ABSTRACT

HUSSEIN, JAWAD. Forecasting Communications Technology Products with Leading Economic Indicators. (Under the direction of Dr. Thom Hodgson and Dr. Russell King.)

This research examines the usefulness of leading economic indicators (LEIs) in predicting short-term demand for communications technology products. The general problem is to accurately predict demand for communications technology products in the short term since the existing forecasting techniques lack the power needed to predict changes in demand patterns outside the component lead-time (typically 3 months) during periods of sudden economic changes. This research provides a causal framework for forecasting short term demand using leading economic indicators such that material/component requirements could be sent out to the supply chain/component suppliers as accurately as possible outside the component lead-time window to avoid extended lead-times, lost sales and customer dissatisfaction.

Simple and multiple regression models are developed using different leading economic indicators (LEIs): S&P1200, IPI (Industrial Production Index), CCI (Consumer Confidence Index), MCI (Main Competitor Stock Index), etc. These models are also compared with the existing forecasting techniques to gauge any forecast accuracy improvements. Microsoft Access 2007 is used as a tool to build these models and to develop a user-friendly interface that can readily be used to create and compare LEI-based forecasts. S&P1200 and IPI linear regression models are found to be on a par with the marketing forecast but outperform the statistical forecast by seven and nine percentage points, respectively in terms of Mean Absolute Percentage of Error (MAPE). Multiple regression models are found to outperform both marketing and statistical forecasts. The $CCI/CCI^2/MCI^{2.3}/S\&P1200^{0.1}$ model accuracy of 95% outperforms the marketing and statistical forecast accuracy by five by thirteen percentage points, respectively over the twelve month period (Apr’2010 – Mar’2011). This research shows that leading economic indicators are very valuable in terms of predicting short-term demand (three to four months out) for communications technology products and should also be considered to forecast demand for technology products that are heavily impacted by economic swings.

Forecasting Communications Technology Products with Leading Economic Indicators

by
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BIOGRAPHY

Jawad Hussein was born in Lahore, Pakistan on April 17, 1977 to Gulshan Ara and Abdul Qadeer Bhatti. He attended Cathedral School No-2, Lahore from KG to Grade 10 before receiving the high school diploma from Government College, Lahore in 1995. He received his B.S., degree in Mechanical Engineering from Ghulam Ishaq Khan Institute of Engineering Sciences and Technology (GIKI) in 1999. He came to the USA in the fall of 1999 to attend the Integrated Manufacturing Systems Engineering Institute at North Carolina State University in Raleigh, NC. He received a Masters degree in Integrated Manufacturing Systems Engineering in 2001.

He did internships at Magneti Marelli, USA and Timco Aviation Services as an Industrial Engineering Intern before landing a full time job at Lowe's Companies Inc. He worked as a forecast analyst, senior project forecast analyst and later as a forecast manager – projects at Lowe's Companies Inc. He received the unsung hero award in 2006 from Lowe's for developing forecasting tools while working on multiple forecast improvement initiatives. He gained valuable retail supply chain and forecasting experience at Lowe's. He currently works as a global demand planning manager for a company in the communications technology sector. He likes to play cricket in his free time and is an avid watcher of this game.

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This Ph.D. process has been a very long but quite rewarding journey for me. It has not only increased my knowledge in the field of industrial engineering but also taught me this valuable lesson along the way that: "Our greatest glory is not in never falling but in rising every time we fall", and I definitely had my share of falling and rising in this long journey.

I thank my entire advisory committee: Dr. Thom Hodgson, Dr. Russell King, Dr. Steven Jackson and Dr. Kristin Thoney for their support and guidance throughout this process. I especially want to thank Dr. Thom Hodgson for his relentless support. He encouraged me to work on a real-world problem and cheered me up when I was down. I have known Dr. Thom Hodgson and Dr. Russell King since 1999 and learned a lot from them in terms of problem solving approach. Dr. Steven Jackson's innovative comments and his Wall Street background encouraged me to think like a financial whiz.

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CHAPTER 1 PROBLEM DESCRIPTION

1.1 General Description

Forecasting or demand planning is the back bone of any organization and is a key to its operational efficiency and vitality. Accurate forecasting leads to lower inventory levels, fewer lost sales and higher profitability. A vast majority of the forecasting techniques used in the communications technology sector rely on historical data (time series analysis) to predict future demand of IT equipment and services at the operational and tactical levels (short to medium term). This might be a good enough approach under normal economic conditions to predict future demand but may not suffice during periods of significant economic expansion and contraction due to its lagging nature.

Demand for technology products is impacted far more heavily due to economic swings than any other single sector of economy. Thus, there is a stronger need than ever to model product demand in the technology sector using leading economic indicators to predict the turning points in the economy sufficiently ahead of time (at least outside the longest component lead-time) in order to be able to revamp material, inventory and production plans immediately to avoid lost sales, longer lead times or inventory charge offs. The purpose of this research is to find a short term forecasting framework for communications technology products that fills this current gap.

The demand planning function at big technology companies typically uses an analytically-driven, consensus demand planning (CDP) process to produce the demand signal for their supply chains. The consensus demand planning process at the partner company involves inputs from marketing, sales and analytical teams to create a bookings forecast, also called the consensus book plan (CBP). The demand planning team at the partner company owns the CBP that is sent to the supply chain after applying book to ship lead-time offset. The product marketing team creates the marketing forecast based on market intelligence/sales inputs. The analytics group creates the statistical forecast using the advanced and sophisticated forecasting techniques through the SAS forecasting engine. However, the lack of predictive modeling using leading economic indicators makes it harder to gauge sudden subjective changes in forecasts that could be merely driven by fear or optimism regarding the underlying economic conditions. The goal of this research is to provide a causal framework for gauging sudden changes in forecasts driven by marketing/sales teams during cycles of economic expansion and contraction by using a Leading Economic Indicators (LEI)-based approach.

The ability to accurately predict communications technology product demand two to three months out is critical as the component suppliers would need this much time to react to any sudden change in customer demand (assuming the longest component lead-time is around three months, which is typical in electronic manufacturing). Re-order point logic is used in a lean model to trigger material and production down the supply chain. Since demand outside the component lead time is typically used for the re-order point calculation, the focus of this research is to predict demand at a lead time of three to four months using leading economic indicators.

1.2 Proposed Research

The purpose of this research is to formulate a mathematical forecasting model using leading economic indicators to predict demand for communications technology products in the short term (three to four months out) such that material/component requirements could be sent out to the supply chain/component suppliers as accurately as possible outside the component lead-time window (typically 3 months) to avoid extended lead-times, lost sales and customer dissatisfaction.

The model should be generic enough to be employed for any product series but also specific enough to exactly cater to the specific demand characteristics of a given product series.

The impetus for this research is the formation of large inventory build ups and severe component shortages during periods of sudden economic contraction and expansion, respectively, which the author has observed while working in the communications technology industry. This is due to the lack of high predictive power of the existing techniques (both naïve and qualitative) to predict changes in demand patterns sufficiently ahead of time (at least 3 months) before the actual demand is materialized during periods of sudden economic changes. The existing forecasting techniques tend to work fairly well under normal conditions; however, they fail to meet the challenges of the fragile and volatile economic environment we all live in.

Forecasting using LEI has been found useful in predicting turning points in the economy. For example, Chow and Choy [4] developed a VAR module that uses a set of four leading indicators and found it useful in predicting turning points in the global electronics industry. Qin, Cagas, Ducanes, Ramos and Quising [6] studied the forecast performance of automatic leading indicators (ALIs) and concluded through comparison experiments that the ALI can outperform macroeconometric structural models (MESMs) in short-run forecasts. Several other studies have highlighted the effectiveness of the LEI approach for forecasting, which are discussed in detail in the literature review section. However, the available literature on LEI has not addressed the specific demand characteristics of communications technology products and specifically how the LEI approach could be used robustly to model these products to improve the overall customer experience. The proposed research aims to close this gap by providing a mathematical frame-work geared specifically towards communications technology products that could be used repeatedly and robustly to predict future bookings based on the LEI approach.

Several different causal models (regression, multiple regression etc.) using the LEI approach are developed and compared with each other to find the best model based on historical MAPE (Mean Absolute Percentage Error) using data from a partner company. The models are also compared with the existing forecasting techniques to gauge any improvements over the current forecasting techniques. Microsoft Access 2007 is used as a tool to build these models and to develop a user friendly interface that could be readily used to create and compare LEI-based forecasts.

Chapter 2 provides a summary of the current literature available on the use of leading economic indicators to forecast sales, growth, output, consumption etc. Several leading economic indicators (stock market indices, business and consumer confidence etc.) are studied in Chapter 3 to determine their correlation with the actual bookings for communications technology products. Chapter 4 contains results of linear regression analysis using leading economic indicators identified earlier. A comparison of regression models with the existing forecasting techniques (statistical forecast, marketing/sales forecast) is also presented in this chapter.

Multiple and polynomial regression models using LEI are studied in Chapter 5. Results from multiple regression models are compared with simple regression models and the existing forecasting techniques (statistical and marketing forecast) in this chapter to show the best forecasting model in terms of accuracy for the selected product series. Conclusions and further research are discussed in Chapter 6. Instructions on how to use the forecasting software to readily forecast communications technology products using LEIs are outlined in the Appendix. The future cannot be predicted absolutely, but it can be forecast in a way that facilitates better business planning and management.

CHAPTER 2 LITERATURE REVIEW

There is vast literature related to the topic of demand forecasting. However, there is not much literature available on the use of leading economic indicators to forecast sales, specifically in the context of the communications technology sector. The literature reviewed here relates to forecasting using leading economic indicators.

2.1 Forecasting the global electronics cycle with leading indicators

Chow and Choy [4] proposed a unified framework for forecasting the global electronics cycle by constructing a Vector Autoregressive (VAR) model [13] that uses a set of four leading indicators representing expectations, orders, inventories and prices. They first tested the ability of the indicators to predict world semiconductor sales using Granger causality tests. They then generated out-of-sample forecasts of global chip sales from two variants of the VAR model, i.e., the Bayesian VAR (BVAR) and Bayesian Error Correction Mechanism (BECM) and compared it with forecasts from a bivariate model which uses a composite index of the leading indicators and a univariate autoregressive model. Forecasting performance of the VAR model was found to be superior to the composite index and univariate Autoregressive (AR) models. Between the two Bayesian models, the BVAR appears to be superior to the BECM model in short-term forecasting.

They argued that leading economic indicators give mixed signals at each point in time, thereby making it harder to predict world electronics activity. The predictive value of each indicator might vary depending on the stage of the product lifecycle as the indicators span the whole spectrum of activities in the semiconductor production process. The result is different lead times for the indicators, which are not explicitly included by construction of a composite index using component indicators. For this reason, they proposed a unified framework for forecasting the global electronics cycle by constructing a VAR model which incorporates a set of four leading indicators identified from a longer list of electronic series. They claimed that rather than combine the leading series into a composite index, the use of the VAR framework for forecasting may be better because it explicitly includes economic variables representing expectations, orders, inventories, prices and shipments by accommodating the different lead times of these indicators, thereby resulting in more accurate forecasts. They concluded that their VAR model could be used as a good quantitative predictor of world semiconductor sales, and it also predicts the turning points in the global electronics cycle.

2.2 Economic indicators for the US transportation sector

Lahiri and Yao [12] studied both the classical business cycles and the growth cycles of the US transportation sector using economic indicators. They developed indicators for this sector to identify its current state, and predict its future. They defined the reference cycle, including both business and growth cycles, for this sector over the period from 1979 to 2002 using both the conventional National Bureau of Economic Research (NBER) method [2] and modern time series models [10]. They found a one-to-one correspondence between cycles in the transportation sector and those in the aggregate economy. However, both the business and growth cycles of transportation often start earlier and end later than those of the overall economy. In other words, recessions in this sector often start earlier and end later.

They also constructed an index of leading indicators for the transportation sector using statistical procedures and concluded that it performs well as a forecasting tool. They produced an initial list of twenty-two leading indicators using all the possible transportation-related, as well as economy-wide, leading indicators. The initial list of leading indicators was then reduced to fourteen indicators by applying six indicator selection criteria. Granger-causality tests were performed to test their predictive power. These tests removed five more indicators to leave nine indicators remaining. They then used standard and robust *t*-statistics to test whether Ho: Serial Correlation = 0 was true. A robust *t*-test was preferred considering the high serial correlation among the variables. Two variables were removed from the list for lack of common cycles with the other seven variables. Transportation Composite Leading Index(CLI) was then constructed based on these remaining seven variables (Dow Jones Transportation Average, Purchasing Manager's Index, New Orders, Shipments, Production, Payrolls, and Consumer Sentiment Index) using the conventional NBER method [2]. They concluded that overall for transportation business cycles, the leading index of the US transportation sector leads its coincident indicator by 10 months at peaks and 6 months at troughs on average. Transportation CLI was also used to predict growth cycles of the transportation sector, and they concluded that the transportation CLI gives early signals of the peaks and troughs of the transportation growth cycles, on average by 6 and 12 months, respectively, without any false signal or missing any turn.

2.3 Forecasting Australian Gross Domestic Product (GDP) and consumption using consumer sentiment and its components

Chua and Tsiaplias [5] examined whether the disaggregation of consumer sentiment data into its sub-components could improve GDP and consumption forecasting. They concluded that a Bayesian Error Correction Model (BECM) [21] augmented with consumer sentiment sub-indices produces better forecasts of GDP and consumption than a BECM augmented with the consumer sentiment index.

They observed that forecasts from the BECM augmented with either the consumer sentiment sub-indices or the aggregate consumer sentiment index are more accurate than those from a standard BECM. The better forecasting models for either GDP or consumption are also found to contain the shorter term sub-indices concerning family finances consistently at all forecasting horizons. They also introduced a method of generating composite forecasts leveraging the Winkler (1981) approach and found that the composite forecasts for GDP are better than the composite forecasts based on the simple averaging and MSE (Mean Square Error) methods in the medium-term. However, composite forecasts for consumption are only found to be better than the forecasts generated from the standard BECM models.

2.4 Automatic leading indicators versus macroeconometric structural models: A comparison of inflation and GDP growth forecasting

Qin, Cagas, Ducanes, Ramos and Quising [6] studied the forecast performance of Automatic Leading Indicators (ALIs) and Macroeconometric Structural Models (MESMs) [17] using inflation and GDP growth data from China, Indonesia and Philippines. The ALI method [3] consisted of two steps: factor extraction using a Dynamic Factor Model (DFM) and forecasting using a Vector Auto Regression (VAR) model.

They concluded through the comparison experiments that i) The ALI can outperform MESMs in short-run forecasts as ALI is largely immune to the location-shift problem but this advantage fades away as the forecast horizon increases; ii) The performance of ALIs depend greatly on the choice of indicator variable sets and that the longer-term forecast accuracy of ALI could be improved by inclusion of long-term disequilibrium indicators derived from MESMs as an additional type of indicator variable in the ALI; (iii) The use of high frequency data (monthly vs. quarterly) does not always help to improve forecast; (iv) The ALI method involves greater uncertainty, and one way to reduce that is to adopt the general-to-specific modeling procedure from MESMs as it helps to trim out unwanted noise from the ALI forecasts and also enables modelers to access the robustness of the VAR model specification.

2.5 Reliable leading indicators for US inflation and GDP growth

Banerjee and Marcellino [1] performed empirical comparison of three alternative approaches to extracting information from a large data set for forecasting: (i) The use of an automated model selection procedure; (ii) The adoption of a factor model to summarize the available information; and (iii) Single indicator-based forecast pooling.

In the automated model selection procedure [7], they allowed for the selection of the best leading indicator and the appropriate lag length using a model selection procedure developed by Hendry and Krolzig (1999) that relies on the joint application of information criteria, significance testing on the parameters, and residual-based tests for correct model selection. The procedure was implemented with their software PcGets. They also considered groups of indicators, where grouping was based either on economic considerations or on the forecasting performance of the single indicators.

They considered pooling (combining) the single indicator forecasts as pooled forecasts have been shown to perform very well for macroeconomic variables (Hendry and Clements, 2004; and Stock and Watson, 1999b). They also reassessed the usefulness of factor models in forecasting inflation and GDP growth. Factor analysis extracts the main deriving factors from the entire data set, and the factors themselves usually cannot be given natural or self-evident economic interpretations.

They conducted forecast comparison among these three approaches using an ex-post and a pseudo ex-ante approach. Future values of the exogenous regressors are assumed to be known in the ex-post evaluation, and the grouping of the leading indicators is based on the overall (average over all the periods) forecasting performance of the single indicators. No future information is used in the ex-ante framework, future values of the regressors are forecast, and the choice of indicators is based on their past forecasting performance. They drew five main conclusions from this comparison both for inflation and GDP. For inflation: (i) Univariate leading indicator models are better than autoregressive ex post, but the best indicator changes over time; (ii) Grouping the indicators is better than using factor models for inflation; (iii) The results are robust to the degree of differencing, the use of rolling estimation, and the choice of forecasting horizon; (iv) The median pooled estimator performs better than the average, but a careful selection of the single forecasts to be pooled is required for it to beat the Autoregressive (AR) model, and finally; (v) The indicators can hardly beat the autoregressions more than 50% of the time in a pseudo-ex-ante context, which shows AR model as a robust forecasting device for inflation using their loss function. For GDP forecasting, conclusions are the same except that forecast pooling works in only a fraction of cases, and the indicators can beat the autoregressions ex-ante more than 80% of the time.

2.6 Timing and accuracy of leading and lagging business cycle indicators: A new approach

Seip and McNown [20] characterized the leading and lagging indexes of the US business cycles in terms of timing and accuracy by an examination of the rotational features of the phase diagrams relating indicators and targets. This examination revealed useful information about the timing and accuracy of these indicators. They presented the results in the form of topological graphs that give the relative position of leading and lagging indexes along two axes, one representing timing and one representing accuracy. Timing is the lead or lagging time relative to a target time series (Industrial Production-IP) here while accuracy is measured by the correspondence between the directions of changes in the indicator and the target.

They found that the National Bureau of Economic Research (NBER) composite leading index had lead times similar to those previously reported by plotting candidate leading and trailing time series and the target time series in phase plots and using the rotational properties of such trajectories. Interest rate spread is found to be coincident or slightly lagging. The composite indicators, as well as average working hours per week and the consumer price index, behaved as expected.

They stated that the methodology used to characterize indexes distinguished itself from other methods in three ways: i) it focuses on the contemporaneous interaction between the indicator considered and the target index, as opposed to leading or lagging relationships between the two indexes; ii) it does not focus on the peak or trough episodes of the target index, but rather considers interactions between the series over the entire business cycle, and; iii) the important features of the relationships between indicators and targets are compactly summarized through principal component analysis.

2.7 Multiple time series modeling of macroeconomic series

Narayan [15] investigated the relationships between the state of the economy as measured by Gross National Product (GNP), and a number of economic indicators. Bivariate autoregressive moving average models for GNP and each of the indicator series were constructed, and a comparison of ex-ante forecasts from these models was made with the ex-ante forecasts resulting from a comparable univariate model for GNP.

The results indicated that some relations exist between GNP and certain indicator series. However, these relations were not significantly better than the ex-ante forecasts from corresponding univariate models. The author concluded that based on his experience leading indicators can be of little value in short term forecasting by a multiple time series procedure.

2.8 Residential construction demand forecasting using economic indicators: A comparative study of artificial neural networks and multiple regression

Hua [9] proposed the use of economic indicators to predict demand for residential construction in Singapore. Artificial Neural Networks (ANN) and Multiple Regression (MR) forecasting techniques were applied to forecast residential construction demand. A comparative study was then carried out to determine which one of the two techniques would produce better forecasts with the use of economic indicators.

A total of twelve economic indicators were identified as significantly related (10% significance level) to demand for residential construction. Quarterly data (74 data points from the third quarter of 1975 to the fourth quarter of 1993) from these twelve indicators were used to develop the ANN and MR models. A comparison between the two models showed that Mean Absolute Percentage Error (MAPE) of the ANN model was about one fifth of the MR model. Economic indicators might be used as reliable inputs for the modeling of residential construction demand in Singapore given the low MAPE values (less than 10%) obtained for both models.

A typical three-layered backpropagation neural network architecture was chosen for the ANN model. Backpropagation is a supervised learning procedure adopting the error-correction rule [19]. It consisted of an input layer of twelve nodes, each representing one of the twelve selected economic indicators, a hidden layer with five nodes and an output layer with one node. Hidden layers act as layers of abstraction, pulling features from inputs. Increasing the number of sequential hidden layers augments the processing power of the neural network but significantly complicates training and intensifies black box effects, which results in errors being more difficult to trace. The output layer was comprised of one node which corresponds with the output variable, Gross Fixed Capital Formation (GFCF) for residential buildings.

The twelve indicators used in the ANN model were adopted as independent variables in the regression analysis to estimate the dependent variable, GFCF for residential buildings. The statistical analysis was first carried out using the SAS Regression (REG) procedure. The results of the REG procedure revealed the presence of autocorrelated errors, which was confirmed by the Durbin-Watson statistic. Another problem often associated with multiple regression analysis is the existence of multicollinearity. It was assumed that no serious problem of multicollinearity was present in the regression model.

2.9 Linear and threshold forecasts of output and inflation using stock and housing prices

Tkacz and Wilkins [22] examined whether simple measures of Canadian equity and housing price misalignments contain leading information to help predict output and inflation over forecast horizons spanning one to sixteen quarters using linear models. They also used two-regime threshold models in an attempt to capture potential nonlinearities in the relationship between asset prices and macroeconomic variables and compared forecasts from the threshold models relative to those of the linear models.

The results suggested that housing prices are useful for predicting GDP growth, even within a linear context. Both stock and housing prices could improve inflation forecasts, especially when using a threshold specification. However, the model specification, and the optimal forecast horizon, was different for both output and inflation.

2.10 Forecasting the New York State economy: The coincident and leading indicators approach

Megna and Xu [14] attempted to provide a structured approach to analyzing business cycles and fiscal performance for New York State in order to provide policy makers useful summary measures of economic and fiscal conditions. They explored the ability of leading economic indicators to predict future changes in state revenues.

Their model is based on the single-index methodology developed by Stock and Watson. They constructed a coincident economic index to date New York business cycles and compare local cyclical behavior with the nation as a whole. A leading index of economic indicators was developed to predict future movements in the coincident index. A fiscal index was then created by applying the same state-space model to the tax receipts, which acted as a summary indicator of revenue performance for New York. The leading index is then used to predict the fiscal index.

The results indicated that cyclical activity for New York State follows national patterns, but with substantial differences in timing and duration. The leading economic series was found useful in predicting both the probability of a future recession and the future direction of the fiscal index. The fiscal index was very sensitive to changes in the economic index and both the economic and fiscal indices were deemed to help policymakers at the state and local level prepare for future changes in the economic and fiscal environment. Their models predicted a substantial slowing of future revenue growth and that began to manifest itself in mid-2001.

2.11 A leading indicator approach to predicting short-term shifts in demand for business travel by air to and from the UK

Njegovan [16] examined whether leading indicator information could be used to predict short-term shifts in demand for business travel by air to and from the UK using the SAS probit regression model. Leading indicators considered include measures of business expectations, availability of funds for corporate travel and some well-known macroeconomic indicators.

The selected model was shown to be capable of delivering timely predictions of the early 1980s and 1990s recessions in both in- and out-of-sample forecasting exercises. It was also shown to be more accurate than the linear leading indicator model used to mimic the current forecasting practice in the air transport industry.

2.12 An evaluation of the leading indicators for the Canadian economy using time series analysis

Veloce [24] conducted an in-depth statistical evaluation of the ability of Statistics Canada's leading indicators in order to predict changes in GDP. Statistics Canada is the Canadian federal government agency mandated with producing statistics to better understand the population, resources, and economy of Canada. He built empirical transfer function models to describe the dynamic relationship between the leading indicator series and GDP for Canada. These models revealed a stable relationship for all of the indicator series with most indicators containing useful information for forecasting GDP. However, the average lead times were too short for most of the indicators. The new composite index (NEWCOMP) [18] designed specifically to give more lead time showed an average lead time of one month but it did reveal substantial explanatory power regarding the variability of GDP.

The new composite index gave better forecasts than the univariate Seasonal Autoregressive Integrated Moving Average (SARIMA) model for GDP. However, most of the component indicators were found to give better forecasts than the new composite index, thus indicating that there might be additional information in the component series which is not present in the NEWCOMP index.

2.13 Predicting the natural gas demand based on economic indicators: Case of Turkey

Toksari [23] studied the estimation of Turkey's natural gas demand based on a simulated annealing approach using economic indicators such as GDP, population, import and export estimates. Simulated annealing can locate a good approximation to the global optimum of a given function in a large search space.

Linear and quadratic forms of Simulated Annealing Natural Gas Demand Estimation (SANGDE) were proposed using twenty-three data (1984-2006). Two scenarios were proposed to estimate Turkey's natural gas demand in the years 2008-2025 using the two forms of the SANGDE. The results showed that quadratic_SANGDE provided a better fit solution due to the fluctuations of the economic indicators.

CHAPTER 3 LEADING ECONOMIC INDICATORS FOR COMMUNICATIONS TECHNOLOGY PRODUCTS

3.1 Leading Economic Indicators

A Leading Economic Indicator (LEI) is an economic indicator that changes before the economy. Examples of leading indicators are stock prices, consumer sentiment, housing permits, IT investments etc. Leading economic indicators are useful in predicting short-term changes in the economy.

Lagging indicators change after the economy while coincident indicators change about the same time as the economy. Industrial production and gross domestic product are coincident indicators while consumer price index is an example of a lagging indicator. Coincident and lagging indicators are of little or no value in predicting changes in the economy.

3.2 Correlation Analysis

Correlation calculation is the first step towards causal model development as correlation determines the predictive power of the leading economic indicator and the model that uses it.

The following economic indicators are analyzed first to determine the strength of their correlation with the actual bookings for a selected product series (referred to as XYZ):

1) Dow Jones Industrial Index (DJI)
2) S&P500 Index
3) S&P1200 Index (Global)
4) S&P700 Index (Non-USA)
5) NASDAQ Composite Index
6) NASDAQ Computer Index
7) NASDAQ Telecom
8) Consumer Confidence Index (CCI)
9) Business Confidence Index (BCI)
10) Industrial Production Index (IPI)

11) Company Stock Index (CI)
12) Main Competitor Stock Index (MCI)

S&P1200 is a global index that is comprised of two indices: S&P500 for United States and S&P700 for non-United States. S&P700 index is a composite of seven regional indices: S&P Europe 350, S&P TOPIX 150 (Japan), S&P/TSX 60 (Canada), S&P/ASX All Australian 50, S&P Asia 50, and S&P Latin America 40. The top 10 constituents of S&P700 are: Nestle SA Reg (Consumer Staples), HSBC Holdings Plc (Financials), BHP Billiton Ltd (Materials), Novartis AG Reg (Health Care), Total SA (Energy), Vodafone Group (Telecommunication Services), BP (Energy), Royal Dutch Shell PLC (Energy), Samsung Electronics Co. (Information Technology) and Siemens AG (Industrials).

