8-2013

Forecasting Foreign Exchange Rates

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FORECASTING FOREIGN EXCHANGE RATES

A THESIS IN
ECONOMICS AND FINANCE

BY

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SUBMITTED IN PARTIAL FULFILLMENT
OF THE REQUIREMENTS
FOR THE DEGREE OF

MASTER OF ARTS
AUGUST 2013

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Acknowledgements

No successful work can ever be the effect of a single individual effort. I take this opportunity to express my deep gratitude towards everyone who has been of immense help throughout, until the completion of the project. I earnestly wish to express my heartfelt thanks for Dr. Byrley (Associate Professor, Economics and Finance) whose invaluable guidance and advice let me achieve the goal of this project. My sincere thanks are extended to Dr. Kasper (Assistant Professor, Economics and Finance) who has been instrumental in the successful culmination of this work.

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1.0 Introduction

1.1 Background

Determination of exchange rates was once fairly simple. During the years of the Bretton Woods System (a system put in place in 1944 when the leaders of allied nations met at Bretton Woods, NH to set up a stable economic structure out of the chaos of World War II), there were long periods of exchange rate stability. Despite the inherent problems, pegged systems lend a degree of confidence to currency price predictions. There were major readjustments to the system if a currency became too far out of line with economics, but there were few surprises because adjustments could be anticipated well in advance. This is no longer the case.

Current practices rely on exchange rate forecasts as a cornerstone of most, if not all, international business and banking decisions. Speculations based on exchange rate forecasts provide the opportunity to create sizeable profits for businesses and banks. The constant movement of rates in the foreign exchange market, combined with the rapid internationalization of business, has resulted in the demand for forecasting methods.

In general, forecasting requires the presumption of a set of relationships among variables. In other words, economic forecasting requires models. Forecasting techniques are based on formal models and may rely on an assumed sequence of casual relationships (e.g., simulation models), or on the data-based development of statistical relationships between the variable of interest and past values of the same series (intrinsic models), and/or past values of various exogenous variables (extrinsic models).[1]

One feature common to both exploratory and causal and extrinsic and intrinsic statistical models is that their predictive ability depends on the assumption that relationships established in the past will continue reasonably unchanged into the future. It makes little difference whether the nature of this relationship is specified in terms of a logical or theoretical framework, or a statistical dependence. The stability of the forecasting model is not the only condition necessary for profitable forecasting. A more fundamental condition is that the actions of other forecasters do not wipe out any possible profit from successful prediction. Recent developments in time series theory have led to the frequent use of methods that forecast by fitting some functional relation to the historical values of the series and extrapolating them into the future.

The international monetary environment in which the exchange rate forecasts are made has passed through several transitions. The most common transition is that national monetary authorities have pledged to maintain exchange rates within small margins around a target rate or a "par value." This value could be changed whenever the balance of payments of a country moves in disequilibrium and when it becomes clear that various alternative policies are ineffective. Forecasting procedures developed in this environment consist of a three-step process: the examination of the balance of payments and other trends one derives from pressure on a currency; the indication from the level of central bank foreign exchange reserves (including borrowing facilities) of the point in

[1] Ian H. Giddy and Gunter Dufey, "The Random Behavior of Flexible Exchange Rates: Implications for Forecasting." *Journal of International Business Studies*, 1 (1975): 1-32.

time when a situation becomes critical; and the crucial prediction of which one of the rather limited policy options economic decision-makers resort to in times of crisis.

1.2 Problem Statement and Purpose of the Thesis

World currencies are being traded everyday against one another to the tune of trillions of dollars per day. Through this trading each currency is pegged and measured against the other by an exchange rate. An exchange rate is the price of one currency expressed in terms of another currency. The question that arises is: what causes exchange rates to change, and how does one predict future value?

Time series analysis involves both model identification and parameter estimation. Most analyses would agree the identification problem is more difficult. Once the functional form of a model is specified, estimating the model parameters is usually straightforward. To identify a model that best represents a time series, it is necessary to be clear about the purpose of the model. Is the model's chief objective to explain the nature of the system generating the series? Or, is the model to be judged on its ability to predict future values of the time series? Therefore, to arrive at a model that represents only the main features of the series, a selection criterion, which balances model, fit, and model complexity, must be used.[2]

The purpose of this thesis is to seek answers to different questions regarding the forecasting of foreign exchange rates. Exchange rate movement is regularly monitored by central banks for macroeconomic analysis and market surveillance purposes. Results in the literature show exchange rate models perform poorly in out-of-sample prediction

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[2] Eily Murphee and Anne Koehler, "A comparison of the Akaike and Schwarz Criteria for Selecting Model Order." *Applied Statistic*, 37 (1988): 187-195.

analysis, even though some models have good in-sample analysis. The results were found using methods including moving average, exponential smoothing, random walk, and Box-Jenkins transfer function. The questions that I ask are: how accurate are these models when compared to a random prediction of future exchange rates, and what variables, if any, allow for the most accurate prediction? I am motivated to research this issue because I currently work in the insurance business and am interested in actuarial science.

This thesis is to research a variety of foreign exchange forecasting models and gather data for several different countries and variables in order to compare the future predictions to a random walk model. There are several objectives I will pursue to determine if this thesis is valid. One objective is to define the specific formulas used for each model, including which variable each model uses. Another objective is to run tests of all the models, variables, and data, and compare the viability of the results. A number of questions will arise and will be investigated.

The outcome of this course is my written statement. My anticipation of this thesis is that foreign exchange rate forecast models do not outperform a random walk model when predicting future rates. The evaluation of this course will be the assessment of my thesis and oral defense by my thesis committee.

1.3 Significance of the Thesis

International forecasts are usually settled in the near future. Exchange rate forecasts are necessary to evaluate the foreign denominated cash flows involved in international transactions. Thus, exchange rate forecasting is very important to evaluate the benefits and risks attached to the international business environment.

A wide variety of forecasting techniques and models claim that they are able to help predict future values of exchange rates. There is a need to investigate and evaluate these forecasting claims and compare the results accordingly.

This thesis provides comparative results that are important for forecast model selection used in predicting and trading foreign exchange rates. The results of this thesis will provide a foundation as to whether there is a clear-cut model that should be used in predicting foreign exchange rates.

The first question that arises is: are there different methods used in order to forecast different currencies? There are different methods of forecasting exchange rates. One approach may consider various factors specific to long-term cycle rise. For instance, data for a certain country would be looked at based on productivity indices, inflation, unemployment rate, trade balance, and more. A different approach focuses on the current and past real value of the exchange rate. Forecasting can be based on the investor, so changes in rate can be determined and patterns charted. There can be any number of methods used to attempt to predict the trend of the exchange rate and information such as political instability, natural disasters and speculation.

Currency speculation involves buying, selling and holding currencies in order to make a profit from favorable fluctuations in exchange rates. It involves a high degree of risk since predicting what events will influence exchange rates during a specific period of time, as well as the magnitude of the influence, is very difficult. Currency speculation can have serious consequences on a national currency and accordingly on a country's economy. While a major benefit of speculation is an increase in liquidity (more units of currency being used in transactions rather than reserves), speculation can also devalue or inflate a currency to the point at which a country's stock market and overall economy starts to follow suit. Heavy trading in a currency creates "artificial demand" and can increase the prices of goods beyond an inflation-adjusted level.

The second question that arises is: what are the macro variables that should be used for forecasting variables? Information plays an important role in regarding the potential return on foreign exchange trading. The general view about exchange rates is if the exchange rate of a country is properly valued, it does not substantially affect the macroeconomic variables and, therefore, the macroeconomic performance of that country. Volatility in exchange rate of a country can affect the investment in that country adversely. It creates an uncertain environment for investment in that country and requires that the country's resources be reallocated among various sectors of the country's economy.

One variable that plays a role in the movement of the exchange rate is foreign direct investment. The role of foreign direct investment for the growth of developing countries is very important. Foreign investors are motivated to invest in a host country if the prospects of earning long-term profits by contributing towards the country's production sector are obvious. Foreign direct investment not only contributes towards capital formation in developing countries, but it is also a source of transfer of technological and innovative skills from developed to developing countries.

Inflation can also affect the fluctuation of an exchange rate. Inflation affects the value of goods and services because purchasing power parity is a fundamental determinant of exchange rates. Inflation in one country translates into a rise in the price of goods and services in that country, whereas the value of products in other countries remains unchanged where inflation is subdued. The result of this discrepancy is that the currency of the country experiencing inflation plummets against those other currencies that do not, resulting in a devaluation of their currency.

An example of variables affecting the foreign exchange rate of a local currency can be seen in gross domestic product. If a country imports more goods and services than it exports, then the result is a current account deficit. That country must finance that current account deficit, either by international borrowing or by selling more capital assets than it buys internationally. Conversely, when the country exports more than it imports, its trading partners must finance their current account deficits, either by borrowing or by selling more capital assets than they purchased, both affecting the rate.

Another question now arises. Is forecasting feasible? In many ways, there is no conflict between fundamental and technical analysis. The decisions that result from economic or policy changes are far reaching; these actions may cause a long-term change in the direction of prices and may not be reflected immediately. Actions based on long-term forecasts may involve considerable risk. Integrated with a technical method of known risk, which determines price trends over shorter intervals, investors and researchers have gained practical solutions to their forecasting problems.

A fundamental study may be a composite of supply and demand elements such as statistical reports, expected use, political ramifications, labor influence, price support programs, and industrial development. The result of a fundamental analysis is a forecast. Technical analysis is a study of patterns and movements. Its elements are normally limited to price, volume, and open interest. It is considered to be the study of the market itself. The results of technical analysis may be a short- or long-term forecast based on recurring patterns; however, technical methods often limit their goals to the statement that prices are moving either up or down. One advantage of technical analysis is it is completely self-contained. The accuracy of the data is certain.

To successfully forecast, one must act on news that has not yet been printed and anticipate changes. One must recognize recurring patterns in price movement and determine the most likely results of such patterns. One must also determine the trend of the market by isolating the basic direction of data over a selected time interval.

Forecasts are limited by the data used in the analysis. This raises the question: what data should be used? There is a multitude of statistical data that might be used other than the data related to a specific inquiry. Some of this data is easily included such as prices, but other data may add to a more certain forecast; however, the data may not be that readily available. The time frame of the data impacts both the type of forecast as well as the nature of the forecast. For example, if using only weekly data, there is so much emphasis on the trend that your forecast is already pre-determined. A shorter time may guarantee a faster response to changes, but it does not assure better results.

When sampling is used to obtain data, it is common to divide entire subsets of data into discrete parts and attempt a representative sampling of each portion. These samples are then weighted to reflect the perceived impact of each part on the whole. Such a weighting will magnify or reduce the errors in each of the discrete sections. The result of such weighting may cause an error in bias. Even large numbers within a sample cannot overcome intentional bias introduced by weighting one or more parts.

Technical analysis is based on a perfect set of data. Each price that is recorded is exact and reflects the netting out of all information at that moment. Most other statistical data, although appearing to be very specific, are normally an average value, which can represent a broad range of numbers, all of them either large or small. When an average is used, it is necessary to collect enough data to make that average accurate. When using small, incomplete, or representative sets of data, the approximate error, or accuracy of the sample, should be known. A critical element of forecasting is the recognition that there exists a pattern in the time series data. Forecasting a trend or cycle requires a methodology different from that of forecasting seasonal differences. A time series is nothing more than observed successive values of a variable or variables over regular intervals of time.

There are four basic components that make up time series data that can influence our forecast of future outcomes:

Secular trend (T)

Seasonal variation (S)

Cyclical variations (C)

Random or irregular variation (I)[3]

[3] J.K. Sharma, *Business Statistics* (New Delhi, India: Dorling Kindersley, 2007), 543.

The time series model that is generally used is a multiplicative model that shows the relationship between each component and the original data of a time series (Y) as:

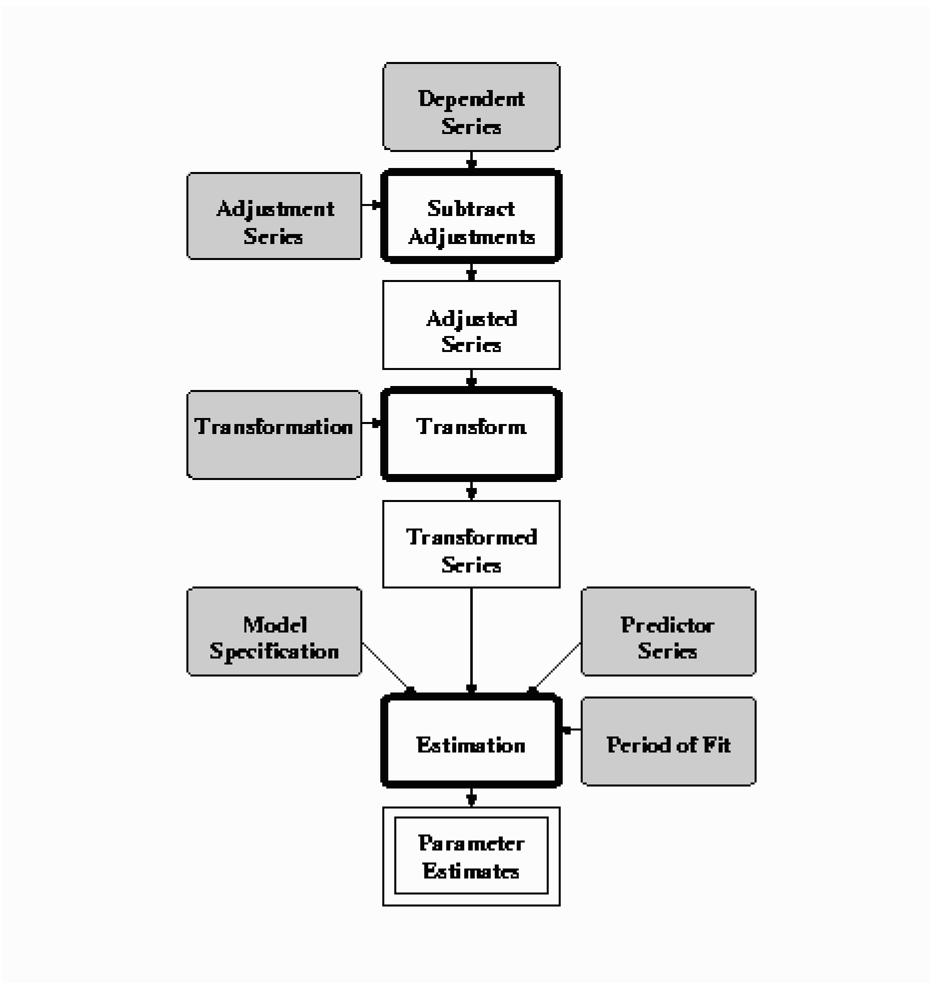
$$Y = T * S * C * I$$

Secular trend is the long-term growth movement of a time series. The trend may be upward, downward, or steady. Seasonal variation refers to repetitive fluctuations that occur within a period of one year. Cyclical variations are wave-like movements that are observable over extended periods of time. Random variation refers to variation in a time series that is not accounted for by trend, seasonal, or cyclical variations. Because of its unsystematic nature, the random or irregular variation is erratic with no discernible pattern.

The final question that needs to be answered is: do any of the techniques outperform the random walk model? Some methods of analyzing data are more complex than others. All good forecasting methods begin with a sound premise. One must first know what he or she is trying to extract from the data before selecting a technique. The choice of methods depends on the specifics of the situation as well as the formal statistical criteria that guide model selection within certain approaches. The choice of selecting a technique depends on the objectives of that forecast.

Forecasting methodologies fall into three categories: quantitative models, qualitative models, and technological approaches. Quantitative models, also known as statistical models, are objective approaches to forecasting. They dominate the field as they provide a systematic series of steps that can be replicated and applied to a variety of conditions. The qualitative methods of forecasting are called non-statistical or judgmental approaches to making forecasts. These approaches depend heavily on expert opinion and the forecaster's judgment. The qualitative approaches are adopted when historical data are scarce. The techniques used in the technological approach combine the quantitative and qualitative approaches so that a long-term forecast is made. The objectives of the model are to respond to technological, societal, political, and economic changes in order to make a forecast.[4] Figure 1-1 shows the process of model selection.

Figure 1-1



[4] Perry J. Kaufman, *Trading Systems and Methods* (New York: John Wiley & Sons, 1998), 1-4.

1.4 The Path of Query

Regression analysis is a way of measuring the relationship between two or more sets of data and involves statistical measurements that determine the type of relationship that exists between the data studied. Regression analysis is often applied separately to the basic components of a time series, that is, the trend, seasonal or secular, and cyclic elements. These three factors are present in all price data. The part of the data that cannot be explained by these three elements is considered random or unaccountable.

Trends are the basis of many trading systems. Long-term trends can be related to economic factors such as inflation or shifts in the U.S. dollar due to the balance of trade or changing interest rates. The reasons for the existence of short-term trends are not always clear since trends that exist over a period of a few days cannot always be related to economic factors but may be strictly behavioral. [5]

The random element of price movement is a composite of everything unexplained. There is a special relationship in the way price moves over various time intervals, the way price reacts to periodic reports, and the way prices fluctuate due to the time of the year. Most trading strategies use one price per day, usually the closing price, but some methods will average the high, low, and closing prices. Economic analysis operates on weekly or monthly average data but may use a single price for convenience. Two reasons for the infrequent data are the availability of most major statistics on supply and demand and the intrinsic long-term perspective of the analysis. The use of less frequent data will cause a smoothing effect. The highest and lowest prices will no longer

[5] Kaufman, *Trading Systems and Methods*, 37-38.

appear, and the data will seem more stable. Even when using daily data, the intraday highs and lows have been eliminated, and the closing prices show less erratic movement.[6]

A regression analysis, which identifies the trend over a specific time period, will not be influenced by cyclic patterns or short-term trends that are the same length as the time interval used in the analysis. The time interval used in the regression analysis is selected to be long (or multiples of other cycles) if the impact of short-term patterns is to be reduced. To emphasize the movement caused by other phenomena, the time interval should be less than one-half of that period. In this way, a trend technique or forecasting model may be used to identify a seasonal or cyclic element. [7]

Having discussed the research problem, purpose and need for evaluating, and selecting forecasting models, we now describe and summarize related research conducted in this field by previous experts and economists. This is followed by a discussion of the methodology that is used along with conclusions and recommendations for future research and development.

Data gathered for this project was collected from the Federal Reserve Bank of St. Louis website. There were three variables used for four different countries. The countries used were Japan, Canada, Great Britain, and the United States. All variables used are for the time period of January 1980 to October 2010, based on a quarterly frequency. The aggregation method used for each variable is an average.

The first variable is foreign exchange rates. The data uses an average of the daily figures based on buying rates in New York City and is based upon one denomination of local currency compared to one U.S. Dollar.

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[6] Cheol S. Eun and Bruce G. Resnick, *International Financial Management (*New Delhi: McGraw Hill, 2008), 59-73.
[7] Ibid., 141-151.

The next variable used is gross domestic product (GDP). The GDP data for Japan is seasonally adjusted based on billions of Japanese YEN. Canadian GDP is seasonally adjusted data based upon millions of Canadian Dollars. GDP in Great Britain is also seasonally adjusted based upon millions of British Pounds.

The third variable used is CPI, or Consumer Price Index. This data is not seasonally adjusted and is denoted as a percentage. These variables are selected for this study after consulting foreign exchange traders at Citibank. Although several other variables can and are used, these are the three that are consistent among the several trading desks.

1.5 Limitations

A forecast represents an expectation about a future value or values of a variable. The expectation is constructed using an information set selected by the forecaster. The exchange rate depends on fundamentals such as relative national money supplies, real incomes, short-term interest rates, expected inflation differentials, and cumulated trade balances. These fundamentals are currently used by the head traders of foreign exchange currencies at Citibank.

There are several limitations that can be identified in evaluating forecasting performance. One limitation in time series forecasting is that the data may or may not be adjusted for seasonality, which is used to balance data fluctuation over a period of time. This can also be referred to as stationarity, in which data is transformed to include or exclude seasonal trends.

There are also factors that lead to long-run real exchange rates that may not be found in historical data. The factors can range from economic crisis to natural disasters. Examples are war, earthquakes, political turmoil, oil prices, and global trade patterns.

The topic of economic forecasting is vast and many models have been presented over the years. There is no way to determine which forecasting model is the best fit due to limitations and the inability to predict future occurrences. The purpose of this thesis is to answer the four main questions that arose during research. Are there different methods used in order to forecast different currencies? What are the macro variables that should be used to forecast currencies? Is forecasting feasible? Do any of the techniques outperform the random walk model?

2.0 Review of Literature

In this study we look to use exchange rate as a dependent variable. The need for the intermediate monetary target variable arises because monetary instruments (e.g., the bank rate, cash reserve requirements, open market operations), and the ultimate goal of monetary policy (e.g., a higher rate of economic growth, price stability, a surplus in the balance of payments) do not have a direct relationship. In order to determine if exchange rates influence GDP and interest rates, we most know the link between them.

