with Brazil as the dependent variable, we found that the optimal number of lags was one.

With this linear model, we also found that only the Brazilian own lags and the U.S. lags were significant predictors, at the 10 percent level, of movements in the Brazilian index.

The following coefficient estimates come from the VAR estimation:

<table>
<thead>
<tr>
<th>Estimate</th>
<th>Country</th>
</tr>
</thead>
<tbody>
<tr>
<td>.0108</td>
<td>Argentina</td>
</tr>
<tr>
<td>.1665</td>
<td>Brazil *</td>
</tr>
<tr>
<td>.0084</td>
<td>Chile</td>
</tr>
<tr>
<td>.0014</td>
<td>Mexico</td>
</tr>
<tr>
<td>.2575</td>
<td>United States *</td>
</tr>
</tbody>
</table>

The asterisk (*) indicates that the coefficient is significant at the ten percent level.

The problem with the classical linear and VAR approach to the analysis of stock-price movements is that it ignores or sidesteps asymmetries in the data. Slow upward movements, followed by quick declines, indicating the bursting of a bubble, indicate nonlinear or at least different statistical processes than those implied by the classical or VAR set up with a constant variance. Furthermore, even though the VAR model with one lag gave significant coefficients for the USA, the overall fit of the model was still not very large. Thus, it is useful to look at alternatives to the linear model, which might outperform it in terms of prediction, and see what it tells us about tequila effects.³

Generalized autoregressive conditional heteroskedastic models, otherwise known as GARCH models, attempt to capture a non-linear component in the stochastic process by allowing the second moment to be time-varying. The GARCH model is represented by the following system, due to Bollerslev (1986):
\[ y_t = \sum_{i=1}^{k} w_i x_{t-i} + \epsilon_t \]

\[ E(\epsilon_t) = 0, \quad \text{Var}(\epsilon_t) = \sigma_t^2 \]

\[ \sigma_t^2 = \omega_0 + \omega_1 \epsilon_{t-1}^2 + \omega_2 \sigma_{t-1}^2 \]

where \( y \) is the dependent variable, in this case the filtered current Brazilian stock return, and the regressors, given by \( x \), are the lagged filtered stock returns for the five countries, while \( \epsilon \) is the disturbance term and \( \sigma^2 \) is the time varying variance. The following coefficients \{\( w, \omega_i \}\) come from the GARCH model with maximum-likelihood estimation, for the same lag structure as the VAR model given above:

<table>
<thead>
<tr>
<th>Estimate</th>
<th>Argument</th>
</tr>
</thead>
<tbody>
<tr>
<td>.0330</td>
<td>Argentina *</td>
</tr>
<tr>
<td>.0474</td>
<td>Brazil</td>
</tr>
<tr>
<td>.6677</td>
<td>Chile *</td>
</tr>
<tr>
<td>.0005</td>
<td>Mexico</td>
</tr>
<tr>
<td>-.1128</td>
<td>United States</td>
</tr>
<tr>
<td>.7986</td>
<td>GARCH ( \omega_0 ) *</td>
</tr>
<tr>
<td>.0665</td>
<td>GARCH ( \omega_1 ) *</td>
</tr>
<tr>
<td>.7754</td>
<td>GARCH ( \omega_2 ) *</td>
</tr>
</tbody>
</table>

The GARCH estimation produces results very different from the purely linear VAR model. Now Argentina and Chile are the only two significant country coefficients. All of the GARCH parameters are also significant, indicating that autoregressive conditional heteroskedasticity plays a significant role in the underlying stochastic process driving the Brazilian stock returns. Of course, the GARCH process in the error-term may simply represent the effects of omitted domestic factors. Since these omitted domestic factors, such as concentration ratios, market capitalization indices, and reform indicators, are hard to capture with daily time series, the GARCH process at least recognizes that something else is going on, besides the effects of lagged stock returns in the domestic and foreign markets, to drive the current stock return. When these factors are taken into account, at least indirectly by the GARCH process, the results show that Chile is the most important information variable, among the competing lagged stock returns, for forecasting the Brazilian share market index.¹

The GARCH model all error-term, and thus allows return in the GARCH model country market returns. The explaining asymmetries in approximation.