The XYZ series is studied here as it represents the highest bookings revenue out of all product series within the business unit selected for this research. This product series represents multiple SKU's (8 main platforms). Monthly bookings data for the XYZ product series is used over three different time frames for correlation calculation purposes. The purpose of using three different data sets (time frames) for XYZ bookings is to identify the time frame that yields the highest correlation. Correlation is calculated at 10 different lags (lag 0 – 9) to see how the correlation between leading economic indicators and actual bookings behaves at different lags. For example, lag-3 correlation means correlation between LEI and actual bookings that are lagging 3 months behind the LEI. Correlation lag of 3 or higher will be of particular interest here as it represents the ability to forecast bookings for time periods 3 or more months out. This could possibly allow predicting changes in XYZ bookings outside the component lead-times (typically 3 months) to avoid material shortages and extended lead-times.

Correlation between actual bookings and market indices (market close value) at different lags using bookings data over different time frames is tabulated in Tables 3-1, 3-2 and 3-3 below.

Table 3 - 1: Correlation Values for Jan'06 to Dec'09 Data Set

Product Type	LEI/Correlation	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8	Lag 9
XYZ	IPI	0.52	0.66	0.56	0.50	0.63	0.50	0.42	0.52	0.41	0.32
XYZ	S&P500	0.52	0.54	0.56	0.56	0.55	0.55	0.53	0.51	0.45	0.43
XYZ	S&P1200	0.50	0.52	0.54	0.54	0.53	0.53	0.50	0.47	0.41	0.38
XYZ	DJI	0.49	0.53	0.55	0.53	0.53	0.52	0.49	0.47	0.40	0.36
XYZ	CCI	0.47	0.46	0.51	0.55	0.52	0.55	0.59	0.58	0.59	0.62
XYZ	S&P700	0.48	0.49	0.52	0.52	0.51	0.51	0.48	0.44	0.38	0.33
XYZ	NASDAQ_Composite	0.46	0.49	0.51	0.51	0.50	0.51	0.49	0.46	0.41	0.39
XYZ	BCI	0.29	0.30	0.42	0.50	0.47	0.55	0.55	0.47	0.52	0.49
XYZ	NASDAQ_Comp	0.35	0.37	0.41	0.45	0.42	0.44	0.44	0.40	0.35	0.32
XYZ	NASDAQ_Telecom	0.36	0.44	0.44	0.40	0.41	0.39	0.37	0.38	0.31	0.27
XYZ	CI	0.28	0.41	0.38	0.35	0.41	0.36	0.35	0.42	0.34	0.29
XYZ	MCI	0.08	0.14	0.15	0.13	0.13	0.11	0.13	0.15	0.06	0.05

Table 3 - 2: Correlation Values for Jan'07 to Dec'09 Data Set

Product Type	LEI/Correlation	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8	Lag 9
XYZ	IPI	0.57	0.67	0.60	0.56	0.64	0.54	0.47	0.53	0.46	0.39
XYZ	S&P500	0.56	0.58	0.61	0.61	0.58	0.59	0.56	0.53	0.50	0.49
XYZ	DJI	0.56	0.58	0.62	0.61	0.58	0.58	0.55	0.52	0.49	0.47
XYZ	S&P1200	0.56	0.57	0.60	0.61	0.58	0.58	0.56	0.52	0.48	0.46
XYZ	S&P700	0.56	0.56	0.60	0.61	0.58	0.58	0.55	0.51	0.47	0.44
XYZ	NASDAQ_Composite	0.50	0.54	0.57	0.58	0.54	0.55	0.53	0.50	0.47	0.46
XYZ	CI	0.45	0.54	0.56	0.55	0.53	0.51	0.51	0.52	0.52	0.52
XYZ	CCI	0.44	0.44	0.53	0.56	0.52	0.56	0.59	0.57	0.63	0.63
XYZ	NASDAQ_Comp	0.43	0.46	0.50	0.53	0.51	0.51	0.50	0.47	0.43	0.42
XYZ	NASDAQ_Telecom	0.48	0.54	0.57	0.54	0.51	0.50	0.47	0.46	0.44	0.42
XYZ	BCI	0.22	0.26	0.39	0.47	0.47	0.55	0.55	0.46	0.52	0.47
XYZ	MCI	0.27	0.36	0.39	0.31	0.32	0.30	0.30	0.37	0.27	0.26

Table 3 - 3: Correlation Values for Jan'08 to Dec'09 Data Set

Product Type	LEI/Correlation	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8	Lag 9
XYZ	IPI	0.58	0.62	0.61	0.57	0.59	0.52	0.47	0.42	0.38	0.33
XYZ	S&P700	0.45	0.50	0.63	0.62	0.54	0.54	0.51	0.43	0.35	0.28
XYZ	S&P1200	0.46	0.51	0.64	0.62	0.53	0.54	0.50	0.43	0.35	0.27
XYZ	DJI	0.47	0.52	0.66	0.62	0.53	0.55	0.51	0.45	0.38	0.28
XYZ	S&P500	0.46	0.52	0.65	0.61	0.52	0.54	0.50	0.43	0.36	0.27
XYZ	CI	0.25	0.43	0.53	0.52	0.52	0.46	0.46	0.46	0.30	0.23
XYZ	NASDAQ_Composite	0.35	0.44	0.59	0.56	0.47	0.49	0.45	0.37	0.31	0.23
XYZ	NASDAQ_Telecom	0.31	0.46	0.56	0.49	0.46	0.45	0.37	0.35	0.27	0.15
XYZ	NASDAQ_Comp	0.25	0.34	0.51	0.53	0.43	0.46	0.47	0.33	0.29	0.24
XYZ	BCI	0.08	0.11	0.28	0.41	0.37	0.45	0.48	0.32	0.37	0.35
XYZ	MCI	0.11	0.22	0.47	0.38	0.36	0.45	0.45	0.41	0.38	0.26
XYZ	CCI	0.28	0.27	0.52	0.52	0.35	0.49	0.61	0.42	0.53	0.47

Figures 3-1, 3-2 and 3-3 represent the correlation data in a graphical format.

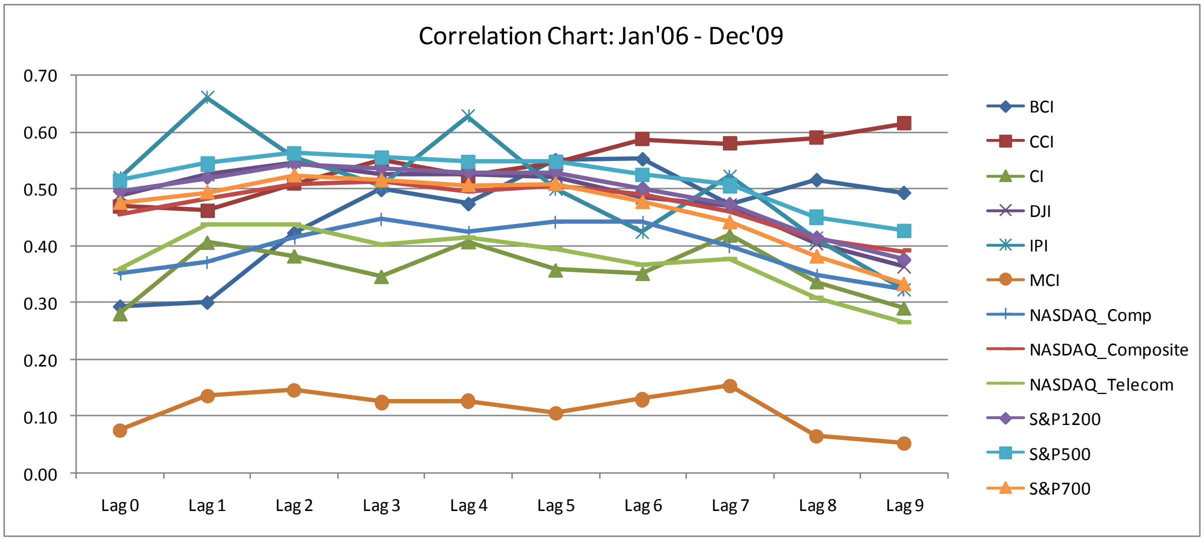

Figure 3 - 1: Correlation Graph for Jan'06 to Dec'09 Data Set

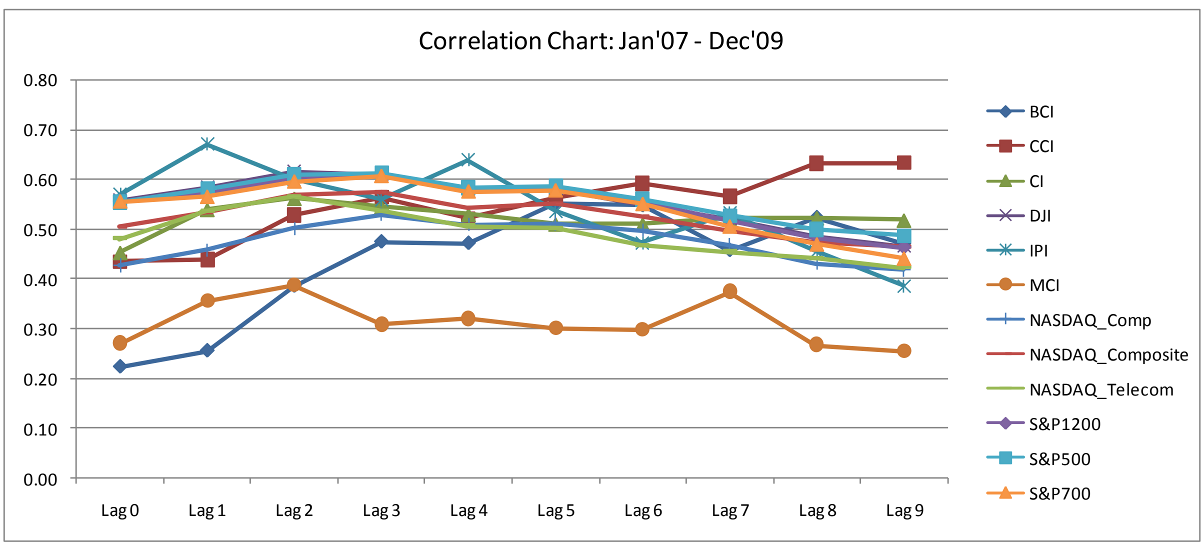

Figure 3 - 2: Correlation Graph for Jan'07 to Dec'09 Data Set

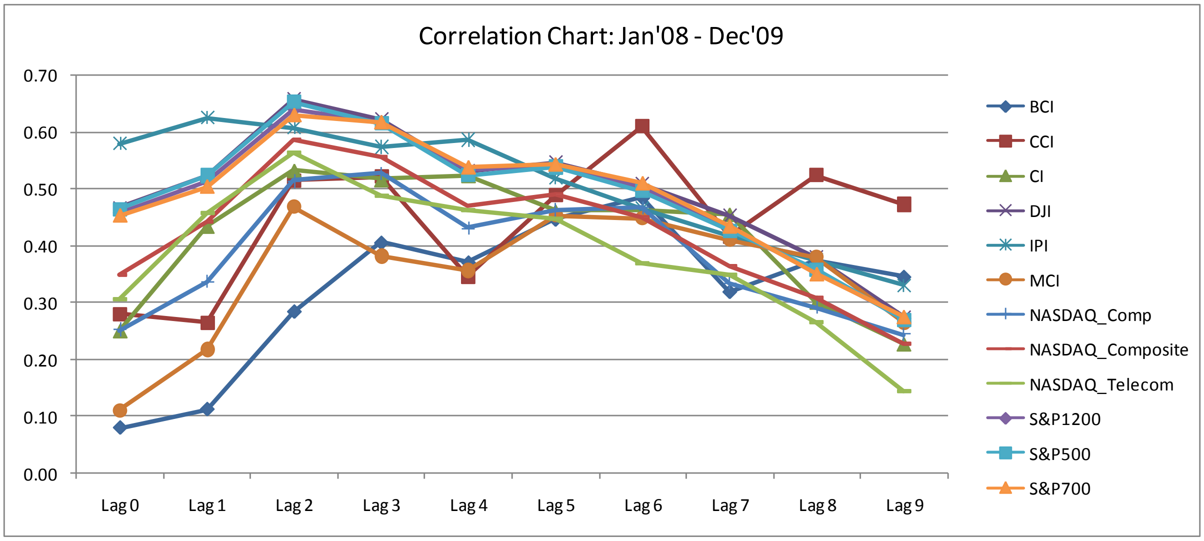

Figure 3 - 3: Correlation Graph for Jan'08 to Dec'09 Data Set

Correlation results show a very weak correlation between market indices (LEI) and actual bookings at all lags. Correlation charts show that correlation values start descending from lag 3 onwards as the lag value is increased. This is an expected behavior as the strength of relationship between leading economic indicators and bookings typically deteriorates as we go further out in time. The highest correlation of 0.67 was found between Industrial Production Index (IPI) and XYZ bookings at lag 1 for the data set: Jan'07 – Dec'09. A correlation value of 0.67 is not good enough to develop a model that could predict bookings with a fairly high accuracy (80% or above).

A close look at the bookings data reveals that the data is seasonal in nature having monthly seasonality within each quarter. In general, quarterly bookings for product series XYZ has the following monthly breakdown: Month 1 (29%), Month 2 (31%), and Month 3 (40%). There are a couple of reasons for month 3 to have higher bookings ratio than the first two months of a quarter. First, month 3 has an extra week than the first two months, which derives higher bookings. Secondly, there is typically a hockey stick effect towards end of the quarter (last couple of weeks in month 3) driven by the sales team push to close in any open deals before the quarter is over from a revenue recognition and sales commission perspective.

The monthly seasonality described above weakens the relationship between monthly bookings and the selected leading economic indicators as shown by low correlation values in Tables 3-1 to 3-3. The main reason for this is that most of the selected indicators (if not all) do not exhibit any monthly seasonality within a quarter unlike the monthly seasonality exhibited by the bookings for product series XYZ. Secondly, these economic indicators follow a calendar quarter while bookings for product series XYZ follows the company's fiscal quarter, which is different than a calendar quarter. This seasonality misalignment between bookings and the selected leading economic indicators could easily derail any strong relationship between the two. This brings up the idea of removing monthly seasonality out of bookings, which might improve the relationship between monthly bookings and the selected leading economic indicators. In order to check for this possibility, the correlation experiment is re-run but this time using a three-month centered moving average (MA) for bookings instead of the original bookings data. Results from this experiment are tabulated below.

Table 3 - 4: Correlation Values for Jan'06 to Dec'09 MA Data Set

Product Type	LEI/Correlation	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8	Lag 9
XYZ	S&P500	0.82	0.86	0.88	0.88	0.87	0.85	0.82	0.77	0.71	0.66
XYZ	IPI	0.92	0.92	0.91	0.89	0.85	0.81	0.75	0.70	0.66	0.60
XYZ	CCI	0.73	0.76	0.80	0.83	0.85	0.87	0.89	0.91	0.92	0.93
XYZ	S&P1200	0.78	0.82	0.85	0.85	0.84	0.82	0.78	0.72	0.65	0.58
XYZ	DJI	0.78	0.82	0.84	0.84	0.82	0.80	0.77	0.71	0.64	0.57
XYZ	S&P700	0.75	0.79	0.81	0.81	0.80	0.78	0.74	0.68	0.60	0.52
XYZ	BCI	0.42	0.54	0.64	0.74	0.80	0.83	0.83	0.80	0.76	0.74
XYZ	NASDAQ_Composite	0.72	0.77	0.80	0.80	0.80	0.78	0.76	0.71	0.65	0.60
XYZ	NASDAQ_Comp	0.54	0.60	0.65	0.68	0.69	0.68	0.67	0.62	0.55	0.49
XYZ	NASDAQ_Telecom	0.59	0.65	0.67	0.66	0.63	0.62	0.59	0.55	0.49	0.43
XYZ	CI	0.49	0.56	0.60	0.60	0.58	0.59	0.59	0.57	0.54	0.49
XYZ	MCI	0.13	0.19	0.21	0.21	0.19	0.19	0.21	0.18	0.15	0.09

Table 3 - 5: Correlation Values for Jan'07 to Dec'09 MA Data Set

Product Type	LEI/Correlation	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8	Lag 9
XYZ	S&P500	0.85	0.89	0.92	0.92	0.91	0.88	0.86	0.81	0.76	0.73
XYZ	DJI	0.86	0.90	0.93	0.92	0.90	0.88	0.85	0.79	0.74	0.70
XYZ	S&P1200	0.84	0.89	0.91	0.91	0.90	0.88	0.85	0.79	0.73	0.69
XYZ	S&P700	0.83	0.88	0.90	0.90	0.90	0.87	0.84	0.77	0.71	0.66
XYZ	IPI	0.94	0.94	0.94	0.92	0.88	0.84	0.79	0.74	0.70	0.66
XYZ	NASDAQ_Composite	0.77	0.82	0.86	0.86	0.85	0.83	0.81	0.76	0.72	0.69
XYZ	CCI	0.67	0.72	0.78	0.82	0.84	0.86	0.88	0.90	0.92	0.92
XYZ	CI	0.72	0.79	0.84	0.83	0.81	0.79	0.79	0.79	0.78	0.78
XYZ	NASDAQ_Comp	0.64	0.71	0.76	0.79	0.79	0.78	0.76	0.71	0.66	0.62
XYZ	NASDAQ_Telecom	0.76	0.81	0.84	0.82	0.79	0.76	0.73	0.69	0.66	0.64
XYZ	BCI	0.30	0.44	0.56	0.68	0.77	0.81	0.81	0.78	0.73	0.70
XYZ	MCI	0.45	0.52	0.53	0.52	0.47	0.47	0.50	0.48	0.46	0.43

Table 3 - 6: Correlation Values for Jan'08 to Dec'09 MA Data Set

Product Type	LEI/Correlation	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8	Lag 9
XYZ	DJI	0.77	0.85	0.93	0.93	0.88	0.83	0.78	0.71	0.62	0.53
XYZ	S&P700	0.72	0.82	0.90	0.91	0.88	0.83	0.78	0.69	0.59	0.50
XYZ	S&P1200	0.74	0.83	0.91	0.92	0.88	0.82	0.77	0.69	0.59	0.51
XYZ	S&P500	0.76	0.85	0.92	0.92	0.87	0.81	0.76	0.68	0.59	0.51
XYZ	IPI	0.94	0.94	0.93	0.90	0.87	0.82	0.73	0.66	0.63	0.56
XYZ	NASDAQ_Composite	0.60	0.71	0.82	0.83	0.79	0.74	0.68	0.60	0.50	0.45
XYZ	CI	0.49	0.62	0.76	0.81	0.78	0.76	0.71	0.64	0.55	0.47
XYZ	NASDAQ_Comp	0.42	0.57	0.71	0.76	0.74	0.71	0.67	0.59	0.48	0.43
XYZ	NASDAQ_Telecom	0.58	0.68	0.78	0.77	0.73	0.67	0.61	0.52	0.42	0.37
XYZ	CCI	0.48	0.55	0.67	0.71	0.70	0.76	0.80	0.82	0.79	0.80
XYZ	BCI	0.07	0.24	0.40	0.55	0.64	0.68	0.68	0.64	0.58	0.55
XYZ	MCI	0.26	0.41	0.54	0.62	0.62	0.65	0.69	0.66	0.59	0.55

Graphical representation of correlation output at different lags is shown below.

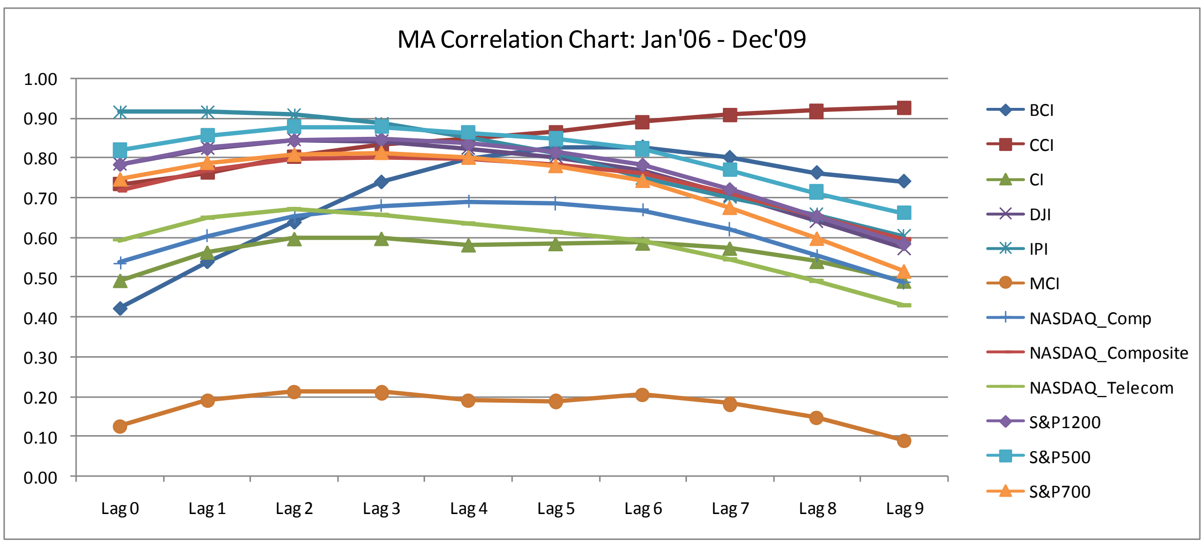

Figure 3 - 4: Correlation Graph for Jan'06 to Dec'09 MA Data Set

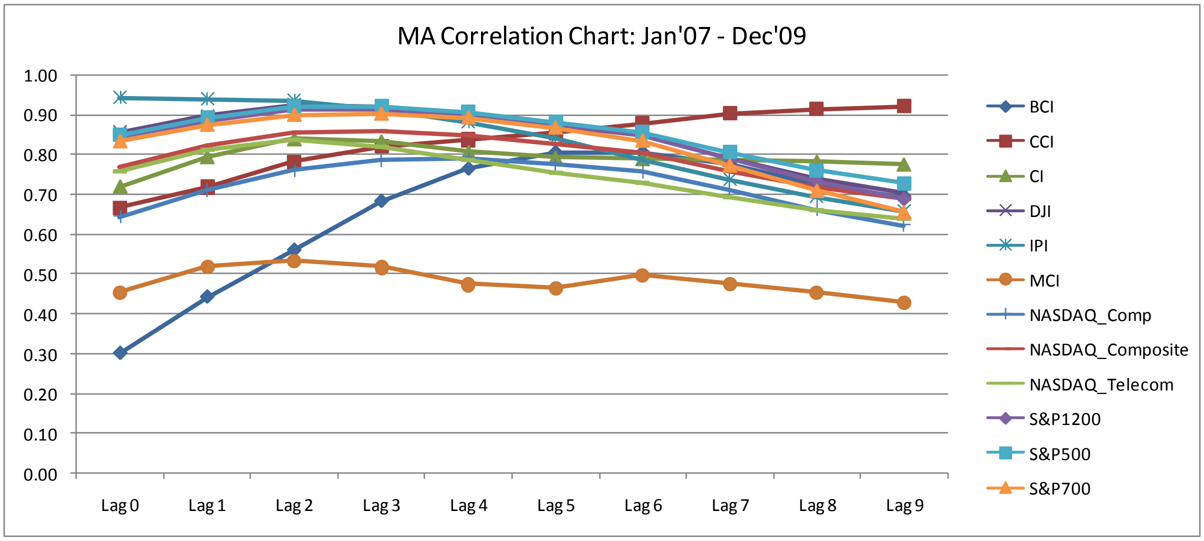

Figure 3 - 5: Correlation Graph for Jan'07 to Dec'09 MA Data Set

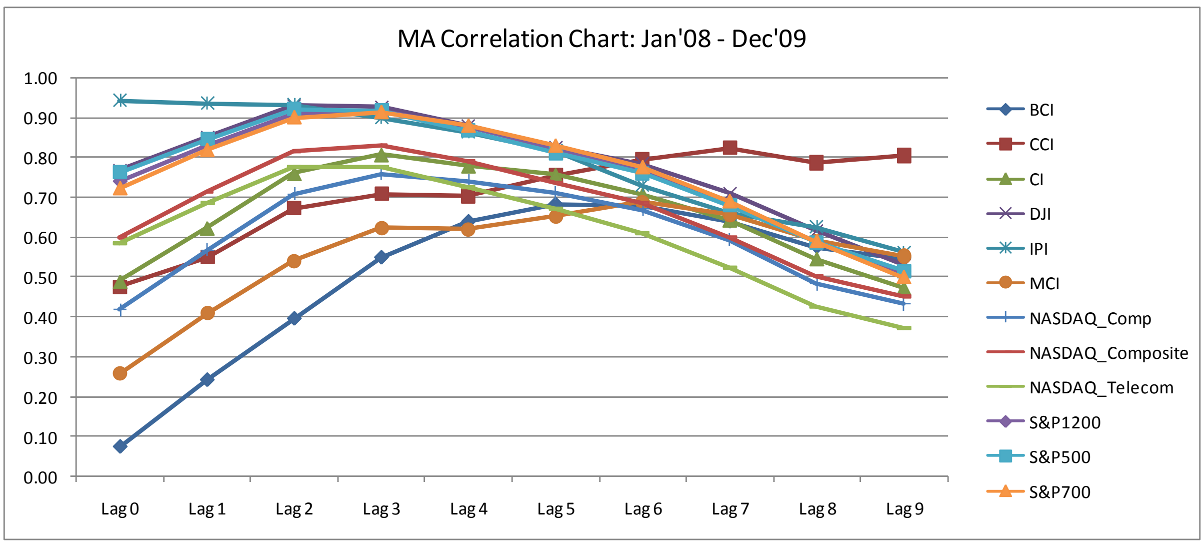

Figure 3 - 6: Correlation Graph for Jan'08 to Dec'09 MA Data Set

The results using a three month bookings moving average are quite encouraging. Correlation values of 0.92 and 0.93 are found between DJI and XYZ bookings at lag 3 for Jan’07 – Dec’09 and Jan’08 – Dec’09 time periods respectively. Similarly, correlation values of 0.92 are found for S&P500 at lag 3 for Jan’07 – Dec’09 and Jan’08 – Dec’09 time periods. Correlation values of 0.91 to 0.90 are also reported at lag 4 for S&P500 and DJI, respectively for Jan’07 – Dec’09 time period.

Correlation charts based on the booking’s moving average also show that the correlation tends to decline from lag 3 onwards as the lag value is increased. For example, correlation dropped from 0.93 to 0.53 for DJI as we move from lag 3 to lag 9 for the data set Jan’08 – Dec’09. Lag 3 seems to be the inflection point where correlation between XYZ bookings and market indices reaches the highest level before it starts declining.

A regression model is built and discussed in the next chapter leveraging from the strong correlation found between XYZ bookings and DJI/S&P500 indices.

CHAPTER 4 LINEAR REGRESSION MODELS FORCOMMUNICATIONS TECHNOLOGY PRODUCTS – LEI APPROACH

4.1 Linear Regression Model

A simple linear regression model is built in this chapter using the least squares methodology to determine how accurate the model is in determining future bookings and how it compares to the existing forecasting techniques, namely a marketing forecast and statistical forecast that the marketing and analytical teams put together every month.

The moving average (MA) data set from Jan-07 to Dec-09 will be used to build the initial regression model as shown below. We have already found a correlation of 0.92 and 0.91 at lag-3 and lag-4, respectively between bookings and S&P500 for this data set. The dependent variable (Y) below represents the 3-month bookings moving average while the independent variable (X) represents S&P500 values (monthly average of S&P500 daily close values).