Exchange rate fluctuations play a key role in determining economic policy. These fluctuations have repercussions on economic performances. It is essentially the dependence with respect to imports and specialization in exports that account for exchange rate fluctuations on the economic performances of countries. In order to stabilize the economy during these fluctuations, government may increase or decrease money supplies, which, in turn, can weaken or strengthen the price of the exchange rate.

In fundamental models of exchange rate, macroeconomic variables such as interest rates, money supplies, gross domestic products, trade account balances, and commodity prices have long been perceived as the determinants of the equilibrium exchange rate. The foreign exchange rate in fundamental models is classified as a highly liquid market where all information is public, and traders in the market share the same expectations with no information advantage over the other.[8]

2.1 Exchange Rate Systems

Confidence in a currency is the greatest determinant of an exchange rate. Decisions based on expected future developments may affect the currency. An exchange of currency can be based on one of four main types of exchange rate systems:

Fully fixed exchange rates

Semi-fixed exchange rates

Free-floating exchange rates

Managed floating exchange rates [9]

The Federal Reserve Bank of New York carries out foreign exchange-related activities on behalf of the Federal Reserve System and the U.S. Treasury. In this capacity, the bank monitors and analyzes global financial market developments, manages

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[8] Andrew W. Mullinex and Victor Murnide, *Handbook of International Banking (*London: Edward Elgar Publishing Limited, 2003), 350-358.
[9] The Federal Reserve Board. "FRB: Speech, Bernanke--International Monetary Reform and Capital Freedom--October 14, 2004." http://www.federalreserve.gov/boarddocs/speeches/2004/20041014/ (accessed 30 March 2009).

the U.S. foreign currency reserves, and from time to time intervenes in the foreign exchange market.

The U.S. Treasury has the overall responsibility for managing the U.S. government's foreign currency holdings. It works closely with the Federal Reserve to regulate the dollar's position in the forex markets. If the Treasury feels there is a need to weaken or strengthen the dollar, it instructs the Federal Reserve Bank of New York to intervene in the forex market as the Treasury's agent. The Federal Reserve Bank of New York buys dollars and sells foreign currency to support the value of the dollar. The bank also sells dollars and buys foreign currency to try to exert downward pressure on the price of the dollar. [10]

The transactions in the intervention are small compared to the total volume of trading in the forex market, and these actions do not shift the balance of supply and demand immediately. Instead, intervention is used as a device to signal a desired exchange rate movement and affect the behavior of investors in the forex market. Central banks in other countries have similar concerns about their currencies and sometimes intervene in the forex market as well. Usually, intervention operations are undertaken in coordination with other central banks. Some countries have special arrangements with other countries to help them keep their currencies stable. Many less developed countries have their currencies pegged to other currencies so that their value rises and falls simultaneously with the stronger currency. [11]

In a fully fixed exchange rate system, the government (or the central bank acting on its behalf) intervenes in the currency market in order to keep the exchange rate close

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[10] The Federal Reserve Board. "FRB: Speech, Bernanke--International Monetary Reform and Capital Freedom--October 14, 2004".
[11] Ibid.

to a fixed target. It is committed to a single fixed exchange rate and does not allow major fluctuations from this central rate. In a semi-fixed exchange rate system, currency can move inside permitted ranges of fluctuation. The exchange rate is the dominant target of economic policy making. Interest rates are set to meet the target, and the exchange rate is given a specific target. This is the major difference between fully and semi-fixed exchanges rates. However, the semi-fixed holds most of the same characteristics as the fully fixed exchange rate. [12]

A floating exchange rate system is a monetary system in which exchange rates are allowed to move due to market forces without interventions of national governments. With floating exchange rates, changes in market demand and supply cause a currency to change a value. Pure free-floating exchange rates are rare. Most governments at one time or another seek to manage the value of their currency through changes in interest. In a free-floating exchange rate system, the value of the currency is determined solely by market supply and demand forces in the foreign exchange market. Trade flows and capital flows are the main factors affecting the exchange rates and other controls.[13]

2.2 Exchange Rate Variables

In looking domestically at the United States, the current account deficit is conceptually equal to the gap between domestic investment and domestic saving as

[12] The Federal Reserve Board. "FRB: Speech, Bernanke--International Monetary Reform and Capital Freedom--October 14, 2004".
[13] Ibid.

matter of international account, which can be seen in the national income identity. The following graph shows the 2012 U.S. trade deficit when compared to China. [14]

2012: U.S. trade in goods with China

NOTE: All figures are in millions of U.S. dollars on a nominal basis, not seasonally adjusted unless otherwise specified. Details may not equal totals due to rounding.

Month	Exports	Imports	Balance
January 2012	8,372.0	34,394.6	-26,022.6
February 2012	8,760.7	28,124.7	-19,363.9
March 2012	9,829.7	31,501.8	-21,672.0
April 2012	8,456.5	33,011.0	-24,554.5
May 2012	8,898.6	34,942.0	-26,043.4
June 2012	8,518.7	35,919.8	-27,401.2
July 2012	8,554.1	37,929.9	-29,375.8
August 2012	8,609.2	37,297.3	-28,688.1
September 2012	8,790.9	37,849.9	-29,059.0
October 2012	10,823.3	40,289.5	-29,466.2
November 2012	10,594.4	39,548.2	-28,953.8
December 2012	10,382.0	34,835.0	-24,453.0
TOTAL 2012	**110,590.1**	**425,643.6**	**-315,053.5**

When investments in the United States are higher than domestic saving, foreigners make up the difference, and the United States has a current account deficit. In contrast, if savings exceed investment in a country, then that country has a current account surplus and its people invest abroad. The growth of the U.S. current account deficit for more than a decade has been linked to high levels of domestic U.S. capital formation compared to domestic U.S. saving. Perceived high rates of return on U.S. assets (based on sustained strong productivity growth relative to the rest of the world)

[14] The United States Census Bureau. "2012: U.S. trade in goods with China." http://www.census.gov/foreign-trade/balance/c5700.html (accessed March 24, 2012).

show U.S. economic performance and the attractiveness of the U.S. investment climate, attracting foreign investment. Sustained external demand for the United States assets has both supported the dollar in the foreign exchange markets over the years and allowed the United States to achieve levels of capital formation that would have otherwise not been possible. Robust growth in investment is critical to the non-inflationary growth of production and employment. [15]

For a country to be involved in international trade, finance, and investment, it is necessary to have access to foreign currencies of other countries. The sale and purchase of foreign currencies take place in the foreign exchange markets. This market allows for the movement of large volumes of funds (about three trillion dollars per year) for investment purposes around the world. Any changes in exchange rates are important because of the effect they have on the prices we pay for imports, the prices we receive for our exports, and the amount of money flowing into and out of the economy.

For example, if the volume of the U.S. dollar appreciates (increases in value), exports become more attractive and overseas customers have to find more U.S. dollars to buy the same volume of exports. If the U.S. dollar depreciates (decreases in value), then U.S. exports become cheaper, and imports become more attractive. U.S. exports are now more competitive in global markets because of the depreciation of the U.S. dollar. Currently, overseas buyers of U.S. products have to find fewer U.S. dollars to buy the same value of exports. Decreasing import prices can decrease production costs and inflation rates in any domestic economy.

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[15] The Federal Reserve Board. "FRB: Speech, Meyer -- The Future of Money and of Monetary Policy." http://www.federalreserve.gov/boarddocs/speeches/2001/20011205/ (accessed March 15 2010).

There are several factors that affect the demand for U.S. dollars. The first factor to look at is the demand for U.S. exports. When overseas consumers buy U.S. goods and services, they need to convert their currency into U.S. dollars to pay for the exports. Therefore, any increase in the demand for U.S. exports should increase the value of the dollar.

Changes in world economic conditions and international competitiveness will affect the demand for the U.S. dollar. High levels of world economic growth can increase the demand for goods and services and the demand for the U.S. dollar. To be competitive in the global market, the United States' goods and services must be as cheap as its international competitors. If U.S. inflation rates and costs are relatively higher than its overseas competitors, then the goods and services will be more expensive. High U.S. inflation rates help cause a loss of export markets, reduce the demand for the dollar, and force a depreciation of the dollar. However, lower rates of inflation typically increase the demand for U.S. exports and appreciate the value of the dollar. [16]

Capital inflow also affects the demand for U.S. dollars. Foreign investors wishing to invest in the United States must also exchange their own currency for dollars. A number of factors may influence the investment decision. If interest rates are relatively higher than overseas interest rates, this will increase the capital inflow and the demand for U.S. dollars. The expectation of higher levels of domestic growth will influence the size of capital inflow and increase the demand for dollars, causing a currency appreciation. A decline in the level of capital inflow, however, may cause a fall in the demand for dollars, resulting in currency depreciation.

[16] The Federal Reserve Board. "FRB: Speech, Meyer -- The Future of Money and of Monetary Policy."

There are also several factors that affect the supply of U.S. dollars. Demand for imports plays a significant role. Just as foreigners must pay for exports with U.S. dollars, we must pay overseas producers foreign currency for imported goods. If the dollar demand for imported goods and services increases, so does the supply of dollars. The increase in the supply of U.S. dollars puts downward pressure on the value of the dollar.

An increase in capital outflow can occur as a result of higher interest repayments on overseas loans (net income transfers) or increased demand for foreign assets. This means that investors need to sell U.S. dollars (increasing the supply) in the foreign exchange market to obtain other countries' currencies. The increase in the supply of dollars could cause a decrease (depreciation) in the value of the U.S. dollar. The level of domestic interest rates and investor confidences in the U.S. dollar also influence the supply. If there are high rates of inflation in the United States, imported goods and services would be cheaper relative to domestically produced products. If speculators lose confidence in the economy and feel that future values of the U.S. dollar will be lower than present levels, a depreciation of the exchange rate can occur. This happens because when speculators sell U.S. dollars to avoid future losses, the supply of dollars increases, putting downward pressure on the exchange rate.

How does this information tie directly into the U.S. economy? The United States budget currently has a deficit or current account deficit. There is a process of adjustment to current account deficit. The possible causes of an emerging or growing current account deficit are the same issues that cause depreciation as discussed earlier. Three of the most prominent causes are: domestic incomes increasing at a faster pace than foreign incomes; domestic inflation at a faster pace than foreign inflation rates; and domestic interest rates that are lower than foreign interest rates.

A growing deficit is likely to increase the supply of domestic money to the foreign exchange market. Assuming that the demand for domestic money has not changed, the resulting excess supply will likely induce depreciation of the domestic currency on the foreign exchange market. The depreciation of the domestic currency makes the nation's exportable goods look cheaper to foreigners and imports from abroad appear more expensive to citizens, thereby alleviating the current deficit. How foreign exchange market transactions affect the domestic supply of a nation depends upon the identities of the purchasers and sellers of the exchange. With a current deficit, one source of the increased supply of domestic currency to the forex market is foreigners who have acquired the domestic currency as export earnings, incomes from investors in the nation, or transfers from citizens or government of the nation. If foreigners supply quantities of the domestic currency to other foreigners through the forex market, the relevant domestic money supply (that which motivates the behavior of citizens of the nation) does not change.

Another source of increased supply of domestic currency to the forex market is the efforts by citizens of the nation to convert quantities of domestic currency into foreign currencies in order to purchase imports from foreign sources, invest overseas, or make transfers to foreigners. To the extent that foreign interests acquire money balances denominated in units of the domestic currency from citizens of the nation, the nation's relevant domestic money supply decreases. Assuming that the domestic demand for money does not change, the domestic money supply decrease may result in falling domestic prices, rising domestic interest rates, and decreasing employment. The falling domestic prices of goods tend to increase the volume of exports and reduce the volume of imports. The rising domestic interest rates tend to decrease the volume of investment by citizens in other countries and increase the volume of investment by foreigners in the nation. The decreasing domestic employment decreases income in the nation and, thus, curbs imports.

One view is that the burden of adjustment borne by domestic prices, interest rates, and employment is lessened by the currency depreciation. Another view is that these three phenomena supplement the depreciation of the domestic currency in alleviating the current deficit. However, if the depreciation of the domestic currency is prevented by government authorities that are resolved to "defend the currency" from further weakening or depreciation, the burden of adjustment to the deficit will descend upon domestic prices, interest rates, and employment. [17]

Some of the domestic money, which is supplied to the forex market, may be acquired by citizens of the nation who may wish to convert foreign currency denominated export earnings, investment income, or gifts from foreigners into domestic currency for repatriation. Such currency transactions between citizens of the same nation do not affect the domestic money supply, even though they pass through the forex market. Such citizen-to-citizen forex market transactions may be large enough relative to the volume of transactions between citizens and foreigners that the reduction of the domestic money supply consequent upon a deficit will itself be diminished. Although the usual presumption is that the domestic money supply decreases, the volume of citizen-to-citizen or foreigner-to-foreigner transactions in the domestic currency is large enough

[17] The Federal Reserve Board. "FRB: Speech, Meyer -- The Future of Money and of Monetary Policy."

that the money supply may be little affected by a deficit. In this case, the domestic macroeconomic adjustment will be minimal, and the correction of the imbalance will depend largely upon depreciation of the currency if the government will let it ensue.

The depressive macroeconomic effects of a decrease of the relevant domestic money supply in response to a deficit may motivate the government of the nation to attempt to neutralize the monetary contraction with offsetting purchases of bonds in the open market. If domestic macroeconomic contraction is prevented, the full burden of the adjustment of the deficit must fall upon exchange rate depreciation. If the government also resolves to prevent its currency from depreciating by intervening in the forex market to purchase quantities of the domestic currency, no mechanism of adjustment is allowed to function, and the current deficit may persist indefinitely. It may be inferred that a fixed exchange rate system is fundamentally incompatible with the exercise of modern macroeconomic policy to stabilize the domestic economy. [18]

2.3 Meese & Rogoff

The difficulty in predicting future exchange rates has been a longstanding issue in international economics. The forecasting experiment proposed by Richard Meese and Kenneth Rogoff is by what exchange rate models are judged. Meese and Rogoff examined the relationship between real exchange rates and real interest rates over the modern (post 1970) flexible rate period. They concluded that the exchange rate depends on fundamentals such as relative national money supplies, real incomes, short-term interest rates, expected inflation differentials, and cumulated trade balances. The

[18] Robert Wade, *Governing The Market*: *Economic Theory and the Role of Government in East Asian Industrialization* (New Jersey: Princeton University Press, 1990), 159-168.

underlying assumption is that goods market prices adjust slowly in response to anticipated disturbances and to excess demand. Consequently, less than perfectly anticipated monetary disturbances can cause temporary deviations in the real exchange rate from its long-run equilibrium value. Meese and Rogoff used the following equation for forecasting exchange rates:

$$\mathrm{E}_t(q_{t+k} - \bar{q}_{t+k}) = \theta^k(q_t - \bar{q}_k), 0 < \theta < 1$$

where E_t is the time expectations operator, $\bar{q}_t$ is the real exchange rate that would prevail at time *t* if all prices were fully flexible, and θ is the speed of adjustment parameter. In addition, θ is a function of the structural parameters of the model.[19] However, additive disturbances (such as money market shocks) do not affect θ. In general, $\mathrm{E}_t\ (\bar{q}_{t+k})$ will not equal $\bar{q}_t$ unless there are no real shocks or unless all real shocks follow random walk processes.[20]

Meese & Rogoff challenged the long-held idea that economic fundamentals determine currency values. They found that a random walk model was just as good at predicting exchange rates as models based on fundamentals. In short, their findings suggest economic fundamentals, like trade balances, money supply, national income, and other key variables, are of little use in forecasting exchange rates between countries with roughly similar inflation rates. [21]

[19] Kenneth Rogoff and Richard Meese, "Was it Real? The Exchange Rate-Interest Differential Relation Over the Modern Floating-Rate Period." *The Journal of Finance*, no. 43 (September 1998): 933-948
[20] Ibid.
[21] Ibid.

2.4 Random Walk Model

It has been the position of many fundamental and economic analysis advocates that there is no sequential correlation between the direction of a price movement from one day to the next. Their position is that prices will seek a level that will balance the supply and demand factors, but that this level will be reached in an unpredictable manner as prices move in an irregular response to the latest available information or news release.

If the random walk theory is correct, many well-defined trading methods based on mathematics and pattern recognition will fail. The strongest argument against the random movement supporters is price anticipation. One can argue that all participants (the market) know exactly where prices should move following the release of news.

Excluding anticipation, the apparent random movement of prices depends on both the time interval and the frequency of data used. When a long time span is used, from one to twenty years, and the data are averaged to increase the smoothing process, the trending characteristics will change, along with seasonal and cyclic variations. Technical methods such as moving averages are often used to isolate these price characteristics. The averaging of data into quarterly prices will smooth out the irregular daily movements and results in noticeably positive correlations between successive prices. The use of daily data over a long-term interval introduces noise and obscures uniform patterns.

In the long run, most future prices find a level of equilibrium and, over some time period, show characteristics of mean reverting (returning to a local average price); however, short-term price movement can be very different from a random series of numbers. It often contains two unique properties: exceptionally long runs of price in a single direction, and asymmetry, the unequal size of moves in different directions.

Although the long-term trends are not of great interest to future traders, short-tern price movements, which are cause by anticipation rather than actual events, and extreme volatility, prices that are seen far from value, countertrend systems that rely on mean reversion, and those that attempt to capture trends of less duration, have been successful.[22]

Meese & Rogoff considered six univariate time series models involving a variety of pre-filtering techniques and lag length selection criteria, a random walk with drift parameter, and an unconstrained vector auto regression; none could out-predict the random walk model: $s_t = s_{t-1} + a_t$, where a_t is white noise with mean zero and constant variance.

The six time series models used were the following: (1) an unconstrained auto regression (AR) in which the longest lag considered (M) is set to equal (*n*/log, *n*), where *n* is the sample size; (2) AR in which lag lengths are determined by Schwarz's criterion; (3) AR in which lag lengths are determined by Akaike's criterion; (4) long AR estimated by using observations that are arbitrarily weighed by powers of 0.95; (5) the Wiener-Kolmogorov prediction formula; (6) AR estimated by minimizing the sum of the absolute values of errors. The pre-filtering techniques involve differencing, de-seasonalizing, and removing time trends.

The following three formulas define the random-walk model:

(1a) $\hat{S}_{t+i} = S_{t+i-1} \qquad i = 1,2,\ldots..15$

[22] Kaufman, *Trading Systems and Methods*, 37.

(1b) $\hat{S}_{t+i} = S_t$ i = 1,2,…..15

(1c) $\hat{S}_{t+i} = i_{\hat{u}} + S_t$ i = 1,2,…..15

where $\hat{u}$ is the simple arithmetic mean of the changes in the values of S_t in the estimation period.[23]

2.5 Akaike and Schwarz Criteria

As stated earlier, time series analysis involves both model identification and parameter estimation, and a selection criterion that balances model, fit, and model complexity must be used to arrive at a model. The Akaike information criterion (AIC) (Akaike, 1974) and Schwarz information criterion (SIC) (Schwarz, 1978) are two objective measures of a model's suitability, which take these considerations into account. They differ in terms of the penalty attached to increasing the model order.

Given observations Y(1)…..Y(n), define M_j (Y(1),…..Y(n)) to be the maximum value of the likelihood for the *j*th model under consideration. The Akaike procedure is to choose the model that minimizes

$$AIC = -2\, ln\, M_j\ (Y(1), \ldots..Y(n)) + 2k_j,$$

where k_j is the number of free parameters in the model. The Schwarz criterion is to choose the model that minimizes

$$SIC = -2\, ln\, M_j\ (Y(1), \ldots..Y(n)) + k_j\, ln\, \boldsymbol{n}$$

[23] Murphree and Koehler, "A comparison of the Akaike and Schwarz Criteria for Selecting Model Order," 187-195.

Therefore, if $n \geq 8$, the Schwarz criterion will tend to favor models of lower dimension than those chosen by the AIC.[24]

This criterion concluded that the AIC would frequently choose higher order models for empirical data. Also, in forecasts for series when the AIC and SIC models differ, there is evidence that neither criterion has a clear edge in identifying models having small prediction set errors. The findings of this study argue for using SUC rather than AIC to choose the order of ARIMA model.

2.6 Wiener-Kolmogorv Filter

The Wiener-Kolmogorov (WK) signal extraction filter, extended to handle nonstationary signal and noise, has minimum Mean Square Error (MSE) among filters that preserve the signal's initial values; however, the stochastic dynamics of the signal estimate typically differ substantially from that of the target. The use of such filters, although widespread, is observed to produce dips in the spectrum of the seasonal adjustments of seasonal time series. These spectral troughs tend to correspond to negative autocorrelations at lags 12 and 24 in practice, a phenomenon that will be called "negative seasonality." So-called "square root" WK filters were introduced by Wecker in the case of stationary signal and noise to ensure that the signal estimate shared the same stochastic dynamics as the original signal, and, therefore, remove the problem of spectral dips.