III. N

Figure V pictures a net index. There is a set of "input lags, summarized by the i" represent three input varia Brazil index. In classical st serve as "regressors" for "regressand", and the weighing the regression coefficients previous section is one ean input variables to observed N1 and N2 process the inc fashion, and then pass their

Because people make decision but also on the basis of un observed inputs to observe may miss important aspects from observed data, process future course of price deve the "learning behavior" of fi layers" of "neurons" to ent parallel as well as sequenti take place in response to in the way output responds, v more effect than others, or re inputs or stimuli.

Sargent (1993) has drawn economic actors in their m actually know the true eco consistently rational manne
The GARCH model allows a non-linear process in the variance of the error-term, and thus allows risks to vary with time. However, the expected return in the GARCH model is still a linear function of the lags of the country market returns. Thus, the model does not take one vary far for explaining asymmetries in the data. For this reason, I use neural network approximation.

III. Neural Network Analysis

Figure V pictures a neural network design for analyzing the Brazilian index. There is a set of “input data” from Chile, Mexico, USA, and Brazil lags, summarized by the input variables x. For space reasons, we only represent three input variables in the graph. The output y is the current Brazil index. In classical statistical analysis, the observed input variables serve as “regressors” for the observed output variable y, known as the “regressand”, and the weights relating the input variables to the output are the regression coefficients. The autoregressive model discussed in the previous section is one example of econometric analysis relating observed input variables to observed output variables. In Figure V, the two neurons N1 and N2 process the information from inputs x1 through x3 in parallel fashion, and then pass their reaction sequentially to output y.

Because people make decisions not only on the basis of observed inputs, but also on the basis of unobservable expectations, any model relating observed inputs to observed outputs with direct weights only on the inputs may miss important aspects of the way economic traders “extract signals” from observed data, process information, and form expectations about the future course of price developments. Neural networks attempt to capture the “learning behavior” of financial market participants, by allowing “hidden layers” of “neurons” to enter into the way inputs affect outputs, through parallel as well as sequential processing. Several reactions, not just one, take place in response to input stimuli, and these reactions in turn affect the way output responds, with some reactions, called “neurons”, having more effect than others, or responding in different ways to different observed inputs or stimuli.

Sargent (1993) has drawn attention to the fact that economists endow economic actors in their models with too much information: the agents actually know the true economic environment, and make decisions in a consistently rational manner. He has used neural networks to show how
economic traders in models “learn”—in essence, behave like economists who have to work with imperfect data—in order to make rational decisions.

The drawback of the neural network as a “model” of learning behavior is that it requires an increasing large number of parameters. For researchers who look for simplicity and parsimony, the neural network approach has too many “free parameters”. Too many different outcomes are consistent with learning. As yet, there are not enough restrictions, both on the number of “neurons”, and on the functional form of the neurons, the way the neurons react to input stimuli, and the way the neurons affect output. Neural networks represent a line of research with obvious appeal to economic modelers, but await further theoretical development.

Figure V pictures a single layer of two hidden neurons, N1 and N2, in a typical neural system, which stand between the effects of inputs from x and output y. In more formal terms, with n neurons, output y is a linear function of the n neurons, with weights γ and bias or constant γ0. In turn, each neuron Ni acts as a “squasher”, processing the information from the inputs xi, j = 1,...,k, from Chile and Mexico, with weights w and bias or constant factor b, and transforming this value through a log-sigmoid function to a value Ni:

\[ y = y_0 + \sum_{i=1}^{n} \gamma_i N_i \]

\[ N_i = \frac{1}{1 + e^{-n_i}} \]

\[ n_i = b_i + \sum_{j=1}^{k} w_{ij} x_j \]

(2)

In equation (2), I show a neural system with one hidden layer. It is called a single hidden-layer feedforward system, with a log-sigmoid activation function for the neurons, and a pure linear relation between the final output and the neurons in the hidden layer. Of course, the system can be extended to several hidden layers. The parameters of the system, \{w, b, \gamma, \gamma_0, \gamma_i\} are estimated by backpropagation methods, through training algorithms, usually with a sample with 75 percent of the available data.