Table 4 - 1: Monthly MA Bookings Data

Month	*X* (S&P500)	*Y* (Bookings)	Month	*X* (S&P500)	*Y* (Bookings)
Jan-07	1424	466	Jul-08	1257	513
Feb-07	1445	466	Aug-08	1281	506
Mar-07	1407	485	Sep-08	1217	445
Apr-07	1464	491	Oct-08	969	446
May-07	1511	506	Nov-08	883	442
Jun-07	1514	524	Dec-08	878	395
Jul-07	1521	491	Jan-09	866	360
Aug-07	1455	489	Feb-09	805	336
Sep-07	1497	518	Mar-09	757	335
Oct-07	1540	563	Apr-09	848	336
Nov-07	1463	566	May-09	902	336
Dec-07	1479	505	Jun-09	926	352
Jan-08	1379	463	Jul-09	936	349
Feb-08	1355	456	Aug-09	1010	348
Mar-08	1317	484	Sep-09	1045	313
Apr-08	1370	500	Oct-09	1068	327
May-08	1403	488	Nov-09	1088	337
Jun-08	1341	519	Dec-09	1110	332

We assume forecasting Apr-10 bookings in the beginning of Jan-10, which represents forecasting at lag-4. For this reason, we use lag-4 data to build the model using S&P500 and 3-month moving average of bookings. The lag-4 transformation of the above original data is shown below (32 data points in total).

Table 4 - 2: Lag-4 Monthly MA Bookings Data

Month	*X* (S&P500)	*Y* (Bookings)
Jan-07	1424	506
Feb-07	1445	524
Mar-07	1407	491
Apr-07	1464	489
May-07	1511	518
Jun-07	1514	563
Jul-07	1521	566
Aug-07	1455	505
Sep-07	1497	463
Oct-07	1540	456
Nov-07	1463	484
Dec-07	1479	500
Jan-08	1379	488
Feb-08	1355	519
Mar-08	1317	513
Apr-08	1370	506
May-08	1403	445
Jun-08	1341	446
Jul-08	1257	442
Aug-08	1281	395
Sep-08	1217	360
Oct-08	969	336
Nov-08	883	335
Dec-08	878	336
Jan-09	866	336
Feb-09	805	352
Mar-09	757	349
Apr-09	848	348
May-09	902	313
Jun-09	926	327
Jul-09	936	337
Aug-09	1010	332

A simple linear regression equation for the lag-4 data (Table 4-2) is as follows:

$$Y_c = c + m * X = 88.95 + 0.28 * X$$

where *m* represents slope of the line, and *c* represents the y-intercept.

We perform a sequence of tests on the regression model to check its validity before using the model to forecast bookings for Apr-10 and compare the results with the current forecasting techniques. The sequence of tests is listed below:

a) Quality of Fit (R^2) Test
b) Significance Test (Test of Hypothesis/F-test)
c) Autocorrelation Test

4.2 Quality of Fit (R^2) Test

The coefficient of determination (R^2) measures the degree of closeness of the X and Y variables and indicates how much of the variation is explained by the independent variable (X). The R^2 value is simply the square of the correlation coefficient and is always between 0 and 1. The correlation value for the lag-4 data set (Table 4-2) is calculated as 0.91, and the corresponding R^2 value is 0.82.

This shows that about 82% of the variability in bookings is attributable to the S&P500 indicator, and approximately 18% of the variability is unexplained. The R^2 value is high enough to indicate a strong positive relationship between bookings and S&P500 index.

4.3 Significance Test (Test of Hypothesis/F-test)

The possibility that chance plays a major role in the association indicated by the R^2 value must be considered. This possibility grows where there are a limited number of data points. There are several procedures available to test the significance and one of them is the F-test. F-test checks the significance of the relationship by comparing the explained and unexplained variances. The F-test assumes that the dependent variable (Y) is normally distributed.

Variations are computed using the lag-4 bookings moving average data (Table 4-2) as below:

Total Variation = $\sum(\mathrm{Y} - Y_{avg})^2$ = 208652

Unexplained Variation = $\sum(Y - Y_c)^2$ = 37122

Explained Variation = Total Variation – Unexplained Variation = 171530

The degrees of freedom D_1 and D_2 (number of variables that can vary freely in the equation) for Regression and Residual, respectively, are as follows:

$D_1 = k - 1 = 2 - 1 = 1$

$D_2 = n - k = 32 - 2 = 30$

where k is the number of constants in the regression equation (m and c) and n is the total number of observations.

Unexplained Variation ÷ D_2 = 1237

Explained Variation ÷ D_1 = 171530

F = (Explained Variation/D_1) ÷ (Unexplained Variation/D_2) = 138.62

F distribution critical value at 5% probability (95% confidence level) with numerator degrees of freedom (D_1) of 1 and denominator degrees of freedom (D_2) of 30 is 4.17. The critical value at 99% confidence level is 7.56.

There is a significant relationship between bookings and S&P500 index since the F-test value is greater than the critical value at both the 95% and 99% confidence levels. Therefore, we can conclude with practical certainty that the relationship between bookings and the S&P500 index is sound.

4.4 Autocorrelation Test (Durbin-Watson Test)

The purpose of autocorrelation test is to determine whether the residuals (errors) are random. Residuals are the unexplained differences that occur because the forecast computed by the regression equation does not equal the actual values. If the residuals indicate some sort of pattern, it would suggest presence of autocorrelation and that the dependent variable (Y) is influenced by outside forecasts. Autocorrelation could lead to inaccurate forecasts, and it is necessary to test for this condition. The Durbin-Watson test assumes that errors (e_t) are stationary and normally distributed with mean zero.

The Durbin-Watson test statistic is always between 0 and 4 with 2 being the best score (zero autocorrelation). If e_t is the residual associated with the observation at time t, then the test statistic 'd' is:

$$d = \frac{\sum_{t=2}^{n}(e_t - e_{t-1})^2}{\sum_{t=1}^{n} {e_t}^2}$$

where n is the number of observations. The lower and upper critical values for the test statistic are 1.37 and 1.50 respectively at 95% confidence level with one X variable in the regression equation. The test shows that there is statistical evidence that the residuals are positively autocorrelated since the test statistics (0.80) is less than the lower critical value of 1.37. It is a cause of concern but not alarming since a Durbin-Watson test statistic well below 1.0 usually indicates a fundamental structural problem in the model.

We can conclude that the relationship between bookings and S&P500 is strong and significant with the statistical evidence that the residuals are positively autocorrelated at lag-1. Overall, we can conclude that the model is valid to forecast future bookings.

Now we will use the model to forecast Apr-10 bookings using a lag of 4 between S&P500 index and the bookings. The regression model is:

$Y_c = 89.1 + 0.28 * X$

The 3-point moving average for Apr-10 bookings using S&P500 value from Dec-09 is computed as:

Y_c = 89.1 + 0.28*1110 (Dec-09 S&P500 Value) = 400 units

400 units here represents the 3-point moving average for Mar-10, Apr-10 and May-10. Total forecast for the 3 month period would be 400*3 = 1200 units

Now in order to compute the Apr-10 bookings forecast from the total 3 month forecast, we calculate the ratio between April bookings and the corresponding 3 month period bookings based on historical bookings data. Table below shows this ratio (or monthly index) for the years 2005 through 2009.

Table 4 - 3: Monthly Seasonality Index for April

Month	Index
Apr-05	0.390
Apr-06	0.436
Apr-07	0.404
Apr-08	0.426
Apr-09	0.404

The average index for April for the years (2007 – 2009) is 0.411.

Apr-10 Bookings Forecast = 0.411 * 1200 units (Total 3 month forecast for Mar, Apr and May) = 493 units

Thus, our model forecasts 493 units for Apr-10. We now calculate the accuracy of Apr-10 forecast using the standard accuracy formula.

4.5 Forecast Accuracy Calculation

Actual Apr-10 units are turned out to be 515 units. The accuracy of our model forecast could then be computed as:

$$Accuracy = Max\ \left[0, 1 - \frac{Abs(Forecast\ - Actuals\ )}{Actuals}\right] = 0.957\ (95.7\%)$$

Apr-10 forecast accuracy is 95.7% using the forecast from the linear regression model.

Now we compare our model's forecast accuracy with the accuracy of the marketing and statistical forecasts for the month of Apr-10. Table 4-4 below shows a comparison between different forecasting models.

Table 4 - 4: Forecast Accuracy Calculation (Apr'10)

Forecasting Model	Forecast	Actuals	Accuracy
Linear Regression LEI Model	493	515	96%
Marketing Forecast	491	515	95%
Statistical Forecast	400	515	78%

The accuracy comparison among the three models shows that the linear regression model (using LEI) is slightly better than the marketing model and significantly better than the statistical model in terms of accuracy for the month of Apr-10.

4.6 Forecast Generation using Linear Regression

Leading economic indicators are used in this section to generate monthly bookings forecast for product series XYZ from Apr-10 through Mar-11 time frame. Different models (each representing a leading economic indicator) are analyzed to select the best model for forecast generation. The model selection process is based on the historical performance as measured by forecast accuracy/MAPE. The LEI model forecast is also compared with the existing forecast techniques (statistical forecast and marketing/sales forecast) to gauge any forecast accuracy improvement.

The following five models/LEI are initially selected out of the twelve economic indicators to forecast Apr-10 through Sep-10 bookings since they represent the top five indicators in terms of descending lag-4 correlation values (see Table 3-5 for comparison of correlation values among the twelve indicators).

1) S&P500 Model

2) DJI Model

3) S&P1200 Model

4) S&P700 Model

5) IPI Model

Each of the above regression models uses a leading economic indicator as the *X* (independent) variable. For example, the S&P500 model uses the S&P500 as the leading economic indicator while the IPI model uses the Industrial Production Index as the leading economic indicator. The lag-4 transformation of the moving average bookings data is used for all the models to forecast Apr-10 through Sep-10 bookings using the 36-month rolling moving average bookings data. The model with the highest accuracy (lowest MAPE) during the past six months is then used to forecast bookings for future months. This process is repeated every three months to ensure that recent MAPE values from the past six months are factored into the forecast model selection process. For example, we use the model that exhibits the best accuracy performance during Apr-10 to Sep-10 time period (past six months) to generate the lag-4 forecast for the Jan-11 to Mar-11 time period.

Table 4-5 outlines the regression parameters for the five models using the Jan'07 – Dec'09 data set. This is to ensure that all the five models are statistically sound before they are used for forecasting purposes.

Table 4 - 5: Regression Parameters for Selected Models

Model	R^2 Value	F-test Statistics	Durbin-Watson test Statistics
S&P500	0.82	$138.75 > F_{crt}(4.17)$	$0.80 < L_{crt}(1.37)$
		Pass	Fail
DJI	0.82	$133.66 > F_{crt}(4.17)$	$0.78 < L_{crt}(1.37)$
		Pass	Fail
S&P1200	0.81	$131.66 > F_{crt}(4.17)$	$0.74 < L_{crt}(1.37)$
		Pass	Fail
S&P700	0.8	$120.78 > F_{crt}(4.17)$	$0.68 < L_{crt}(1.37)$
		Pass	Fail
IPI	0.78	$105.91 > F_{crt}(4.17)$	$0.67 < L_{crt}(1.37)$
		Pass	Fail

The regression parameters outlined above suggest that the five selected models use economic indicators that have a strong and significant relationship with actual bookings. However, they all have residuals that are positively autocorrelated. Lag-1 autocorrelation is more likely to represent persistence in most real systems than the autocorrelation at some higher lag.

The linear regression equations for the five selected models are shown below. The data set used for the model equations is Jan'07 - Dec'09 and the forecast lag used is 4.

S&P500 Model:

$$Y_c = 89.1 + 0.28 * S\&P500$$

DJI Model:

$$Y_c = 51.9 + 0.03 * DJI$$

S&P1200 Model:

$$Y_c = 112.8 + 0.22 * S\&P1200$$

S&P700 Model:

$$Y_c = 134.1 + 0.18 * S\&P700$$

IPI Model:

$$Y_c = -638.2 + 11.3 * IPI$$

Y_c here represents 3-point moving average bookings forecast. The monthly seasonal index is used to transform 3-point moving average bookings forecast into the regular monthly bookings forecast as shown in section 4.4.

Table 4-6 shows a comparison of forecast accuracy and correlation among the five selected models during the Apr-10 to Sep-10 time period. The comparison shows that all five models have an average accuracy greater than 85%. The IPI model stands out as the best model in terms of accuracy with an average accuracy of 92%. IPI model accuracy also outperforms the accuracy for the marketing forecast and the statistical forecast by 1 and 19 percentage points, respectively. However, the IPI model has a standard deviation of error higher than the other models. The average accuracy for the S&P1200 model over the Apr-10 to Sep-10 time frame is 2% points below the marketing forecast accuracy but 16% points above the statistical forecast accuracy. The S&P1200 model is better than the S&P500 and the DJI models both in terms of standard deviation of error and the forecast accuracy. This indicates that the demand for product series XYZ is more influenced by changes in the global equity market than the USA alone.

Table 4 - 6: Accuracy Comparison for Simple Regression Model Selection (Apr'10 - Sep'10)

Model	Month	Forecast	Actuals	LEI Model Accuracy	Marketing Forecast Accuracy	Statistical Forecast Accuracy	Forecast Error	Std. Deviation of Error	Correlation Value	Data Start Month	Data End Month
S&P500	Apr-10	493	516	96%	95%	78%	-23	-	0.91	Jan-07	Dec-09
	May-10	340	298	86%	78%	91%	42	-	0.91	Feb-07	Jan-10
	Jun-10	341	365	94%	93%	85%	-24	-	0.90	Mar-07	Feb-10
	Jul-10	537	485	89%	94%	88%	52	-	0.90	Apr-07	Mar-10
	Aug-10	314	266	82%	91%	34%	48	-	0.90	May-07	Apr-10
	Sep-10	362	302	80%	94%	65%	60	-	0.89	Jun-07	May-10
	Average			88%	91%	73%	26	54	0.90		
DJI	Apr-10	501	516	97%	95%	78%	-15	-	0.90	Jan-07	Dec-09
	May-10	343	298	85%	78%	91%	45	-	0.90	Feb-07	Jan-10
	Jun-10	346	365	95%	93%	85%	-19	-	0.90	Mar-07	Feb-10
	Jul-10	540	485	89%	94%	88%	55	-	0.90	Apr-07	Mar-10
	Aug-10	315	266	82%	91%	34%	49	-	0.90	May-07	Apr-10
	Sep-10	364	302	79%	94%	65%	62	-	0.90	Jun-07	May-10
	Average			88%	91%	73%	30	54	0.90		
S&P1200	Apr-10	496	516	96%	95%	78%	-20	-	0.90	Jan-07	Dec-09
	May-10	341	298	86%	78%	91%	43	-	0.90	Feb-07	Jan-10
	Jun-10	338	365	93%	93%	85%	-27	-	0.90	Mar-07	Feb-10
	Jul-10	529	485	91%	94%	88%	44	-	0.90	Apr-07	Mar-10
	Aug-10	306	266	85%	91%	34%	40	-	0.89	May-07	Apr-10
	Sep-10	347	302	85%	94%	65%	45	-	0.89	Jun-07	May-10
	Average			89%	91%	73%	21	46	0.90		
S&P700	Apr-10	498	516	97%	95%	78%	-18	-	0.90	Jan-07	Dec-09
	May-10	342	298	85%	78%	91%	44	-	0.89	Feb-07	Jan-10
	Jun-10	336	365	92%	93%	85%	-29	-	0.89	Mar-07	Feb-10
	Jul-10	523	485	92%	94%	88%	38	-	0.89	Apr-07	Mar-10
	Aug-10	300	266	87%	91%	34%	34	-	0.89	May-07	Apr-10
	Sep-10	336	302	89%	94%	65%	34	-	0.88	Jun-07	May-10
	Average			90%	91%	73%	17	41	0.89		
IPI	Apr-10	420	516	82%	95%	78%	-96	-	0.88	Jan-07	Dec-09
	May-10	298	298	100%	78%	91%	0	-	0.89	Feb-07	Jan-10
	Jun-10	306	365	84%	93%	85%	-59	-	0.89	Mar-07	Feb-10
	Jul-10	480	485	99%	94%	88%	-5	-	0.88	Apr-07	Mar-10
	Aug-10	265	266	100%	91%	34%	-1	-	0.87	May-07	Apr-10
	Sep-10	338	302	88%	94%	65%	36	-	0.87	Jun-07	May-10
	Average			92%	91%	73%	-21	59	0.88		

The accuracy comparison for the 6 months (Apr’10 – Sep’10) also shows that the IPI model is better than the marketing forecast 50% of the time (3 out of 6 months) while both the IPI and S&P1200 models are better than the statistical forecast 83% of the time (5 out of 6 months). This clearly demonstrates the predictive power of leading economic indicators to forecast demand for communications technology products.

Both the IPI and S&P1200 models are selected to forecast bookings for the Jan-11 to Mar-11 time period since the IPI model yielded the highest average accuracy (92%) while the S&P1200 model has a standard deviation of error (44 units) that is 22% less than the IPI model. The forecast accuracy results for the twelve month time period (Apr-2010 to Mar-2011) are tabulated in Table 4-7.

Table 4 - 7: Linear Regression Model Forecast and Accuracy (Apr'2010 - Mar'2011)

Model	Month	Forecast	Actuals	LEI Model Accuracy	Marketing Forecast Accuracy	Statistical Forecast Accuracy	Forecast Error	Std. Deviation of Error	Correlation Value	Data Start Month	Data End Month
S&P1200	Apr-10	496	516	96%	95%	78%	-20	-	0.90	Jan-07	Dec-09
	May-10	341	298	86%	78%	91%	43	-	0.90	Feb-07	Jan-10
	Jun-10	338	365	93%	93%	85%	-27	-	0.90	Mar-07	Feb-10
	Jul-10	529	485	91%	94%	88%	44	-	0.90	Apr-07	Mar-10
	Aug-10	306	266	85%	91%	34%	40	-	0.89	May-07	Apr-10
	Sep-10	347	302	85%	94%	65%	45	-	0.89	Jun-07	May-10
	Oct-10	463	480	96%	99%	92%	-17	-	0.89	Jul-07	Jun-10
	Nov-10	332	343	97%	84%	96%	-11	-	0.89	Aug-07	Jul-10
	Dec-10	376	371	99%	84%	92%	5	-	0.87	Sep-07	Aug-10
	Jan-11	425	360	82%	75%	74%	65	-	0.87	Oct-07	Sep-10
	Feb-11	334	285	83%	94%	98%	49	-	0.87	Nov-07	Oct-10
	Mar-11	386	322	80%	99%	94%	64	-	0.86	Dec-07	Nov-10
	Average			89%	90%	82%	23	44	0.89		
IPI	Apr-10	420	516	82%	95%	78%	-96	-	0.88	Jan-07	Dec-09
	May-10	298	298	100%	78%	91%	0	-	0.89	Feb-07	Jan-10
	Jun-10	306	365	84%	93%	85%	-59	-	0.89	Mar-07	Feb-10
	Jul-10	480	485	99%	94%	88%	-5	-	0.88	Apr-07	Mar-10
	Aug-10	265	266	100%	91%	34%	-1	-	0.87	May-07	Apr-10
	Sep-10	338	302	88%	94%	65%	36	-	0.87	Jun-07	May-10
	Oct-10	495	480	97%	99%	92%	15	-	0.86	Jul-07	Jun-10
	Nov-10	341	343	100%	84%	96%	-2	-	0.87	Aug-07	Jul-10
	Dec-10	405	371	91%	84%	92%	34	-	0.86	Sep-07	Aug-10
	Jan-11	438	360	78%	75%	74%	78	-	0.86	Oct-07	Sep-10
	Feb-11	324	285	86%	94%	98%	39	-	0.86	Nov-07	Oct-10
	Mar-11	368	322	86%	99%	94%	46	-	0.84	Dec-07	Nov-10
	Average			91%	90%	82%	7	50	0.87		

4.8 Forecast Accuracy Comparison – Linear Regression

The forecast accuracy comparison table above (Table 4-7) shows that the IPI model average accuracy over the twelve month period (Apr-2010 to Mar-2011) is slightly better than the average marketing forecast accuracy but is significantly better than the statistical forecast accuracy. The IPI model accuracy is better than the marketing and statistical forecasts by one and nine percentage points, respectively. The comparison also shows that the IPI model forecast is better than the marketing forecast 50% of the time (6 out of 12 months) and better than the statistical forecast 67% of the time (8 out of 12 months).

S&P1200 model accuracy is one percentage point below the average marketing forecast accuracy but is higher than the statistical accuracy by seven percentage points. Both the S&P1200 and IPI models outperform the statistical forecast but are on a par with the marketing forecast. Standard deviation of error for the S&P1200 model (44 units) is 12% less than the IPI model during the Apr-2010 to Mar-2011 time period. Autocorrelation function for the S&P1200 model residuals shows low serial correlation values compared to the IPI model as shown in Figure 4-1. For example, lag-4 autocorrelation value for the S&P1200 model residuals is 0.03 compared to 0.75 for the IPI model. This shows that the S&P1200 model is statistically a better model than the IPI model even though average accuracy for the IPI model is marginally better than the S&P1200 model over the Apr-2010 to Mar-2011 time period.

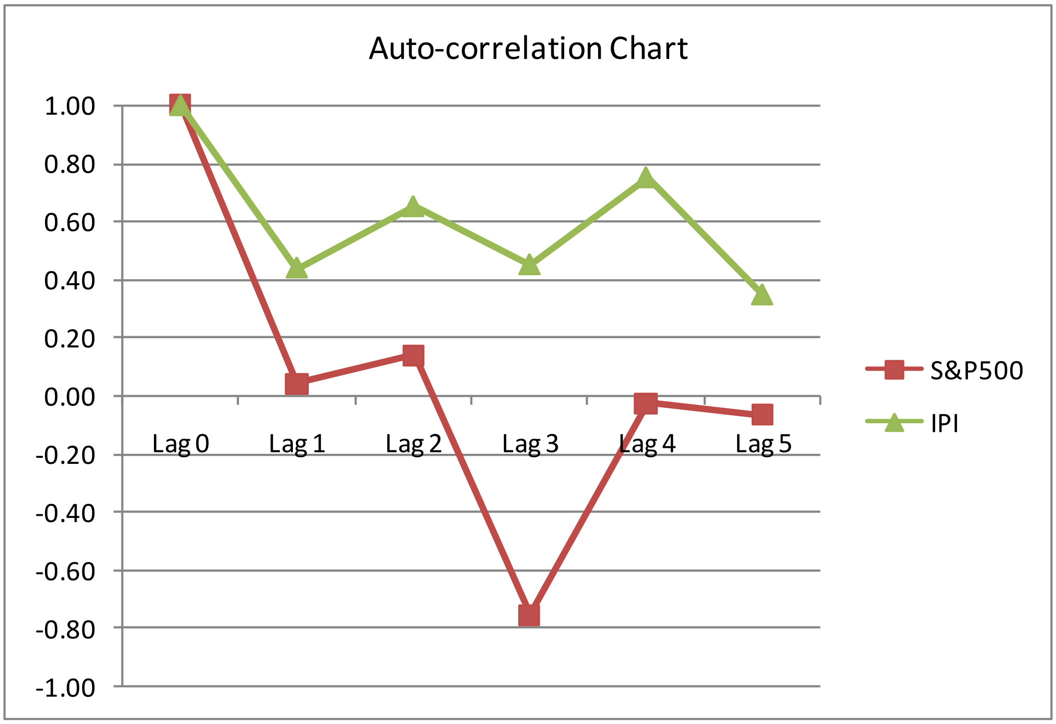

Figure 4 - 1: Auto-correlation Chart for Simple Regression Residuals (Apr'2010 – Mar'2011)

CHAPTER 5 MULTIPLE REGRESSION MODELS FOR COMMUNICATIONS TECHNOLOGY PRODUCTS – LEI APPROACH

The cumulative effect of multiple leading economic indicators on the demand for product series XYZ is studied in this chapter by using multiple regression models. The use of multiple economic indicators to predict demand for communications technology products might be more effective in terms of forecast accuracy than the use of any individual economic indicator.

5.1 Multiple Correlation Analysis

The following five economic indicators are analyzed together to determine the strength of their correlation with the actual bookings for product series XYZ.

1) S&P1200 (S&P1200 Global Index)
2) IPI (Industrial Production Index)
3) CCI (Consumer Confidence Index)
4) MCI (Main Competitor Stock Index)
5) CI (Company Stock Index)

The S&P1200 and IPI economic indicators are also selected for multiple regression since they yielded the highest correlation and accuracy, respectively, while used in linear regression. The stock indices for the company and its main competitor are selected to see the impact of the company's performance as well as its competitor's performance on the demand for product series XYZ. Finally, the consumer confidence index was selected to see if consumer optimism in the overall state of the economy has any impact on demand. Consumer confidence is important to look at since customers like distributors, retailers, banks and government agencies use various assessments of consumer confidence in planning their purchasing actions.

There are 26 possible combinations of the five indicators above. The $AdjR^2$ and correlation values for each combination are shown below in Table 5-1 and Table 5-2, respectively, using the moving average data set from Jan-07 to Dec-09.