This represents a different statistical philosophy: not only do we want to closely estimate a target quantity, but also we desire that the internal properties and dynamics of our estimate closely resemble those of the target. The MSE criterion ignores this aspect

[24] Ibid.

of the signal extraction problem, whereas the square root WK filters account for this issue at the cost of accruing additional MSE. This paper provides empirical documentation of negative seasonality and provides matrix formulas for square root WK filters that are appropriate for finite samples of non-stationary time series. We apply these filters to produce seasonal adjustments without inappropriate spectral troughs.[25]

2.7 Engel & West

A well-known stylized fact about nominal exchange rates among low-inflation advanced countries, particularly U.S. exchange rates, is that their logs are approximately random walks. Meese and Rogoff (1983) found that the structural models of the 1970s could not "beat" a random walk in explaining exchange-rate movements.

Why? One obvious explanation is that the macroeconomic variables that determine exchange rates themselves follow random walks. If the log of the nominal exchange rate is a linear function of forcing variables that are random walks, then it will inherit the random walk property. The problem with this explanation is that the economic "fundamentals" proposed in the most popular of exchange rates do not, in fact, follow simple random walks.

One resolution to this problem is that there may be some other fundamentals, ones that have been proposed in some models but are not easily measurable or ones that have not yet been proposed at all, that are important in determining exchange rates. If these "unobserved" fundamentals follow random walks and dominate the variation in exchange

[25] Tucker McElroy, "A Modified Model-based Seasonal Adjustment that Reduces Spectral Troughs and Negative Seasonal Correlation." http://www.census.gov/srd/www/abstract/rrs2008-12.htm (accessed 2 March 2009).

rate changes, then exchange rates will nearly be random walks (even if the standard "observed" fundamentals are not).[26]

Engel & West conclude that asset-market models, in which the exchange rate is expressed as a discontinued sum of the current and expected future values of the observed fundamentals, can account for a sizeable fraction of the variance when the discount factor is large. The Engel & West explanation for a random walk provides a rationale for a substantial fraction of the movement in exchange rates. But there is still a role for left-out forcing variables, perhaps money demand errors, a risk premium, mis-measurement of the fundamentals, or other variables implied by other theories or noise.

2.8 McCracken & Sapp

Since the breakdown of the Bretton Woods agreement, researchers have used a wide variety of structural models to try to predict exchange rate movements. Finding consistent evidence that these models outperform a random walk has proven elusive. McCracken & Sapp use *p* values based on developed tests of forecast accuracy and encompassing *q* values designed to mitigate multiple testing problems. Both *p* and *q* values can be interpreted as measures of a statistics significance. For example, if a test statistic has a *p* value of 5%, one would expect that among a random sample of pairs of statistics and hypothesis from the same population as the statistic, that on average 5% of those hypothesis are null and have statistics that will reject. Conversely, if a statistic has

[26] Kenneth D. West and Charles Engel, "Accounting for Exchange-Rate Variability in Present-Value Models When the Discount Factor Is near 1." *The American Economic Review* 94 (2004): 119-125.

a *q* value of 5%, you would expect on average that 5% of the statistics that reject actually correspond to the null hypothesis.[27]

The other statistic used to test for significance is MSE *t* statistic. These statistics provide evidence of short, medium, and long horizon predictability.

Out of 400 tests, there were 154 cases where the *p* values are less than 5%. Similarly, of the 400 tests, 338 have *q* values less than 10%, while 210 have *q* values less than 5%. The MSE *t* statistic shows that there are no significant changes in predictive ability. All cases show values less than 10%.

Their findings suggest that detecting predictability in exchange rates using regressions can be strongly influenced by the choice of test statistics and the manner in which it is employed. The results also yielded evidence that structural exchange rate models do not exhibit an ability to predict exchange rates. Similar to other studies, the evidence is consistent with there being more short-term predictability in exchange rates, and the results are relatively insensitive to the choice of the model.

2.9 Zhang & Berardi

Artificial neural networks have been widely used as a promising alternative approach to time series forecasting. Neural networks are data-driven, self-adaptive nonlinear methods that do not require specific assumptions about the underlying model. Instead of fitting the data with a pre-specified model form, neural networks let the data itself serve as direct evidence to support the model's estimation of the underlying generation process. The network ultimately selected may not be the true optimal model

[27] Michael, W. McCracken and Stephen G. Sapp, "Evaluating the Predictability of Exchange Rates Using Long-Horizon Regressions: Mind your p's and q's." *Journal of Money, Credit and Banking,* Vol. 37, No. 3 (June 2005): 473-494.

because of a large number of factors that could affect neural network training and model selection. These factors include network architecture, activation functions, training algorithm, and data normalization. Alternative data sampling from a stationary process can have a significant effect on individual model selection and prediction. This impact may be magnified if the process parameters evolve or shift over time.

For the methodology in this example, Zhang and Berardi use weekly exchange rate data. They combine neural networks trained with different initial random weights but with the same data. The neural network trained with different starting weights may be stuck with different minimums, each of which can have different forecasting performances.

Results show that different approaches to forming ensembles for time series forecasting have quite different effects on forecasting results. Neural network ensembles created by simply varying the starting random weights are not as competent as the traditional random walk model. Therefore, this method of ensemble forecasting may not be effective for forecasting exchange rates. [28]

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[28] G.P. Zhang and V.L. Berardi, "Time Series Forecasting with Neural Network Ensembles: An application for Exchange Rate Prediction." *The Journal of the Operational Research Society,* Vol. 52, 6 (June 2001): 652-664.

3.0 Methodology

Much of the probability theory of time series assumes that time series exhibit a constant mean and constant variance over time, a condition known as stationarity. Non-stationary components of time series can usually be removed to make the series stationary. For example, one can take differences of a time series to remove trends or seasonal variations.

Forecasts are generated with forecasting equations consistent with the method used to estimate the model parameters. Thus, the estimation method specified controls the way the forecast produces results. The forecast procedure provides a way of forecasting one or more time series automatically. It does not enable you to identify models or test for model adequacy. This is why it is important to test and select the correct forecast model.

Statistical measures are helpful in determining the appropriate mathematical form for the forecast model (i.e. in deciding whether an autoregressive model, a moving average model, or a mixed model should be used for a particular time series).[29]

Once one knows there is a fundamental relationship between data, based on the measuring of the properties of dependence and correlation, a formula can be found that expresses one price movement in terms of the other prices and data. The predictive qualities of these methods are best when applied to data that has been seen before, as in prices that are within the range of historic data. Forecasting reliability decreases sharply when values are based on extrapolation outside the previous occurrences. This phenomenon will also be true of other trending methods. This is based on the movement

[29] Kaufman, *Trading Systems and Methods*, 63.

of historical data; when prices move to new levels, the result of the model will often deteriorate. The techniques most commonly used for evaluating the direction or tendency of prices, both within prior ranges and at new levels, are called autoregressive functions.

3.1 Estimation and Forecasting Methods

Time series forecasting methods are based on analysis of historical data. These methods support the assumption that past patterns in data can be used to forecast future data points. The following statistics are used to measure the forecast error:

1. Moving averages (simple moving average, weighted moving average): forecast is based on arithmetic average of a given number of past data points
2. Exponential smoothing (single exponential smoothing, double exponential smoothing): a type of weighted moving average that allows inclusion of trends, etc.
3. Mathematical models (trend lines, log-linear models, Fourier series, etc.): linear or non-linear models fitted to time-series data, usually by regression methods
4. Box-Jenkins method: autocorrelation methods used to identify underlying time series and to fit the "best" model

The components of the time series forecast model used contain the following components:

1. Average: the mean of the observations over time
2. Trend: a gradual increase or decrease in the average over time
3. Seasonal influence**:** predictable, short-term cycling behavior due to time of day, week, month, season, year, etc.

4. Cyclical movement: unpredictable, long-term cycling behavior due to business cycle or product/service life cycle

5. Random error: remaining variation that cannot be explained by the other four components

There are two aspects of forecasting errors to be concerned about: bias and accuracy. A forecast is biased if it errs more in one direction than in the other. The method tends to under-forecast or over-forecast. A forecast accuracy refers to the distance of the forecasts from actual demand, ignoring the direction of that error. [30]

3.1.1 Least Squared Model

The least-squares regression model can be used to find the relationship between two dependent variables or to find how prices move when driven by known related factors. A simple error analysis can be used to evaluate the predictive qualities of this method. Assume that there is a lengthy price series for foreign exchange rates, and we would like to know how many prior quarters are optimum for predicting the next quarter's price. The answer is found by looking at the average error in the predictions. If the number of quarters in the calculation increases and the predictive error decreases, then the answer is improving; if the error stops decreasing, then the accuracy limit has been reached. Error analysis can improve most trend calculation.

Determination of the best predictive model using error analysis can be applied to any forecasting technique. This works particularly well when comparing the error of two different forecasting methods evaluated over the same number of periods, eliminating the

[30] Ibid., 55-65.

bias caused by longer and shorter intervals. It is also practical to carry the error analysis one step further and include the results of the prediction error. This gives a measure of out-of-sample forecast accuracy and lends confidence to the predictive qualities of the technique.

Having selected the most accurate forecast model, the size of the prior period predictive error can be used to resolve the future decision. Consider the following situations:

1. The prediction and the actual price are very close (high confidence level). For example, the error may have 1 standard deviation = .25.
2. The current forecast error is within 1 standard deviation of expectations; therefore, we continue to follow the trend strategy.
3. The current forecast error is between 1 and 3 standard deviations of expectations; therefore, we are cautious, yet understand that this is normal but less frequent.
4. The current forecast error is greater than 3 standard deviations of expectations. This is unusual, indicates high risk, and may identify a price shock. Alternately, it could indicate a trend turning point.

3.1.2 Regression

When most people talk about regression, they think about a straight line, which is the most popular application. A linear regression is the straight line relationship of two sets of data. It is most often found using a technique called a best fit, which selects the straight line that comes closest to most of the data points. Using the prices of two variables, such as foreign exchange rates and interest rates, their linear relationship is the straight line (or first order) equation.

The linear correlation, which uses a value called the coefficient of determination or the correlation coefficient, expresses the relationship of the data on a scale of +1 (perfect positive correlation), 0 (no relationship between the data), and -1 (perfect negative correlation). The correlation coefficient is derived from the deviation, or variation, in the data. It is based on the relationship total deviation = explained deviation + unexplained deviation.

The linear regression slope returns the slope of the straight line given the data series and the period over which the line will be drawn. The linear regression value calculates the slope of the regression line and then projects that line into the future, returning the value of the future point. This requires the user to specify the data series, the period over which the line will be calculated, and the number of periods into the future. Projecting the value can be done by finding the slope and performing the following calculation:

Projected price = starting price + slope *x* (calculated period + projection period)

where the starting price is the beginning of the calculation period. The following graphs are examples of auto correlation and partial auto correlation for AR (1) process, AR (2) process, and a MA (1) process.

Figure 3-1: ACF and PACF for an AR(1) process

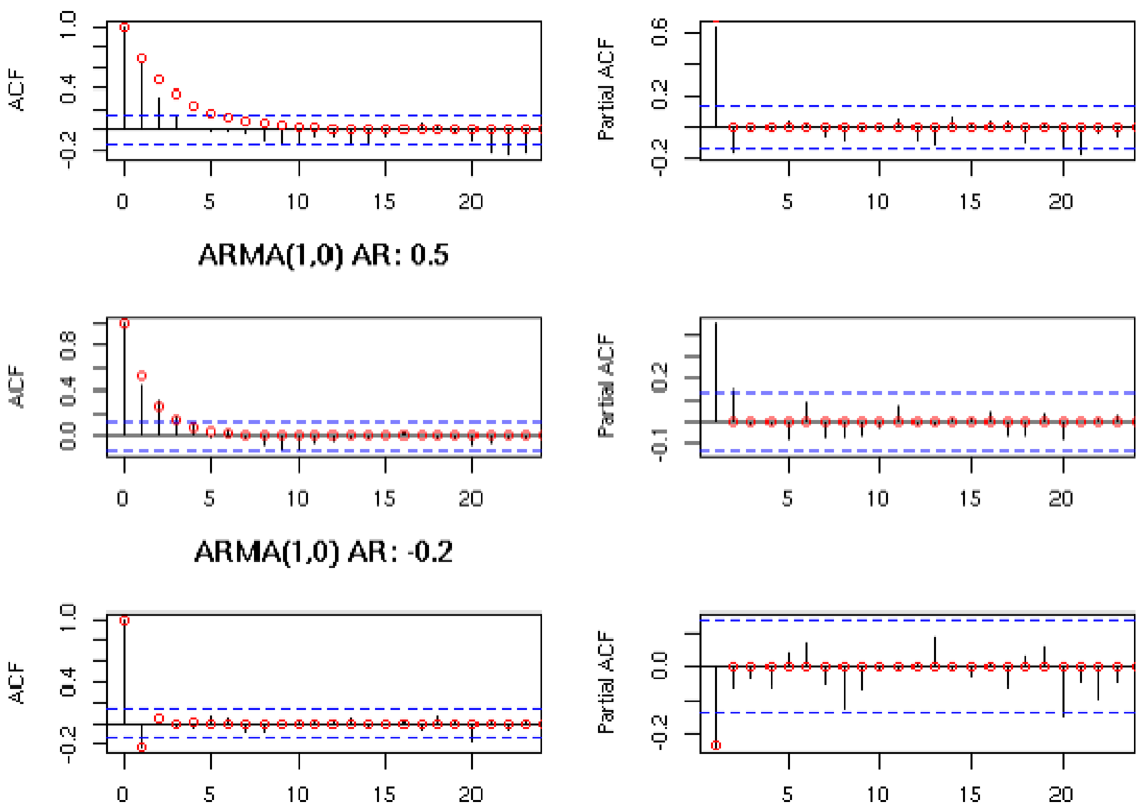


Figure 3-2: ACF and PACF for an AR(2) process

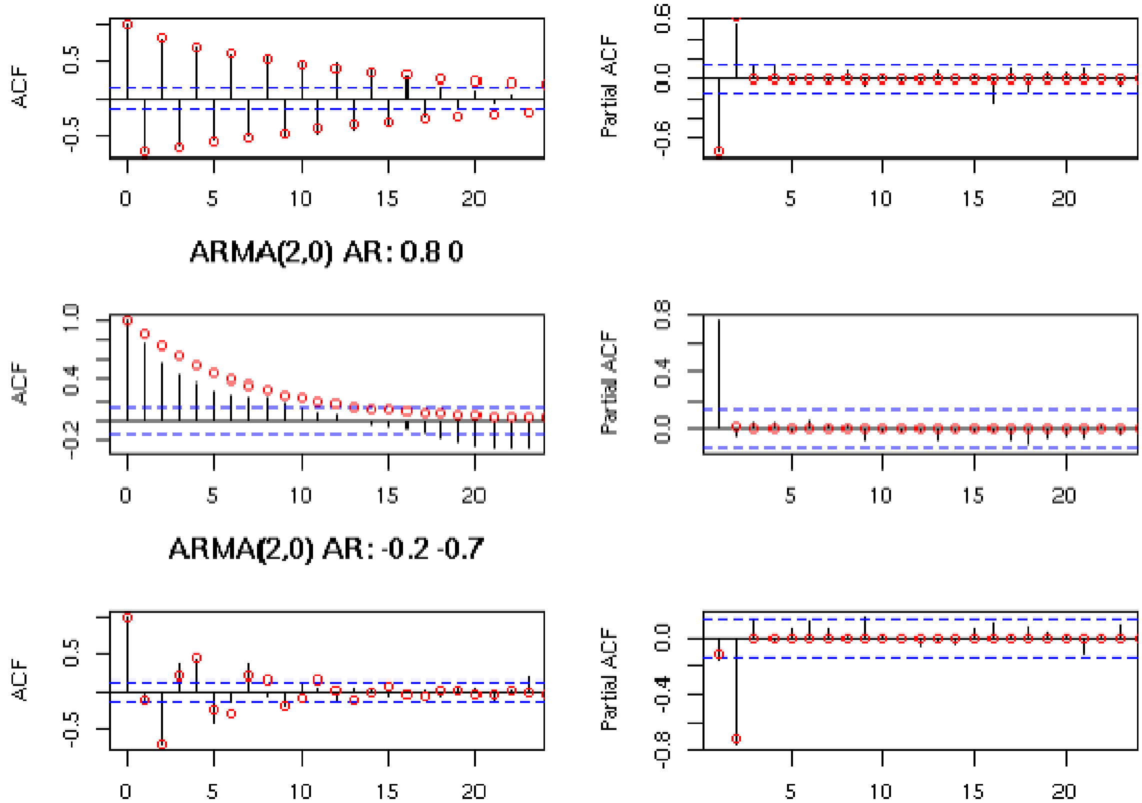
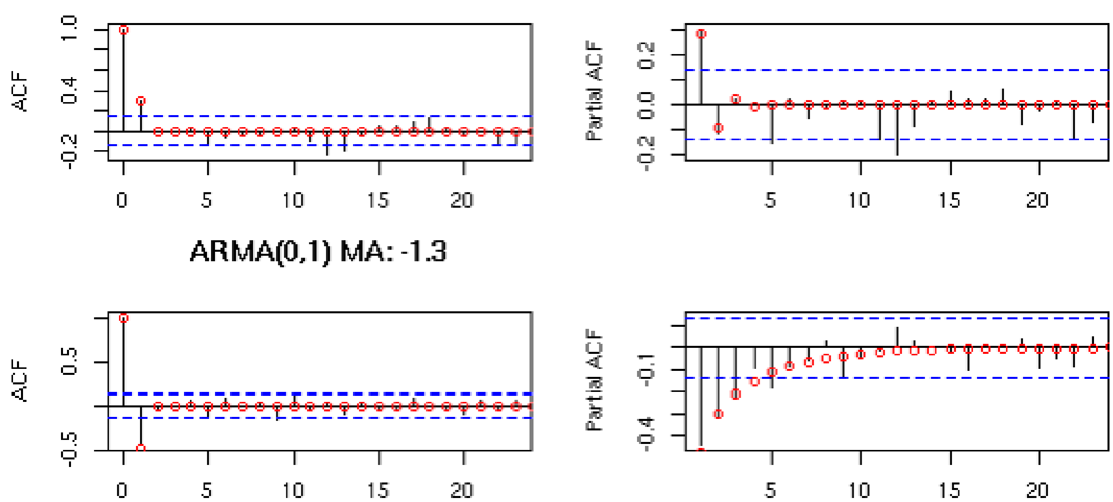


Figure 3-3: ACF and PACF for a MA(1) process



3.1.3 Box-Jenkins

The two important terms in ARIMA are auto-regression and moving average. Auto-regression refers to the use of the same data to self-predict. Moving average refers to the normal concept of smoothing price fluctuations using an average of the past *n* days. This technique has become the industry standard in forecasting referred to as the Box-Jenkins forecast.

The contribution of Box and Jenkins was to stress the simplicity of the solution. They determined that the auto-regression and moving average steps could be limited to first- or second-order processed. To do this, it was necessary to de-trend the data, thereby making it stationary. De-trending can be accomplished most easily by differencing the data, meaning creating a new series by subtracting each previous term, $P_{t-1,}$ from the next, P_t. The ARIMA program must remember all of these changes, or transformations, to restore the final forecast to the proper price notation by applying all of these operations in reverse. If a stationary solution is not found in the Box-Jenkins process, it is because the data are still not stationary and further differencing is necessary.

Because of the three features just discussed, the Box-Jenkins forecast is usually shown as ARIMA (*p, d, q*), where *p* is the number of autoregressive terms, *d* is the number of differences, and *q* is the number of moving average terms. The expression ARIMA (0,11) is equivalent to simple exponential smoothing.

When its normal, the Box-Jenkins ARIMA process performs the following steps:

1. Specification: preliminary steps for determining the order of auto-regression and moving average to be used

The variance must be stabilized. In many price series, increased volatility is directly related to increased price. A simple test for variance stability, using the log function, is checked before more complex transformations are used.

Prices are de-trended. This uses the technique of first differences; however, a second difference (or more) will be performed if it helps to remove further trending properties in the series.

Specify the order of the auto-regressive and moving average components. This fixes the number of prior terms to be used in the approximations (not necessarily the same number). In the Box-Jenkins approach, these numbers are usually small, often one for both. Large numbers require a rapidly expanding amount of calculation.

2. Estimation: determining the coefficients

The previous steps were used to reduce the number of auto-regressive and moving average terms necessary to the estimation process. The ARIMA method of solution is one of minimizing the errors in the forecast. In minimization, the method will perform a linear or nonlinear regression on price (depending on the number of coefficients selected), determine the errors in the estimation, and then approximate those errors using a moving average. It will next look at the resulting new error series, attempt to estimate and correct the errors in that one, and repeat the process until it accounts for all price movement. Once the coefficients have been determined, they are used to calculate the forecast value.[31]

[31] Kaufman, *Trading Systems and Methods*, 55-60

Since the appearance of the book by Box and Jenkins (1976), the use of auto regressive moving average (ARMA) models are used in many areas of forecasting. It includes a special case and many other methods, including the various forms of exponential smoothing. The whole Box-Jenkins approach revolves around three basic models: autoregressive (AR), moving average (MA), and mixed auto regressive moving average (ARMA) models. The auto regressive model of order *p* written as $AR_{(p)}$ is defined as:

$$z_t = \theta_1 z_{t-1} + \theta_2 z_{t-2} + \theta_p z_{t-p} + a_t$$

where a_t is the sequence of random or white noise and is assumed that it follows a normal distribution.