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As mentioned above, both in-sample data, and network performs, relative Figure VI pictures the with six neurons, and five There are 1327 observatory the linear VAR, the GAR
Of course, it should about as well or outperform respect to in-sample errors The sum of squared residual tougher test is out-of-sam percent of the sample, sur models for out-of-sample three models are 3.4925 \& 3.4902 for the neural net neural system as well as ti of-sample forecasts. They at the time of the Mexican
The behavior like economists to make rational decisions. The model of learning behavior parameters. For researchers, the network approach has been outcomes are consistent with the number of neurons, the way the neurons dictate output. Neural networks are used by modelers, but with neurons, N1 and N2, the effects of inputs from x neurons, output y is a linear bias or constant \( y \). In turn, the information from the \( i \)th weights \( w \) and bias \( \beta \) through a log-sigmoid function with one hidden layer. It is a linear function between the elements of the system, \( \{w_{ij}\}_i \), through training of the available data.

**Figure V:**

**Feedforward Neural Network: One Hidden Layer**

3 Inputs, 2 Neurons

![Diagram of a feedforward neural network with one hidden layer showing inputs from Chile, Mexico, and USA leading to neurons 1 and 2, which then output to Brazil.](image)

As mentioned above, for model evaluation one usually simulates with both in-sample data, and out-of-sample data, to see how well the neural network performs, relative to linear classical systems, or to GARCH models.

Figure VI pictures the in-sample squared errors of a single-layer model, with six neurons, and five inputs (one lagged stock price for each country). There are 1327 observations for each in-sample test. I show the errors for the linear VAR, the GARCH, and the neural models.

Of course, it should not be surprising that the neural network does about as well as the pure linear model or GARCH model with respect to in-sample errors. After all, the neural system has more parameters. The sum of squared residuals for all three models are about the same. A tougher test is out-of-sample squared prediction errors. The remaining 25 percent of the sample, summing to 444 observations, is used to test the three models for out-of-sample performance. The root mean square error for the three models are 3.4925 for the linear model, 3.5270 for the GARCH, and 3.4902 for the neural network. Figure VII shows that the log-sigmoid external neural system as well the linear system and GARCH system for the out-of-sample forecasts. The very large error at the end of the sample, coming at the time of the Mexican crash, is cut slightly when one moves from pure...
linear methods to the neural network. As should be clear, reducing forecast errors in stock prices reduces risk!

The analysis suggests that the neural network is a more reliable method than pure linear or GARCH systems for forecasting stock prices. While contemporaneous correlation shows that Mexico was most important, while linear VAR models show that the United States S&P index was most important, both the GARCH and neural network models show that Chile dominates.

Figure VIII, called a Hinton diagram, pictures the relative sizes of the weights and biases $b_i$ and $w_{ij}$ in the single-layer network with five lags for each country and six neurons. An opaque box represents a negative value for the relative weight, while a clear box represents a positive value. The results show that the weights for Chile dominate the weights for both the United States and Mexico, for all three neurons. In terms of the sum of the absolute values of the weights, Chile ranks first, followed by the U.S, Mexico, Brazil, and Argentina.

The relatively more accurate neural network tells us that the Chile market, rather than the Mexican or United States market, should get most attention, if one is interested in forecasting developments in the Brazilian market. The bottom line is that the Pisco sour effect dominates the Tequila effect.

IV. Conclusion

The results showing the relative importance of Chile make sense, if one sees the Chilean market as the least distorted market in the region, and thus a market more indicative of the longer-term regional growth possibilities for the Latin American region. Argentina and Brazil, by contrast, have experienced extreme macroeconomic instability, while the Mexican reform process was handicapped this past year by an overvalued exchange rate. Chile, on the other had, has had a history of stable inflation and a competitive exchange rate since the mid-1980's. Thus, its stock market may be the most stable predictor or indicator of what the region has to offer.