Table 5- 1: AdjR^2 Values for the Jan'07 to Dec'09 Moving Average Data Set

Product Type	LEI/AdjR^2	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8	Lag 9
XYZ	CCI, CI, IPI, S&P1200	0.89	0.88	0.88	0.87	0.87	0.85	0.82	0.79	0.83	0.88
XYZ	CCI, CI, IPI, MCI, S&P1200	0.88	0.88	0.88	0.87	0.87	0.84	0.81	0.79	0.82	0.89
XYZ	CCI, CI, S&P1200	0.73	0.78	0.82	0.84	0.87	0.85	0.83	0.80	0.83	0.89
XYZ	CCI, CI, MCI, S&P1200	0.73	0.78	0.83	0.84	0.87	0.85	0.82	0.79	0.83	0.89
XYZ	CCI, IPI, MCI, S&P1200	0.89	0.88	0.88	0.87	0.86	0.83	0.80	0.80	0.82	0.85
XYZ	CCI, MCI, S&P1200	0.73	0.79	0.83	0.85	0.86	0.83	0.81	0.80	0.82	0.86
XYZ	MCI, S&P1200	0.72	0.78	0.84	0.85	0.86	0.81	0.74	0.63	0.53	0.46
XYZ	IPI, MCI, S&P1200	0.88	0.88	0.89	0.87	0.86	0.81	0.73	0.61	0.51	0.43
XYZ	CI, MCI, S&P1200	0.73	0.78	0.83	0.85	0.85	0.81	0.73	0.69	0.72	0.76
XYZ	CI, IPI, MCI, S&P1200	0.88	0.88	0.89	0.86	0.85	0.80	0.72	0.67	0.71	0.75
XYZ	CCI, IPI, S&P1200	0.89	0.88	0.89	0.87	0.84	0.81	0.79	0.80	0.82	0.85
XYZ	CCI, IPI, MCI	0.89	0.88	0.88	0.86	0.84	0.81	0.79	0.80	0.82	0.85
XYZ	CCI, CI, IPI	0.89	0.89	0.89	0.86	0.83	0.81	0.79	0.80	0.82	0.86
XYZ	CCI, IPI	0.89	0.88	0.88	0.87	0.83	0.81	0.79	0.81	0.83	0.85
XYZ	CCI, CI, IPI, MCI	0.89	0.88	0.89	0.86	0.83	0.80	0.78	0.80	0.82	0.86
XYZ	CI, IPI, S&P1200	0.88	0.88	0.89	0.86	0.83	0.77	0.69	0.59	0.57	0.57
XYZ	CI, S&P1200	0.74	0.78	0.83	0.83	0.83	0.77	0.70	0.61	0.58	0.59
XYZ	CCI, S&P1200	0.70	0.78	0.82	0.83	0.82	0.80	0.80	0.81	0.83	0.86
XYZ	IPI, S&P1200	0.88	0.88	0.89	0.86	0.82	0.76	0.70	0.59	0.50	0.43
XYZ	CI, IPI, MCI	0.88	0.88	0.89	0.85	0.80	0.75	0.68	0.68	0.71	0.73
XYZ	CI, IPI	0.88	0.89	0.89	0.84	0.78	0.71	0.64	0.60	0.58	0.58
XYZ	IPI, MCI	0.88	0.88	0.87	0.83	0.77	0.70	0.59	0.51	0.45	0.40
XYZ	CCI, CI, MCI	0.51	0.63	0.73	0.74	0.72	0.73	0.75	0.80	0.82	0.84
XYZ	CI, MCI	0.53	0.64	0.74	0.74	0.72	0.69	0.66	0.69	0.72	0.73
XYZ	CCI, CI	0.50	0.62	0.70	0.72	0.71	0.73	0.76	0.80	0.83	0.84
XYZ	CCI, MCI	0.44	0.53	0.62	0.67	0.68	0.71	0.76	0.80	0.83	0.84

Table 5- 2: Multiple Correlation Values for the Jan'07 to Dec'09 Moving Average Data Set

Product Type	LEI/Correlation	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8	Lag 9
XYZ	CCI, CI, IPI, MCI, S&P1200	0.95	0.95	0.95	0.94	0.94	0.93	0.92	0.91	0.93	0.95
XYZ	CCI, CI, IPI, S&P1200	0.95	0.95	0.95	0.94	0.94	0.93	0.92	0.91	0.92	0.95
XYZ	CCI, CI, MCI, S&P1200	0.87	0.90	0.92	0.93	0.94	0.93	0.92	0.91	0.92	0.95
XYZ	CCI, IPI, MCI, S&P1200	0.95	0.95	0.95	0.94	0.94	0.92	0.91	0.91	0.92	0.94
XYZ	CCI, CI, S&P1200	0.87	0.89	0.92	0.93	0.94	0.93	0.92	0.91	0.92	0.95
XYZ	CCI, MCI, S&P1200	0.87	0.90	0.92	0.93	0.94	0.92	0.91	0.91	0.92	0.94
XYZ	CI, IPI, MCI, S&P1200	0.95	0.94	0.95	0.94	0.93	0.91	0.87	0.85	0.87	0.89
XYZ	IPI, MCI, S&P1200	0.94	0.94	0.95	0.94	0.93	0.91	0.87	0.81	0.75	0.71
XYZ	CI, MCI, S&P1200	0.87	0.89	0.92	0.93	0.93	0.91	0.87	0.85	0.87	0.89
XYZ	MCI, S&P1200	0.86	0.89	0.92	0.93	0.93	0.91	0.87	0.81	0.75	0.71
XYZ	CCI, IPI, S&P1200	0.95	0.95	0.95	0.94	0.92	0.91	0.90	0.91	0.92	0.93
XYZ	CCI, CI, IPI, MCI	0.95	0.95	0.95	0.94	0.92	0.91	0.90	0.91	0.92	0.94
XYZ	CCI, IPI, MCI	0.95	0.94	0.94	0.93	0.92	0.91	0.90	0.91	0.92	0.93
XYZ	CCI, CI, IPI	0.95	0.95	0.95	0.93	0.92	0.91	0.90	0.91	0.92	0.94
XYZ	CCI, IPI	0.95	0.94	0.94	0.93	0.92	0.91	0.90	0.91	0.92	0.93
XYZ	CI, IPI, S&P1200	0.94	0.94	0.95	0.93	0.92	0.89	0.85	0.80	0.78	0.79
XYZ	CI, S&P1200	0.87	0.89	0.91	0.92	0.92	0.89	0.85	0.80	0.78	0.79
XYZ	CCI, S&P1200	0.85	0.89	0.91	0.92	0.91	0.90	0.90	0.91	0.92	0.93
XYZ	IPI, S&P1200	0.94	0.94	0.95	0.93	0.91	0.88	0.85	0.79	0.73	0.69
XYZ	CI, IPI, MCI	0.95	0.94	0.95	0.93	0.91	0.88	0.84	0.85	0.86	0.87
XYZ	CI, IPI	0.94	0.94	0.95	0.92	0.89	0.85	0.82	0.79	0.78	0.78
XYZ	IPI, MCI	0.94	0.94	0.94	0.92	0.88	0.85	0.79	0.74	0.70	0.67
XYZ	CCI, CI, MCI	0.74	0.82	0.87	0.87	0.87	0.87	0.88	0.90	0.92	0.92
XYZ	CI, MCI	0.74	0.82	0.87	0.87	0.86	0.84	0.83	0.85	0.86	0.87
XYZ	CCI, CI	0.73	0.80	0.85	0.86	0.85	0.86	0.88	0.90	0.92	0.92
XYZ	CCI, MCI	0.69	0.75	0.80	0.83	0.84	0.86	0.88	0.90	0.92	0.92

A graphical representation of AdjR^2 and correlation output at different lags is shown below.

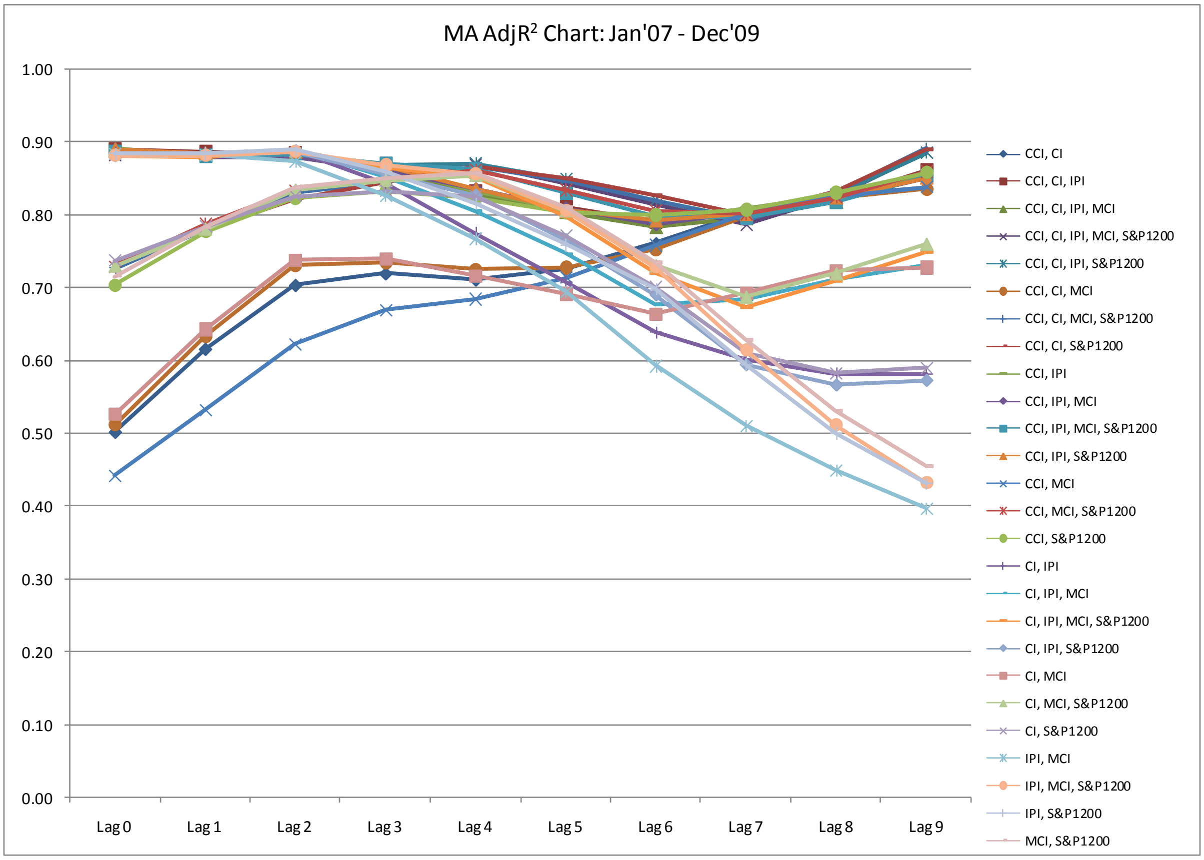

Figure 5 - 1: AdjR^2 Graph for the Jan'07 to Dec'09 Moving Average Data Set

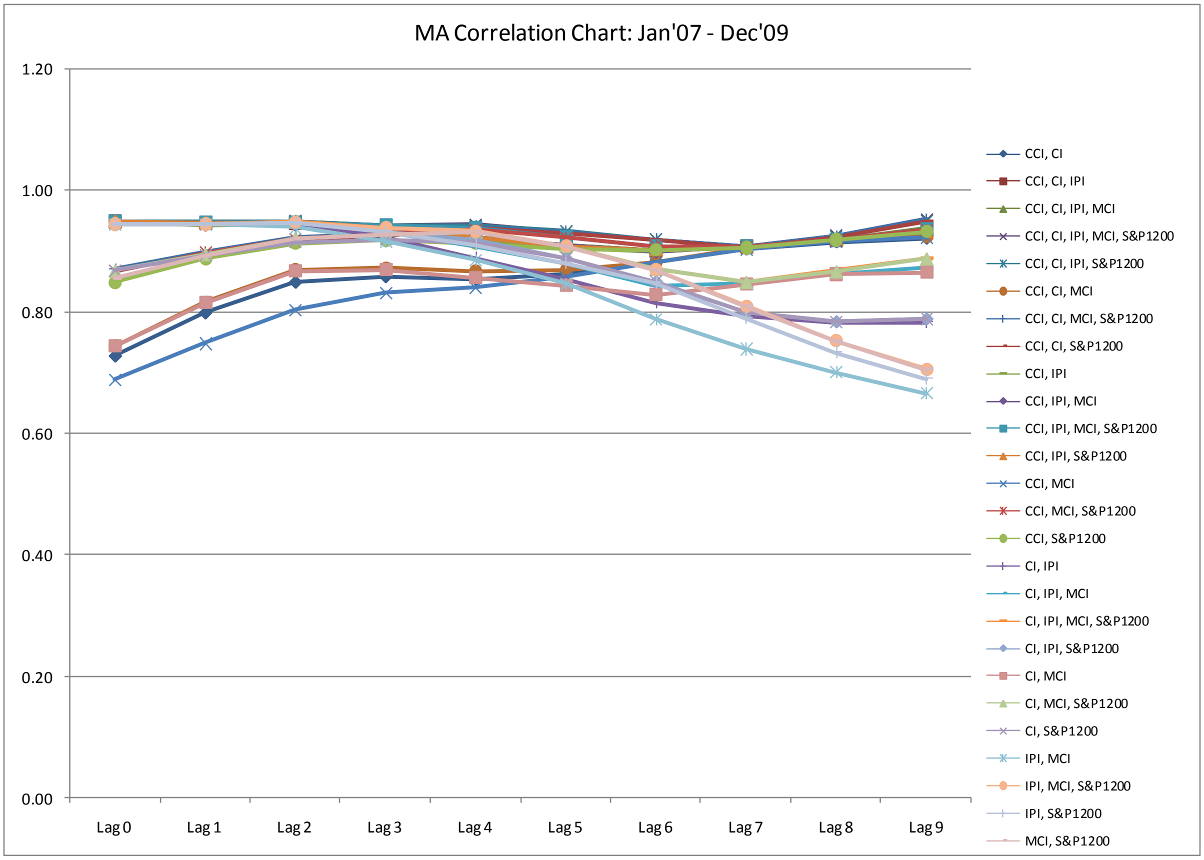

Figure 5 - 2: Correlation Graph for the Jan'07 to Dec'09 Moving Average Data Set

Combinations presented in Table 5-3 below represent the top five multiple economic indicator combinations in terms of AdjR^2 value. Lag-4 AdjR^2 value is used instead of R^2 value (or correlation value) to rank the multiple economic indicator combinations since R^2 systematically overstates goodness of fit in a model with more than one independent variable.

Table 5- 3: Lag-4 AdjR^2 Ranking for Multiple Economic Indicator Combinations

Product Type	LEI/AdjR^2	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8	Lag 9
XYZ	CCI, CI, IPI, S&P1200	0.89	0.88	0.88	0.87	0.87	0.85	0.82	0.79	0.83	0.88
XYZ	CCI, CI, IPI, MCI, S&P1200	0.88	0.88	0.88	0.87	0.87	0.84	0.81	0.79	0.82	0.89
XYZ	CCI, CI, S&P1200	0.73	0.78	0.82	0.84	0.87	0.85	0.83	0.80	0.83	0.89
XYZ	CCI, CI, MCI, S&P1200	0.73	0.78	0.83	0.84	0.87	0.85	0.82	0.79	0.83	0.89
XYZ	CCI, IPI, MCI, S&P1200	0.89	0.88	0.88	0.87	0.86	0.83	0.80	0.80	0.82	0.85

5.2 Forecast Generation using Multiple Regression

The following five multiple regression models are used in this section to generate monthly bookings forecast for product series XYZ since they represent the top five multiple economic indicator combinations in terms of $AdjR^2$ value as shown in Table 5-3.

1) CCI, CI, IPI and S&P1200 Model
2) CCI, CI, IPI, MCI and S&P1200 Model
3) CCI, CI and S&P1200 Model
4) CCI, CI, MCI and S&P1200 Model
5) CCI, IPI, MCI and S&P1200 Model

All five combinations are used initially to generate lag-4 forecasts for the Apr-10 to Sep-10 time frame using the past 36-month rolling data. The economic indicator combination with the highest accuracy value during the Apr-10 through Sep-10 time frame is then used to generate a lag-4 forecast for the Jan-11 to Mar-11 time period.

Table 5-4 outlines the regression parameters for the five multiple regression models using the Jan'07 – Dec'09 data set. This is to ensure that all the five models are statistically sound before they are used for forecasting purposes.

Table 5- 4: Multiple Regression Parameters for Selected Models

Model	$AdjR^2$ Value	F-test Statistics	Durbin-Watson test Statistics
CCI, CI, IPI and S&P1200	0.87	$53.62 > F_{crt}(2.73)$ Pass	$0.91 < L_{crt}(1.37)$ Fail
CCI, CI, IPI, MCI and S&P1200	0.87	$42.12 > F_{crt}(2.59)$ Pass	$0.85 < L_{crt}(1.37)$ Fail
CCI, CI and S&P1200	0.87	$68.29 > F_{crt}(2.95)$ Pass	$1.01 < L_{crt}(1.37)$ Fail
CCI, CI, MCI and S&P1200	0.87	$51.38 > F_{crt}(2.73)$ Pass	$0.91 < L_{crt}(1.37)$ Fail
CCI, IPI, MCI and S&P1200	0.86	$49.73 > F_{crt}(2.73)$ Pass	$0.76 < L_{crt}(1.37)$ Fail

Regression parameters outlined above suggest that the five selected models are using economic indicators that collectively have strong and significant relationship with actual bookings. However, they all have residuals that are positively autocorrelated.

The multiple regression equations for the five selected models are shown below. The data set used for the model equations is Jan'07 - Dec'09 and the forecast lag used is 4.

CCI/CI/IPI/S&P1200 Model:

$$Y_c = -41.9 + 1.2 * CCI - 10.8 * CI + 3.3 * IPI + 0.22 * S\&P1200$$

CCI/CI/IPI/MCI/S&P1200 Model:

$$Y_c = -21.7 + 1.0 * CCI - 8.1 * CI + 3.0 * IPI - 1.4 * MCI + 0.23 * S\&P1200$$

CCI/CI/S&P1200 Model:

$$Y_c = 191.6 + 1.2 * CCI - 11.9 * CI + 0.30 * S\&P1200$$

CCI/CI/MCI/S&P1200 Model:

$$Y_c = 182.1 + 0.9 * CCI - 7.9 * CI - 2.0 * MCI + 0.29 * S\&P1200$$

CCI/IPI/MCI/S&P1200 Model:

$$Y_c = -41.8 + 0.56 * CCI + 2.9 * IPI - 3.7 * MCI + 0.17 * S\&P1200$$

Y_c here represents 3-point moving average bookings forecast. A monthly seasonal index is used to transform the 3-point moving average bookings forecast into the regular monthly bookings forecast as shown in chapter 4 (section 4.4).

The regression coefficients for IPI, CCI and S&P1200 are positive. This means that the bookings for product series XYZ go up when these indices go up and vice versa. However, the interesting thing to note here is that the regression coefficients for CI and MCI are negative. This shows that the bookings for product series XYZ go up when the main competitor stock index (MCI) goes down. This could mean that when the main competitor is performing well in terms of market capitalization, it could in fact take some market share from the technology group for products series XYZ and thus affecting the demand for product series XYZ negatively.

Table 5-5 shows a comparison of forecast accuracy and standard deviation of error among the five selected models during the Apr-10 to Sep-10 time period. The comparison shows that all five models have an average accuracy greater than 90%. The "CCI, IPI, MCI and S&P1200" model stands out as the best model in terms of accuracy with an average accuracy of 93%. This model also has a standard deviation of error (91 units) that is lower than three of the other four models. A correlation value of 0.94 and $AdjR^2$ value of 0.87, which is quite high, signifies a strong relationship between the set of economic indicators (CCI, IPI, MCI, S&P1200) and the demand for product series XYZ. The model accuracy also outperforms the accuracy for the marketing forecast and the statistical forecast by 2 and 20 percentage points, respectively.

Table 5- 5: Accuracy Comparison for Multiple Regression Model Selection (Apr'10 - Sep'10)

Model	Month	Forecast	Actuals	LEI Model Accuracy	Marketing Forecast Accuracy	Statistical Forecast Accuracy	Forecast Error	Std. Deviation of Error	$AdjR^2$ Value	Correlation Value	Data Start Month	Data End Month
CCI, CI, IPI and S&P1200	Apr-10	434	516	84%	95%	78%	-82	-	0.87	0.94	Jan-07	Dec-09
	May-10	305	298	98%	78%	91%	7	-	0.87	0.94	Feb-07	Jan-10
	Jun-10	294	365	81%	93%	85%	-71	-	0.87	0.94	Mar-07	Feb-10
	Jul-10	457	485	94%	94%	88%	-28	-	0.86	0.94	Apr-07	Mar-10
	Aug-10	262	266	99%	91%	34%	-4	-	0.86	0.94	May-07	Apr-10
	Sep-10	317	302	95%	94%	65%	15	-	0.85	0.93	Jun-07	May-10
	Average			92%	91%	73%	-27	113	0.86	0.94		
CCI, CI, IPI, MCI and S&P1200	Apr-10	437	516	85%	95%	78%	-79	-	0.87	0.94	Jan-07	Dec-09
	May-10	307	298	97%	78%	91%	9	-	0.87	0.94	Feb-07	Jan-10
	Jun-10	296	365	81%	93%	85%	-69	-	0.87	0.94	Mar-07	Feb-10
	Jul-10	460	485	95%	94%	88%	-25	-	0.86	0.94	Apr-07	Mar-10
	Aug-10	266	266	100%	91%	34%	0	-	0.88	0.95	May-07	Apr-10
	Sep-10	320	302	94%	94%	65%	18	-	0.89	0.95	Jun-07	May-10
	Average			92%	91%	73%	-24	N/A	0.87	0.94		
CCI, CI and S&P1200	Apr-10	454	516	88%	95%	78%	-62	-	0.87	0.94	Jan-07	Dec-09
	May-10	316	298	94%	78%	91%	18	-	0.87	0.94	Feb-07	Jan-10
	Jun-10	300	365	82%	93%	85%	-65	-	0.87	0.94	Mar-07	Feb-10
	Jul-10	460	485	95%	94%	88%	-25	-	0.86	0.93	Apr-07	Mar-10
	Aug-10	264	266	99%	91%	34%	-2	-	0.86	0.94	May-07	Apr-10
	Sep-10	347	302	95%	94%	65%	45	-	0.86	0.93	Jun-07	May-10
	Average			92%	91%	73%	-15	74	0.87	0.94		
CCI, CI, MCI and S&P1200	Apr-10	456	516	88%	95%	78%	-60	-	0.87	0.94	Jan-07	Dec-09
	May-10	318	298	93%	78%	91%	20	-	0.87	0.94	Feb-07	Jan-10
	Jun-10	303	365	83%	93%	85%	-62	-	0.86	0.94	Mar-07	Feb-10
	Jul-10	462	485	95%	94%	88%	-23	-	0.86	0.94	Apr-07	Mar-10
	Aug-10	266	266	100%	91%	34%	0	-	0.88	0.95	May-07	Apr-10
	Sep-10	322	302	93%	94%	65%	20	-	0.89	0.95	Jun-07	May-10
	Average			92%	91%	73%	-18	94	0.87	0.94		
CCI, IPI, MCI and S&P1200	Apr-10	451	516	87%	95%	78%	-65	-	0.86	0.94	Jan-07	Dec-09
	May-10	317	298	94%	78%	91%	19	-	0.86	0.94	Feb-07	Jan-10
	Jun-10	310	365	85%	93%	85%	-55	-	0.86	0.94	Mar-07	Feb-10
	Jul-10	469	485	97%	94%	88%	-16	-	0.86	0.94	Apr-07	Mar-10
	Aug-10	268	266	100%	91%	34%	2	-	0.88	0.95	May-07	Apr-10
	Sep-10	320	302	94%	94%	65%	18	-	0.90	0.95	Jun-07	May-10
	Average			93%	91%	73%	-16	91	0.87	0.94		

The accuracy comparison for 6 months (Apr'10 – Sep'10) also shows that the "CCI, IPI, MCI, and S&P1200" model is better than the marketing forecast and the statistical forecast 67% of the time (4 out of 6 months).

The "CCI, IPI, MCI, and S&P1200" model is selected to forecast bookings for Jan-11 to Mar-11 time period since this model yielded the highest average accuracy (93%). The S&P1200/IPI and S&P1200/MCI models are also used to generate forecasts along with the "CCI, IPI, MCI, and S&P1200" model. The"S&P1200 and IPI" model is chosen to see if the combination of the two best economic indicators (IPI, S&P1200) from linear regression would together produce better accuracy results in multiple regression. The "S&P1200 and MCI" model is chosen to gauge the effect of the competitor's stock performance on the overall forecast accuracy of product series XYZ. The forecast accuracy results for the twelve month time period (Apr-2010 to Mar-2011) are tabulated in Table 5-6.

Table 5- 6: Multi Regression Model Forecast and Accuracy (Apr'2010 - Mar'2011)

Model	Month	Forecast	Actuals	LEI Model Accuracy	Marketing Forecast Accuracy	Statistical Forecast Accuracy	Forecast Error	Std. Deviation of Error	AdjR^2 Value	Correlation Value	Data Start Month	Data End Month
CCI, IPI, MCI and S&P1200	Apr-10	451	516	87%	95%	78%	-65	-	0.86	0.94	Jan-07	Dec-09
	May-10	317	298	94%	78%	91%	19	-	0.86	0.94	Feb-07	Jan-10
	Jun-10	310	365	85%	93%	85%	-55	-	0.86	0.94	Mar-07	Feb-10
	Jul-10	469	485	97%	94%	88%	-16	-	0.86	0.94	Apr-07	Mar-10
	Aug-10	268	266	100%	91%	34%	2	-	0.88	0.95	May-07	Apr-10
	Sep-10	320	302	94%	94%	65%	18	-	0.90	0.95	Jun-07	May-10
	Oct-10	437	480	91%	99%	92%	-43	-	0.88	0.94	Jul-07	Jun-10
	Nov-10	302	343	88%	84%	96%	-41	-	0.85	0.93	Aug-07	Jul-10
	Dec-10	336	371	91%	84%	92%	-35	-	0.84	0.93	Sep-07	Aug-10
	Jan-11	356	360	99%	75%	74%	-4	-	0.84	0.93	Oct-07	Sep-10
	Feb-11	280	285	98%	94%	98%	-5	-	0.83	0.92	Nov-07	Oct-10
	Mar-11	330	322	98%	99%	94%	8	-	0.80	0.91	Dec-07	Nov-10
	Average			93%	90%	82%	-18	43	0.86	0.94		
S&P1200 and IPI	Apr-10	468	516	91%	95%	78%	-48	-	0.82	0.91	Jan-07	Dec-09
	May-10	322	298	92%	78%	91%	24	-	0.82	0.91	Feb-07	Jan-10
	Jun-10	321	365	88%	93%	85%	-44	-	0.83	0.92	Mar-07	Feb-10
	Jul-10	508	485	95%	94%	88%	23	-	0.82	0.91	Apr-07	Mar-10
	Aug-10	289	266	92%	91%	34%	23	-	0.81	0.91	May-07	Apr-10
	Sep-10	342	302	87%	94%	65%	40	-	0.81	0.90	Jun-07	May-10
	Oct-10	473	480	99%	99%	92%	-7	-	0.80	0.90	Jul-07	Jun-10
	Nov-10	335	343	98%	84%	96%	-8	-	0.81	0.91	Aug-07	Jul-10
	Dec-10	389	371	95%	84%	92%	18	-	0.80	0.90	Sep-07	Aug-10
	Jan-11	432	360	80%	75%	74%	72	-	0.79	0.90	Oct-07	Sep-10
	Feb-11	330	285	85%	94%	98%	45	-	0.80	0.90	Nov-07	Oct-10
	Mar-11	379	322	83%	99%	94%	57	-	0.78	0.89	Dec-07	Nov-10
	Average			90%	90%	82%	16	45	0.81	0.91		
S&P1200 and MCI	Apr-10	470	516	91%	95%	78%	-46	-	0.86	0.93	Jan-07	Dec-09
	May-10	328	298	90%	78%	91%	30	-	0.86	0.93	Feb-07	Jan-10
	Jun-10	322	365	88%	93%	85%	-43	-	0.85	0.93	Mar-07	Feb-10
	Jul-10	481	485	99%	94%	88%	-4	-	0.85	0.93	Apr-07	Mar-10
	Aug-10	275	266	97%	91%	34%	9	-	0.86	0.93	May-07	Apr-10
	Sep-10	318	302	95%	94%	65%	16	-	0.86	0.93	Jun-07	May-10
	Oct-10	447	480	93%	99%	92%	-33	-	0.84	0.92	Jul-07	Jun-10
	Nov-10	315	343	92%	84%	96%	-28	-	0.83	0.92	Aug-07	Jul-10
	Dec-10	353	371	95%	84%	92%	-18	-	0.83	0.92	Sep-07	Aug-10
	Jan-11	388	360	92%	75%	74%	28	-	0.83	0.92	Oct-07	Sep-10
	Feb-11	300	285	95%	94%	98%	15	-	0.83	0.92	Nov-07	Oct-10
	Mar-11	340	322	95%	99%	94%	18	-	0.80	0.90	Dec-07	Nov-10
	Average			94%	90%	82%	-5	31	0.84	0.92		

The multiple regression equations for the S&P1200/IPI and S&P1200/MCI models are shown below. The data set used for the model equations is Jan'07 - Dec'09 and the forecast lag used is 4.