The moving average model of order *q* denoted as $MA_{(q)}$ is defined as:

$$z_t = a_t \theta_1 a_{t-1} + \theta_2 a_{t-2} + \theta_q a_{t-q}$$

The mixed auto regressive model of order (*p*, *q*) denoted as $ARMA_{(p,q)}$ is defined as:

$$z_t = \theta_1 z_{t+1} + \theta_2 z_{t-2} + \theta_p z_{t-p} + a_t - \theta_1 a_{t-1} + \theta_2 a_{t-2} + \theta_q a_{t-q}$$ [32]

[32] Mohammed Ahmed Ali Alsaleh, "On Forecasting Exchange Rate: A Time Series Analysis." http://www.statistics.gov.uk/IAOSlondon2002/contributed_papers/downloads/CP_Alsaleh.pdf+on+forecasting+exchange+rate+a+time+series+analysis&hl=en&ct=clnk&cd=1&gl=us (accessed 9 March 2009).

3.1.4 Simple Moving Average

Moving average techniques forecast demand by calculating an average of actual demands from a specified number of prior periods. For each new forecast, the demand drops in the oldest period and replaces it with the demand in the most recent period; thus, the data in the calculation "moves" over time.

Simple moving average can be viewed as:

$$A_t = D_t + D_{t-1} + D_{t-2} + \dots + D_{t-N+1} \div N$$

where $\underline{N}$ = total number of periods in the average.

Forecast for period:

$$t + 1: F_{t+1} = A_t$$

The key decision that needs to be made for $\underline{N}$ is how many periods should be considered in the forecast. The higher the value of $\underline{N}$, the greater the smoothing and lower the responsiveness. The lower the value of $\underline{N}$, the lesser amount of smoothing and responsiveness. The more periods ($\underline{N}$) over which the moving average is calculated, the less susceptible the forecast is to random variations, but the less responsive it is to changes.

A large value of $\underline{N}$ is appropriate if the underlying pattern of demand is stable. A smaller value of $\underline{N}$ is appropriate if the underlying pattern is changing or if it is important to identify short-term fluctuations.

3.1.5 Exponential Smoothing

Exponential smoothing gives greater weight to demand in more recent periods and less weight to demand in earlier periods:

$$MA: A_t = a\,D_t + (1 - a)A_{t-1} = a\,D_t + (1 - a)F_t$$

Forecast for period:

$$t + 1: F_{t+1} = A_t$$

where A_{t-1} = "series average" calculated by the exponential smoothing model to period t-1, and a = smoothing parameter between 0 and 1.

The larger the smoothing parameter, the greater the weight given to the most recent demand will be.

3.1.6 Mean Square Error & Root Square Error

The Mean Squared Error (MSE) is a measure of how close a fitted line is to data points. For every data point, you take the distance vertically from the point to the corresponding *y* value on the curve fit (the error) and then square the value. Then, add all those values for all data points and divide by the number of points. The squaring is done so that negative values do not cancel positive values. The smaller the MSE, the closer the fit is to the data. The MSE has the units squared of what is plotted on the vertical axis. The MSE can be calculated by taking the actual minus the forecast, divided by the actual.

Another quantity that we calculate is the Root Mean Squared Error (RMSE). It is the square root of the mean square error. This is probably the most easily interpreted statistic since it has the same units as the quantity plotted on the vertical axis. The RMSE is, therefore, the distance, on average, of a data point from the fitted line, measured along a vertical line.

The RMSE is directly interpretable in terms of measurement units, and, thus, is a better measure of goodness of fit than a correlation coefficient. One can compare the RMSE to observed variation in measurements of a typical point. The two should be similar for a reasonable fit.

3.1.7 Theil's U Statistic

Theil's U statistic is a relative accuracy measure that compares the forecasted results with a naïve forecast. It can be calculated by taking the standard error of the forecasting model and dividing it by the standard error of the naïve model. The naïve model can be a random number or random walk model. It also squares the deviations to give more weight to large errors and to exaggerate errors, which can help eliminate methods with large errors. The closer the value of U is to zero, the better the forecast method. A value of 1 means the forecast is no better than a naïve guess.

Thiel's inequality coefficient, also known as Thiel's U, provides a measure of how well a time series of estimated values compares to a corresponding time series of observed values. The statistic measures the degree to which one time series ({Xi}, i = 1,2,3, ...n) differs from another ({Yi}, i = 1, 2, 3, ...n). Thiel's U is calculated as:

$$U = \frac{\sqrt{\frac{1}{n}\sum_i (X_i - Y_i)^2}}{\sqrt{\frac{1}{n}\sum_i X_i^2} + \sqrt{\frac{1}{n}\sum_i Y_i^2}}$$ [33]

3.2 Model Comparisons

Our analysis included 124 quarterly observations from 1980 to 2010, as well as four different countries' variables. The countries include the United States, Great Britain, Japan, and Canada. We tested the data using several methodologies.

Exponential smoothing was used at alpha levels .1, .5, and .9. The forecast was derived by multiplying the previous quarter's exchange rate by the alpha rate plus the previous quarter forecasted rate multiplied by the remainder of the alpha.

Another method of forecast used was moving average. The calculation simply uses the average of the quarters (current quarter and previous two).

The random walk methodology was also used in forecasting the exchange rates. The formula used to derive the forecast is RAND() * (b-a) + a, where *b* is the high value of the data set and *a* is the low value of the data set.

The univariate and transfer function forecasts were derived using BMDP statistical software.

[33] Friedhelm Bliemel, "Theil's Forecast Accuracy Coefficient: A Clarification." *The Journal of Marketing Research,* Vol. 10, 4 (Nov. 1973): 444-446.

3.3 Data Elements

The financial data used was gathered from the Federal Reserve Bank of St Louis. The variables of foreign exchange rate, gross domestic product, and Consumer Price Index included quarterly data ranging from the year 1980 to 2010.[34] The forecasts begin in the first quarter of 2011.

The foreign exchange rates are averages of daily figures based on noon buying rates in New York City for cable transfers payable in foreign currencies. The rate is based on one domestic unit of currency to one foreign unit of currency. The Consumer Price Index includes all items in the specific country and is not seasonally adjusted. These units are based out of 100 and use a quarterly average aggregate method. Gross domestic product figures are seasonally adjusted and a quarterly amount of millions of the local currency, except in the country of Japan, which uses billions of local currency.

4.0 Analysis of Tables

The results of the analysis are summarized in Tables 4.1.A–4.1.C. The tables provide a list of selection criteria analyzed and their forecasted values over a period of seven quarters. For each category, the three different currencies were screened. Forecasted returns for each quarter year were calculated for the different methods according to the calculated value.

[34] Federal Reserve Bank of St. Louis. "FRED Economic data." http://research.stlouisfed.org/fred2 (accessed March 11, 2009).

4.1 Forecast Methods

To assess the forecasts, we used exponential smoothing, moving average, random walk model, a univariate and transfer function model calculated using Box-Jenkins. Finally, we present a comparative analysis between the forecast methods based against the actual currency price of that time period. [35]

Associated with the point estimate of each parameter in a Box-Jenkins model is its standard error and t-value. Let θ denote any particular parameter in a Box-Jenkins model. Let $\hat{\theta}$ denote the point estimate of θ and $s_{\hat{\theta}}$ denote the standard error of the point estimate $\hat{\theta}$. Then, the t-value associated with $\hat{\theta}$ is calculated by the equation, $t_{\hat{\theta}} = \frac{\hat{\theta}}{s_{\hat{\theta}}}$.

If the absolute value of $t_{\hat{\theta}}$ is "large," then $\hat{\theta}$ is "large." This implies that θ does not equal zero, and thus, that we should reject H_0:θ= 0, which implies that we should include the parameter θ in the Box-Jenkins model.

To decide how large $t_{\hat{\theta}}$ must be before we reject H_0:θ= 0, we consider the errors that can be made in testing. A Type I error is committed if we reject H_0:θ= 0 when H_0:θ= 0 is true. A Type II error is committed if we do not reject H_0:θ= 0 when H_0:θ= 0 is false. We desire that both the probability of a Type I error, and the probability of a Type II error be small. [36] We are looking at the model to discern that there is no pattern left in the model or white noise.

[35] The exponential smoothing technique takes the previous period's forecast and adjusts up or down by calculating a weighted average of the two values. For this study, exponential smoothing was calculated at alphas of .1, .5, and .9. Moving average was calculated by using a rolling average where each value possessed the same weight. The random walk model was simply taking a random walk formula in excel to predict future value based against the actual foreign exchange rate for each currency. The univariate and multivariate forecast (transfer function) was derived by using a Box-Jenkins model and calculated using BMDP software.

[36] Bruce L. Boweman and Richard T. O'Connell, *Time Series Forecasting: Unified Concepts and Computer Implementation* (Boston: PWS Publishers. 1987), 138-139.

For the Canadian currency, the moving average forecast appears to outperform the multivariate transfer function as well as the other forecasts. Out of the nine evaluations, moving average figures are the lowest in all except for standard deviation and root mean square error. The moving average is simply taking the previous forecasts and averaging them to calculate the current forecast. We also are able to determine that the T-Ratios are significant, given the value of the Chi Square at the given level of alpha .05 and the given degrees of freedom in Table 4.1.A. We can then assume that the observed relationship between the variables exist and reject the null hypothesis.

Table 4.1.A

	Standard Deviation	*Theil's U1*	*Theil's U2*	*Mean Absolute Deviation*	*Mean Square Error*	*Tracking Signal*	*Mean Absolute Percent Error*	*Cumulative Forecast Error*	*Root Mean Square Error*
Exp Smoothing CAD Alpha = .1	**0.0170**	**0.0085**	**1.0233**	**0.0203**	**0.0006**	**0.8387**	**2.0900%**	**0.0203**	**0.0240**
Exp Smoothing CAD Alpha = .5	**0.0199**	**0.0100**	**1.3660**	**0.0235**	**0.0008**	**1.7826**	**2.3696%**	**0.0567**	**0.0288**
Exp Smoothing CAD Alpha = .9	**0.0136**	**0.0074**	**6.8057**	**0.1578**	**0.0253**	**-3.5000**	**15.8556%**	**-0.5751**	**0.1590**
Moving Average CAD	**0.0138**	**0.0069**	**0.7962**	**0.0153**	**0.0004**	**1.1730**	**1.5307%**	**0.0241**	**0.0195**
Random Walk CAD	**0.0181**	**0.0091**	**1.0889**	**0.0214**	**0.0007**	**1.8069**	**2.1701%**	**0.0533**	**0.0263**
Univariate CAD	**0.0142**	**0.0073**	**2.0029**	**0.0375**	**0.0018**	**-3.5000**	**3.7233%**	**-0.1054**	**0.0425**
Transfer Function CAD	**0.0181**	**0.0093**	**2.5603**	**0.0476**	**0.0029**	**-3.5000**	**4.7276%**	**-0.1293**	**0.0540**

For the British Pound, the exponential smoothing forecast at alpha .1 appears to outperform the univariate and multivariate Box-Jenkins forecasts. The exponential smoothing forecast is calculated by multiplying .9 by the previous period actual foreign exchange value, and then multiplying that by (.1 x previous period forecasted foreign exchange rate). Exponential smoothing at alpha .1 was the best forecast in six out of the nine parameters. We also are able to determine that the T-Ratios are significant, given the value of the Chi Square at the given level of alpha .05 and the given degrees od freedom in Table 4.1.B. We can then assume that the observed relationship between their variables exist and reject the null hypothesis.

Table 4.1.B

	Standard Deviation	Theil's U1	Theil's U2	Mean Absolute Deviation	Mean Square Error	Tracking Signal	Mean Absolute Percent Error	Cumulative Forecast Error	Root Mean Square Error
Exp Smoothing GBP Alpha = .1	**0.0404**	**0.0128**	**0.5489**	**0.0539**	**0.0050**	**2.7468**	**3.6085%**	**0.1815**	**0.0707**
Exp Smoothing GBP Alpha = .5	**0.0410**	**0.0130**	**0.5891**	**0.0566**	**0.0047**	**2.2021**	**3.7601%**	**0.1443**	**0.6885**
Exp Smoothing GBP Alpha = .9	**0.0535**	**0.0187**	**3.3026**	**0.2505**	**0.0685**	**-3.5000**	**16.0059%**	**-0.0941**	**0.2617**
Moving Average GBP	**0.0432**	**0.0137**	**0.6094**	**0.0603**	**0.0054**	**2.4212**	**4.0124%**	**0.1773**	**0.0737**
Random Walk GBP	**0.0495**	**0.0157**	**0.8147**	**0.0714**	**0.0075**	**2.4747**	**4.7474%**	**0.1861**	**0.0865**
Univariate GBP	**0.0522**	**0.0167**	**0.6779**	**0.0663**	**0.0062**	**1.4789**	**4.3698%**	**0.1218**	**0.0786**
Transfer Function GBP	**0.0585**	**0.0189**	**0.8142**	**0.0677**	**0.0071**	**0.0065**	**4.3725%**	**0.0098**	**0.0842**

For Japanese Yen, the moving average forecast appears to be best among the forecasts. The moving average forecast outperformed the other forecasts in slightly over half of the parameters. We also are able to determine that the T-Ratios are significant, given the value of the Chi Square at the given level of alpha .05 and the given degrees of freedom in Table 4.1.C. We can then assume that the observed relationship between the variables exist and reject the null hypothesis.

Table 4.1.C

	Standard Deviation	Theil's U1	Theil's U2	Mean Absolute Deviation	Mean Square Error	Tracking Signal	Mean Absolute Percent Error	Cumulative Forecast Error	Root Mean Square Error
Exp Smoothing JPY Alpha = .1	**1.9918**	**0.0107**	**0.9737**	**2.6771**	**8.8632**	**1.4757**	**2.8724%**	**4.6088**	**2.9771**
Exp Smoothing JPY Alpha = .5	**1.7186**	**0.0091**	**0.9913**	**2.7494**	**10.2615**	**2.6271**	**2.9765%**	**8.3042**	**3.2034**
Exp Smoothing JPY Alpha = .9	**6.2553**	**0.0424**	**12.6529**	**38.8613**	**1588.4584**	**-0.3500**	**41.6631%**	**-150.6484**	**39.8550**
Moving Average JPY	**1.7440**	**0.0095**	**0.6896**	**2.3400**	**8.1923**	**2.3246**	**2.5217%**	**6.7550**	**2.8622**
Random Walk JPY	**1.8479**	**0.0096**	**2.6942**	**6.7550**	**52.4595**	**3.5000**	**7.3350%**	**20.3550**	**7.4290**
Univariate JPY	**1.7422**	**0.0095**	**1.0914**	**2.4176**	**10.0956**	**-0.3027**	**2.5489%**	**-9.7251**	**3.1774**
Transfer Function JPY	**3.5126**	**0.0205**	**5.8488**	**14.8765**	**245.9856**	**-3.5000**	**16.0677%**	**-44.2914**	**15.6839**

5.0 Conclusion and Recommendations

From the results of our analysis we draw some useful conclusions about forecasting techniques related to foreign exchange prices. Our analysis focused on answering the following questions.

Are there different methods used in order to forecast different currencies? Although it is impossible to forecast the unknown, our analysis shows that there are different forecasting methods that proved to forecast better for the specific currencies. There are several factors that can be used to forecast exchange rates. The exchange market itself can be a major contributing factor as to the type of forecast method used. For example, if a currency uses a pegged or fixed exchange rate, where the local currency is compared to a specific single currency, a single measure of value, or another specific measure of value, that forecast will differ significantly from a floating exchange rate system. In a floating exchange rate system, the value of a currency is determined by the market. Because there are a wide array of variables and conditions that can affect foreign exchange rates, it is best to forecast using several methods in order to determine the best fit for that specific local currency.

Is forecasting feasible? Forecasting is not only feasible, but in some cases necessary. Whether it’s a foreign exchange trade made for profit or borrowing currency from a foreign bank for business purposes, it is necessary to account for different local factors such as inflation, government restrictions, and weather catastrophes. We see evidence of this in the United States. With the rewriting of Basel III, and the introduction of the Volker Rule, currency trading in the United States now has specific restrictions that can impact currency trading.

This leads to the question: what variables should be used? There are many variables that can be used in currency forecasting. The main variable has to be current and past prices. There is a consensus that the best forecast of a currency is its previous and current value. Gross domestic product will give you a value of all the final goods and services provided by a country. Currency prices tend to move in the same direction as GDP. Two other variables that are linked are inflation and money supply. When inflation occurs, the buying value of a currency unit erodes. Money supply and inflation are linked because a high quantity of money usually devalues demand for money.

Political variables may also play a role in determining the price of a currency. Governments may lean towards a fixed exchange rate system to control the prices. A central bank can also buy and sell domestic currency to stabilize it as it deems ideal.

Growing tensions and possible conflict will also result in instability in the foreign exchange market. In general, the more stable the country is, the more stable its currency will be.

The ultimate question is: how accurate are these models when compared to a random prediction of future exchange rates, and what variables, if any, allow for the most accurate prediction?

We wanted to investigate whether a transfer function model, which uses multiple variables, was more accurate in forecasting as opposed to using simple methods that looked at one variable, which was the past and current price. There are several factors that can contribute to the movement of currency price. Some may directly impact price, while others may play a role in speculation, which cannot be foreseen.

Balance of payments of a country will cause the exchange rate of its domestic currency to fluctuate, as well as supply and demand of foreign currencies. This is the reason behind GDP as a variable for our model.

When a country's key interest rate rises higher or falls lower than that of another country, the currency of the nation with the lower interest rate will be sold and the other currency will be bought to gain higher returns. In order to account for interest rate changes, we used the Consumer Price Index to gauge the fluctuation of rates.

Given the data and results in Table 4.1.A, 4.1.B, and 4.1.C, moving average was the best forecast in predicting foreign exchange rates for two of the three currencies used in this study. The tables show the mean scores of the forecasted values made up over three quarters. We attempted to prove that a transfer function model given multiple variables would outperform more simplistic methods. This proved to be untrue.

The foreign exchange market does not always follow a logical pattern of change. Rates are sometimes also affected by emotions, judgments, and politics. Forecasts based solely on data are not adequate to determine price. You also must be able to determine possible market information to the release of new data. Most foreign exchange transactions are actual speculative trades that cause movement in the actual rates. Until there becomes a method to forecast speculation, it appears the best forecasts of foreign exchange rates rest with current and past prices.