The problem with the neural network analysis is the interpretation of the weights for the inputs to the neurons and the weights from the neurons in each hidden layer to other hidden layers, and to the output. As yet, economic theory has little to offer, to help one make sense of the weights and biases in the neurons. The network tells us that the most important
rk is a more reliable method forecasting stock prices. While 5 was most important, while S&P index was most nk models show that Chile

tes the relative sizes of the network with five lags for represents a negative value represents a positive value. The ike the weights for both the . In terms of the sum of the fnst, followed by the U.S, k thus tells us that the Chile market, should get most developments in the Brazilian effect dominates the Tequila

cence of Chile make sense, if the market in the region, and fer-term regional growth Argentina and Brazil, by somatic instability, while the past year by an overvalued a history of stable inflation 80's. Thus, its stock market of what the region has to

ysis is the interpretation of e weights from the neurons and to the output. As yet, make sense of the weights as that the most important
relative weights are those attached to Chile. If the neural network is simply a "shortcut" for nonlinear analysis, then the use of a multiple layer network, as opposed to a single or double layer network, indicates that a more complex nonlinear structure is being approximated. Beyond that, however, there is not much more information that can be exploited from the coefficients from one hidden neuron to another hidden neuron. The neural system is simply trying to mimic an expectation formation mechanism based on "bounded rationality", in which information is compressed and processed in parallel fashion, before decisions are made, as Sargent (1993) points out in his discussion of neural networks and bounded rationality.

This analysis has concentrated on national market indices. Of course, one can look at particular stock prices within one national market, and examine how well information on other stocks in the same national market, on particular stocks in other markets, or on commodity and bond prices, helps predict stock-price movements.

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Figure VIII:

Hinton Diagram of Relative Weights in NNet Model

1. "Pisco sour" is a popular nat. However, its origin is in Peru, understanding from Peruvians f
2. It is also true that Brazilian market capitalization relative to stock-price movements. Bekae
the neural network is simply of a multiple layer network, indicates that a more complex beyond that however, there is plied from the coefficients neuron. The neural system is nation mechanism based on is compressed and processed , as Sargent (1993) points out added rationality.

market indices. Of course, in one national market, and in the same national market, commodity and bond prices,

Obviously, market participants in Brazil are "learning" from other experiences in the region. By approximating more accurately the way these participants learn, the neural network may emerge as the more reliable forecasting tool of the share prices as well. Previous studies of the US market did not give much support to neural networks as helpful predictors of particular stock prices. However, the emerging markets of Latin America, where deregulation and privatization experiences abound, may be more fertile territory for the use of this tool, at once powerful and simple, for forecasting and prediction.

V. References


Trippi, Robert R. And Efraim Turban, (1992), editors, Neural Networks in Finance and Investing. Chicago, Ill.: Probus Publishing Co.


VI. Endnotes

1 "Pisco sour" is a popular national drink of Chile, made from fermented grape juice. However, its origin is in Peru, where it is also popular. The author begs tolerance and understanding from Peruvians for applying this term to Chile.

2 It is also true that Brazilian-specific factors, such as indices of market concentration, market capitalization relative to GDP, and indicators of reform, would also help to explain stock-price movements. Bekaert and Harvey (1995) pursue this line of analysis, with monthly data for a large set of emerging markets.
Glosten, Jagannathan, and Runkle (1993) developed an asymmetric GARCH model, whereby negative shocks have positive effects on the conditional variance. Using monthly data, Bekaert and Harvey (1995) found the coefficient of the asymmetric effect significant for several emerging markets.

Neural network estimation was done with MATLAB, with programs written by Demuth and Beale (1994).

White (1992) offers several tests for examining the significance of coefficients in neural network models.

See White (1988) for an analysis of IBM stock returns with neural networks. He confirms the efficient market hypothesis, which holds that returns cannot be predicted.

This paper looks at Western communist countries with an emphasis on the nature of international bank investment to international banks. It considers the costs of operating at a distance and the advantages of offsetting factors such as local competitors. The paper concludes that the environment developing in these countries is one in which banks operating or contemplating future strategies must be prepared to determine their entry strategies into the actual cases.

I. The Nature of International Banking

The concept of international banking encompasses the sale of foreign currencies to individual banks, it may mean with a limited involvement in the sales of foreign currencies, or more complex strategies involving the physical presence in a foreign country or subsidiary. In essence, international banking is still evolving, with more countries and more currencies, differing in their regulatory frameworks and market conditions.