S&P1200/IPI Model:

$$Y_c = -167.4 + 4.1 * IPI + 0.15 * S\&P1200$$

S&P1200/MCI Model:

$$Y_c = 142.5 - 4.7 * MCI + 0.28 * S\&P1200$$

Y_c here represents 3-point moving average bookings forecast.

5.3 Forecast Accuracy Comparison – Multiple Regression

The forecast accuracy comparison table above (Table 5-6) shows that the "CCI, IPI, MCI, and S&P1200" model average accuracy over the twelve month period (Apr-2010 to Mar-2011) is better than the average marketing forecast and statistical forecast accuracy by 3 and 11 percentage points, respectively. The "S&P1200 and IPI" model accuracy turned out to be lower than the "CCI, IPI, MCI, and S&P1200" model accuracy by 3 percentage points. This model also did not outperform the marketing forecast over the twelve month period. This shows that combination of S&P1200 and IPI economic indicators in multiple regression did not result in any accuracy improvement over the linear regression.

The "S&P1200 and MCI" model accuracy turned out to be slightly better than the "CCI, IPI, MCI, and S&P1200" model accuracy. The "S&P1200 and MCI" model produced the highest average accuracy of 94% in comparison to the marketing forecast accuracy of 90% and statistical forecast accuracy of 82% for the same twelve month period. This clearly shows that the "S&P1200 and MCI" model outperformed the marketing forecast by 4 percentage points and the statistical forecast by 12 percentage points. This comparison also shows that the"S&P1200 and MCI" model forecast is better than the marketing forecast 67% of the time (8 out of 12 months) and better than statistical forecast 75% of the time (9 out of 12 months).The standard deviation of error for the "S&P1200 and MCI" model (31 units) is

28% lower than the “CCI, IPI, MCI and S&P1200” model and 31% lower than the “S&P1200 and IPI” model.

The auto-correlation function for the “S&P1200 and MCI” model residuals also shows low serial correlation values compared to the “S&P1200 and IPI” model as shown in Figure 5-3. For example, lag-4 auto-correlation value for the “S&P1200 and MCI” model residuals is 0.20 compared to 0.36 for the “S&P1200 and IPI” model. Auto-correlation function for the “S&P1200 and MCI” model is on a par with the auto-correlation function for the “CCI, IPI, MCI, and S&P1200” model. This clearly shows that “S&P1200 and MCI” model outperforms the other two multiple regression models both in terms of average accuracy and standard deviation over the Apr-2010 to Mar-2011 time period.

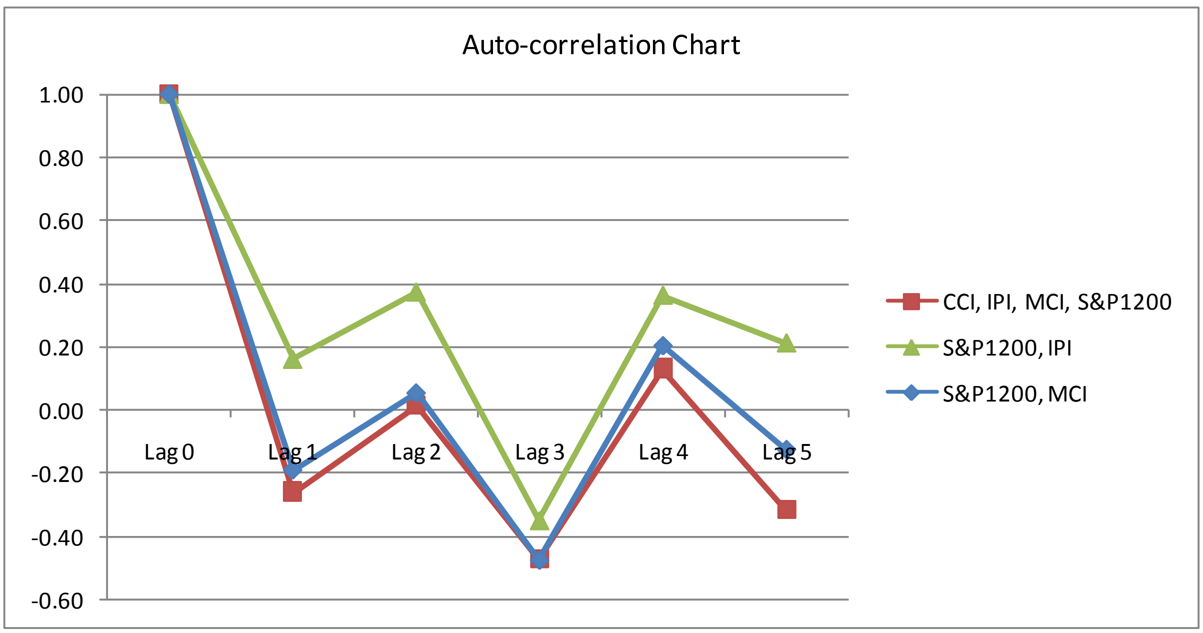

Figure 5 - 3: Auto-correlation Chart for Multiple Regression Residuals (Apr’2010 – Mar’2011)

5.4 Polynomial Regression to Model a Non-Linear Relationship

Polynomial regression can be used to model a non-linear relationship between the independent and dependent variables. S&P1200 and MCI leading economic indicators from the best multiple regression model (“S&P1200 and MCI”) are selected to model any possible non-linear relationship with the bookings for product series XYZ in this section. Square and square root (convex and concave) functions of S&P1200 and MCI are used to find a non-linear combination of S&P1200 and MCI indices that yields the highest accuracy with the lowest standard deviation of error. The following combination or model has the highest accuracy of 94% with the lowest standard deviation of error (29 units) among all possible non-linear combinations (i.e., combinations of S&P1200, S&P1200^2, √S&P1200, MCI, MCI^2 and √MCI) over the twelve month time period (Apr-2010 to Mar-2011). The data set used for the model equation is Jan'07 - Dec'09 and the forecast lag used is 4.

S&P1200/MCI^2 Model:

$$Y_c = 92.59 + 0.27 * S\&P1200 - 0.085 * MCI^2$$

Y_c here represents 3-point moving average bookings forecast. A comparison of different non-linear combinations of the 12 selected leading economic indicators (section 3.3) shows that the "CCI/CCI^2/MCI$^{2.3}$/S&P1200$^{0.1}$" model is the best non-linear model in terms of forecast accuracy. The details of linear and non-linear combinations are in the Appendix.

CCI/CCI^2/MCI$^{2.3}$/S&P1200$^{0.1}$ Model:

$$Y_c = -2751 - 4.32 * CCI + 0.031 * CCI^2 - 0.014 * MCI^{2.3} + 1615 * S\&P1200^{0.1}$$

where MCI$^{2.3}$ is MCI variable raised to the power 2.3 and S&P1200$^{0.1}$ is S&P1200 variable raised to the power 0.1. Forecast accuracy results for the polynomial regression models for the twelve month time period (Apr-2010 to Mar-2011) are tabulated in Table 5-7.

Table 5- 7: Polynomial Regression Model Forecast and Accuracy (Apr'2010 - Mar'2011)

Model	Month	Forecast	Actuals	LEI Model Accuracy	Marketing Forecast Accuracy	Statistical Forecast Accuracy	Forecast Error	Std. Deviation of Error	$AdjR^2$ Value	Correlation Value	Data Start Month	Data End Month
	Apr-10	476	516	92%	95%	78%	-40	-	0.85	0.93	Jan-07	Dec-09
	May-10	332	298	89%	78%	91%	34	-	0.85	0.93	Feb-07	Jan-10
	Jun-10	326	365	89%	93%	85%	-38	-	0.84	0.92	Mar-07	Feb-10
	Jul-10	488	485	99%	94%	88%	3	-	0.84	0.92	Apr-07	Mar-10
	Aug-10	279	266	95%	91%	34%	12	-	0.85	0.93	May-07	Apr-10
S&P1200/ MCI^2	Sep-10	324	302	93%	94%	65%	22	-	0.84	0.92	Jun-07	May-10
	Oct-10	453	480	94%	99%	92%	-27	-	0.83	0.92	Jul-07	Jun-10
	Nov-10	320	343	93%	84%	96%	-23	-	0.82	0.91	Aug-07	Jul-10
	Dec-10	358	371	97%	84%	92%	-12	-	0.82	0.91	Sep-07	Aug-10
	Jan-11	390	360	92%	75%	74%	30	-	0.82	0.91	Oct-07	Sep-10
	Feb-11	297	285	96%	94%	98%	12	-	0.82	0.91	Nov-07	Oct-10
	Mar-11	332	322	97%	99%	94%	10	-	0.79	0.90	Dec-07	Nov-10
	Average			94%	90%	82%	-1	29	0.83	0.92		
	Apr-10	479	516	93%	95%	78%	-37	-	0.86	0.94	Jan-07	Dec-09
	May-10	329	298	90%	78%	91%	31	-	0.86	0.94	Feb-07	Jan-10
	Jun-10	333	365	91%	93%	85%	-31	-	0.85	0.93	Mar-07	Feb-10
	Jul-10	493	485	98%	94%	88%	8	-	0.85	0.93	Apr-07	Mar-10
	Aug-10	275	266	97%	91%	34%	9	-	0.87	0.94	May-07	Apr-10
CCI, CCI^2, $MCI^{2.3}$ and $S\&P1200^{0.1}$	Sep-10	321	302	94%	94%	65%	19	-	0.89	0.95	Jun-07	May-10
	Oct-10	448	480	93%	99%	92%	-32	-	0.87	0.94	Jul-07	Jun-10
	Nov-10	310	343	91%	84%	96%	-32	-	0.85	0.93	Aug-07	Jul-10
	Dec-10	348	371	94%	84%	92%	-22	-	0.85	0.93	Sep-07	Aug-10
	Jan-11	378	360	95%	75%	74%	18	-	0.85	0.93	Oct-07	Sep-10
	Feb-11	288	285	99%	94%	98%	3	-	0.85	0.93	Nov-07	Oct-10
	Mar-11	321	322	100%	99%	94%	-1	-	0.82	0.92	Dec-07	Nov-10
	Average			95%	90%	82%	-6	31	0.86	0.93		

The average forecast accuracy of the "S&P1200 and MCI^2" model over the twelve month period (Apr-2010 to Mar-2011) is four percentage points better than the marketing forecast and twelve percentage points better than the statistical forecast. This polynomial regression model does outperform the "S&P1200 and MCI" multiple regression model from section 5.2 in terms of standard deviation of error, which is 6% less than the "S&P1200 and MCI" model. However, they both have the same average accuracy of 94% over the twelve month period (Apr-2010 to Mar-2011).The average forecast accuracy for the "$CCI/CCI^2/MCI^{2.3}/S\&P1200^{0.1}$" model is 95%, which is 5% better than the marketing forecast and 13% better than the statistical forecast. However, the standard deviation of error for this model is 7% higher than the "S&P1200 and MCI^2" model.

The auto-correlation for the "$CCI/CCI^2/MCI^{2.3}/S\&P1200^{0.1}$" model at lag-4 is slightly lower than the "S&P1200 and MCI" model while auto-correlation for the "S&P1200 and MCI^2" model is higher than the "S&P1200 and MCI" model as shown in Figure 5-4. Overall, both the "S&P1200 and MCI^2" and the "$CCI/CCI^2/MCI^{2.3}/S\&P1200^{0.1}$" models are slightly better forecasting models to predict demand for product series XYZ at lag-4 than the "S&P1200 and MCI" model.

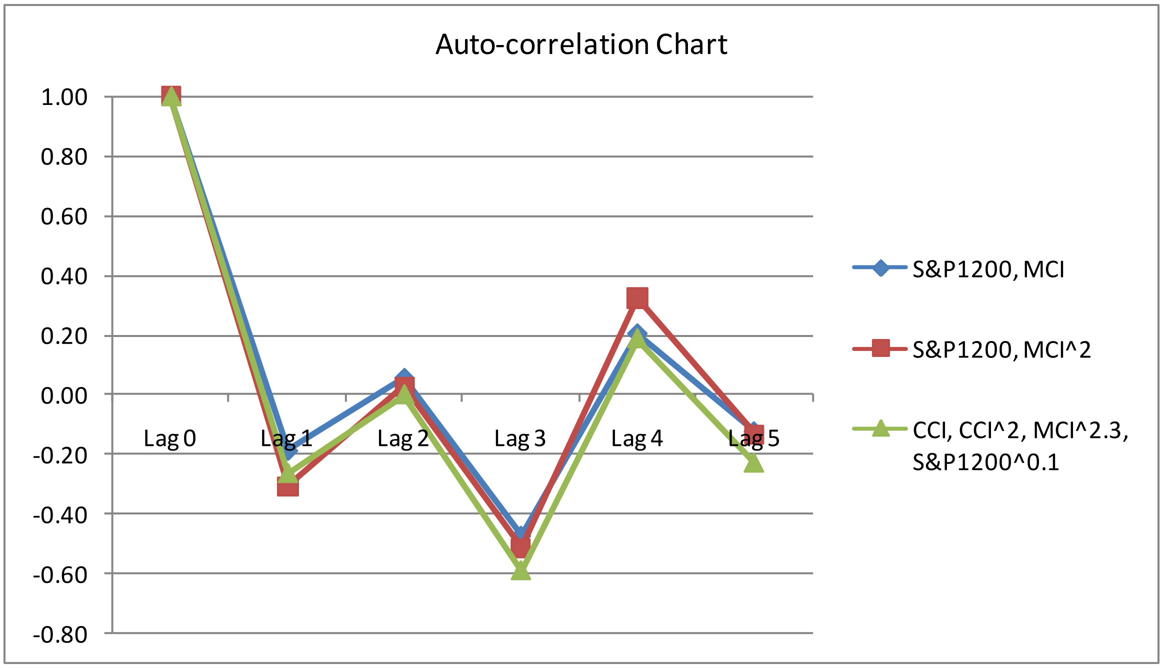

Figure 5 - 4: Auto-correlation Chart for Polynomial Regression Residuals (Apr'2010 – Mar'2011)

5.5 Forecast Accuracy Comparison – Simple and Multiple Regression

Forecast accuracy comparison between simple and multiple linear regression models is discussed in this section. Table 5-8 shows the twelve month (Apr'2010 to Mar'2011) accuracy for simple (S&P1200, IPI), multiple ("S&P1200/MCI" and "CCI/IPI/MCI/S&P1200") and polynomial ("S&P1200/MCI^2" and "CCI/CCI^2/$MCI^{2.3}$/$S\&P1200^{0.1}$") linear regression models along with the marketing and statistical forecast accuracy.

The accuracy comparison in Table 5-8 shows that the multiple regression models produced better forecast accuracy than the simple regression models. For example, the "S&P1200 and MCI" multiple regression model has an average accuracy of 94%, which is 3 percentage points better than the best simple regression model (IPI model). The "S&P1200 and MCI" multiple regression model accuracy is also better than the marketing forecast more times than the IPI or S&P1200 simple regression models over the twelve month period Apr'2010 to Mar'2011. The IPI model, for example, is better than the marketing forecast

50% of the time but the “S&P1200 and MCI” model is better than the marketing forecast 67% of the time. The “S&P1200 and MCI” multiple regression model is better than the statistical forecast 75% of the time in comparison to the simple regression IPI model which is better 67% of the time.

The average forecast accuracy for the “S&P1200 and MCI^2” polynomial regression model is the same as the “S&P1200 and MCI” multiple regression model. However, the standard deviation of error for the “S&P1200 and MCI^2” model is the lowest among all other models presented in Table 5-8. It is 34% lower than the standard deviation of error for the marketing forecast and 63% lower than the statistical forecast. The “CCI, CCI^2, $MCI^{2.3}$ and $S\&P1200^{0.1}$” model is the best model in terms of forecast accuracy with an average accuracy of 95% over the twelve month period Apr’2010 – Mar’2011. It is better than the marketing forecast 67% of the time and statistical forecast 83% of the time.

Simple, multiple and polynomial regression models outperformed the statistical forecast significantly in terms of average accuracy. Multiple and polynomial regression models (“S&P1200/MCI” and “$CCI/CCI^2/MCI^{2.3}/S\&P1200^{0.1}$”) also outperformed the marketing forecast by four and five percentage points, respectively. Linear regression models (S&P1200 and IPI) were on a par with the marketing forecast.

The “$S\&P1200/MCI^2$” model has the lowest standard deviation of error (29 units) compared to the other models. The auto-correlation function for the “$CCI/CCI^2/MCI^{2.3}/S\&P1200^{0.1}$” model shows the lowest correlation value of 0.19 at lag-4 in comparison to the “S&P1200/MCI” and “$S\&P1200/MCI^2$” models as shown in Figure 5-5.

A histogram of the standardized residuals for the “$CCI/CCI^2/MCI^{2.3}/S\&P1200^{0.1}$” model is shown in Figure 5-6 along with the cumulative distribution functions for the standardized residuals and the standard normal distribution in order to test the normality assumption for the residuals. It is hard to state that the residuals don’t come from a normal distribution by comparing the two cumulative distribution functions. However, Anderson-Darling Normality test on the “$CCI/CCI^2/MCI^{2.3}/S\&P1200^{0.1}$” model residuals shows no significant departure from normality since the p-value for the residuals (0.14) is greater than the critical p-value (0.05) at the 95% significance level. Therefore, we can say that statistically there is no evidence that the residuals for the "CCI/CCI^2/MCI$^{2.3}$/S&P1200$^{0.1}$" model are not normally distributed.

In short, the "CCI/CCI^2/MCI$^{2.3}$/S&P1200$^{0.1}$" polynomial regression model stands out as the best model based on the accuracy performance to predict bookings for product series XYZ. This model also does not violate the normality assumption of regression and exhibits low auto-correlation (0.19) at lag-4.

Table 5 - 8: Forecast Accuracy Comparison

	Simple Regression Model		Multiple Regression Model		Polynomial Regression Model			
Month/Model Accuracy	**S&P1200**	**IPI**	**S&P1200 and MCI**	**CCI, IPI, MCI and S&P1200**	**S&P1200 and MCI^2**	**CCI/CCI^2/MCI$^{2.3}$/S&P1200$^{0.1}$**	**Marketing**	**Statistical**
Apr-10	96%	82%	91%	87%	92%	93%	95%	78%
May-10	86%	100%	90%	94%	89%	90%	78%	91%
Jun-10	93%	84%	88%	85%	89%	91%	93%	85%
Jul-10	91%	99%	99%	97%	99%	98%	94%	88%
Aug-10	85%	100%	97%	100%	95%	97%	91%	34%
Sep-10	85%	88%	95%	94%	93%	94%	94%	65%
Oct-10	96%	97%	93%	91%	94%	93%	99%	92%
Nov-10	97%	100%	92%	88%	93%	91%	84%	96%
Dec-10	99%	91%	95%	91%	97%	94%	84%	92%
Jan-11	82%	78%	92%	99%	92%	95%	75%	74%
Feb-11	83%	86%	95%	98%	96%	99%	94%	98%
Mar-11	80%	86%	95%	98%	97%	100%	99%	94%
Average Accuracy	89%	91%	94%	93%	94%	95%	90%	82%
% of the time model accuracy better than Marketing:	42%	50%	67%	67%	58%	67%	N/A	33%
% of the time model accuracy better than Stat:	67%	67%	75%	67%	75%	83%	67%	N/A
Standard Deviation of Error	44	50	31	43	29	31	44	79

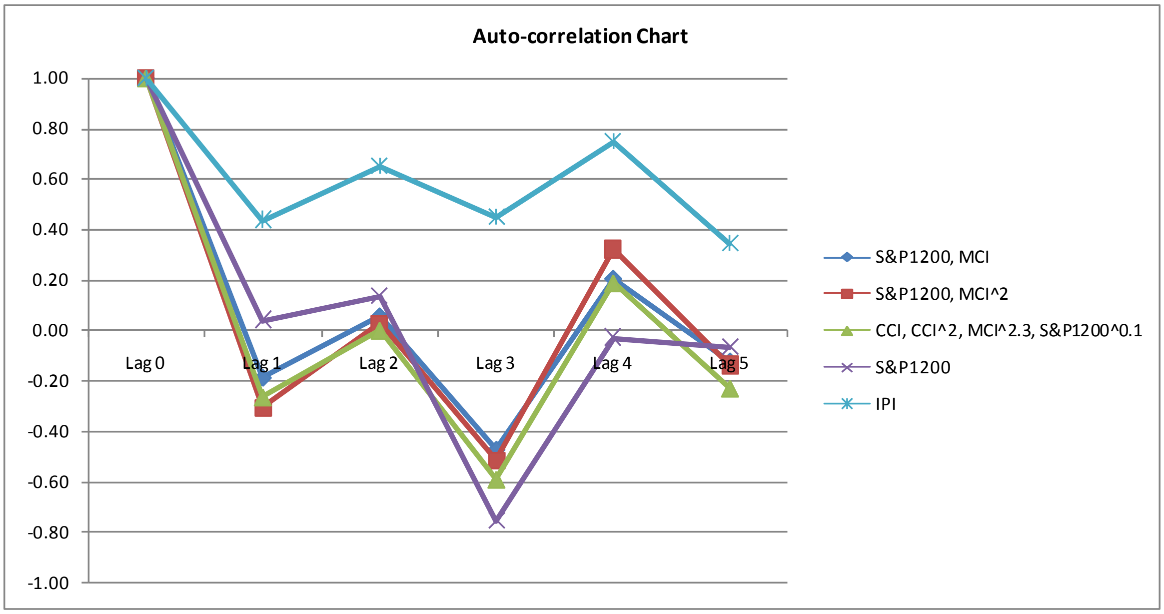

Figure 5 - 5: Auto-correlation Comparison for Simple, Multiple and Polynomial Regression Residuals

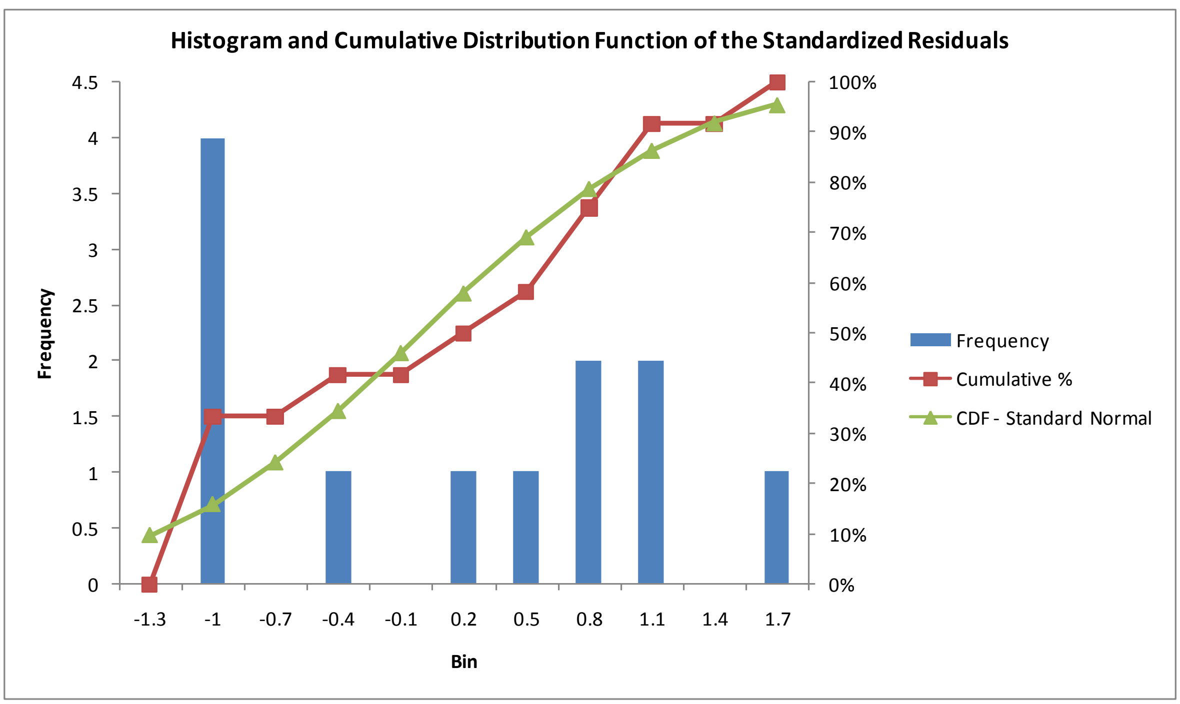

Figure 5 - 6: Histogram and Cumulative Distribution Function for the Standardized Residuals of CCI/CCI^2/MCI$^{2.3}$/S&P1200$^{0.1}$ Model

CHAPTER 6 CONCLUSIONS AND FUTURE RESEARCH

6.1 Conclusions

This research presents the use of leading economic indicators during uncertain economic times to predict short term demand for communications technology products. It showed that demand for the selected communications technology product (XYZ) is best predicted by the combination of S&P1200, consumer confidence index and the main competitor's stock price performance using a multiple regression model. S&P1200 represents the global index covering all 3 regions: NA (North America), EMEA (Europe, Middle East and Africa) and APAC (Asia Pacific). This explains why demand for product series XYZ is best predicted by the combination of S&P1200, consumer confidence index and the main competitor's stock price because approximately 60% of the demand for this product series comes from outside the USA. The main competitor's stock price also plays a role in improving the overall demand predictability for product series XYZ, thus showing that its demand does get affected by the main competitor's performance highlighting the presence of competitive insertion in the accounts. It is worth noting that the S&P1200 and MCI (main competitor stock index) alone do not yield the highest accuracy, but together they produce the highest accuracy for product series XYZ when combined via multiple regression.

Linear regression models (S&P1200 and IPI) are on a par with the marketing forecast but they outperformed the statistical forecast by seven and nine percentage points, respectively. The multiple regression models ("S&P1200/MCI" and "CCI/IPI/MCI/S&P1200") and the polynomial regression models ("S&P1200/MCI^2" and "CCI/CCI^2/$MCI^{2.3}$/S&$P1200^{0.1}$") outperform both the marketing and the statistical forecasts. The "CCI/CCI^2/$MCI^{2.3}$/S&$P1200^{0.1}$" polynomial regression model stands out as the best forecast model based on the average accuracy of 95% over the twelve month period (Apr'2010 to Mar'2011). The "CCI/CCI^2/$MCI^{2.3}$/S&$P1200^{0.1}$" model accuracy outperforms the marketing forecast accuracy by five percentage points and statistical forecast accuracy by thirteen percentage points. This highlights the power of leading economic indicators in predicting short term demand for communications technology products.

Leading economic indicators should be also considered to forecast demand for communications technology products which are heavily impacted by economic swings. This research has shown that leading economic indicators are very valuable in terms of predicting short-term demand (three to four months out) for these products. It is critical to send material/component requirements to the supply chain/component suppliers as accurately as possible outside the component lead-time window (typically 3 months) to avoid extended lead-times or inventory charge-offs in times of sudden economic expansion or contraction. The forecast accuracy improvement of 5% for product series XYZ using the leading economic indicators-based forecast translates into approximately $3,400,000 in annual cost savings based on a separate study done at the partner company. The different cost elements considered in the study were: 1) E&O (excess and obsolete), buy down and inventory holding costs, 2) PPV (purchase price variance) cost, 3) freight expedite cost, 4) productivity loss cost, and 5) cost of lost sales. Leading economic indicators have shown their ability to accurately predict these short term requirements outside the component lead-time window. The use of a leading economic indicator model along with the business intelligence (big deals, etc.) from marketing/sales should result in even higher accuracy. Therefore, the leading economic indicators-based forecast should be used as another forecast input into the consensus demand planning process which involves inputs from marketing, sales and analytical teams to create a bookings forecast that is sent to the supply chain (after applying book to ship lead-time offset) for material pipelining.