Table 4-2

TRANSFER FUNCTION												
Parameter	Variable	Type	Factor	Order	Estimate	St Err	T-Ratio					
1	CADFX	MA	1	1	-0.4059	0.0842	-4.82					
2	CADFX	MA	1	3	-0.1537	0.0852	-1.8					
3	CADFX	TRND	1	0	-0.007988E-02	0.0042	-1.9					
4	CADCPI	UP	1	0	0.8974E-02	0.0039	2.29					
5	CADGDP	UP	1	0	0.6215E-06	0	1.93					
12 Observations 5 Parameters = 7 Degrees of Freedom												
24 Observations - 5 Parameters = 19 Degrees of Freedom												
25 Observations - 5 Parameters = 20 Degrees of Freedom												
1-12 LBQ	0.1	0.3	0.4	3.3	5	6.3	8	8.5	8.5	8.5	9.5	9.5
13-24 LBQ	11	12	12	12	12	17	18	18	19	21	21	21
25 LBQ	21											
Q Statistic Chi Squared												
7	14.0671											
19	30.1435											
20	31.4104											
UNIVARIATE												
Parameter	Variable	Type	Factor	Order	Estimate	St Err	T-Ratio					
1	CADFX	MA	1	1	-0.3977	0.0824	-4.83					
2	CADFX	MA	1	3	-0.1951	0.0832	-2.35					
12 Observations 2 Parameters = 10 Degrees of Freedom												
24 Observations - 2 Parameters = 22 Degrees of Freedom												
25 Observations - 2 Parameters = 23 Degrees of Freedom												
1-12 LBQ	0	0.1	0.1	2.7	6.9	7.1	7.8	9.5	9.6	9.7	9.8	9.8
13-24 LBQ	12	13	13	13	13	16	16	17	17	18	19	19
25 LBQ	19											
Q Statistic Chi Squared												
10	21.0261											
22	35.1725											

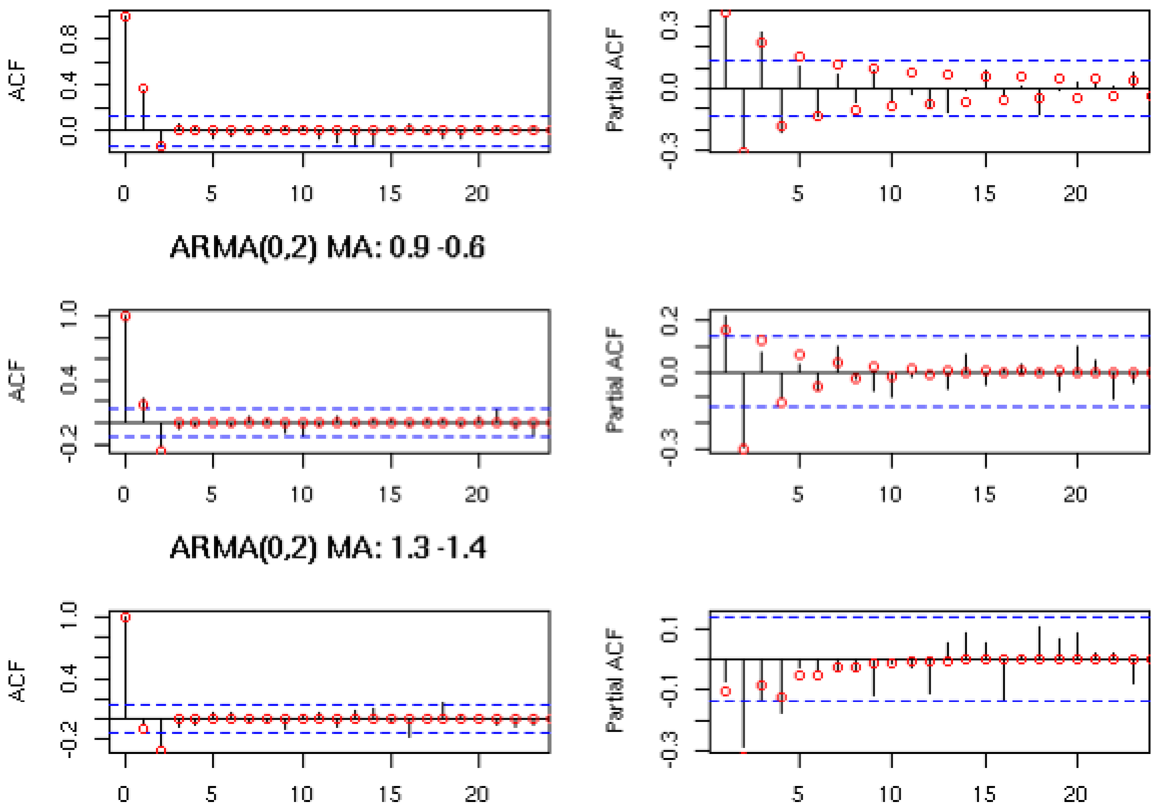
Table 4-3

TRANSFER FUNCTION												
Parameter	Variable	Type	Factor	Order	Estimate	St Err	T-Ratio					
1	JPYFX	MA	1	1	-0.49	0.0867	-5.65					
2	JPYFX	TRND	1	0	0.8710E-02	0.0057	1.51					
3	JPYCPI	UP	1	0	0.7213E-02	0.0043	1.68					
4	JPYGDP	UP	1	0	-0.2082E-05	0	-2.56					
12 Observations 4 Parameters = 8 Degrees of Freedom												
24 Observations - 4 Parameters = 20 Degrees of Freedom												
25 Observations - 4 Parameters = 21 Degrees of Freedom												
1-12 LBQ	2.3	7.1	13	13	14	14	14	14	15	15	16	17
13-24 LBQ	23	26	26	30	31	32	32	32	32	35	35	36
25 LBQ	43											
Q Statistic Chi Squared												
8	15.5073											
20	31.4104											
21	32.6705											
UNIVARIATE												
Parameter	Variable	Type	Factor	Order	Estimate	St Err	T-Ratio					
1	JPYFX	MA	1	1	-0.4215	0.0857	-4.92					
12 Observations 1 Parameters – 11 Degrees of Freedom												
24 Observations - 1 Parameters = 23 Degrees of Freedom												
25 Observations - 1 Parameters = 24 Degrees of Freedom												
1-12 LBQ	0.2	0.3	1.7	1.8	2	3.3	4	4	4.3	5	5.2	5.3
13-24 LBQ	13	15	21	22	22	22	22	22	23	24	24	24
25 LBQ	24											
Q Statistic Chi Squared												
11	22.3621											
23	36.4151											
24	37.6525											

Table 4-4

TRANSFER FUNCTION													
Parameter	Variable	Type	Factor	Order	Estimate	St Err	T-Ratio						
1	UKFX	MA	1	1	-0.3471	0.0864	-4.02						
2	UKFX	TRND	1	0	-0.9669E-02	0.0135	-0.72						
3	UKCPI	UP	1	0	-0.3259E-03	0.0103	-0.03						
4	UKGDP	UP	1	0	0.3541E-05	0	0.76						
12 Observations4 Parameters = 8 Degrees of Freedom													
24 Observations - 4 Parameters = 20 Degrees of Freedom													
25 Observations - 4 Parameters = 21 Degrees of Freedom													
1-12 LBQ	0.10	1.40	1.50	1.50	2.50	4.40	5.20	5.30	6.30	6.30	6.40	6.50	
13-24 LBQ	7.1	8.3	8.8	18	18	19	19	22	25	25	30	31	
25 LBQ	31												
Q Statistic Chi Squared													
8	15.5073												
20	31.4104												
21	32.6705												
UNIVARIATE													
Parameter	Variable	Type	Factor	Order	Estimate	St Err	T-Ratio						
1	UKFX	MA	1	1	-0.368	0.084	-4.38						
12 Observations1 Parameter = 11 Degrees of Freedom													
24 Observations - 1 Parameter = 23 Degrees of Freedom													
25 Observations - 1 Parameter = 24 Degrees of Freedom													
1-12 LBQ	0.10	0.80	0.90	1.00	1.80	3.50	3.90	4.00	4.70	4.70	4.80	5.00	
13-24 LBQ	5.7	7.2	7.2	16	16	17	17	21	23	23	29	29	
25 LBQ	29												
Q Statistic Chi Squared													
11	22.3621												
23	36.4151												
24	37.6525												

Figure 3-4: ACF and PACF for a MA(2) process



The diagnostic patterns of ACF and PACF for an AR model are:
ACF: declines in geometric progression from its highest value at lag 1

PACF: cuts off abruptly after lag 1
The opposite types of patterns apply to an MA process:
ACF: cuts off abruptly after lag 1

PACF: declines in geometric progression from its highest value at lag 1

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7.0 Appendix

UK Transfer Function Output

```
SUMMARY OF THE MODEL

 OUTPUT VARIABLE -- UKFX
 INPUT VARIABLES -- NOISE    UKCPI    UKGDP


 PARAMETER VARIABLE   TYPE  FACTOR  ORDER ESTIMATE        ST. ERR.  T-RATIO
       1  UKFX         MA      1      1    -0.3473         0.0864     -4.02
       2  UKFX        TRND     1      0    -0.9614E-02     0.0135     -0.71
       3  UKCPI        UP      1      0    -0.3193E-03     0.0103     -0.03
       4  UKGDP        UP      1      0     0.3512E-05     0.0000      0.76


 ESTIMATION BY BACKCASTING METHOD

 RELATIVE CHANGE IN RESIDUAL SUM OF SQUARES LESS THAN 0.5000E-04


 SUMMARY OF THE MODEL

 OUTPUT VARIABLE -- UKFX
 INPUT VARIABLES -- NOISE    UKCPI    UKGDP


 PARAMETER VARIABLE   TYPE  FACTOR  ORDER ESTIMATE        ST. ERR.  T-RATIO
       1  UKFX         MA      1      1    -0.3471         0.0864     -4.02
       2  UKFX        TRND     1      0    -0.9669E-02     0.0135     -0.72
       3  UKCPI        UP      1      0    -0.3259E-03     0.0103     -0.03
       4  UKGDP        UP      1      0     0.3541E-05     0.0000      0.76



ACF           Var is UKFXresidb.   Maxlag is 25. lbq./


 AUTOCORRELATIONS

   1- 12    -.03 -.10 -.04  0.0 -.09  .12  .08 -.04 -.08 -.02  .03  .02
   ST.E.     .09  .09  .09  .09  .09  .09  .09  .09  .09  .09  .09  .09
 L.-B. Q     .10  1.4  1.5  1.5  2.5  4.4  5.2  5.3  6.3  6.3  6.4  6.5

  13- 24    -.07  .11 -.01 -.25  .02  .07  .02 -.15  .13 -.04 -.19 -.03
   ST.E.     .09  .09  .10  .10  .10  .10  .10  .10  .10  .10  .10  .11
 L.-B. Q     7.1  8.8  8.8  18.  18.  19.  19.  22.  25.  25.  30.  31.

  25- 25     .04
   ST.E.     .11
 L.-B. Q     31.
```

```
 PLOT OF AUTOCORRELATIONS

           -1.0 -0.8 -0.6 -0.4 -0.2  0.0  0.2  0.4  0.6  0.8  1.0
 LAG   CORR. +----+----+----+----+----+----+----+----+----+----+
                                     I
   1  -0.028                     +  XI   +
   2  -0.099                     + XXI   +
   3  -0.037                     +  XI   +
   4   0.004                     +   I   +
   5  -0.086                     + XXI   +
   6   0.121                    +    IXXX +
   7   0.075                    +    IXX  +
   8  -0.036                    +   XI    +
   9  -0.082                    +  XXI    +
  10  -0.018                    +    I    +
  11   0.033                    +    IX   +
  12   0.022                    +    IX   +
  13  -0.068                    +  XXI    +
  14   0.109                    +    IXXX +
  15  -0.008                    +    I    +
  16  -0.250                   X+XXXXI    +
  17   0.024                    +    IX   +
  18   0.074                    +    IXX  +
  19   0.018                    +    I    +
  20  -0.148                    +XXXXI    +
  21   0.129                    +    IXXX +
  22  -0.040                    +   XI    +
  23  -0.192                    XXXXXI    +
  24  -0.033                    +   XI    +
  25   0.040                    +    IX   +


PACF          Var is UKFXresidb.   Maxlag is 25./


 PARTIAL AUTOCORRELATIONS

   1- 12    -.03 -.10 -.04 -.01 -.10  .12  .07 -.02 -.06 -.03  .04  .01
   ST.E.     .09  .09  .09  .09  .09  .09  .09  .09  .09  .09  .09  .09

  13- 24    -.09  .10  0.0 -.23  .02  .01  .04 -.17  .09  .01 -.18 -.06
   ST.E.     .09  .09  .09  .09  .09  .09  .09  .09  .09  .09  .09  .09

  25- 25    -.04
   ST.E.     .09
```

```
PLOT OF PARTIAL AUTOCORRELATIONS

          -1.0 -0.8 -0.6 -0.4 -0.2  0.0  0.2  0.4  0.6  0.8  1.0
LAG   CORR. +----+----+----+----+----+----+----+----+----+----+
                                     I
  1  -0.028                      +  XI   +
  2  -0.100                      +XXXI   +
  3  -0.043                      +  XI   +
  4  -0.008                      +   I   +
  5  -0.095                      + XXI   +
  6   0.115                      +   IXXX+
  7   0.066                      +   IXX +
  8  -0.015                      +   I   +
  9  -0.062                      + XXI   +
 10  -0.031                      +  XI   +
 11   0.037                      +   IX  +
 12   0.013                      +   I   +
 13  -0.086                      + XXI   +
 14   0.105                      +   IXXX+
 15   0.002                      +   I   +
 16  -0.231                    XX+XXXI   +
 17   0.017                      +   I   +
 18   0.011                      +   I   +
 19   0.036                      +   IX  +
 20  -0.166                      XXXXI   +
 21   0.091                      +   IXX +
 22   0.006                      +   I   +
 23  -0.183                     X+XXXI   +
 24  -0.063                      + XXI   +
 25  -0.044                      +  XI   +

CCF          Var are Rx, UKFXresidb.  Maxlag is 24./

CORRELATION        OF Rx          AND UKFXresi  IS   -0.02

CROSS CORRELATIONS OF Rx      (I) AND UKFXresi(I+K)

  1- 12    -.06  .09 -.09  .12  .15 -.18  .03  0.0 -.08 -.11  0.0 -.06
  ST.E.     .09  .09  .09  .09  .09  .09  .09  .09  .10  .10  .10  .10

 13- 24    -.04  .05 -.06 -.01 -.08 -.12  .01  0.0  .06  .04  .02 -.11
  ST.E.     .10  .10  .10  .10  .10  .10  .10  .10  .10  .10  .10  .10

CROSS CORRELATIONS OF UKFXresi(I) AND Rx      (I+K)

  1- 12     .06 -.01  .08  .04 -.01  .14  .03 -.02 -.22  .11 -.08  .10
  ST.E.     .09  .09  .09  .09  .09  .09  .09  .09  .10  .10  .10  .10

 13- 24     .11  .13  0.0 -.04  .09  .08 -.01  .08 -.05 -.07 -.01  .05
  ST.E.     .10  .10  .10  .10  .10  .10  .10  .10  .10  .10  .10  .10
```

TRANSFER FUNCTION WEIGHTS

LAG	SCCF(X(I),Y(I+K)) *SY/SX	*SX/SY	SCCF(Y(I),X(I+K)) *SY/SX	*SX/SY
0	−0.00292	−0.08726	−0.00292	−0.08726
1	−0.01177	−0.35226	0.01044	0.31248
2	0.01729	0.51751	−0.00243	−0.07266
3	−0.01650	−0.49376	0.01494	0.44713
4	0.02141	0.64055	0.00727	0.21753
5	0.02695	0.80649	−0.00115	−0.03442
6	−0.03338	−0.99881	0.02538	0.75963
7	0.00597	0.17869	0.00608	0.18196
8	0.00079	0.02351	−0.00421	−0.12611
9	−0.01453	−0.43489	−0.04003	−1.19788
10	−0.02062	−0.61699	0.02050	0.61348
11	0.00077	0.02292	−0.01407	−0.42100
12	−0.01052	−0.31485	0.01804	0.53986
13	−0.00703	−0.21048	0.02009	0.60106
14	0.00830	0.24830	0.02301	0.68851
15	−0.01078	−0.32261	−0.00061	−0.01817
16	−0.00233	−0.06978	−0.00821	−0.24557
17	−0.01479	−0.44268	0.01651	0.49405
18	−0.02276	−0.68096	0.01478	0.44236
19	0.00112	0.03341	−0.00260	−0.07775
20	0.00020	0.00602	0.01503	0.44984
21	0.01069	0.32001	−0.00949	−0.28398
22	0.00675	0.20192	−0.01223	−0.36586
23	0.00315	0.09441	−0.00125	−0.03743
24	−0.01924	−0.57572	0.00980	0.29320

WHERE X(I) IS THE FIRST SERIES, Y(I) THE SECOND SERIES, SX THE STANDARD ERROR OF X(I), AND SY THE STANDARD ERROR OF Y(I)

```
PLOT OF CROSS CORRELATIONS

          -1.0 -0.8 -0.6 -0.4 -0.2  0.0  0.2  0.4  0.6  0.8  1.0
 LAG   CORR. +----+----+----+----+----+----+----+----+----+----+
                                    I
 -24   0.054                   +    IX   +
 -23  -0.007                   +    I    +
 -22  -0.067                   +  XXI    +
 -21  -0.052                   +   XI    +
 -20   0.082                   +    IXX  +
 -19  -0.014                   +    I    +
 -18   0.081                   +    IXX  +
 -17   0.090                   +    IXX  +
 -16  -0.045                   +   XI    +
 -15  -0.003                   +    I    +
 -14   0.126                   +    IXXX +
 -13   0.110                   +    IXXX +
 -12   0.099                   +    IXX  +
 -11  -0.077                   +  XXI    +
 -10   0.112                   +    IXXX +
  -9  -0.219                   XXXXXI    +
  -8  -0.023                   +   XI    +
  -7   0.033                   +    IX   +
  -6   0.139                   +    IXXX +
  -5  -0.006                   +    I    +
  -4   0.040                   +    IX   +
  -3   0.082                   +    IXX  +
  -2  -0.013                   +    I    +
  -1   0.057                   +    IX   +
   0  -0.016                    +   I   +
   1  -0.064                   +  XXI    +
   2   0.095                   +    IXX  +
   3  -0.090                   +  XXI    +
   4   0.117                   +    IXXX +
   5   0.147                   +    IXXXX+
   6  -0.183                   XXXXXI    +
   7   0.033                   +    IX   +
   8   0.004                   +    I    +
   9  -0.079                   +  XXI    +
  10  -0.113                   + XXXI    +
  11   0.004                   +    I    +
  12  -0.058                   +   XI    +
  13  -0.038                   +   XI    +
  14   0.045                   +    IX   +
  15  -0.059                   +   XI    +
  16  -0.013                   +    I    +
  17  -0.081                   +  XXI    +
  18  -0.124                   + XXXI    +
  19   0.006                   +    I    +
  20   0.001                   +    I    +
  21   0.058                   +    IX   +
  22   0.037                   +    IX   +
  23   0.017                   +    I    +
  24  -0.105                   + XXXI    +
```

```
CCF            Var are Rz, UKFXresidb.  Maxlag is 24./


CORRELATION       OF Rz          AND UKFXresi  IS   -0.06

CROSS CORRELATIONS OF Rz      (I) AND UKFXresi(I+K)

  1- 12     .17  .04  .05 -.11  .07  .05 -.12 -.03  .08  .11 -.14  .11
  ST.E.     .09  .09  .09  .09  .09  .09  .09  .09  .09  .09  .09  .10

 13- 24     0.0 -.08  .07  .02  .09 -.06  .01  .02 -.06 -.06  .17 -.09
  ST.E.     .10  .10  .10  .10  .10  .10  .10  .10  .10  .10  .10  .10

CROSS CORRELATIONS OF UKFXresi(I) AND Rz      (I+K)

  1- 12     .12  .04 -.03  .03 -.01 -.14 -.14  .18  .04 -.15  .02  .14
  ST.E.     .09  .09  .09  .09  .09  .09  .09  .09  .09  .09  .09  .10

 13- 24    -.05 -.03 -.05 -.04 -.01 -.13 -.06 -.13 -.05  .08 -.01 -.12
  ST.E.     .10  .10  .10  .10  .10  .10  .10  .10  .10  .10  .10  .10


TRANSFER FUNCTION WEIGHTS

         SCCF(X(I),Y(I+K))       SCCF(Y(I),X(I+K))
  LAG    *SY/SX     *SX/SY       *SY/SX     *SX/SY

   0    0.00000-1045.97168    0.00000-1045.97168
   1    0.00001 2964.16382    0.00001 2195.97852
   2    0.00000  790.36121    0.00000  781.38202
   3    0.00000  848.15997    0.00000 -486.46616
   4   -0.00001-1953.31458    0.00000  520.46820
   5    0.00000 1278.01343    0.00000 -232.91913
   6    0.00000  927.20282   -0.00001-2583.44189
   7   -0.00001-2157.64502   -0.00001-2580.37134
   8    0.00000 -487.15939    0.00001 3261.94067
   9    0.00000 1508.58594    0.00000  702.39929
  10    0.00001 1978.64709   -0.00001-2614.45215
  11   -0.00001-2484.01025    0.00000  296.38187
  12    0.00001 1928.05713    0.00001 2488.11011
  13    0.00000  -38.79346    0.00000 -930.44269
  14    0.00000-1422.75769    0.00000 -457.82623
  15    0.00000 1227.00415    0.00000 -925.75903
  16    0.00000  405.16898    0.00000 -662.14160
  17    0.00001 1616.67615    0.00000 -219.36798
  18    0.00000-1104.38452   -0.00001-2363.70068
  19    0.00000  243.61572    0.00000-1159.70154
  20    0.00000  431.63895   -0.00001-2369.34058
  21    0.00000-1100.03650    0.00000 -953.98151
  22    0.00000-1070.74438    0.00000 1359.90308
  23    0.00001 3015.40332    0.00000 -181.38884
  24   -0.00001-1676.61523   -0.00001-2064.61060

  WHERE X(I) IS THE FIRST SERIES, Y(I) THE SECOND
  SERIES, SX THE STANDARD ERROR OF X(I), AND SY
  THE STANDARD ERROR OF Y(I)
```

PLOT OF CROSS CORRELATIONS

```
           -1.0 -0.8 -0.6 -0.4 -0.2  0.0  0.2  0.4  0.6  0.8  1.0
 LAG   CORR. +----+----+----+----+----+----+----+----+----+----+
                                      I
 -24  -0.116                     + XXXI    +
 -23  -0.010                     +    I    +
 -22   0.076                     +    IXX  +
 -21  -0.053                     +   XI    +
 -20  -0.133                     + XXXI    +
 -19  -0.065                     +  XXI    +
 -18  -0.132                     + XXXI    +
 -17  -0.012                     +    I    +
 -16  -0.037                     +   XI    +
 -15  -0.052                     +   XI    +
 -14  -0.026                     +   XI    +
 -13  -0.052                     +   XI    +
 -12   0.139                     +    IXXX +
 -11   0.017                     +    I    +
 -10  -0.147                     +XXXXI    +
  -9   0.039                     +    IX   +
  -8   0.183                     +    IXXXXX
  -7  -0.145                     +XXXXI    +
  -6  -0.145                     +XXXXI    +
  -5  -0.013                     +    I    +
  -4   0.029                     +    IX   +
  -3  -0.027                      +  XI   +
  -2   0.044                      +   IX  +
  -1   0.123                      +   IXXX+
   0  -0.059                      +  XI   +
   1   0.166                      +   IXXXX
   2   0.044                      +   IX  +
   3   0.048                      +   IX  +
   4  -0.109                     + XXXI    +
   5   0.072                     +    IXX  +
   6   0.052                     +    IX   +
   7  -0.121                     + XXXI    +
   8  -0.027                     +   XI    +
   9   0.085                     +    IXX  +
  10   0.111                     +    IXXX +
  11  -0.139                     + XXXI    +
  12   0.108                     +    IXXX +
  13  -0.002                     +    I    +
  14  -0.080                     +  XXI    +
  15   0.069                     +    IXX  +
  16   0.023                     +    IX   +
  17   0.091                     +    IXX  +
  18  -0.062                     +  XXI    +
  19   0.014                     +    I    +
  20   0.024                     +    IX   +
  21  -0.062                     +  XXI    +
  22  -0.060                     +  XXI    +
  23   0.169                     +    IXXXX+
  24  -0.094                     +  XXI    +
```

```
ARIMA        VAR IS UKCPI. Dforder is 1.
             Arorder is '(4)'.
             Maorder is '(5)'./
```