6.2 Future Research

An area for additional research is to explore the usefulness of leading economic indicators in predicting long term demand for communications technology products. Leading economic indicators forecast would have to be used to generate a medium to long term forecast for communications technology products.

Another area for future research is the development of a leading economic indicator(s) around the customer base for products that have a majority of the demand (90% or more) coming from a few set of customers. This will show if a customer-based indicator approach could lead to a better leading economic indicator and thus better demand predictability than the non-customer based indicator approach for products with a small set of customers. For example, the stock price of top customers could be used to develop a customer-based composite index by assigning weights to their stock price according to their contribution to the overall demand.

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APPENDICES

Appendix A. Monthly Seasonal Index Table for Forecasting

The seasonal index for a month represents the ratio of the month's actual bookings to the actual bookings over a 3 month period (one month before and after the month). For example, the April monthly index would be calculated as: April bookings / (March+April+May bookings).

The table below shows the monthly seasonal index for twelve months (Apr'2010 to Mar'2011) during the last three years for the product series XYZ. The average index during the last 3 years is used as the forecast index to forecast bookings for most months in the Apr'2010 – Mar'2011 time frame unless there is an outlier. "Comments" column in the table below explains the methodology used to calculate the index when there is an outlier.

Forecast Index Table

	Seasonal Index					
Period Forecasted	**Year - 1**	**Year - 2**	**Year - 3**	**Average Index**	**Forecast Index**	**Comments**
Apr-10	40.4%	42.6%	40.4%	41.1%	41.1%	
May-10	28.0%	27.3%	29.3%	28.2%	28.2%	
Jun-10	30.0%	27.3%	30.3%	29.2%	29.2%	
Jul-10	43.7%	47.7%	44.2%	45.2%	44.0%	(Year-2) is an outlier. Average of (Year-1) and (Year-3) is used.
Aug-10	26.1%	25.1%	23.6%	24.9%	24.9%	
Sep-10	33.6%	30.2%	30.3%	31.4%	30.2%	(Year-1) is an outlier. Average of (Year-2) and (Year-3) is used.
Oct-10	35.8%	41.2%	43.6%	40.2%	41.2%	(Year-2) is used as both (Year-1) and (Year-3) are on the extreme.
Nov-10	31.0%	29.0%	28.4%	29.4%	29.4%	
Dec-10	34.8%	33.0%	31.7%	33.1%	33.1%	
Jan-11	32.1%	38.0%	40.0%	36.7%	36.7%	
Feb-11	35.5%	27.7%	25.8%	29.7%	27.7%	(Year-2) is used as both (Year-1) and (Year-3) are on the extreme.
Mar-11	26.8%	31.7%	31.7%	30.1%	31.7%	(Year-1) is an outlier. Average of (Year-2) and (Year-3) is used.

Appendix B. LEI Model Accuracy Data

The comparison of lag-4 forecast accuracy and standard deviation of error for simple, multiple and polynomial regression models studied as part of this research is presented in the tables below for quick reference:

Simple Regression Models using 12 Leading Economic Indicators

ProductType	Simple Regression Model	LEI Model Forecast Accuracy	Forecast Error	Std. Deviation of Forecast Error	Marketing Forecast Accuracy	Stat Forecast Accuracy
XYZ	IPI	91%	7	50	90%	82%
XYZ	CCI	90%	19	41	90%	82%
XYZ	S&P700	90%	19	41	90%	82%
XYZ	S&P1200	89%	23	44	90%	82%
XYZ	S&P500	89%	29	49	90%	82%
XYZ	DJI	88%	34	52	90%	82%
XYZ	NASDAQ_Telecom	88%	39	55	90%	82%
XYZ	CI	86%	48	63	90%	82%
XYZ	NASDAQ_Composite	81%	63	79	90%	82%
XYZ	MCI	80%	67	84	90%	82%
XYZ	NASDAQ_Comp	76%	85	99	90%	82%
XYZ	BCI	73%	97	119	90%	82%

Multiple Regression Models (All possible multiple combinations of S&P1200, IPI, CCI, MCI, CI and NASDAQ_Telecom)

ProductType	Multiple Regression Model	LEI Model Forecast Accuracy	Forecast Error	Std. Deviation of Forecast Error	Marketing Forecast Accuracy	Stat Forecast Accuracy
XYZ	CCI,MCI,S&P1200	94%	-10	33	90%	82%
XYZ	CCI,CI,MCI,S&P1200	94%	-14	41	90%	82%
XYZ	MCI,S&P1200	94%	-5	31	90%	82%
XYZ	IPI,MCI,S&P1200	93%	-6	35	90%	82%
XYZ	CCI,IPI,MCI,S&P1200	93%	-18	43	90%	82%
XYZ	CCI,CI,IPI,MCI,NASDAQ_Telecom	93%	-15	58	90%	82%
XYZ	MCI,NASDAQ_Telecom	93%	8	30	90%	82%
XYZ	CCI,CI,IPI,MCI	93%	-7	50	90%	82%
XYZ	CCI,CI,IPI,MCI,S&P1200	93%	-23	53	90%	82%
XYZ	CCI,MCI	93%	12	35	90%	82%
XYZ	CCI,CI,IPI,MCI,NASDAQ_Telecom,S&P1200	93%	-10	50	90%	82%
XYZ	IPI,MCI,NASDAQ_Telecom,S&P1200	92%	0	41	90%	82%
XYZ	CCI,CI,MCI,NASDAQ_Telecom,S&P1200	92%	-2	45	90%	82%
XYZ	CCI,IPI,MCI,NASDAQ_Telecom,S&P1200	92%	-7	46	90%	82%
XYZ	MCI,NASDAQ_Telecom,S&P1200	92%	2	40	90%	82%
XYZ	CCI,MCI,NASDAQ_Telecom,S&P1200	92%	-1	43	90%	82%
XYZ	CI,IPI,MCI,NASDAQ_Telecom,S&P1200	92%	2	42	90%	82%
XYZ	CI,MCI,S&P1200	92%	0	38	90%	82%
XYZ	CI,IPI,MCI,S&P1200	92%	-2	43	90%	82%
XYZ	CI,MCI,NASDAQ_Telecom,S&P1200	92%	5	41	90%	82%
XYZ	CCI,IPI,MCI,NASDAQ_Telecom	92%	-1	52	90%	82%
XYZ	CCI,MCI,NASDAQ_Telecom	92%	-14	38	90%	82%
XYZ	NASDAQ_Telecom,S&P1200	91%	8	41	90%	82%
XYZ	IPI,NASDAQ_Telecom,S&P1200	91%	8	43	90%	82%
XYZ	CCI,NASDAQ_Telecom,S&P1200	91%	7	44	90%	82%
XYZ	CI,NASDAQ_Telecom,S&P1200	91%	9	44	90%	82%
XYZ	CCI,CI,NASDAQ_Telecom,S&P1200	91%	4	50	90%	82%
XYZ	CI,IPI,NASDAQ_Telecom,S&P1200	91%	9	46	90%	82%
XYZ	CCI,IPI,NASDAQ_Telecom,S&P1200	91%	6	48	90%	82%
XYZ	CCI,CI,IPI,NASDAQ_Telecom,S&P1200	91%	1	56	90%	82%
XYZ	CI,IPI,MCI,NASDAQ_Telecom	91%	12	52	90%	82%
XYZ	CCI,IPI	91%	9	49	90%	82%
XYZ	CI,IPI,S&P1200	91%	7	52	90%	82%
XYZ	CCI,IPI,NASDAQ_Telecom	91%	9	54	90%	82%
XYZ	CCI,CI,IPI	91%	6	57	90%	82%
XYZ	CI,IPI,MCI	90%	14	49	90%	82%
XYZ	CI,IPI,NASDAQ_Telecom	90%	14	51	90%	82%
XYZ	IPI,NASDAQ_Telecom	90%	12	50	90%	82%
XYZ	CCI,CI,IPI,NASDAQ_Telecom	90%	1	64	90%	82%
XYZ	CI,S&P1200	90%	9	49	90%	82%
XYZ	IPI,S&P1200	90%	16	45	90%	82%
XYZ	CI,IPI	90%	15	48	90%	82%
XYZ	CCI,IPI,S&P1200	90%	14	50	90%	82%
XYZ	CCI,IPI,MCI	90%	8	59	90%	82%
XYZ	CCI,CI,IPI,S&P1200	90%	-2	62	90%	82%
XYZ	CI,MCI,NASDAQ_Telecom	90%	3	48	90%	82%
XYZ	IPI,MCI,NASDAQ_Telecom	90%	12	58	90%	82%
XYZ	CCI,CI	90%	27	46	90%	82%
XYZ	CCI,CI,S&P1200	90%	1	56	90%	82%
XYZ	CCI,CI,NASDAQ_Telecom	90%	18	51	90%	82%
XYZ	CCI,NASDAQ_Telecom	89%	26	48	90%	82%
XYZ	CCI,S&P1200	89%	22	47	90%	82%
XYZ	IPI,MCI	89%	12	59	90%	82%
XYZ	CI,MCI	87%	4	64	90%	82%
XYZ	CCI,CI,MCI,NASDAQ_Telecom	87%	-26	71	90%	82%
XYZ	CI,NASDAQ_Telecom	86%	45	65	90%	82%
XYZ	CCI,CI,MCI	84%	-19	81	90%	82%

Polynomial Regression Models (All possible multiple combinations of S&P1200, S&P1200SQ, S&P1200SQRT, MCI, MCISQ and MCISQRT)

ProductType	Polynomial Regression Model	LEI Model Forecast Accuracy	Forecast Error	Std. Deviation of Forecast Error	Marketing Forecast Accuracy	Stat Forecast Accuracy
XYZ	MCISQ,S&P1200	94%	-1	29	90%	82%
XYZ	MCISQ,S&P1200SQRT	94%	4	28	90%	82%
XYZ	MCI,S&P1200SQRT	94%	-1	29	90%	82%
XYZ	MCISQ,S&P1200SQ	94%	-10	33	90%	82%
XYZ	MCI,MCISQ,MCISQRT,S&P1200,S&P1200SQRT	94%	-13	45	90%	82%
XYZ	MCI,MCISQ,MCISQRT,S&P1200SQ,S&P1200SQRT	94%	-13	44	90%	82%
XYZ	MCI,MCISQ,MCISQRT,S&P1200,S&P1200SQ	94%	-12	44	90%	82%
XYZ	MCI,S&P1200	94%	-5	31	90%	82%
XYZ	MCISQRT,S&P1200SQRT	93%	-2	30	90%	82%
XYZ	MCI,MCISQ,MCISQRT,S&P1200SQ	93%	-6	38	90%	82%
XYZ	MCI,MCISQ,MCISQRT,S&P1200,S&P1200SQ,S&P1200SQRT	93%	-13	51	90%	82%
XYZ	MCISQRT,S&P1200	93%	-6	32	90%	82%
XYZ	MCI,S&P1200SQ	93%	-11	36	90%	82%
XYZ	MCI,MCISQ,S&P1200SQ,S&P1200SQRT	93%	-17	45	90%	82%
XYZ	MCI,MCISQ,S&P1200,S&P1200SQ	93%	-16	45	90%	82%
XYZ	MCI,MCISQ,S&P1200,S&P1200SQRT	93%	-17	46	90%	82%
XYZ	MCISQ,MCISQRT,S&P1200SQ,S&P1200SQRT	93%	-17	46	90%	82%
XYZ	MCISQ,MCISQRT,S&P1200,S&P1200SQ	93%	-16	45	90%	82%
XYZ	MCI,MCISQ,S&P1200SQ	93%	-10	38	90%	82%
XYZ	MCISQ,S&P1200,S&P1200SQ	93%	-16	42	90%	82%
XYZ	MCISQ,MCISQRT,S&P1200,S&P1200SQRT	93%	-17	46	90%	82%
XYZ	MCISQ,MCISQRT,S&P1200SQ	93%	-10	38	90%	82%
XYZ	MCISQ,S&P1200SQ,S&P1200SQRT	93%	-16	43	90%	82%
XYZ	MCI,MCISQRT,S&P1200SQ	93%	-10	39	90%	82%
XYZ	MCI,MCISQRT,S&P1200,S&P1200SQ	93%	-16	46	90%	82%
XYZ	MCI,MCISQRT,S&P1200SQ,S&P1200SQRT	93%	-17	46	90%	82%
XYZ	MCISQRT,S&P1200SQ	93%	-11	38	90%	82%
XYZ	MCISQ,S&P1200,S&P1200SQRT	93%	-16	43	90%	82%
XYZ	MCI,S&P1200,S&P1200SQ	93%	-14	43	90%	82%
XYZ	MCI,MCISQRT,S&P1200,S&P1200SQRT	93%	-17	47	90%	82%
XYZ	MCI,S&P1200SQ,S&P1200SQRT	93%	-14	43	90%	82%
XYZ	MCI,MCISQ,S&P1200,S&P1200SQ,S&P1200SQRT	93%	-14	50	90%	82%
XYZ	MCISQ,MCISQRT,S&P1200,S&P1200SQ,S&P1200SQRT	93%	-14	51	90%	82%
XYZ	MCI,S&P1200,S&P1200SQRT	93%	-14	43	90%	82%
XYZ	MCISQRT,S&P1200,S&P1200SQ	93%	-13	42	90%	82%
XYZ	MCISQRT,S&P1200SQ,S&P1200SQRT	93%	-13	43	90%	82%
XYZ	MCI,MCISQRT,S&P1200,S&P1200SQ,S&P1200SQRT	93%	-15	51	90%	82%
XYZ	MCI,MCISQ,MCISQRT,S&P1200	92%	-1	38	90%	82%
XYZ	MCI,MCISQ,S&P1200	92%	-5	38	90%	82%
XYZ	MCISQRT,S&P1200,S&P1200SQRT	92%	-13	43	90%	82%
XYZ	MCISQ,MCISQRT,S&P1200	92%	-5	38	90%	82%
XYZ	MCI,MCISQRT,S&P1200	92%	-5	38	90%	82%
XYZ	MCI,MCISQ,S&P1200SQRT	92%	-1	38	90%	82%
XYZ	MCISQ,MCISQRT,S&P1200SQRT	92%	-2	38	90%	82%
XYZ	MCISQ,S&P1200,S&P1200SQ,S&P1200SQRT	92%	-13	48	90%	82%
XYZ	MCI,MCISQRT,S&P1200SQRT	92%	-2	38	90%	82%
XYZ	MCI,MCISQ,MCISQRT,S&P1200SQRT	92%	3	39	90%	82%
XYZ	MCI,S&P1200,S&P1200SQ,S&P1200SQRT	92%	-11	48	90%	82%
XYZ	MCISQRT,S&P1200,S&P1200SQ,S&P1200SQRT	92%	-10	48	90%	82%
XYZ	S&P1200SQ,S&P1200SQRT	91%	6	39	90%	82%
XYZ	S&P1200,S&P1200SQ	91%	7	39	90%	82%
XYZ	S&P1200,S&P1200SQRT	91%	5	40	90%	82%
XYZ	S&P1200,S&P1200SQ,S&P1200SQRT	90%	2	47	90%	82%
XYZ	MCI,MCISQRT	79%	71	92	90%	82%
XYZ	MCISQ,MCISQRT	79%	71	92	90%	82%
XYZ	MCI,MCISQ	79%	71	93	90%	82%
XYZ	MCI,MCISQ,MCISQRT	78%	75	105	90%	82%

MCISQ=MCI^2, MCISQRT = $\sqrt{}$MCI, S&P1200SQ= S&P1200^2 and S&P1200SQRT= $\sqrt{}$S&P1200

Polynomial Regression Models (S&P1200/MCI: To find power for the MCI that gives highest accuracy with the S&P1200)

ProductType	Polynomial Regression Model	LEI Model Forecast Accuracy	Forecast Error	Std. Deviation of Forecast Error	Marketing Forecast Accuracy	Stat Forecast Accuracy
XYZ	S&P1200,MCI2.1	94%	-1	29	90%	82%
XYZ	S&P1200,MCI2.2	94%	-1	28	90%	82%
XYZ	S&P1200,MCI2.3	94%	0	28	90%	82%
XYZ	S&P1200,MCI1.9	94%	-2	29	90%	82%
XYZ	S&P1200,MCI2.4	94%	0	28	90%	82%
XYZ	S&P1200,MCI1.8	94%	-2	29	90%	82%
XYZ	S&P1200,MCI2.5	94%	1	28	90%	82%
XYZ	S&P1200,MCI1.7	94%	-3	29	90%	82%
XYZ	S&P1200,MCI2.6	94%	1	28	90%	82%
XYZ	S&P1200,MCI2.6	94%	1	28	90%	82%
XYZ	S&P1200,MCI1.6	94%	-3	29	90%	82%
XYZ	S&P1200,MCI2.7	94%	1	28	90%	82%
XYZ	S&P1200,MCI2.8	94%	2	28	90%	82%
XYZ	S&P1200,MCI2.9	94%	2	28	90%	82%
XYZ	S&P1200,MCI1.5	94%	-3	30	90%	82%
XYZ	S&P1200,MCI1.4	94%	-4	30	90%	82%
XYZ	S&P1200,MCI1.3	94%	-4	30	90%	82%
XYZ	S&P1200,MCI1.2	94%	-4	30	90%	82%
XYZ	S&P1200,MCI1.1	94%	-5	31	90%	82%
XYZ	S&P1200,MCI	94%	-5	31	90%	82%
XYZ	S&P1200,MCI	94%	-5	31	90%	82%
XYZ	S&P1200,MCI	94%	-5	31	90%	82%
XYZ	S&P1200,MCI	94%	-5	31	90%	82%
XYZ	S&P1200,MCI	94%	-5	31	90%	82%
XYZ	S&P1200,MCI	94%	-5	31	90%	82%
XYZ	S&P1200,MCI	94%	-5	31	90%	82%
XYZ	S&P1200,MCI	94%	-5	31	90%	82%
XYZ	S&P1200,MCI	94%	-5	31	90%	82%
XYZ	S&P1200,MCI	94%	-5	31	90%	82%
XYZ	S&P1200,MCI2.8,MCI2.9	93%	-2	37	90%	82%
XYZ	S&P1200,MCI2.6,MCI2.7	93%	-3	37	90%	82%
XYZ	S&P1200,MCI2.5,MCI2.6	93%	-3	37	90%	82%
XYZ	S&P1200,MCI2.3,MCI2.4	93%	-4	37	90%	82%
XYZ	S&P1200,MCI2.1,MCI2.2	93%	-4	37	90%	82%
XYZ	S&P1200,MCI,MCI2.9	93%	-4	37	90%	82%
XYZ	S&P1200,MCI,MCI2.8	93%	-4	37	90%	82%
XYZ	S&P1200,MCI,MCI2.7	92%	-4	37	90%	82%
XYZ	S&P1200,MCI,MCI2.6	92%	-4	37	90%	82%
XYZ	S&P1200,MCI,MCI2.6	92%	-4	37	90%	82%
XYZ	S&P1200,MCI,MCI2.5	92%	-4	37	90%	82%
XYZ	S&P1200,MCI1.1,MCI1.2,MCI	92%	-1	38	90%	82%
XYZ	S&P1200,MCI,MCI2.4	92%	-4	37	90%	82%
XYZ	S&P1200,MCI1.7,MCI1.8	92%	-4	37	90%	82%
XYZ	S&P1200,MCI,MCI2.3	92%	-4	38	90%	82%
XYZ	S&P1200,MCI,MCI2.2	92%	-4	38	90%	82%
XYZ	S&P1200,MCI,MCI2.1	92%	-5	38	90%	82%
XYZ	S&P1200,MCI1.5,MCI1.6	92%	-4	38	90%	82%
XYZ	S&P1200,MCI1.3,MCI1.4,MCI	92%	-1	38	90%	82%
XYZ	S&P1200,MCI1.9,MCI	92%	-5	38	90%	82%
XYZ	S&P1200,MCI1.8,MCI	92%	-5	38	90%	82%
XYZ	S&P1200,MCI1.7,MCI	92%	-5	38	90%	82%
XYZ	S&P1200,MCI1.3,MCI1.4	92%	-5	38	90%	82%
XYZ	S&P1200,MCI1.6,MCI	92%	-5	38	90%	82%
XYZ	S&P1200,MCI1.5,MCI	92%	-5	38	90%	82%
XYZ	S&P1200,MCI1.4,MCI	92%	-5	38	90%	82%
XYZ	S&P1200,MCI1.5,MCI1.6,MCI	92%	-1	38	90%	82%
XYZ	S&P1200,MCI1.3,MCI	92%	-5	38	90%	82%
XYZ	S&P1200,MCI1.1,MCI1.2	92%	-5	38	90%	82%
XYZ	S&P1200,MCI1.2,MCI	92%	-5	38	90%	82%
XYZ	S&P1200,MCI1.1,MCI	92%	-5	38	90%	82%
XYZ	S&P1200,MCI1.7,MCI1.8,MCI	92%	-1	38	90%	82%
XYZ	S&P1200,MCI,MCI2.1,MCI2.2	92%	-1	39	90%	82%
XYZ	S&P1200,MCI,MCI2.3,MCI2.4	92%	-1	39	90%	82%
XYZ	S&P1200,MCI,MCI2.5,MCI2.6	92%	-1	39	90%	82%
XYZ	S&P1200,MCI,MCI2.6,MCI2.7	92%	-1	39	90%	82%
XYZ	S&P1200,MCI,MCI2.8,MCI2.9	92%	-1	39	90%	82%

MCI2.3 = $MCI^{2.3}$

Polynomial Regression Models (Multiple combinations of MCI2.3, S&P1200, S&P1200SQ, S&P1200SQRT, CCI, CCISQ and CCISQRT)

ProductType	Polynomial Regression Model	LEI Model Forecast Accuracy	Forecast Error	Std. Deviation of Forecast Error	Marketing Forecast Accuracy	Stat Forecast Accuracy
XYZ	CCI,CCISQ,MCI2.3,S&P1200SQRT	95%	-8	32	90%	82%
XYZ	CCISQ,CCISQRT,MCI2.3,S&P1200SQRT	95%	-8	33	90%	82%
XYZ	CCI,CCISQRT,MCI2.3,S&P1200SQRT	95%	-9	34	90%	82%
XYZ	CCI,CCISQ,MCI2.3,S&P1200	94%	-10	34	90%	82%
XYZ	CCISQRT,MCI2.3,S&P1200	94%	-3	30	90%	82%
XYZ	CCISQ,CCISQRT,MCI2.3,S&P1200	94%	-10	35	90%	82%
XYZ	CCISQRT,MCI2.3,S&P1200SQRT	94%	0	30	90%	82%
XYZ	CCI,MCI2.3,S&P1200	94%	-6	30	90%	82%
XYZ	CCI,CCISQRT,MCI2.3,S&P1200	94%	-11	36	90%	82%
XYZ	CCI,MCI2.3,S&P1200SQRT	94%	-3	30	90%	82%
XYZ	CCI,MCI2.3,S&P1200SQ	94%	-12	34	90%	82%
XYZ	CCISQ,MCI2.3,S&P1200SQ	94%	-14	35	90%	82%
XYZ	CCISQ,MCI2.3,S&P1200	94%	-10	31	90%	82%
XYZ	CCISQ,MCI2.3,S&P1200SQRT	94%	-7	30	90%	82%
XYZ	CCI,CCISQ,CCISQRT,MCI2.3,S&P1200SQRT	94%	-11	40	90%	82%
XYZ	CCISQRT,MCI2.3,S&P1200SQ	94%	-10	34	90%	82%
XYZ	CCI,CCISQ,MCI2.3,S&P1200SQ	94%	-14	39	90%	82%
XYZ	CCI,CCISQ,CCISQRT,MCI2.3,S&P1200	94%	-13	42	90%	82%
XYZ	CCISQ,CCISQRT,MCI2.3,S&P1200SQ	94%	-14	39	90%	82%
XYZ	MCI2.3,S&P1200	94%	0	28	90%	82%
XYZ	CCI,CCISQRT,MCI2.3,S&P1200SQ	94%	-15	40	90%	82%
XYZ	CCI,CCISQRT,MCI2.3,S&P1200,S&P1200SQ	94%	-16	45	90%	82%
XYZ	MCI2.3,S&P1200SQ	94%	-9	32	90%	82%
XYZ	CCI,CCISQRT,MCI2.3,S&P1200SQ,S&P1200SQRT	94%	-16	46	90%	82%
XYZ	CCISQ,MCI2.3,S&P1200,S&P1200SQ	94%	-18	43	90%	82%
XYZ	CCISQ,CCISQRT,MCI2.3,S&P1200,S&P1200SQ	94%	-16	46	90%	82%
XYZ	MCI2.3,S&P1200SQRT	94%	5	28	90%	82%
XYZ	CCISQ,MCI2.3,S&P1200SQ,S&P1200SQRT	94%	-18	44	90%	82%
XYZ	CCISQ,CCISQRT,MCI2.3,S&P1200SQ,S&P1200SQRT	94%	-17	47	90%	82%
XYZ	CCI,CCISQ,MCI2.3,S&P1200,S&P1200SQ	94%	-17	47	90%	82%
XYZ	CCI,CCISQRT,MCI2.3,S&P1200,S&P1200SQRT	94%	-17	47	90%	82%
XYZ	CCI,CCISQ,MCI2.3,S&P1200SQ,S&P1200SQRT	94%	-17	47	90%	82%
XYZ	CCISQ,MCI2.3,S&P1200,S&P1200SQRT	94%	-18	44	90%	82%
XYZ	CCISQ,CCISQRT,MCI2.3,S&P1200,S&P1200SQRT	93%	-18	48	90%	82%
XYZ	CCI,CCISQ,CCISQRT,MCI2.3,S&P1200,S&P1200SQ	93%	-16	52	90%	82%
XYZ	CCI,MCI2.3,S&P1200,S&P1200SQ	93%	-17	44	90%	82%
XYZ	CCI,CCISQ,CCISQRT,MCI2.3,S&P1200SQ,S&P1200SQRT	93%	-17	53	90%	82%
XYZ	CCI,CCISQ,MCI2.3,S&P1200,S&P1200SQRT	93%	-18	49	90%	82%
XYZ	CCI,CCISQ,CCISQRT,MCI2.3,S&P1200SQ	93%	-16	46	90%	82%
XYZ	CCI,MCI2.3,S&P1200SQ,S&P1200SQRT	93%	-17	44	90%	82%
XYZ	CCI,CCISQ,CCISQRT,MCI2.3,S&P1200,S&P1200SQRT	93%	-17	53	90%	82%
XYZ	CCI,MCI2.3,S&P1200,S&P1200SQRT	93%	-18	45	90%	82%
XYZ	CCISQRT,MCI2.3,S&P1200,S&P1200SQ	93%	-17	44	90%	82%
XYZ	CCISQRT,MCI2.3,S&P1200SQ,S&P1200SQRT	93%	-17	45	90%	82%
XYZ	CCISQRT,MCI2.3,S&P1200,S&P1200SQRT	93%	-17	46	90%	82%
XYZ	CCI,MCI2.3	93%	9	34	90%	82%
XYZ	MCI2.3,S&P1200,S&P1200SQ	93%	-16	42	90%	82%
XYZ	MCI2.3,S&P1200SQ,S&P1200SQRT	93%	-16	43	90%	82%
XYZ	CCISQ,MCI2.3,S&P1200,S&P1200SQ,S&P1200SQRT	93%	-14	48	90%	82%
XYZ	MCI2.3,S&P1200,S&P1200SQRT	93%	-16	43	90%	82%
XYZ	CCI,CCISQ,CCISQRT,MCI2.3,S&P1200,S&P1200SQ,S&P1200SQRT	93%	-15	61	90%	82%
XYZ	CCISQ,MCI2.3	93%	10	34	90%	82%
XYZ	CCI,CCISQRT,MCI2.3	93%	11	37	90%	82%
XYZ	CCISQ,CCISQRT,MCI2.3,S&P1200,S&P1200SQ,S&P1200SQRT	93%	-15	55	90%	82%
XYZ	CCI,MCI2.3,S&P1200,S&P1200SQ,S&P1200SQRT	93%	-14	49	90%	82%
XYZ	CCI,CCISQ,MCI2.3,S&P1200,S&P1200SQ,S&P1200SQRT	93%	-15	55	90%	82%
XYZ	CCI,CCISQ,MCI2.3	93%	11	38	90%	82%
XYZ	CCISQ,CCISQRT,MCI2.3	93%	12	37	90%	82%
XYZ	CCISQRT,MCI2.3,S&P1200,S&P1200SQ,S&P1200SQRT	92%	-14	50	90%	82%
XYZ	CCI,CCISQ,CCISQRT,MCI2.3	92%	4	46	90%	82%
XYZ	CCISQRT,MCI2.3	92%	13	37	90%	82%
XYZ	MCI2.3,S&P1200,S&P1200SQ,S&P1200SQRT	92%	-14	48	90%	82%
XYZ	CCI,CCISQRT,MCI2.3,S&P1200,S&P1200SQ,S&P1200SQRT	92%	-13	58	90%	82%
XYZ	CCI,CCISQ,CCISQRT,S&P1200,S&P1200SQRT	91%	6	47	90%	82%
XYZ	S&P1200SQ,S&P1200SQRT	91%	6	39	90%	82%
XYZ	CCI,CCISQ,CCISQRT,S&P1200SQ,S&P1200SQRT	91%	8	46	90%	82%
XYZ	S&P1200,S&P1200SQ	91%	7	39	90%	82%
XYZ	CCI,CCISQ,CCISQRT,S&P1200,S&P1200SQ	91%	8	47	90%	82%
XYZ	S&P1200,S&P1200SQRT	91%	5	40	90%	82%
XYZ	CCI,CCISQ,S&P1200,S&P1200SQRT	91%	6	45	90%	82%
XYZ	CCI,CCISQ,S&P1200SQ,S&P1200SQRT	91%	8	45	90%	82%
XYZ	CCI,CCISQ,S&P1200,S&P1200SQ	91%	9	45	90%	82%
XYZ	CCI,CCISQ,CCISQRT,S&P1200SQ	91%	7	46	90%	82%

MCI2.3= $MCI^{2.3}$, CCISQ = CCI^2, CCISQRT = $\sqrt{CCI}$, S&P1200SQ = $S\&P1200^2$ and S&P1200SQRT = $\sqrt{S\&P1200}$

Polynomial Regression Models (Multiple combinations of MCI2.3, S&P1200, S&P1200SQ, S&P1200SQRT, CCI, CCISQ and CCISQRT) - Continued

ProductType	Polynomial Regression Model	LEI Model Forecast Accuracy	Forecast Error	Std. Deviation of Forecast Error	Marketing Forecast Accuracy	Stat Forecast Accuracy
XYZ	CCISQ,CCISQRT,S&P1200,S&P1200SQRT	91%	7	45	90%	82%
XYZ	CCISQ,CCISQRT,S&P1200SQ,S&P1200SQRT	91%	8	45	90%	82%
XYZ	CCISQ,S&P1200SQ,S&P1200SQRT	91%	7	42	90%	82%
XYZ	CCISQ,S&P1200,S&P1200SQ	91%	7	42	90%	82%
XYZ	CCI,CCISQRT	91%	18	41	90%	82%
XYZ	CCISQ,CCISQRT,S&P1200,S&P1200SQ	91%	9	45	90%	82%
XYZ	CCISQ,S&P1200,S&P1200SQRT	91%	5	43	90%	82%
XYZ	CCI,S&P1200SQ,S&P1200SQRT	91%	6	43	90%	82%
XYZ	CCISQRT,S&P1200SQ,S&P1200SQRT	91%	6	43	90%	82%
XYZ	CCI,S&P1200,S&P1200SQ	91%	7	43	90%	82%
XYZ	CCISQRT,S&P1200,S&P1200SQ	91%	7	43	90%	82%
XYZ	CCI,S&P1200,S&P1200SQRT	91%	5	43	90%	82%
XYZ	CCISQRT,S&P1200,S&P1200SQRT	91%	5	44	90%	82%
XYZ	CCI,CCISQRT,S&P1200,S&P1200SQRT	91%	7	45	90%	82%
XYZ	CCI,CCISQRT,S&P1200SQ,S&P1200SQRT	91%	9	45	90%	82%
XYZ	CCI,CCISQ,S&P1200SQ	91%	8	44	90%	82%
XYZ	CCI,CCISQRT,S&P1200,S&P1200SQ	91%	9	46	90%	82%
XYZ	CCISQ,CCISQRT,S&P1200SQ	91%	8	44	90%	82%
XYZ	CCISQ,CCISQRT	91%	19	42	90%	82%
XYZ	CCI,CCISQRT,S&P1200SQ	91%	7	44	90%	82%
XYZ	CCI,CCISQ,CCISQRT	91%	15	46	90%	82%
XYZ	CCI,CCISQ,CCISQRT,S&P1200	91%	10	47	90%	82%
XYZ	CCI,CCISQ	91%	20	42	90%	82%
XYZ	CCI,CCISQ,S&P1200	91%	12	45	90%	82%
XYZ	CCISQ,CCISQRT,S&P1200	90%	12	45	90%	82%
XYZ	CCI,CCISQ,CCISQRT,S&P1200SQRT	90%	13	48	90%	82%
XYZ	CCI,CCISQRT,S&P1200	90%	11	45	90%	82%
XYZ	CCI,CCISQ,S&P1200SQRT	90%	15	46	90%	82%
XYZ	CCISQ,CCISQRT,S&P1200SQRT	90%	14	46	90%	82%
XYZ	CCI,CCISQRT,S&P1200SQRT	90%	13	46	90%	82%
XYZ	S&P1200,S&P1200SQ,S&P1200SQRT	90%	2	47	90%	82%
XYZ	CCISQ,S&P1200SQ	90%	15	44	90%	82%
XYZ	CCI,CCISQ,CCISQRT,S&P1200,S&P1200SQ,S&P1200SQRT	90%	2	60	90%	82%
XYZ	CCI,CCISQ,S&P1200,S&P1200SQ,S&P1200SQRT	90%	4	54	90%	82%
XYZ	CCISQ,CCISQRT,S&P1200,S&P1200SQ,S&P1200SQRT	90%	4	55	90%	82%
XYZ	CCI,S&P1200SQ	90%	16	45	90%	82%
XYZ	CCISQ,S&P1200,S&P1200SQ,S&P1200SQRT	90%	4	51	90%	82%
XYZ	CCI,CCISQRT,S&P1200,S&P1200SQ,S&P1200SQRT	90%	4	55	90%	82%
XYZ	CCI,S&P1200,S&P1200SQ,S&P1200SQRT	90%	3	51	90%	82%
XYZ	CCISQRT,S&P1200,S&P1200SQ,S&P1200SQRT	90%	3	52	90%	82%
XYZ	CCISQRT,S&P1200SQ	90%	16	45	90%	82%
XYZ	CCISQ,S&P1200	90%	20	46	90%	82%
XYZ	CCISQ,S&P1200SQRT	89%	22	46	90%	82%
XYZ	CCI,S&P1200	89%	22	47	90%	82%
XYZ	CCISQRT,S&P1200	89%	23	48	90%	82%
XYZ	CCI,S&P1200SQRT	89%	25	49	90%	82%
XYZ	CCISQRT,S&P1200SQRT	89%	26	50	90%	82%

MCI2.3= $MCI^{2.3}$, CCISQ = CCI^2, CCISQRT = $\sqrt{CCI}$, S&P1200SQ = $S\&P1200^2$ and S&P1200SQRT = $\sqrt{S\&P1200}$

Polynomial Regression Models (To find power for the S&P1200 that gives highest accuracy with the "MCI2.3, CCI, CCISQ" combination)

ProductType	Polynomial Regression Model	LEI Model Forecast Accuracy	Forecast Error	Std. Deviation of Forecast Error	Marketing Forecast Accuracy	Stat Forecast Accuracy
XYZ	'CCI','CCISQ','JNPR2.3','S&P1200P0.4'	95%	-7	32	90%	82%
XYZ	'CCI','CCISQ','JNPR2.3','S&P1200P0.5'	95%	-8	32	90%	82%
XYZ	'CCI','CCISQ','JNPR2.3','S&P1200P0.6'	95%	-8	33	90%	82%
XYZ	'CCI','CCISQ','JNPR2.3','S&P1200P0.3'	95%	-7	32	90%	82%
XYZ	'CCI','CCISQ','JNPR2.3','S&P1200P0.7'	95%	-9	33	90%	82%
XYZ	'CCI','CCISQ','JNPR2.3','S&P1200P0.2'	95%	-6	31	90%	82%
XYZ	'CCI','CCISQ','JNPR2.3','S&P1200P0.8'	95%	-9	33	90%	82%
XYZ	'CCI','CCISQ','JNPR2.3','S&P1200P0.1'	95%	-6	31	90%	82%
XYZ	'CCI','CCISQ','JNPR2.3','S&P1200P0.9'	94%	-10	34	90%	82%
XYZ	'CCI','JNPR2.3','S&P1200P0.6'	94%	-4	30	90%	82%
XYZ	'CCI','JNPR2.3','S&P1200P0.7'	94%	-5	30	90%	82%
XYZ	'CCI','JNPR2.3','S&P1200P0.8'	94%	-5	30	90%	82%
XYZ	'CCI','JNPR2.3','S&P1200P0.9'	94%	-6	30	90%	82%
XYZ	'CCI','JNPR2.3','S&P1200P0.5'	94%	-3	30	90%	82%
XYZ	'CCI','JNPR2.3','S&P1200P0.4'	94%	-3	29	90%	82%
XYZ	'CCI','JNPR2.3','S&P1200P0.3'	94%	-2	29	90%	82%
XYZ	'CCI','JNPR2.3','S&P1200P0.2'	94%	-2	29	90%	82%
XYZ	'CCI','JNPR2.3','S&P1200P0.1'	94%	-1	29	90%	82%
XYZ	'CCISQ','JNPR2.3','S&P1200P0.9'	94%	-9	31	90%	82%
XYZ	'CCISQ','JNPR2.3','S&P1200P0.8'	94%	-9	31	90%	82%
XYZ	'CCISQ','JNPR2.3','S&P1200P0.7'	94%	-8	30	90%	82%
XYZ	'CCISQ','JNPR2.3','S&P1200P0.6'	94%	-8	30	90%	82%
XYZ	'CCISQ','JNPR2.3','S&P1200P0.5'	94%	-7	30	90%	82%
XYZ	'CCISQ','JNPR2.3','S&P1200P0.4'	94%	-7	30	90%	82%
XYZ	'CCISQ','JNPR2.3','S&P1200P0.3'	94%	-6	30	90%	82%
XYZ	'CCISQ','JNPR2.3','S&P1200P0.2'	94%	-6	30	90%	82%
XYZ	'CCISQ','JNPR2.3','S&P1200P0.1'	94%	-5	29	90%	82%
XYZ	'JNPR2.3','S&P1200P0.9'	94%	1	28	90%	82%
XYZ	'JNPR2.3','S&P1200P0.8'	94%	2	28	90%	82%
XYZ	'JNPR2.3','S&P1200P0.7'	94%	3	28	90%	82%
XYZ	'JNPR2.3','S&P1200P0.6'	94%	4	28	90%	82%
XYZ	'JNPR2.3','S&P1200P0.5'	94%	5	28	90%	82%
XYZ	'JNPR2.3','S&P1200P0.4'	94%	6	29	90%	82%
XYZ	'JNPR2.3','S&P1200P0.3'	94%	7	29	90%	82%
XYZ	'CCISQ','JNPR2.3','S&P1200P0.8','S&P1200P0.9'	94%	-18	44	90%	82%
XYZ	'CCISQ','JNPR2.3','S&P1200P0.7','S&P1200P0.9'	94%	-18	44	90%	82%
XYZ	'CCISQ','JNPR2.3','S&P1200P0.7','S&P1200P0.8'	94%	-18	44	90%	82%
XYZ	'JNPR2.3','S&P1200P0.2'	94%	8	29	90%	82%
XYZ	'CCISQ','JNPR2.3','S&P1200P0.5','S&P1200P0.6'	93%	-18	45	90%	82%
XYZ	'CCISQ','JNPR2.3','S&P1200P0.4','S&P1200P0.6'	93%	-18	45	90%	82%
XYZ	'JNPR2.3','S&P1200P0.1'	93%	9	30	90%	82%
XYZ	'CCISQ','JNPR2.3','S&P1200P0.4','S&P1200P0.5'	93%	-18	45	90%	82%
XYZ	'CCI','CCISQ','JNPR2.3','S&P1200P0.8','S&P1200P0.9'	93%	-18	49	90%	82%
XYZ	'CCI','CCISQ','JNPR2.3','S&P1200P0.7','S&P1200P0.9'	93%	-18	49	90%	82%
XYZ	'CCISQ','JNPR2.3','S&P1200P0.1','S&P1200P0.3'	93%	-18	45	90%	82%
XYZ	'CCI','CCISQ','JNPR2.3','S&P1200P0.7','S&P1200P0.8'	93%	-18	49	90%	82%
XYZ	'CCISQ','JNPR2.3','S&P1200P0.1','S&P1200P0.2'	93%	-18	45	90%	82%
XYZ	'CCI','CCISQ','JNPR2.3','S&P1200P0.5','S&P1200P0.6'	93%	-18	49	90%	82%
XYZ	'CCI','CCISQ','JNPR2.3','S&P1200P0.4','S&P1200P0.6'	93%	-18	49	90%	82%
XYZ	'CCI','CCISQ','JNPR2.3','S&P1200P0.4','S&P1200P0.5'	93%	-18	49	90%	82%
XYZ	'CCI','JNPR2.3','S&P1200P0.8','S&P1200P0.9'	93%	-18	45	90%	82%
XYZ	'CCI','CCISQ','JNPR2.3','S&P1200P0.2','S&P1200P0.3'	93%	-18	50	90%	82%
XYZ	'CCI','JNPR2.3','S&P1200P0.7','S&P1200P0.9'	93%	-18	45	90%	82%
XYZ	'CCI','CCISQ','JNPR2.3','S&P1200P0.1','S&P1200P0.3'	93%	-18	50	90%	82%
XYZ	'CCI','JNPR2.3','S&P1200P0.7','S&P1200P0.8'	93%	-18	45	90%	82%
XYZ	'CCI','CCISQ','JNPR2.3','S&P1200P0.1','S&P1200P0.2'	93%	-18	50	90%	82%
XYZ	'CCI','JNPR2.3','S&P1200P0.5','S&P1200P0.6'	93%	-18	45	90%	82%
XYZ	'CCI','JNPR2.3','S&P1200P0.4','S&P1200P0.6'	93%	-18	45	90%	82%
XYZ	'CCI','JNPR2.3','S&P1200P0.4','S&P1200P0.5'	93%	-18	45	90%	82%
XYZ	'CCI','JNPR2.3','S&P1200P0.2','S&P1200P0.3'	93%	-18	45	90%	82%
XYZ	'CCI','JNPR2.3','S&P1200P0.1','S&P1200P0.3'	93%	-18	45	90%	82%
XYZ	'CCI','JNPR2.3','S&P1200P0.1','S&P1200P0.2'	93%	-18	45	90%	82%
XYZ	'CCISQ','JNPR2.3','S&P1200P0.1','S&P1200P0.2','S&P1200P0.3'	93%	-14	47	90%	82%
XYZ	'CCI','JNPR2.3'	93%	9	34	90%	82%
XYZ	'CCI','JNPR2.3'	93%	9	34	90%	82%
XYZ	'CCI','JNPR2.3'	93%	9	34	90%	82%
XYZ	'CCISQ','JNPR2.3','S&P1200P0.4','S&P1200P0.5','S&P1200P0.6'	93%	-14	47	90%	82%
XYZ	'CCISQ','JNPR2.3','S&P1200P0.7','S&P1200P0.8','S&P1200P0.9'	93%	-14	48	90%	82%
XYZ	'CCI','CCISQ','JNPR2.3','S&P1200P0.1','S&P1200P0.2','S&P1200P0.3'	93%	-15	54	90%	82%
XYZ	'CCI','JNPR2.3','S&P1200P0.1','S&P1200P0.2','S&P1200P0.3'	93%	-14	48	90%	82%

$MCI2.3 = MCI^{2.3}$, $CCISQ = CCI^2$ and $S\&P1200P0.1 = S\&P1200^{0.1}$

Polynomial Regression Models (To find power for the S&P1200 that gives highest accuracy with the "MCI2.3, CCI, CCISQ" combination) - Continued

ProductType	Polynomial Regression Model	LEI Model Forecast Accuracy	Forecast Error	Std. Deviation of Forecast Error	Marketing Forecast Accuracy	Stat Forecast Accuracy
XYZ	'JNPR2.3','S&P1200P0.8','S&P1200P0.9'	93%	-16	43	90%	82%
XYZ	'JNPR2.3','S&P1200P0.7','S&P1200P0.9'	93%	-16	43	90%	82%
XYZ	'JNPR2.3','S&P1200P0.7','S&P1200P0.8'	93%	-16	43	90%	82%
XYZ	'CCI','CCISQ','JNPR2.3','S&P1200P0.4','S&P1200P0.5','S&P1200P0.6'	93%	-15	54	90%	82%
XYZ	'CCI','JNPR2.3','S&P1200P0.4','S&P1200P0.5','S&P1200P0.6'	93%	-14	48	90%	82%
XYZ	'CCISQ','JNPR2.3','S&P1200P0.2','S&P1200P0.3'	93%	-16	46	90%	82%
XYZ	'CCISQ','JNPR2.3'	93%	10	34	90%	82%
XYZ	'CCISQ','JNPR2.3'	93%	10	34	90%	82%
XYZ	'CCISQ','JNPR2.3'	93%	10	34	90%	82%
XYZ	'JNPR2.3','S&P1200P0.5','S&P1200P0.6'	93%	-16	44	90%	82%
XYZ	'JNPR2.3','S&P1200P0.4','S&P1200P0.6'	93%	-16	44	90%	82%
XYZ	'JNPR2.3','S&P1200P0.4','S&P1200P0.5'	93%	-16	44	90%	82%
XYZ	'CCI','CCISQ','JNPR2.3','S&P1200P0.7','S&P1200P0.8','S&P1200P0.9'	93%	-15	55	90%	82%
XYZ	'JNPR2.3','S&P1200P0.2','S&P1200P0.3'	93%	-16	44	90%	82%
XYZ	'JNPR2.3','S&P1200P0.1','S&P1200P0.3'	93%	-16	44	90%	82%
XYZ	'JNPR2.3','S&P1200P0.1','S&P1200P0.2'	93%	-15	44	90%	82%
XYZ	'CCI','JNPR2.3','S&P1200P0.7','S&P1200P0.8','S&P1200P0.9'	93%	-14	49	90%	82%
XYZ	'CCI','CCISQ','JNPR2.3'	93%	11	38	90%	82%
XYZ	'CCI','CCISQ','JNPR2.3'	93%	11	38	90%	82%
XYZ	'CCI','CCISQ','JNPR2.3'	93%	11	38	90%	82%
XYZ	'JNPR2.3','S&P1200P0.1','S&P1200P0.2','S&P1200P0.3'	92%	-13	47	90%	82%
XYZ	'JNPR2.3','S&P1200P0.4','S&P1200P0.5','S&P1200P0.6'	92%	-13	47	90%	82%
XYZ	'JNPR2.3','S&P1200P0.7','S&P1200P0.8','S&P1200P0.9'	92%	-13	47	90%	82%
XYZ	'S&P1200P0.8','S&P1200P0.9'	91%	5	40	90%	82%
XYZ	'S&P1200P0.7','S&P1200P0.9'	91%	5	40	90%	82%
XYZ	'S&P1200P0.7','S&P1200P0.8'	91%	5	40	90%	82%
XYZ	'S&P1200P0.5','S&P1200P0.6'	91%	4	40	90%	82%
XYZ	'S&P1200P0.4','S&P1200P0.6'	91%	4	40	90%	82%
XYZ	'S&P1200P0.4','S&P1200P0.5'	91%	4	40	90%	82%
XYZ	'S&P1200P0.2','S&P1200P0.3'	91%	4	40	90%	82%
XYZ	'S&P1200P0.1','S&P1200P0.3'	91%	4	41	90%	82%
XYZ	'CCI','CCISQ','S&P1200P0.7','S&P1200P0.8'	91%	6	45	90%	82%
XYZ	'S&P1200P0.1','S&P1200P0.2'	91%	4	41	90%	82%
XYZ	'CCI','CCISQ','S&P1200P0.7','S&P1200P0.9'	91%	6	45	90%	82%
XYZ	'CCI','CCISQ','S&P1200P0.4','S&P1200P0.6'	91%	6	45	90%	82%
XYZ	'CCI','CCISQ','S&P1200P0.8','S&P1200P0.9'	91%	7	45	90%	82%
XYZ	'CCI','CCISQ','S&P1200P0.4','S&P1200P0.5'	91%	6	45	90%	82%
XYZ	'CCI','CCISQ','S&P1200P0.2','S&P1200P0.3'	91%	5	45	90%	82%
XYZ	'CCI','CCISQ','S&P1200P0.1','S&P1200P0.3'	91%	5	45	90%	82%
XYZ	'CCI','CCISQ','S&P1200P0.1','S&P1200P0.2'	91%	5	45	90%	82%
XYZ	'CCISQ','S&P1200P0.8','S&P1200P0.9'	91%	5	43	90%	82%
XYZ	'CCISQ','S&P1200P0.7','S&P1200P0.9'	91%	5	43	90%	82%
XYZ	'CCISQ','S&P1200P0.7','S&P1200P0.8'	91%	5	43	90%	82%
XYZ	'CCISQ','S&P1200P0.5','S&P1200P0.6'	91%	5	43	90%	82%
XYZ	'CCI','S&P1200P0.8','S&P1200P0.9'	91%	5	43	90%	82%
XYZ	'CCISQ','S&P1200P0.4','S&P1200P0.6'	91%	5	43	90%	82%
XYZ	'CCI','S&P1200P0.7','S&P1200P0.9'	91%	5	43	90%	82%
XYZ	'CCI','S&P1200P0.7','S&P1200P0.8'	91%	5	43	90%	82%
XYZ	'CCISQ','S&P1200P0.4','S&P1200P0.5'	91%	4	43	90%	82%
XYZ	'CCI','S&P1200P0.5','S&P1200P0.6'	91%	4	44	90%	82%
XYZ	'CCI','S&P1200P0.4','S&P1200P0.6'	91%	4	44	90%	82%
XYZ	'CCISQ','S&P1200P0.2','S&P1200P0.3'	91%	4	44	90%	82%
XYZ	'CCI','S&P1200P0.4','S&P1200P0.5'	91%	4	44	90%	82%
XYZ	'CCISQ','S&P1200P0.1','S&P1200P0.3'	91%	4	44	90%	82%
XYZ	'CCISQ','S&P1200P0.1','S&P1200P0.2'	91%	4	44	90%	82%
XYZ	'CCI','S&P1200P0.2','S&P1200P0.3'	91%	4	44	90%	82%
XYZ	'CCI','S&P1200P0.1','S&P1200P0.3'	91%	4	44	90%	82%
XYZ	'CCI','S&P1200P0.1','S&P1200P0.2'	91%	4	44	90%	82%
XYZ	'CCI','CCISQ','S&P1200P0.5','S&P1200P0.6'	91%	1	47	90%	82%
XYZ	'CCI','CCISQ'	91%	20	42	90%	82%
XYZ	'CCI','CCISQ'	91%	20	42	90%	82%
XYZ	'CCI','CCISQ'	91%	20	42	90%	82%
XYZ	'CCI','CCISQ','S&P1200P0.9'	91%	13	45	90%	82%
XYZ	'CCI','CCISQ','S&P1200P0.8'	90%	13	45	90%	82%
XYZ	'CCI','CCISQ','S&P1200P0.7'	90%	14	45	90%	82%
XYZ	'CCI','CCISQ','S&P1200P0.6'	90%	14	46	90%	82%
XYZ	'CCI','CCISQ','S&P1200P0.5'	90%	15	46	90%	82%
XYZ	'CCI','CCISQ','S&P1200P0.4'	90%	15	46	90%	82%
XYZ	'CCI','CCISQ','S&P1200P0.3'	90%	16	46	90%	82%
XYZ	'CCI','CCISQ','S&P1200P0.2'	90%	16	46	90%	82%
XYZ	'CCI','CCISQ','S&P1200P0.1'	90%	17	46	90%	82%

MCI2.3 = $MCI^{2.3}$, CCISQ = CCI^2 and S&P1200P0.1 = $S\&P1200^{0.1}$

Polynomial Regression Models (To find power for the S&P1200 that gives highest accuracy with the “MCI2.3, CCI, CCISQ” combination) - Continued

ProductType	Polynomial Regression Model	LEI Model Forecast Accuracy	Forecast Error	Std. Deviation of Forecast Error	Marketing Forecast Accuracy	Stat Forecast Accuracy
XYZ	'S&P1200P0.1','S&P1200P0.2','S&P1200P0.3'	90%	5	46	90%	82%
XYZ	'S&P1200P0.4','S&P1200P0.5','S&P1200P0.6'	90%	4	46	90%	82%
XYZ	'S&P1200P0.7','S&P1200P0.8','S&P1200P0.9'	90%	3	46	90%	82%
XYZ	'CCI','CCISQ','S&P1200P0.1','S&P1200P0.2','S&P1200P0.3'	90%	6	53	90%	82%
XYZ	'CCI','CCISQ','S&P1200P0.4','S&P1200P0.5','S&P1200P0.6'	90%	5	53	90%	82%
XYZ	'CCI','CCISQ','S&P1200P0.7','S&P1200P0.8','S&P1200P0.9'	90%	5	54	90%	82%
XYZ	'CCISQ','S&P1200P0.1','S&P1200P0.2','S&P1200P0.3'	90%	6	50	90%	82%
XYZ	'CCISQ','S&P1200P0.4','S&P1200P0.5','S&P1200P0.6'	90%	6	50	90%	82%
XYZ	'CCI','S&P1200P0.1','S&P1200P0.2','S&P1200P0.3'	90%	6	50	90%	82%
XYZ	'CCISQ','S&P1200P0.7','S&P1200P0.8','S&P1200P0.9'	90%	5	51	90%	82%
XYZ	'CCI','S&P1200P0.4','S&P1200P0.5','S&P1200P0.6'	90%	5	51	90%	82%
XYZ	'CCI','S&P1200P0.7','S&P1200P0.8','S&P1200P0.9'	90%	4	51	90%	82%
XYZ	'CCISQ','S&P1200P0.9'	90%	20	46	90%	82%
XYZ	'CCISQ','S&P1200P0.8'	90%	21	46	90%	82%
XYZ	'CCISQ','S&P1200P0.7'	89%	21	46	90%	82%
XYZ	'CCISQ','S&P1200P0.6'	89%	22	46	90%	82%
XYZ	'CCISQ','S&P1200P0.5'	89%	22	46	90%	82%
XYZ	'CCISQ','S&P1200P0.4'	89%	23	47	90%	82%
XYZ	'CCISQ','S&P1200P0.3'	89%	23	47	90%	82%
XYZ	'CCISQ','S&P1200P0.2'	89%	23	47	90%	82%
XYZ	'CCISQ','S&P1200P0.1'	89%	24	47	90%	82%
XYZ	'CCI','S&P1200P0.9'	89%	23	48	90%	82%
XYZ	'CCI','S&P1200P0.8'	89%	23	48	90%	82%
XYZ	'CCI','S&P1200P0.7'	89%	24	48	90%	82%
XYZ	'CCI','S&P1200P0.6'	89%	24	48	90%	82%
XYZ	'CCI','S&P1200P0.5'	89%	25	49	90%	82%
XYZ	'CCI','S&P1200P0.4'	89%	25	49	90%	82%
XYZ	'CCI','S&P1200P0.3'	89%	26	49	90%	82%
XYZ	'CCI','S&P1200P0.2'	89%	26	49	90%	82%
XYZ	'CCI','S&P1200P0.1'	89%	27	50	90%	82%

MCI2.3 = $MCI^{2.3}$, CCISQ = CCI^{2} and S&P1200P0.1 = $S\&P1200^{0.1}$

Appendix C. LEI Forecasting Tool

Microsoft Access 2007 is used as the software development environment to build the LEI Forecasting Tool. The LEI forecasting tool consists of two modules: 1) Back End Data Management Module and 2) User Interface Module. The Back End Module contains the main data tables for forecasting. The User Interface module is the GUI to generate LEI based forecasts and to compare them with the existing forecasting techniques.