THE CURRENT MODEL HAS
OUTPUT VARIABLE = UKCPI
INPUT VARIABLE = NOISE

ESTIMATION BY CONDITIONAL LEAST SQUARES METHOD

RELATIVE CHANGE IN RESIDUAL SUM OF SQUARES LESS THAN 0.5000E-04

SUMMARY OF THE MODEL

OUTPUT VARIABLE -- UKCPI
INPUT VARIABLES -- NOISE

PARAMETER	VARIABLE	TYPE	FACTOR	ORDER	ESTIMATE	ST. ERR.	T-RATIO
1	UKCPI	MA	1	5	0.1262	0.0989	1.28
2	UKCPI	AR	1	4	0.8526	0.0457	18.66

```
Forecast     Cases are 25. Join./
```

FORECAST ON VARIABLE UKCPI

PERIOD	FORECASTS	ST. ERR.	ACTUAL	RESIDUAL
125	116.47323	0.45107		
126	117.58923	0.63790		
127	117.80406	0.78127		
128	118.84435	0.90213		
129	119.29721	1.22968		
130	120.24866	1.45550		
131	120.43182	1.65071		
132	121.31873	1.82515		
133	121.70481	2.13439		
134	122.51598	2.38223		
135	122.67213	2.60661		
136	123.42826	2.81315		
137	123.75742	3.11493		
138	124.44897	3.37384		
139	124.58211	3.61425		
140	125.22675	3.83963		
141	125.50738	4.13489		
142	126.09697	4.39827		
143	126.21047	4.64675		
144	126.76007	4.88261		
145	126.99932	5.17086		
146	127.50198	5.43454		
147	127.59875	5.68601		
148	128.06731	5.92682		
149	128.27129	6.20749		

STANDARD ERROR = 0.451065 BY CONDITIONAL METHOD

```
ARIMA        VAR IS UKGDP. Dforder is 1.
             Arorder is '(1)'. /

THE CURRENT MODEL HAS
OUTPUT VARIABLE = UKGDP
INPUT  VARIABLE = NOISE


ESTIMATION BY CONDITIONAL LEAST SQUARES METHOD

RELATIVE CHANGE IN EACH ESTIMATE LESS THAN 0.1000E-03


SUMMARY OF THE MODEL

OUTPUT VARIABLE -- UKGDP
INPUT VARIABLES -- NOISE


PARAMETER VARIABLE   TYPE  FACTOR  ORDER ESTIMATE        ST. ERR.  T-RATIO
     1  UKGDP        AR      1      1     0.7599         0.0585     13.00


Forecast     Cases are 25. Join./


 FORECAST ON VARIABLE UKGDP

 PERIOD          FORECASTS      ST.  ERR.      ACTUAL         RESIDUAL
  125       327644.12500     1436.66895
  126       326470.15600     2908.06494
  127       325578.03100     4442.19971
  128       324900.12500     5969.99756
  129       324384.96900     7456.51367
  130       323993.50000     8885.02246
  131       323696.03100    10248.77540
  132       323469.96900    11546.56150
  133       323298.18800    12780.20020
  134       323167.65600    13953.08890
  135       323068.46900    15069.35550
  136       322993.09400    16133.35550
  137       322935.81200    17149.38870
  138       322892.28100    18121.54490
  139       322859.18800    19053.61720
  140       322834.06200    19949.08590
  141       322814.96900    20811.10350
  142       322800.46900    21642.50980
  143       322789.43800    22445.85350
  144       322781.06200    23223.42190
  145       322774.68800    23977.25590
  146       322769.84400    24709.19140
  147       322766.15600    25420.86130
  148       322763.37500    26113.73830
  149       322761.25000    26789.14060

STANDARD ERROR =  1436.67         BY CONDITIONAL METHOD
```

```
ARIMA        VAR IS UKFX. Dforder is 1.
             MAorder is '(1)'./

THE CURRENT MODEL HAS
OUTPUT VARIABLE = UKFX
INPUT  VARIABLE = NOISE


ESTIMATION BY CONDITIONAL LEAST SQUARES METHOD

RELATIVE CHANGE IN EACH ESTIMATE LESS THAN 0.1000E-03


SUMMARY OF THE MODEL

OUTPUT VARIABLE -- UKFX
INPUT VARIABLES -- NOISE


PARAMETER VARIABLE   TYPE  FACTOR  ORDER ESTIMATE        ST. ERR.  T-RATIO
      1  UKFX         MA      1      1    -0.3679         0.0841     -4.37

 Forecast    Cases are 25./


 FORECAST ON VARIABLE UKFX

 PERIOD          FORECASTS      ST.  ERR.      ACTUAL         RESIDUAL
  125            1.58113        0.07754
  126            1.58113        0.13139
  127            1.58113        0.16887
  128            1.58113        0.19942
  129            1.58113        0.22587
  130            1.58113        0.24954
  131            1.58113        0.27115
  132            1.58113        0.29116
  133            1.58113        0.30988
  134            1.58113        0.32753
  135            1.58113        0.34428
  136            1.58113        0.36025
  137            1.58113        0.37554
  138            1.58113        0.39023
  139            1.58113        0.40439
  140            1.58113        0.41807
  141            1.58113        0.43132
  142            1.58113        0.44417
  143            1.58113        0.45666
  144            1.58113        0.46882
  145            1.58113        0.48067
  146            1.58113        0.49223
  147            1.58113        0.50353
  148            1.58113        0.51458
  149            1.58113        0.52540

STANDARD ERROR = 0.775418E-01     BY CONDITIONAL METHOD


ESTIMATION BY CONDITIONAL LEAST SQUARES METHOD

RELATIVE CHANGE IN RESIDUAL SUM OF SQUARES LESS THAN 0.5000E-04
```

SUMMARY OF THE MODEL

OUTPUT VARIABLE -- UKFX
INPUT VARIABLES -- NOISE UKCPI UKGDP

PARAMETER	VARIABLE	TYPE	FACTOR	ORDER	ESTIMATE	ST. ERR.	T-RATIO
1	UKFX	MA	1	1	-0.3473	0.0864	-4.02
2	UKFX	TRND	1	0	-0.9614E-02	0.0135	-0.71
3	UKCPI	UP	1	0	-0.3193E-03	0.0103	-0.03
4	UKGDP	UP	1	0	0.3512E-05	0.0000	0.76

Forecast Cases are 25./

FORECAST ON VARIABLE UKFX

PERIOD	FORECASTS	ST. ERR.	ACTUAL	RESIDUAL
125	1.57205	0.07822		
126	1.55796	0.13124		
127	1.54515	0.16831		
128	1.53282	0.19858		
129	1.52125	0.22481		
130	1.50996	0.24828		
131	1.49924	0.26972		
132	1.48855	0.28958		
133	1.47821	0.30816		
134	1.46788	0.32568		
135	1.45787	0.34230		
136	1.44775	0.35816		
137	1.43783	0.37334		
138	1.42784	0.38793		
139	1.41807	0.40199		
140	1.40816	0.41557		
141	1.39839	0.42872		
142	1.38854	0.44148		
143	1.37885	0.45389		
144	1.36903	0.46596		
145	1.35932	0.47773		
146	1.34953	0.48921		
147	1.33987	0.50043		
148	1.33010	0.51141		
149	1.32041	0.52215		

STANDARD ERROR = 0.782195E-01 BY CONDITIONAL METHOD

BMDP2T - BOX-JENKINS TIME SERIES ANALYSIS

Statistical Solutions Ltd. | Statistical Solutions
Unit 1A, South Ring Business Park | Stonehill Corporate Center, Suite 104
Kinsale Road, Cork, Ireland | 999 Broadway, Saugus, MA 01906, USA
Phone: + 353 21 4319629 | Phone: 781.231.7680
Fax: + 353 21 4319630 | Fax: 781.231.7684
e-mail: sales@statsol.ie | e-mail: info@statsolusa.com
Website: http://www.statsol.ie | Website: http://www.statsolusa.com

Release: 8.1 (Windows 9x, 2000, Me, Xp) Date: 10/20/12 at 13:25:28
Manual: BMDP Manual Volumes 1, 2, and 3.

```
Digest: BMDP User's Digest.
IBM PC: BMDP PC Supplement -- Installation and Special Features.
```

JPY Transfer Function Output

```
SUMMARY OF THE MODEL

 OUTPUT VARIABLE -- JPYFX
 INPUT VARIABLES -- NOISE    JPYCPI   JPYGDP


 PARAMETER VARIABLE   TYPE  FACTOR  ORDER ESTIMATE        ST. ERR.  T-RATIO
       1  JPYFX        MA      1      1    -0.5497         0.0808     -6.81
       2  JPYFX       TRND     1      0     -1.629         1.1184     -1.46
       3  JPYCPI       UP      1      0     -1.607         0.7302     -2.20
       4  JPYGDP       UP      1      0     0.3078E-03     0.0002      2.05


 ESTIMATION BY BACKCASTING METHOD

 RELATIVE CHANGE IN RESIDUAL SUM OF SQUARES LESS THAN 0.5000E-04


 SUMMARY OF THE MODEL

 PARAMETER VARIABLE   TYPE  FACTOR  ORDER ESTIMATE        ST. ERR.  T-RATIO
       1  JPYFX        MA      1      1    -0.5507         0.0804     -6.85
       2  JPYFX       TRND     1      0     -1.628         1.1212     -1.45
       3  JPYCPI       UP      1      0     -1.607         0.7336     -2.19
       4  JPYGDP       UP      1      0     0.3081E-03     0.0002      2.05


 ACF           Var is JPYFXresidb.   Maxlag is 25. lbq./

 AUTOCORRELATIONS

   1- 12    -.07 -.05  .13  .01  .03 -.16 -.02  .01 -.02  .07  .04 -.01
   ST.E.     .09  .09  .09  .10  .10  .10  .10  .10  .10  .10  .10  .10
 L.-B. Q     .60  .90  2.8  2.8  3.0  6.0  6.1  6.1  6.2  6.8  7.0  7.1

  13- 24    -.19  .09 -.13 -.13  .04 -.13  .10  0.0  .02  .05 -.03 -.03
   ST.E.     .10  .10  .10  .10  .11  .11  .11  .11  .11  .11  .11  .11
 L.-B. Q     12.  13.  16.  18.  18.  20.  22.  22.  22.  22.  22.  22.

  25- 25     .02
   ST.E.     .11
 L.-B. Q     22.
```

```
PLOT OF AUTOCORRELATIONS

          -1.0 -0.8 -0.6 -0.4 -0.2  0.0  0.2  0.4  0.6  0.8  1.0
LAG   CORR. +----+----+----+----+----+----+----+----+----+----+
                                     I
  1  -0.073                    +  XXI    +
  2  -0.048                    +   XI    +
  3   0.126                    +    IXXX +
  4   0.014                    +    I    +
  5   0.029                    +    IX   +
  6  -0.158                    +XXXXI    +
  7  -0.015                    +    I    +
  8   0.014                    +    I    +
  9  -0.025                    +   XI    +
 10   0.071                    +    IXX  +
 11   0.041                    +    IX   +
 12  -0.011                    +    I    +
 13  -0.193                    XXXXXI    +
 14   0.095                    +    IXX  +
 15  -0.131                    + XXXI    +
 16  -0.125                    + XXXI    +
 17   0.041                    +    IX   +
 18  -0.129                    + XXXI    +
 19   0.102                    +    IXXX +
 20  -0.003                    +    I    +
 21   0.022                    +    IX   +
 22   0.049                    +    IX   +
 23  -0.025                    +   XI    +
 24  -0.034                    +   XI    +
 25   0.018                    +    I    +


PACF          Var is JPYFXresidb.   Maxlag is 25./


PARTIAL AUTOCORRELATIONS

  1- 12    -.07 -.05  .12  .03  .04 -.17 -.04 -.01  .02  .09  .07 -.02
  ST.E.     .09  .09  .09  .09  .09  .09  .09  .09  .09  .09  .09  .09

 13- 24    -.24  .04 -.15 -.05  .04 -.09  .06  0.0  .02 -.02  .03 -.09
  ST.E.     .09  .09  .09  .09  .09  .09  .09  .09  .09  .09  .09  .09

 25- 25     .03
  ST.E.     .09
```

```
PLOT OF PARTIAL AUTOCORRELATIONS

          -1.0 -0.8 -0.6 -0.4 -0.2  0.0  0.2  0.4  0.6  0.8  1.0
 LAG   CORR. +----+----+----+----+----+----+----+----+----+----+
                                    I
   1  -0.073                   +  XXI    +
   2  -0.054                   +   XI    +
   3   0.120                   +    IXXX +
   4   0.030                   +    IX   +
   5   0.045                   +    IX   +
   6  -0.170                   +XXXXI    +
   7  -0.043                   +   XI    +
   8  -0.015                   +    I    +
   9   0.017                   +    I    +
  10   0.090                   +    IXX  +
  11   0.068                   +    IXX  +
  12  -0.022                   +   XI    +
  13  -0.242                  X+XXXXI    +
  14   0.042                   +    IX   +
  15  -0.155                   +XXXXI    +
  16  -0.054                   +   XI    +
  17   0.041                   +    IX   +
  18  -0.094                   +  XXI    +
  19   0.059                   +    IX   +
  20  -0.004                   +    I    +
  21   0.021                   +    IX   +
  22  -0.016                   +    I    +
  23   0.026                   +    IX   +
  24  -0.087                   +  XXI    +
  25   0.034                   +    IX   +


 CCF           Var are Rx, JPYFXresidb.  Maxlag is 24./


 CORRELATION        OF Rx          AND JPYFXres  IS    0.02

 CROSS CORRELATIONS OF Rx      (I) AND JPYFXres(I+K)

   1- 12    -.03  .07  .11  0.0 -.04 -.13  .05  .01 -.03 -.08  .01 -.05
   ST.E.     .10  .10  .10  .10  .10  .10  .10  .10  .10  .10  .10  .10

  13- 24    -.12 -.02  .06 -.05  .07  .02  .12 -.03 -.04  .08 -.08  .05
   ST.E.     .10  .10  .10  .10  .10  .10  .10  .10  .11  .11  .11  .11

 CROSS CORRELATIONS OF JPYFXres(I) AND Rx      (I+K)

   1- 12     0.0  .04  .11 -.06  .06 -.14  .03 -.02 -.14  .06  .04 -.24
   ST.E.     .10  .10  .10  .10  .10  .10  .10  .10  .10  .10  .10  .10

  13- 24     .15 -.21 -.12  .07 -.06 -.14  0.0  .04 -.02 -.04 -.04  .02
   ST.E.     .10  .10  .10  .10  .10  .10  .10  .10  .11  .11  .11  .11
```

TRANSFER FUNCTION WEIGHTS

	SCCF(X(I),Y(I+K))		SCCF(Y(I),X(I+K))	
LAG	*SY/SX	*SX/SY	*SY/SX	*SX/SY
0	0.32712	0.00129	0.32712	0.00129
1	−0.45519	−0.00179	0.04122	0.00016
2	1.06297	0.00418	0.68518	0.00269
3	1.80648	0.00710	1.75597	0.00690
4	0.06132	0.00024	−0.92917	−0.00365
5	−0.60187	−0.00236	0.92852	0.00365
6	−2.01049	−0.00790	−2.18333	−0.00858
7	0.73064	0.00287	0.41595	0.00163
8	0.12123	0.00048	−0.25807	−0.00101
9	−0.42877	−0.00168	−2.17425	−0.00854
10	−1.31059	−0.00515	0.91730	0.00360
11	0.19535	0.00077	0.61070	0.00240
12	−0.82290	−0.00323	−3.74991	−0.01473
13	−1.89470	−0.00744	2.42988	0.00955
14	−0.39404	−0.00155	−3.41082	−0.01340
15	0.90936	0.00357	−1.83708	−0.00722
16	−0.80811	−0.00317	1.09116	0.00429
17	1.12752	0.00443	−0.89791	−0.00353
18	0.33669	0.00132	−2.20531	−0.00866
19	1.92400	0.00756	−0.05447	−0.00021
20	−0.42394	−0.00167	0.68925	0.00271
21	−0.68885	−0.00271	−0.36278	−0.00143
22	1.29024	0.00507	−0.68394	−0.00269
23	−1.29312	−0.00508	−0.57641	−0.00226
24	0.73830	0.00290	0.39286	0.00154

WHERE X(I) IS THE FIRST SERIES, Y(I) THE SECOND SERIES, SX THE STANDARD ERROR OF X(I), AND SY THE STANDARD ERROR OF Y(I)

```
PLOT OF CROSS CORRELATIONS

          -1.0 -0.8 -0.6 -0.4 -0.2  0.0  0.2  0.4  0.6  0.8  1.0
 LAG   CORR. +----+----+----+----+----+----+----+----+----+----+
                                    I
 -24   0.025                   +    IX   +
 -23  -0.036                   +   XI    +
 -22  -0.043                   +   XI    +
 -21  -0.023                   +   XI    +
 -20   0.043                   +    IX   +
 -19  -0.003                   +    I    +
 -18  -0.138                   + XXXI    +
 -17  -0.056                   +   XI    +
 -16   0.068                   +    IXX  +
 -15  -0.115                   + XXXI    +
 -14  -0.214                   XXXXXI    +
 -13   0.152                   +    IXXXX+
 -12  -0.235                  X+XXXXI    +
 -11   0.038                   +    IX   +
 -10   0.057                   +    IX   +
  -9  -0.136                   + XXXI    +
  -8  -0.016                   +    I    +
  -7   0.026                   +    IX   +
  -6  -0.137                   + XXXI    +
  -5   0.058                   +    IX   +
  -4  -0.058                   +   XI    +
  -3   0.110                   +    IXXX +
  -2   0.043                   +    IX   +
  -1   0.003                   +    I    +
   0   0.021                   +    IX   +
   1  -0.029                   +   XI    +
   2   0.067                   +    IXX  +
   3   0.113                   +    IXXX +
   4   0.004                   +    I    +
   5  -0.038                   +   XI    +
   6  -0.126                   + XXXI    +
   7   0.046                   +    IX   +
   8   0.008                   +    I    +
   9  -0.027                   +   XI    +
  10  -0.082                   +  XXI    +
  11   0.012                   +    I    +
  12  -0.052                   +   XI    +
  13  -0.119                   + XXXI    +
  14  -0.025                   +   XI    +
  15   0.057                   +    IX   +
  16  -0.051                   +   XI    +
  17   0.071                   +    IXX  +
  18   0.021                   +    IX   +
  19   0.121                   +    IXXX +
  20  -0.027                   +   XI    +
  21  -0.043                   +   XI    +
  22   0.081                   +    IXX  +
  23  -0.081                   +  XXI    +
  24   0.046                   +    IX   +
```

CCF Var are Rz, JPYFXresidb. Maxlag is 24./

CORRELATION OF Rz AND JPYFXres IS -0.04

CROSS CORRELATIONS OF Rz (I) AND JPYFXres(I+K)

1- 12	-.07	.04	-.04	-.07	.05	.08	.05	-.03	.02	.03	-.12	-.08
ST.E.	.09	.10	.10	.10	.10	.10	.10	.10	.10	.10	.10	.10
13- 24	.07	-.11	-.10	.01	.01	-.01	.01	.02	-.02	-.09	.08	.08
ST.E.	.10	.10	.10	.10	.10	.10	.10	.10	.10	.11	.11	.11

CROSS CORRELATIONS OF JPYFXres(I) AND Rz (I+K)

1- 12	-.11	.11	.01	-.01	-.04	-.16	-.06	-.09	.04	-.16	.06	.19
ST.E.	.09	.10	.10	.10	.10	.10	.10	.10	.10	.10	.10	.10
13- 24	-.17	-.02	-.08	0.0	-.05	0.0	-.06	-.03	.21	.05	.09	-.07
ST.E.	.10	.10	.10	.10	.10	.10	.10	.10	.10	.11	.11	.11