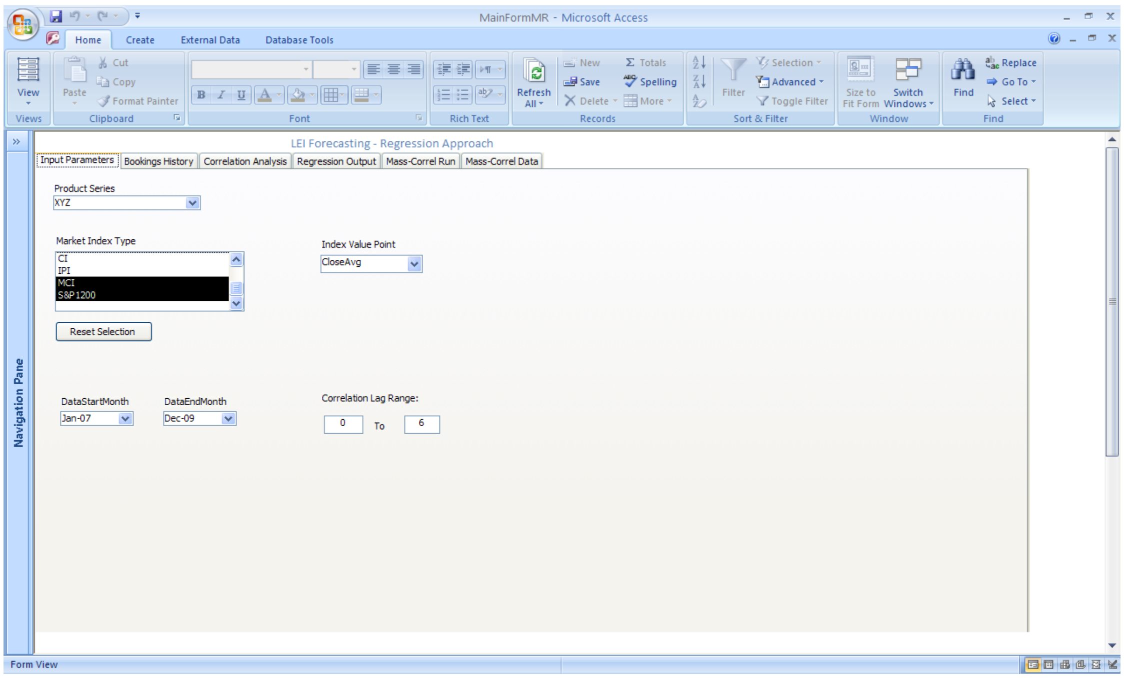
The User Interface module has six main tabs:

1) Input Parameters
2) Bookings History
3) Correlation Analysis
4) Regression Output
5) Mass-Correl Run
6) Mass-Correl Data

The first four tabs are used to generate and compare LEI based forecasts with the existing forecasting techniques. The last 2 tabs are used to run correlation experiments for multiple products and leading economic indicators across multiple data ranges.

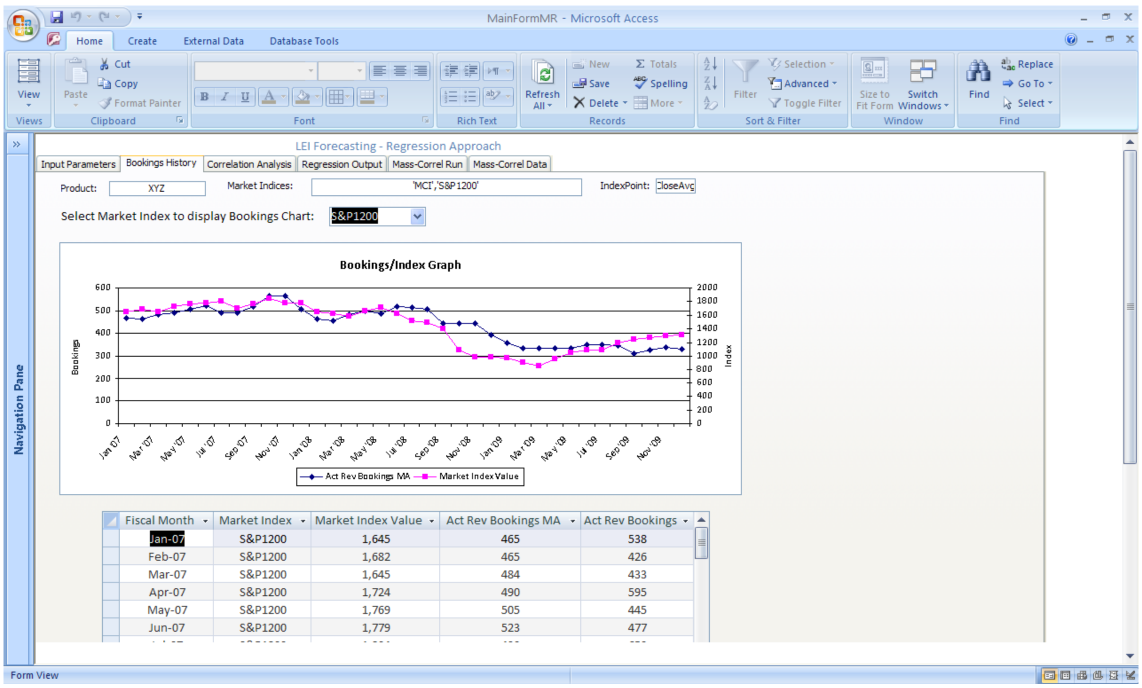
The "Input Parameters" tab is used to select product series, market index type, and index value point. The user also selects start and end months of the data range as well as the correlation lag range in this tab. The user could either select a single market index to create a linear regression forecast or multiple market indices to create a multiple regression forecast.

Input Parameters Tab



The “Bookings History” tab shows the graphical view of bookings and the market index over the selected data range. This graphical view should help the user to see how bookings are trending compared to the market index. The user can only select one market index at a time in this tab to generate the bookings graph view.

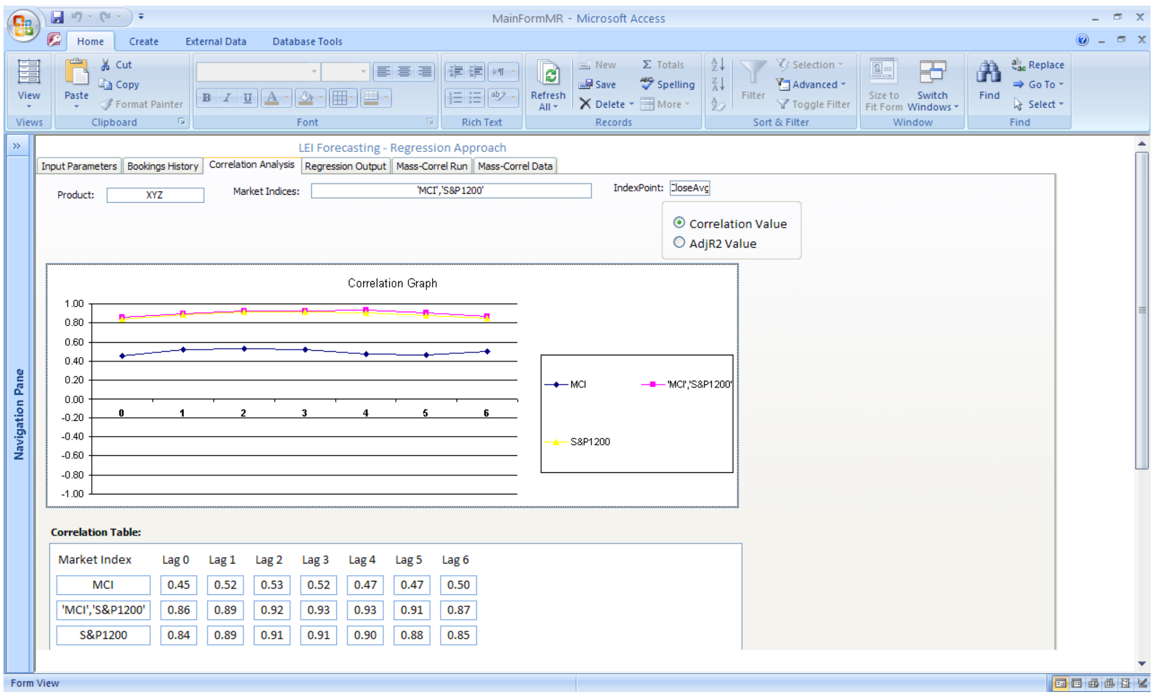
Bookings History Tab



Fiscal Month	Market Index	Market Index Value	Act Rev Bookings MA	Act Rev Bookings
Jan-07	S&P1200	1,645	465	538
Feb-07	S&P1200	1,682	465	426
Mar-07	S&P1200	1,645	484	433
Apr-07	S&P1200	1,724	490	595
May-07	S&P1200	1,769	505	445
Jun-07	S&P1200	1,779	523	477

The “Correlation Analysis” tab shows the correlation between bookings for the selected product series and market indices in a graphical as well as tabular format. The user also has the option to toggle between the correlation graph and the $AdjR^2$ graph. This view shows the correlation graph for individual market indices as well as the combination of these market indices if multiple market indices were selected on the “Input Parameters” tab.

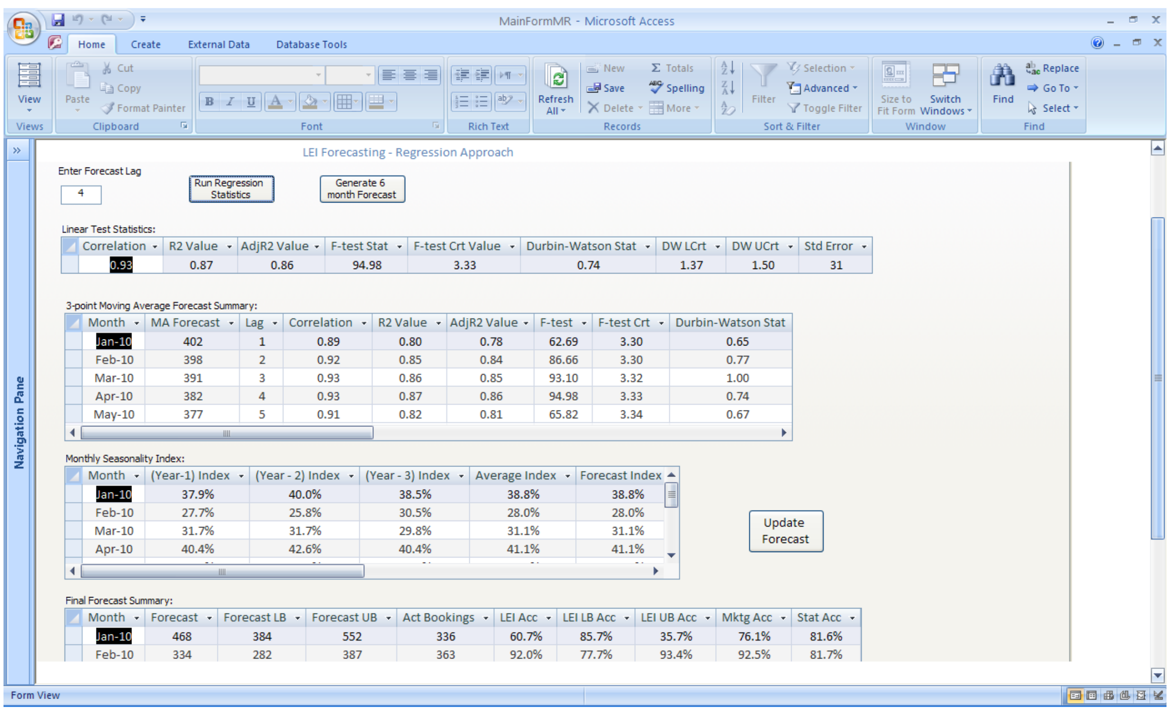
Correlation Analysis Tab



The “Regression Output” tab shows regression test statistics for forecast lag entered by the user. The default value for forecast lag is set to 4 but the user can change it to view regression test statistics at a different lag. This tab also shows the 3-point centered moving average forecast along with different test statistics for the next five months after the “Data End Month” selected on the “Input Parameters” tab. The user also has the option to view monthly seasonal indices and change them as needed to generate the final forecast. The user should click on the “Update” button after changing the forecast index to generate the updated final forecast.

The last table in this tab shows the final monthly forecast. It also shows the forecast accuracy of the final forecast along with the marketing and statistical forecast accuracy.

Regression Output Tab



Correlation	R2 Value	AdjR2 Value	F-test Stat	F-test Crt Value	Durbin-Watson Stat	DW LCrt	DW UCrt	Std Error
0.93	0.87	0.86	94.98	3.33	0.74	1.37	1.50	31

Month	MA Forecast	Lag	Correlation	R2 Value	AdjR2 Value	F-test	F-test Crt	Durbin-Watson Stat
Jan-10	402	1	0.89	0.80	0.78	62.69	3.30	0.65
Feb-10	398	2	0.92	0.85	0.84	86.66	3.30	0.77
Mar-10	391	3	0.93	0.86	0.85	93.10	3.32	1.00
Apr-10	382	4	0.93	0.87	0.86	94.98	3.33	0.74
May-10	377	5	0.91	0.82	0.81	65.82	3.34	0.67

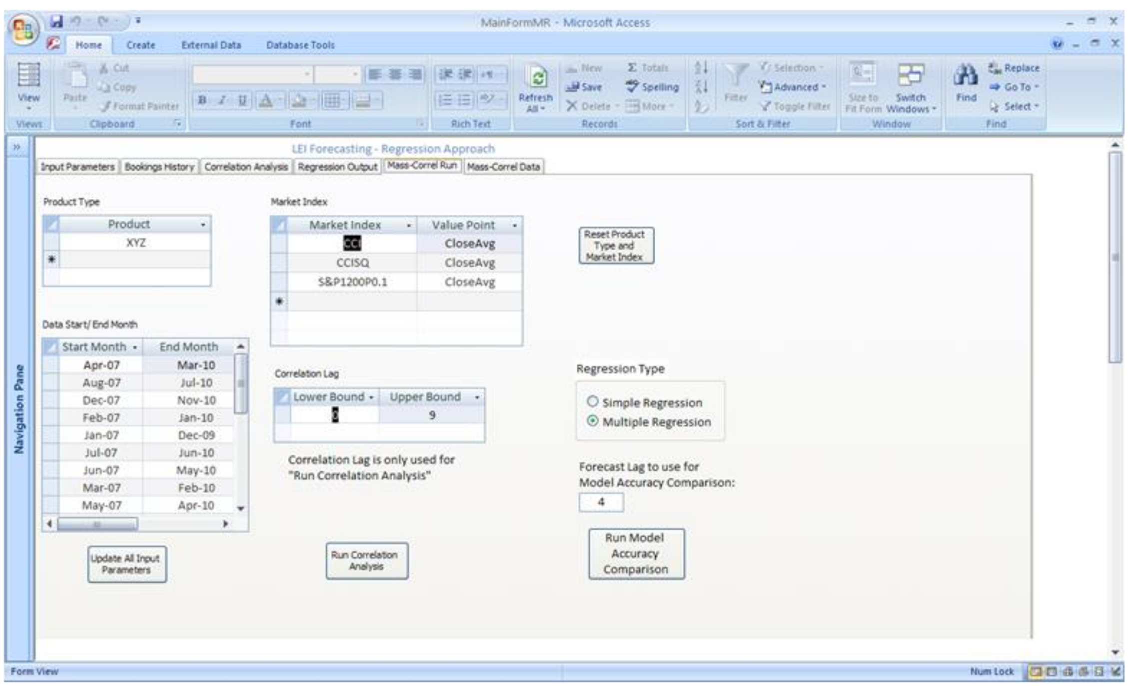
Month	(Year-1) Index	(Year - 2) Index	(Year - 3) Index	Average Index	Forecast Index
Jan-10	37.9%	40.0%	38.5%	38.8%	38.8%
Feb-10	27.7%	25.8%	30.5%	28.0%	28.0%
Mar-10	31.7%	31.7%	29.8%	31.1%	31.1%
Apr-10	40.4%	42.6%	40.4%	41.1%	41.1%

Month	Forecast	Forecast LB	Forecast UB	Act Bookings	LEI Acc	LEI LB Acc	LEI UB Acc	Mktg Acc	Stat Acc
Jan-10	468	384	552	336	60.7%	85.7%	35.7%	76.1%	81.6%
Feb-10	334	282	387	363	92.0%	77.7%	93.4%	92.5%	81.7%

The “Mass-Correl Run” tab is used to set-up the correlation run for simple and multiple correlation analysis. The user could select multiple product types and market indices to run correlation analysis across different sets of data for different lags. The users can change product type, market indices, data range and correlation lag range, but they need to click on the “Update All Input Parameters” command button to commit changes to the back end database. The “Reset Product Type and Market Index” command button is also provided to bring back the original product and market index types from the master data tables. The users need to select the regression type (simple regression or multiple regression) before running the correlation analysis using the “Run Correlation Analysis” command button.

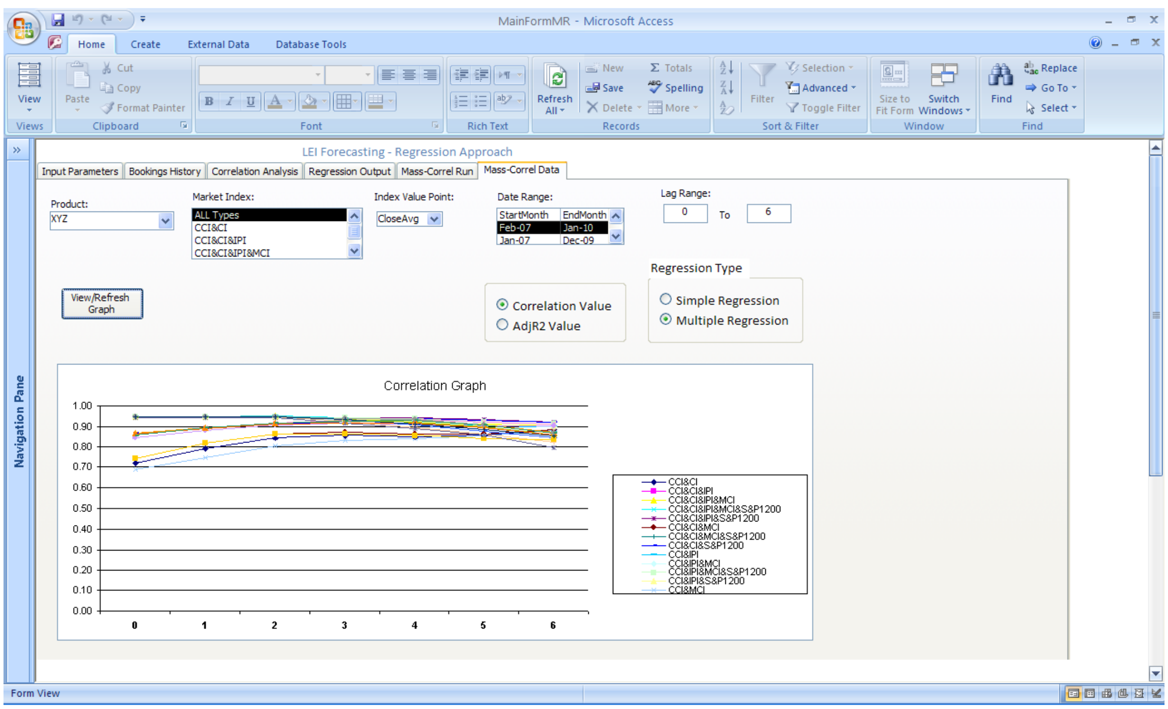
Finally, the “Run Model Accuracy Comparison” command button is used to generate a forecast accuracy comparison .xls file that shows the accuracy comparison among all possible multiple combinations of the selected market indices over the forecasted time period defined by the data end months and the selected forecast lag.

Mass-Correl Run Tab



The “Mass-Correl Data” tab gives the users the ability to view results of the correlation analysis run via the “Mass-Correl Run” tab. Correlation output is shown both in graphical and tabular format. This view is very handy as it would let the forecaster easily view which market index or combination of market indices yields the highest correlation value for a given product series and data range at a certain lag. The user can also toggle between correlation value and AdjR^2 value to see the graphical and tabular view for either correlation or AdjR^2. The default for the “Regression Type” option group is whatever the user selected on the “Mass-Correl Run” tab. However, users can change the regression type to view correlation/AdjR^2 for the chosen regression type (simple or multiple regression).

Mass-Correl Data Tab



Appendix D. Actual Bookings Data

Product Series	Month	Actual Bookings	Actual Bookings (3-point Moving Average)
XYZ	Jan-07	538	466
XYZ	Feb-07	426	466
XYZ	Mar-07	433	485
XYZ	Apr-07	595	491
XYZ	May-07	445	506
XYZ	Jun-07	477	524
XYZ	Jul-07	650	491
XYZ	Aug-07	346	489
XYZ	Sep-07	471	518
XYZ	Oct-07	737	563
XYZ	Nov-07	482	566
XYZ	Dec-07	480	505
XYZ	Jan-08	555	463
XYZ	Feb-08	354	456
XYZ	Mar-08	461	484
XYZ	Apr-08	638	500
XYZ	May-08	400	488
XYZ	Jun-08	425	519
XYZ	Jul-08	734	513
XYZ	Aug-08	381	506
XYZ	Sep-08	403	445
XYZ	Oct-08	551	446
XYZ	Nov-08	384	442
XYZ	Dec-08	391	395
XYZ	Jan-09	410	360
XYZ	Feb-09	280	336
XYZ	Mar-09	318	335
XYZ	Apr-09	407	336
XYZ	May-09	282	336
XYZ	Jun-09	317	352
XYZ	Jul-09	457	349

Product Series	Month	Actual Bookings	Actual Bookings (3-point Moving Average)
XYZ	Aug-09	272	348
XYZ	Sep-09	315	313
XYZ	Oct-09	351	327
XYZ	Nov-09	314	337
XYZ	Dec-09	347	332
XYZ	Jan-10	336	349
XYZ	Feb-10	363	341
XYZ	Mar-10	323	401
XYZ	Apr-10	516	379
XYZ	May-10	298	393
XYZ	Jun-10	365	383
XYZ	Jul-10	485	372
XYZ	Aug-10	266	351
XYZ	Sep-10	302	349
XYZ	Oct-10	480	375
XYZ	Nov-10	343	398
XYZ	Dec-10	371	358
XYZ	Jan-11	360	339
XYZ	Feb-11	285	323
XYZ	Mar-11	322	367

Appendix E. Glossary of Terms

ALI:	Automatic Leading Indicator.
ANN:	Artificial Neural Networks.
AR:	Autoregression.
BCI:	Business Confidence Index.
BECM:	Bayesian Error Correction Mechanism (BECM).
BVAR:	Bayesian Vector Autoregression.
CBP:	Consensus Book Plan. Bookings forecast created by the demand planning team through the consensus demand planning process.
CCI:	Consumer Confidence Index.
CI:	Company stock Index.
CDP:	Consensus Demand Planning process. Collaborative process through which the demand planning team gather inputs and gain insights from marketing/sales and analytics teams to put together the best possible bookings forecast (CBP) for a given product.
CLI:	Composite Leading Index.
Coincident Indicator:	An economic indicator that changes about the same time as the economy.
DFM:	Dynamic Factor Model.
DJI:	Dow Jones Industrial average. It is a stock market index that follows the stock prices of 30 publicly traded USA companies.
Forecast Accuracy:	It is a measure of how close the actual demand is to the forecast. It is always bounded between 0 and 100 and is calculated as Max [0, 1 – Abs (Forecast – Actuals)/Actuals].
Forecast Bias:	It is a measure of the deviation of the actual demand from the forecast. It indicates whether the forecast was high (positive

	bias) or low (negative bias) compared to the actuals. Forecast bias is also called MAPE and is calculated as: (Forecast – Actuals)/Actuals
GDP:	Gross Domestic Product.
GFCF:	Gross Fixed Capital Formation.
GNP:	Gross National Product.
IPI:	Industrial Production Index. An economic indicator that is released monthly by the Federal Reserve Board which measures the amount of output from manufacturing, mining, and utilities.
Lagging Indicator:	An economic indicator that changes after the economy.
LEI:	Leading Economic Indicators. Leading Economic Indicator (LEI) is an economic indicator that changes before the economy.
MAPE:	Mean Absolute Percentage Error.
Marketing Forecast:	Bookings forecast created by the product marketing team based on market intelligence and sales inputs.
MCI:	Main Competitor stock Index.
MCISQ:	Square of Main Competitor stock Index.
MESM:	Macroeconometric Structural Model.
MR:	Multiple Regression.
REG:	SAS Regression procedure.
S&P1200:	Standard & Poors global index of 1200 companies. It is a composite of seven headline indices.
S&P1200SQ:	Square of Standard & Poors global 1200 index.
S&P1200SQRT:	Square Root of Standard & Poors global 1200 index.
S&P500:	Standard & Poors index of 500 USA companies. It is a weighted index of 500 large-cap common stocks actively traded in the USA.

S&P700:	Standard & Poors index of 700 companies. It covers all of the regions included in the S&P1200 index excluding USA, which is represented by the S&P500.
Statistical Forecast:	Forecast created by the analytics group using SAS advanced statistical algorithms.
VAR:	Vector Autoregression.