TRANSFER FUNCTION WEIGHTS

	SCCF(X(I),Y(I+K))		SCCF(Y(I),X(I+K))	
LAG	*SY/SX	*SX/SY	*SY/SX	*SX/SY
0	-0.00007	-23.96902	-0.00007	-23.96902
1	-0.00013	-41.32352	-0.00019	-62.14023
2	0.00007	22.62374	0.00020	65.91998
3	-0.00006	-20.98981	0.00002	7.08367
4	-0.00012	-40.16748	-0.00001	-4.13804
5	0.00008	27.02754	-0.00006	-20.86771
6	0.00014	44.56573	-0.00028	-93.08356
7	0.00008	26.07324	-0.00011	-35.79874
8	-0.00005	-18.10973	-0.00016	-54.01652
9	0.00004	13.75161	0.00008	24.73916
10	0.00006	18.87581	-0.00028	-91.66356
11	-0.00021	-67.80497	0.00010	32.11078
12	-0.00013	-44.41050	0.00033	108.56485
13	0.00012	39.79807	-0.00029	-95.37443
14	-0.00020	-65.31018	-0.00004	-13.04819
15	-0.00017	-56.27103	-0.00014	-46.45267
16	0.00001	4.70671	0.00001	2.66644
17	0.00002	8.07820	-0.00009	-29.41980
18	-0.00002	-5.45219	0.00000	-0.36783
19	0.00001	3.37085	-0.00011	-36.15593
20	0.00004	12.15178	-0.00005	-17.41155
21	-0.00003	-10.79318	0.00036	118.65149
22	-0.00015	-49.00639	0.00009	28.47079
23	0.00013	43.53536	0.00015	50.03826
24	0.00013	43.28736	-0.00013	-41.71620

WHERE X(I) IS THE FIRST SERIES, Y(I) THE SECOND SERIES, SX THE STANDARD ERROR OF X(I), AND SY THE STANDARD ERROR OF Y(I)

PLOT OF CROSS CORRELATIONS

```
          -1.0 -0.8 -0.6 -0.4 -0.2  0.0  0.2  0.4  0.6  0.8  1.0
 LAG   CORR. +----+----+----+----+----+----+----+----+----+----+
                                    I
 -24  -0.073                    +  XXI    +
 -23   0.087                    +     IXX  +
 -22   0.050                    +     IX   +
 -21   0.207                    +     IXXXXX
 -20  -0.030                    +    XI    +
 -19  -0.063                    +  XXI     +
 -18  -0.001                    +     I    +
 -17  -0.051                    +    XI    +
 -16   0.005                    +     I    +
 -15  -0.081                    +  XXI     +
 -14  -0.023                    +    XI    +
 -13  -0.166                    +XXXXI     +
 -12   0.189                    +     IXXXXX
 -11   0.056                    +     IX   +
 -10  -0.160                    +XXXXI     +
  -9   0.043                    +     IX   +
  -8  -0.094                    +  XXI     +
  -7  -0.062                    +  XXI     +
  -6  -0.162                    +XXXXI     +
  -5  -0.036                    +    XI    +
  -4  -0.007                    +     I    +
  -3   0.012                    +     I    +
  -2   0.115                    +     IXXX +
  -1  -0.108                    + XXXI     +
   0  -0.042                    +    XI    +
   1  -0.072                    +  XXI     +
   2   0.039                    +     IX   +
   3  -0.037                    +    XI    +
   4  -0.070                    +  XXI     +
   5   0.047                    +     IX   +
   6   0.078                    +     IXX  +
   7   0.045                    +     IX   +
   8  -0.032                    +    XI    +
   9   0.024                    +     IX   +
  10   0.033                    +     IX   +
  11  -0.118                    + XXXI     +
  12  -0.077                    +  XXI     +
  13   0.069                    +     IXX  +
  14  -0.114                    + XXXI     +
  15  -0.098                    +  XXI     +
  16   0.008                    +     I    +
  17   0.014                    +     I    +
  18  -0.009                    +     I    +
  19   0.006                    +     I    +
  20   0.021                    +     IX   +
  21  -0.019                    +     I    +
  22  -0.085                    +  XXI     +
  23   0.076                    +     IXX  +
  24   0.075                    +     IXX  +
```

```
ARIMA         VAR IS JPYCPI. Dforder is 1.
              Arorder is '(4)'.
              Maorder is '(2,3,5)'./

THE CURRENT MODEL HAS
OUTPUT VARIABLE = JPYCPI
INPUT  VARIABLE = NOISE



ESTIMATION BY CONDITIONAL LEAST SQUARES METHOD

RELATIVE CHANGE IN RESIDUAL SUM OF SQUARES LESS THAN 0.5000E-04


SUMMARY OF THE MODEL

OUTPUT VARIABLE -- JPYCPI
INPUT VARIABLES -- NOISE


PARAMETER VARIABLE   TYPE  FACTOR  ORDER ESTIMATE        ST. ERR.  T-RATIO
      1  JPYCPI       MA      1      2    -0.2311         0.0986     -2.34
      2  JPYCPI       MA      1      3    -0.9222E-01     0.1018     -0.91
      3  JPYCPI       MA      1      5    -0.3505E-01     0.1033     -0.34
      4  JPYCPI       AR      1      4     0.5931         0.0738      8.04



Forecast      Cases are 25. Join./


 FORECAST ON VARIABLE JPYCPI

 PERIOD          FORECASTS       ST.  ERR.      ACTUAL         RESIDUAL
  125         102.03491       0.46268
  126         102.37516       0.65433
  127         102.88356       0.86751
  128         102.47814       1.06181
  129         102.54932       1.38333
  130         102.75111       1.65190
  131         103.05262       1.91376
  132         102.81218       2.15539
  133         102.85439       2.44503
  134         102.97407       2.70794
  135         103.15289       2.96254
  136         103.01029       3.20260
  137         103.03532       3.46133
  138         103.10630       3.70405
  139         103.21236       3.93935
  140         103.12778       4.16424
  141         103.14263       4.39558
  142         103.18472       4.61638
  143         103.24762       4.83097
  144         103.19746       5.03791
  145         103.20627       5.24606
  146         103.23123       5.44679
  147         103.26853       5.64242
  148         103.23878       5.83229
  149         103.24401       6.02114

STANDARD ERROR = 0.462682         BY CONDITIONAL METHOD
```

```
ARIMA         VAR IS JPYGDP. Dforder is 1.
              Arorder is '(1,2,3)'./

THE CURRENT MODEL HAS
OUTPUT VARIABLE = JPYGDP
INPUT  VARIABLE = NOISE


ESTIMATION BY CONDITIONAL LEAST SQUARES METHOD

RELATIVE CHANGE IN EACH ESTIMATE LESS THAN 0.1000E-03


SUMMARY OF THE MODEL

OUTPUT VARIABLE -- JPYGDP
INPUT VARIABLES -- NOISE


PARAMETER VARIABLE   TYPE  FACTOR  ORDER ESTIMATE        ST. ERR.  T-RATIO
     1  JPYGDP        AR      1      1     0.2204         0.0950      2.32
     2  JPYGDP        AR      1      2     0.1731         0.0956      1.81
     3  JPYGDP        AR      1      3     0.3292         0.0948      3.47


Forecast      Cases are 25. Join./


 FORECAST ON VARIABLE JPYGDP

 PERIOD          FORECASTS      ST.  ERR.      ACTUAL         RESIDUAL
  125       531094.62500     4245.46631
  126       524555.50000     6698.43457
  127       516342.25000     9074.92871
  128       511322.84400    12024.95700
  129       506641.90600    14871.55270
  130       502037.43800    17676.85550
  131       498559.78100    20541.68750
  132       495455.15600    23342.54490
  133       492653.00000    26086.61130
  134       490353.03100    28788.51370
  135       488338.93800    31423.25000
  136       486574.37500    33992.31250
  137       485079.59400    36498.65620
  138       483781.59400    38938.22270
  139       482655.81200    41312.77730
  140       481690.87500    43624.45700
  141       480856.00000    45874.19920
  142       480134.34400    48064.27340
  143       479513.09400    50197.01950
  144       478976.37500    52274.56250
  145       478512.93800    54299.28130
  146       478113.34400    56273.51560
  147       477768.34400    58199.52340
  148       477470.56200    60079.53520
  149       477213.65600    61915.70700

STANDARD ERROR =  4245.47         BY CONDITIONAL METHOD
```

```
ARIMA         VAR IS JPYFX. Dforder is 1.
              MAorder is '(1)'./

THE CURRENT MODEL HAS
OUTPUT VARIABLE = JPYFX
INPUT  VARIABLE = NOISE



ESTIMATION BY CONDITIONAL LEAST SQUARES METHOD

RELATIVE CHANGE IN RESIDUAL SUM OF SQUARES LESS THAN 0.5000E-04


SUMMARY OF THE MODEL

OUTPUT VARIABLE -- JPYFX
INPUT VARIABLES -- NOISE


PARAMETER VARIABLE   TYPE  FACTOR  ORDER ESTIMATE        ST. ERR.  T-RATIO
      1  JPYFX        MA      1      1    -0.4188         0.0859     -4.87



Forecast      Cases are 25./


 FORECAST ON VARIABLE JPYFX

 PERIOD          FORECASTS      ST.  ERR.      ACTUAL         RESIDUAL
  125           90.88712        7.52841
  126           90.88712       13.06772
  127           90.88712       16.87760
  128           90.88712       19.97352
  129           90.88712       22.65016
  130           90.88712       25.04232
  131           90.88712       27.22510
  132           90.88712       29.24541
  133           90.88712       31.13490
  134           90.88712       32.91611
  135           90.88712       34.60576
  136           90.88712       36.21666
  137           90.88712       37.75891
  138           90.88712       39.24058
  139           90.88712       40.66831
  140           90.88712       42.04758
  141           90.88712       43.38303
  142           90.88712       44.67858
  143           90.88712       45.93761
  144           90.88712       47.16304
  145           90.88712       48.35742
  146           90.88712       49.52301
  147           90.88712       50.66179
  148           90.88712       51.77552
  149           90.88712       52.86580

STANDARD ERROR =  7.52841          BY CONDITIONAL METHOD
```

SUMMARY OF THE MODEL

OUTPUT VARIABLE -- JPYFX
INPUT VARIABLES -- NOISE   JPYCPI   JPYGDP

PARAMETER	VARIABLE	TYPE	FACTOR	ORDER	ESTIMATE	ST. ERR.	T-RATIO
1	JPYFX	MA	1	1	-0.5497	0.0808	-6.81
2	JPYFX	TRND	1	0	-1.629	1.1184	-1.46
3	JPYCPI	UP	1	0	-1.607	0.7302	-2.20
4	JPYGDP	UP	1	0	0.3078E-03	0.0002	2.05

Forecast   Cases are 25./

FORECAST ON VARIABLE JPYFX

PERIOD	FORECASTS	ST. ERR.	ACTUAL	RESIDUAL
125	87.71048	7.33469		
126	83.52147	13.52783		
127	78.54692	17.66937		
128	76.02389	21.00978		
129	72.83924	23.88756		
130	69.46825	26.45411		
131	66.28389	28.79279		
132	64.08519	30.95527		
133	61.52542	32.97626		
134	58.99577	34.88034		
135	56.45908	36.68573		
136	54.51568	38.40634		
137	52.38596	40.05311		
138	50.24300	41.63479		
139	48.09668	43.15855		
140	46.30619	44.63031		
141	44.39598	46.05507		
142	42.47684	47.43705		
143	40.55519	48.77990		
144	38.84121	50.08675		
145	37.05505	51.36037		
146	35.26258	52.60315		
147	33.46709	53.81725		
148	31.79387	55.00455		
149	30.07703	56.16676		

STANDARD ERROR = 7.33469   BY CONDITIONAL METHOD

BMDP2T - BOX-JENKINS TIME SERIES ANALYSIS

Statistical Solutions Ltd. | Statistical Solutions
Unit 1A, South Ring Business Park | Stonehill Corporate Center, Suite 104
Kinsale Road, Cork, Ireland | 999 Broadway, Saugus, MA 01906, USA
Phone: + 353 21 4319629 | Phone: 781.231.7680
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e-mail: sales@statsol.ie | e-mail: info@statsolusa.com
Website: http://www.statsol.ie | Website: http://www.statsolusa.com

Release: 8.1 (Windows 9x, 2000, Me, Xp)   Date: 07/11/12 at 18:52:30
Manual: BMDP Manual Volumes 1, 2, and 3.
Digest: BMDP User's Digest.

IBM PC: BMDP PC Supplement -- Installation and Special Features.

CAD Transfer Function Output

```
SUMMARY OF THE MODEL

 OUTPUT VARIABLE -- CADFX
 INPUT VARIABLES -- NOISE    CADCPI   CADGDP


 PARAMETER VARIABLE   TYPE  FACTOR  ORDER ESTIMATE        ST. ERR.  T-RATIO
       1  CADFX        MA      1      1    -0.4039         0.0844     -4.78
       2  CADFX        MA      1      3    -0.1518         0.0856     -1.77
       3  CADFX       TRND     1      0    -0.8067E-02     0.0042     -1.93
       4  CADCPI       UP      1      0     0.8966E-02     0.0039      2.29
       5  CADGDP       UP      1      0     0.6268E-06     0.0000      1.94


 ESTIMATION BY BACKCASTING METHOD

 RELATIVE CHANGE IN RESIDUAL SUM OF SQUARES LESS THAN 0.5000E-04


 SUMMARY OF THE MODEL

 OUTPUT VARIABLE -- CADFX
 INPUT VARIABLES -- NOISE    CADCPI   CADGDP


 PARAMETER VARIABLE   TYPE  FACTOR  ORDER ESTIMATE        ST. ERR.  T-RATIO
       1  CADFX        MA      1      1    -0.4059         0.0842     -4.82
       2  CADFX        MA      1      3    -0.1537         0.0852     -1.80
       3  CADFX       TRND     1      0    -0.7988E-02     0.0042     -1.90
       4  CADCPI       UP      1      0     0.8974E-02     0.0039      2.29
       5  CADGDP       UP      1      0     0.6215E-06     0.0000      1.93


 ACF           Var is CADFXresidb.   Maxlag is 25. lbq./


 AUTOCORRELATIONS

   1- 12    -.02 -.04 -.04 -.15 -.11  .10  .11  .06  .01 -.02  .08  .01
   ST.E.     .09  .09  .09  .09  .09  .09  .09  .10  .10  .10  .10  .10
 L.-B. Q     .10  .30  .40  3.3  5.0  6.3  8.0  8.5  8.5  8.5  9.5  9.5

  13- 24    -.10  .07 -.05  .01  .02  .18 -.08 -.07 -.06 -.10  .01  .01
   ST.E.     .10  .10  .10  .10  .10  .10  .10  .10  .10  .10  .10  .10
 L.-B. Q     11.  12.  12.  12.  12.  17.  18.  18.  19.  21.  21.  21.

  25- 25     .01
   ST.E.     .10
 L.-B. Q     21.
```

```
PLOT OF AUTOCORRELATIONS

          -1.0 -0.8 -0.6 -0.4 -0.2  0.0  0.2  0.4  0.6  0.8  1.0
 LAG   CORR. +----+----+----+----+----+----+----+----+----+----+
                                         I
   1  -0.024                      +  XI   +
   2  -0.041                      +  XI   +
   3  -0.036                      +  XI   +
   4  -0.149                      XXXXI   +
   5  -0.112                     + XXXI    +
   6   0.101                     +    IXXX +
   7   0.113                     +    IXXX +
   8   0.057                     +    IX   +
   9   0.009                     +    I    +
  10  -0.016                     +    I    +
  11   0.084                     +    IXX  +
  12   0.011                     +    I    +
  13  -0.100                     + XXXI    +
  14   0.074                     +    IXX  +
  15  -0.051                     +   XI    +
  16   0.005                     +    I    +
  17   0.019                     +    I    +
  18   0.178                     +    IXXXX+
  19  -0.077                     +  XXI    +
  20  -0.067                     +  XXI    +
  21  -0.061                     +  XXI    +
  22  -0.105                     + XXXI    +
  23   0.008                     +    I    +
  24   0.006                     +    I    +
  25   0.009                     +    I    +


 PACF          Var is CADFXresidb.   Maxlag is 25./


 PARTIAL AUTOCORRELATIONS

   1- 12    -.02 -.04 -.04 -.15 -.13  .08  .10  .04 -.01  .01  .15  .06
   ST.E.     .09  .09  .09  .09  .09  .09  .09  .09  .09  .09  .09  .09

  13- 24    -.11  .05 -.03  .04 -.03  .15 -.06 -.07 -.06 -.09  0.0 -.06
   ST.E.     .09  .09  .09  .09  .09  .09  .09  .09  .09  .09  .09  .09

  25- 25    -.07
   ST.E.     .09
```

```
PLOT OF PARTIAL AUTOCORRELATIONS

          -1.0 -0.8 -0.6 -0.4 -0.2  0.0  0.2  0.4  0.6  0.8  1.0
LAG   CORR. +----+----+----+----+----+----+----+----+----+----+
                                     I
  1  -0.024                     +  XI   +
  2  -0.041                     +  XI   +
  3  -0.038                     +  XI   +
  4  -0.153                     XXXXI   +
  5  -0.128                     +XXXI   +
  6   0.080                     +    IXX +
  7   0.103                     +    IXXX+
  8   0.044                     +    IX  +
  9  -0.007                     +    I   +
 10   0.008                     +    I   +
 11   0.149                     +    IXXXX
 12   0.059                     +    IX  +
 13  -0.107                     +XXXI   +
 14   0.052                     +    IX  +
 15  -0.027                     +  XI   +
 16   0.036                     +    IX  +
 17  -0.028                     +  XI   +
 18   0.151                     +    IXXXX
 19  -0.064                     + XXI   +
 20  -0.069                     + XXI   +
 21  -0.063                     + XXI   +
 22  -0.088                     + XXI   +
 23   0.004                     +    I   +
 24  -0.062                     + XXI   +
 25  -0.074                     + XXI   +


CCF           Var are Rx, CADFXresidb.  Maxlag is 24./

CORRELATION        OF Rx          AND CADFXres  IS    0.07

CROSS CORRELATIONS OF Rx      (I) AND CADFXres(I+K)

  1- 12     .02 -.06  .12 -.05 -.03 -.11  .01  .15  .04 -.02 -.12  .03
  ST.E.     .09  .09  .09  .09  .09  .09  .09  .09  .10  .10  .10  .10

 13- 24    -.08  .03 -.05 -.09  .05 -.03  .13  .06  .13 -.03 -.22 -.13
  ST.E.     .10  .10  .10  .10  .10  .10  .10  .10  .10  .10  .10  .10

CROSS CORRELATIONS OF CADFXres(I) AND Rx      (I+K)

  1- 12    -.11  .11  .26  .05 -.09  0.0 -.12 -.06  .01  .08  .01 -.03
  ST.E.     .09  .09  .09  .09  .09  .09  .09  .09  .10  .10  .10  .10

 13- 24    -.05  0.0  .09 -.01 -.18  .03  .05 -.04  .04 -.04 -.14 -.05
  ST.E.     .10  .10  .10  .10  .10  .10  .10  .10  .10  .10  .10  .10
```

TRANSFER FUNCTION WEIGHTS

LAG	SCCF(X(I),Y(I+K)) *SY/SX	*SX/SY	SCCF(Y(I),X(I+K)) *SY/SX	*SX/SY
0	0.00280	1.54633	0.00280	1.54633
1	0.00079	0.43473	−0.00456	−2.51905
2	−0.00270	−1.49456	0.00488	2.69772
3	0.00520	2.87761	0.01097	6.06684
4	−0.00211	−1.16475	0.00209	1.15322
5	−0.00147	−0.81035	−0.00371	−2.05311
6	−0.00466	−2.57445	0.00002	0.01004
7	0.00062	0.34156	−0.00511	−2.82806
8	0.00629	3.47921	−0.00235	−1.30210
9	0.00159	0.88002	0.00036	0.19727
10	−0.00087	−0.48367	0.00332	1.83550
11	−0.00503	−2.78003	0.00053	0.29094
12	0.00132	0.72857	−0.00133	−0.73640
13	−0.00334	−1.84591	−0.00193	−1.06796
14	0.00120	0.66484	−0.00003	−0.01558
15	−0.00219	−1.20927	0.00387	2.13932
16	−0.00392	−2.16985	−0.00031	−0.17165
17	0.00212	1.17258	−0.00754	−4.17040
18	−0.00108	−0.59682	0.00122	0.67649
19	0.00561	3.09983	0.00224	1.23798
20	0.00248	1.37044	−0.00173	−0.95485
21	0.00547	3.02730	0.00153	0.84876
22	−0.00116	−0.64140	−0.00177	−0.97698
23	−0.00953	−5.26942	−0.00596	−3.29873
24	−0.00559	−3.09005	−0.00205	−1.13317

WHERE X(I) IS THE FIRST SERIES, Y(I) THE SECOND SERIES, SX THE STANDARD ERROR OF X(I), AND SY THE STANDARD ERROR OF Y(I)

```
PLOT OF CROSS CORRELATIONS

           -1.0 -0.8 -0.6 -0.4 -0.2  0.0  0.2  0.4  0.6  0.8  1.0
 LAG   CORR. +----+----+----+----+----+----+----+----+----+----+
                                      I
 -24  -0.048                     +   XI    +
 -23  -0.140                     +XXXXI    +
 -22  -0.042                     +   XI    +
 -21   0.036                     +    IX   +
 -20  -0.041                     +   XI    +
 -19   0.053                     +    IX   +
 -18   0.029                     +    IX   +
 -17  -0.177                     +XXXXI    +
 -16  -0.007                     +    I    +
 -15   0.091                     +    IXX  +
 -14  -0.001                     +    I    +
 -13  -0.045                     +   XI    +
 -12  -0.031                     +   XI    +
 -11   0.012                     +    I    +
 -10   0.078                     +    IXX  +
  -9   0.008                     +    I    +
  -8  -0.055                     +   XI    +
  -7  -0.120                     + XXXI    +
  -6   0.000                     +    I    +
  -5  -0.087                     +  XXI    +
  -4   0.049                     +    IX   +
  -3   0.258                     +    IXXXX+X
  -2   0.115                     +    IXXX +
  -1  -0.107                     + XXXI    +
   0   0.066                      +   IXX +
   1   0.018                     +    I    +
   2  -0.064                     +  XXI    +
   3   0.122                     +    IXXX +
   4  -0.050                     +   XI    +
   5  -0.034                     +   XI    +
   6  -0.109                     + XXXI    +
   7   0.015                     +    I    +
   8   0.148                     +    IXXXX+
   9   0.037                     +    IX   +
  10  -0.021                     +   XI    +
  11  -0.118                     + XXXI    +
  12   0.031                     +    IX   +
  13  -0.078                     +  XXI    +
  14   0.028                     +    IX   +
  15  -0.051                     +   XI    +
  16  -0.092                     +  XXI    +
  17   0.050                     +    IX   +
  18  -0.025                     +   XI    +
  19   0.132                     +    IXXX +
  20   0.058                     +    IX   +
  21   0.129                     +    IXXX +
  22  -0.027                     +   XI    +
  23  -0.224                    X+XXXXI    +
  24  -0.131                     + XXXI    +
```

```
CCF             Var are Rz, CADFXresidb.  Maxlag is 24./

CORRELATION        OF Rz          AND CADFXres  IS    0.01

CROSS CORRELATIONS OF Rz      (I) AND CADFXres(I+K)

  1- 12    -.10  .05  .02 -.14 -.04 -.11  .12  .06  .04  .07  .03  0.0
  ST.E.     .09  .09  .09  .09  .09  .09  .09  .09  .09  .09  .09  .09

 13- 24     .04  .07  .08  .04  .01 -.09  .10 -.07  .06  .08  .07  .05
  ST.E.     .10  .10  .10  .10  .10  .10  .10  .10  .10  .10  .10  .10

CROSS CORRELATIONS OF CADFXres(I) AND Rz      (I+K)

  1- 12     .13  .13  0.0  .02 -.16 -.13 -.13  .09  .08 -.08  0.0 -.12
  ST.E.     .09  .09  .09  .09  .09  .09  .09  .09  .09  .09  .09  .09

 13- 24    -.03 -.03  .07 -.09 -.08 -.01 -.03  .03  0.0 -.11 -.13  .02
  ST.E.     .10  .10  .10  .10  .10  .10  .10  .10  .10  .10  .10  .10


TRANSFER FUNCTION WEIGHTS

         SCCF(X(I),Y(I+K))        SCCF(Y(I),X(I+K))
  LAG    *SY/SX     *SX/SY        *SY/SX     *SX/SY

   0    0.00000 3098.00610     0.00000 3098.00610
   1    0.00000***********     0.0000035103.94530
   2    0.0000013831.81540     0.0000035990.76560
   3    0.00000 5675.46436     0.00000-1029.91260
   4    0.00000***********     0.00000 6171.89404
   5    0.00000***********     0.00000***********
   6    0.00000***********     0.00000***********
   7    0.0000032130.59770     0.00000***********
   8    0.0000017233.61910     0.0000025442.22270
   9    0.0000010664.80270     0.0000020898.15630
  10    0.0000019886.11520     0.00000***********
  11    0.00000 7265.21729     0.00000 1103.87256
  12    0.00000 -574.97473     0.00000***********
  13    0.0000010535.85740     0.00000-9210.75781
  14    0.0000018545.57230     0.00000-8923.31152
  15    0.0000020332.32810     0.0000018818.08010
  16    0.0000010211.62700     0.00000***********
  17    0.00000 1701.98303     0.00000***********
  18    0.00000***********     0.00000-1487.45825
  19    0.0000026398.92970     0.00000-8693.40625
  20    0.00000***********     0.00000 7321.97900
  21    0.0000016794.19920     0.00000 1287.10168
  22    0.0000020421.75780     0.00000***********
  23    0.0000017611.66020     0.00000***********
  24    0.0000012364.33500     0.00000 6138.26807

  WHERE X(I) IS THE FIRST SERIES, Y(I) THE SECOND
  SERIES, SX THE STANDARD ERROR OF X(I), AND SY
  THE STANDARD ERROR OF Y(I)
```

```
PLOT OF CROSS CORRELATIONS

           -1.0 -0.8 -0.6 -0.4 -0.2  0.0  0.2  0.4  0.6  0.8  1.0
 LAG   CORR. +----+----+----+----+----+----+----+----+----+----+
                                      I
 -24   0.023                     +    IX   +
 -23  -0.128                     + XXXI    +
 -22  -0.105                     + XXXI    +
 -21   0.005                     +    I    +
 -20   0.027                     +    IX   +
 -19  -0.032                     +   XI    +
 -18  -0.006                     +    I    +
 -17  -0.078                     +  XXI    +
 -16  -0.089                     +  XXI    +
 -15   0.070                     +    IXX  +
 -14  -0.033                     +   XI    +
 -13  -0.034                     +   XI    +
 -12  -0.123                     + XXXI    +
 -11   0.004                     +    I    +
 -10  -0.080                     +  XXI    +
  -9   0.078                     +    IXX  +
  -8   0.095                     +    IXX  +
  -7  -0.128                     + XXXI    +
  -6  -0.131                     + XXXI    +
  -5  -0.159                     +XXXXI    +
  -4   0.023                      +   IX  +
  -3  -0.004                      +   I   +
  -2   0.134                      +   IXXX+
  -1   0.131                      +   IXXX+
   0   0.012                      +   I   +
   1  -0.095                      + XXI   +
   2   0.052                      +   IX  +
   3   0.021                      +   IX  +
   4  -0.136                      +XXXI   +
   5  -0.040                     +   XI    +
   6  -0.106                     + XXXI    +
   7   0.120                     +    IXXX +
   8   0.064                     +    IXX  +
   9   0.040                     +    IX   +
  10   0.074                     +    IXX  +
  11   0.027                     +    IX   +
  12  -0.002                     +    I    +
  13   0.039                     +    IX   +
  14   0.069                     +    IXX  +
  15   0.076                     +    IXX  +
  16   0.038                     +    IX   +
  17   0.006                     +    I    +
  18  -0.091                     +  XXI    +
  19   0.098                     +    IXX  +
  20  -0.072                     +  XXI    +
  21   0.063                     +    IXX  +
  22   0.076                     +    IXX  +
  23   0.066                     +    IXX  +
  24   0.046                     +    IX   +
```

```
ARIMA          VAR IS CADCPI. Dforder is 1.
               Arorder is '(4)'.
               Maorder is '(5)'./

THE CURRENT MODEL HAS
OUTPUT VARIABLE = CADCPI
INPUT  VARIABLE = NOISE


ESTIMATION BY CONDITIONAL LEAST SQUARES METHOD

RELATIVE CHANGE IN RESIDUAL SUM OF SQUARES LESS THAN 0.5000E-04


SUMMARY OF THE MODEL

OUTPUT VARIABLE -- CADCPI
INPUT VARIABLES -- NOISE


PARAMETER VARIABLE   TYPE  FACTOR  ORDER ESTIMATE        ST. ERR.  T-RATIO
      1  CADCPI       MA      1      5    -0.4222E-01     0.0999     -0.42
      2  CADCPI       AR      1      4     0.6629         0.0681      9.74


Forecast       Cases are 25. Join./


 FORECAST ON VARIABLE CADCPI

 PERIOD          FORECASTS      ST.  ERR.      ACTUAL         RESIDUAL
  125          110.21146       0.54108
  126          110.69722       0.76521
  127          111.09259       0.93718
  128          111.53264       1.08217
  129          111.82208       1.40735
  130          112.14407       1.68280
  131          112.40615       1.91911
  132          112.69785       2.12936
  133          112.88970       2.42499
  134          113.10314       2.69487
  135          113.27686       2.94008
  136          113.47021       3.16636
  137          113.59739       3.43554
  138          113.73887       3.68875
  139          113.85402       3.92566
  140          113.98219       4.14907
  141          114.06648       4.39434
  142          114.16026       4.62872
  143          114.23660       4.85178
  144          114.32155       5.06503
  145          114.37743       5.28919
  146          114.43959       5.50545
  147          114.49019       5.71353
  148          114.54650       5.91429
  149          114.58354       6.12010

STANDARD ERROR = 0.541084         BY CONDITIONAL METHOD
```

```
ARIMA         VAR IS CADGDP. Dforder is 1.
              MAorder is '(1,2,3)'./
THE COMPONENT HAS BEEN ADDED TO THE MODEL.

THE CURRENT MODEL HAS
OUTPUT VARIABLE = CADGDP
INPUT  VARIABLE = NOISE


ESTIMATION BY CONDITIONAL LEAST SQUARES METHOD

RELATIVE CHANGE IN RESIDUAL SUM OF SQUARES LESS THAN 0.5000E-04


SUMMARY OF THE MODEL

OUTPUT VARIABLE -- CADGDP
INPUT VARIABLES -- NOISE
```

PARAMETER	VARIABLE	TYPE	FACTOR	ORDER	ESTIMATE	ST. ERR.	T-RATIO
1	CADGDP	MA	1	1	-0.8286	0.0861	-9.63
2	CADGDP	MA	1	2	-0.4643	0.1082	-4.29
3	CADGDP	MA	1	3	-0.3360	0.0864	-3.89

```
Forecast      Cases are 25. Join./


 FORECAST ON VARIABLE CADGDP
```

PERIOD	FORECASTS	ST. ERR.	ACTUAL	RESIDUAL
125	1344924.00000	5991.94922		
126	1349502.00000	12488.38670		
127	1351353.38000	18566.56250		
128	1351353.38000	24348.29880		
129	1351353.38000	28999.34380		
130	1351353.38000	33001.27730		
131	1351353.38000	36567.83590		
132	1351353.38000	39816.19140		
133	1351353.38000	42818.82030		
134	1351353.38000	45624.26560		
135	1351353.38000	48266.92580		
136	1351353.38000	50772.22270		
137	1351353.38000	53159.57810		
138	1351353.38000	55444.23440		
139	1351353.38000	57638.40230		
140	1351353.38000	59752.05470		
141	1351353.38000	61793.44920		
142	1351353.38000	63769.52730		
143	1351353.38000	65686.18750		
144	1351353.38000	67548.48440		
145	1351353.38000	69360.79690		
146	1351353.38000	71126.94530		
147	1351353.38000	72850.28910		
148	1351353.38000	74533.79690		
149	1351353.38000	76180.10940		

```
STANDARD ERROR =  5991.95         BY CONDITIONAL METHOD
```

```
ARIMA         VAR IS CADFX. Dforder is 1.
              MAorder is '(1,3)'./

THE CURRENT MODEL HAS
OUTPUT VARIABLE = CADFX
INPUT  VARIABLE = NOISE

ESTIMATION BY CONDITIONAL LEAST SQUARES METHOD

RELATIVE CHANGE IN RESIDUAL SUM OF SQUARES LESS THAN 0.5000E-04


SUMMARY OF THE MODEL

OUTPUT VARIABLE -- CADFX
INPUT VARIABLES -- NOISE


PARAMETER VARIABLE   TYPE  FACTOR  ORDER ESTIMATE        ST. ERR.  T-RATIO
      1  CADFX        MA      1      1    -0.3961         0.0827     -4.79
      2  CADFX        MA      1      3    -0.1938         0.0835     -2.32

 Forecast     Cases are 25./


 FORECAST ON VARIABLE CADFX

 PERIOD          FORECASTS      ST.  ERR.      ACTUAL         RESIDUAL
  125            0.96018        0.02105
  126            0.95982        0.03615
  127            0.95769        0.04659
  128            0.95769        0.05737
  129            0.95769        0.06642
  130            0.95769        0.07437
  131            0.95769        0.08156
  132            0.95769        0.08816
  133            0.95769        0.09430
  134            0.95769        0.10006
  135            0.95769        0.10551
  136            0.95769        0.11069
  137            0.95769        0.11564
  138            0.95769        0.12039
  139            0.95769        0.12496
  140            0.95769        0.12936
  141            0.95769        0.13362
  142            0.95769        0.13775
  143            0.95769        0.14176
  144            0.95769        0.14565
  145            0.95769        0.14945
  146            0.95769        0.15315
  147            0.95769        0.15677
  148            0.95769        0.16030
  149            0.95769        0.16376

STANDARD ERROR = 0.210523E-01     BY CONDITIONAL METHOD
```

SUMMARY OF THE MODEL

OUTPUT VARIABLE -- CADFX
INPUT VARIABLES -- NOISE   CADCPI   CADGDP

PARAMETER	VARIABLE	TYPE	FACTOR	ORDER	ESTIMATE	ST. ERR.	T-RATIO
1	CADFX	MA	1	1	-0.4039	0.0844	-4.78
2	CADFX	MA	1	3	-0.1518	0.0856	-1.77
3	CADFX	TRND	1	0	-0.8067E-02	0.0042	-1.93
4	CADCPI	UP	1	0	0.8966E-02	0.0039	2.29
5	CADGDP	UP	1	0	0.6268E-06	0.0000	1.94

Forecast   Cases are 25./

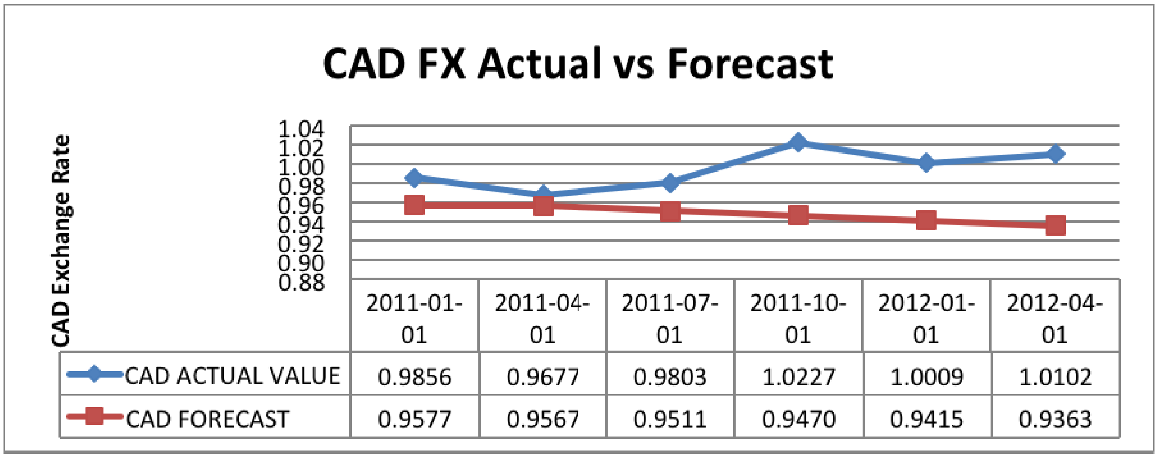
FORECAST ON VARIABLE CADFX

PERIOD	FORECASTS	ST. ERR.	ACTUAL	RESIDUAL
125	0.95765	0.02061		
126	0.95665	0.03553		
127	0.95109	0.04582		
128	0.94697	0.05593		
129	0.94150	0.06447		
130	0.93632	0.07200		
131	0.93060	0.07882		
132	0.92515	0.08509		
133	0.91880	0.09093		
134	0.91265	0.09642		
135	0.90614	0.10161		
136	0.89981	0.10655		
137	0.89288	0.11127		
138	0.88608	0.11580		
139	0.87905	0.12016		
140	0.87213	0.12437		
141	0.86482	0.12843		
142	0.85760	0.13238		
143	0.85021	0.13620		
144	0.84291	0.13993		
145	0.83534	0.14356		
146	0.82783	0.14709		
147	0.82022	0.15055		
148	0.81266	0.15392		
149	0.80492	0.15723		

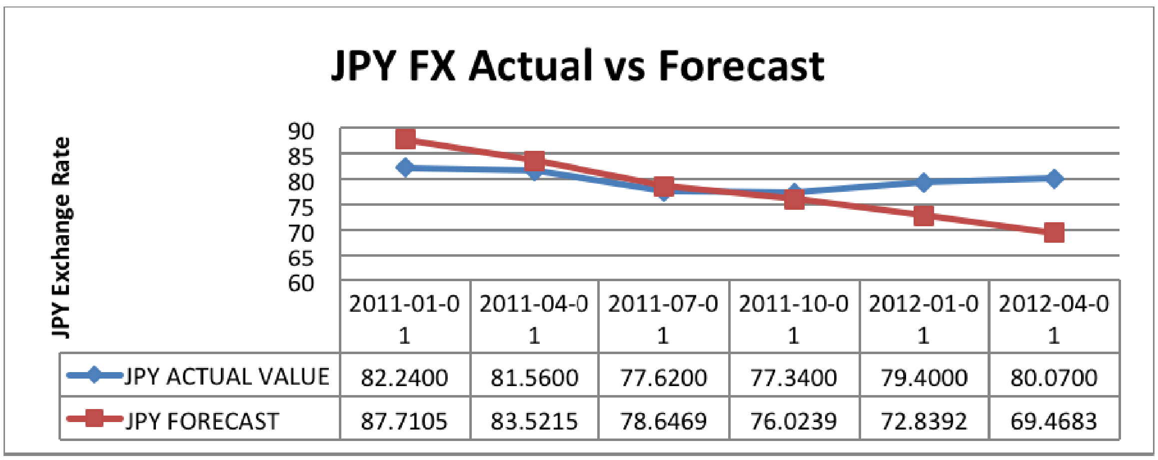
STANDARD ERROR = 0.206117E-01   BY CONDITIONAL METHOD

BMDP2T - BOX-JENKINS TIME SERIES ANALYSIS

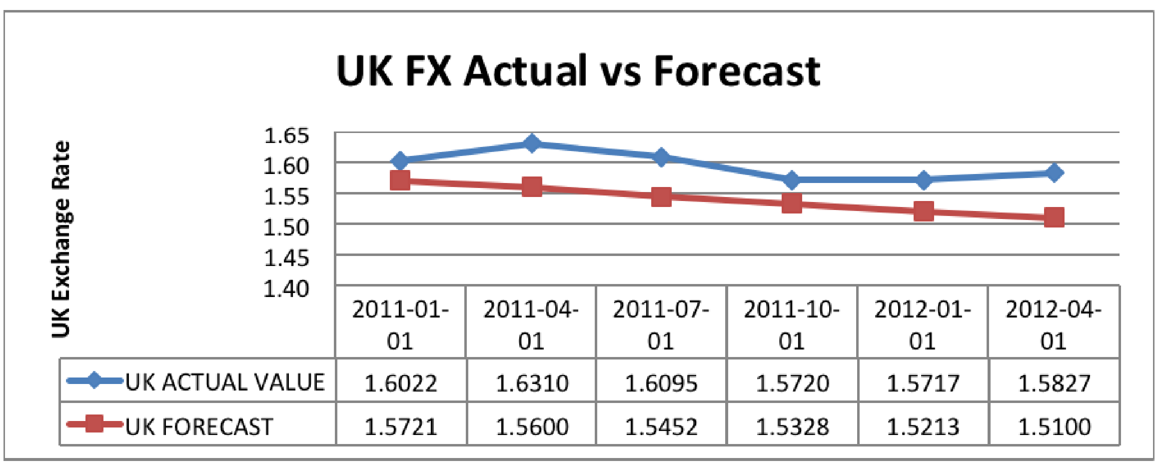
Release: 8.1 (Windows 9x, 2000, Me, Xp)   Date: 02/20/12 at 17:36:12
Manual: BMDP Manual Volumes 1, 2, and 3.
Digest: BMDP User's Digest.
IBM PC: BMDP PC Supplement -- Installation and Special Features.



	2011-01-01	2011-04-01	2011-07-01	2011-10-01	2012-01-01	2012-04-01
CAD ACTUAL VALUE	0.9856	0.9677	0.9803	1.0227	1.0009	1.0102
CAD FORECAST	0.9577	0.9567	0.9511	0.9470	0.9415	0.9363



	2011-01-01	2011-04-01	2011-07-01	2011-10-01	2012-01-01	2012-04-01
JPY ACTUAL VALUE	82.2400	81.5600	77.6200	77.3400	79.4000	80.0700
JPY FORECAST	87.7105	83.5215	78.6469	76.0239	72.8392	69.4683



	2011-01-01	2011-04-01	2011-07-01	2011-10-01	2012-01-01	2012-04-01
UK ACTUAL VALUE	1.6022	1.6310	1.6095	1.5720	1.5717	1.5827
UK FORECAST	1.5721	1.5600	1.5452	1.5328	1.5213	1.5100