METHODOLOGY TO FORECAST PRODUCT RETURNS FOR THE CONSUMER ELECTRONICS INDUSTRY

by

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ABSTRACT

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Reverse logistics has gained much attention in recent years. It is becoming a value added area of a supply chain network day by day. For enterprises, it has therefore become essential to manage the reverse flow of materials in an efficient way to gain competitive advantage. One important aspect of reverse logistics is to have a correct and timely estimation of the reverse flow of materials. Improved forecast accuracy leads to a better decision making in strategic, tactical and operational areas of an organization. Intrinsic (time series) and extrinsic (causal) forecasting are some of the well known and frequently used forecasting techniques.

Very little research has been done about the forecasting aspect of reverse logistics. The initial research that has been carried out in this area was very naive. It used the basic method of probability by proportions of cumulative returns to cumulative sales. For higher forecast accuracy, more robust method is required. The purpose of this research is to develop the methodology that can be used for forecasting product returns. This methodology is developed for the consumer electronics industry.

The methodology in this research is based on return reason codes (RC). The reason code based forecasting is a unique part of this research. The incoming returns are split into different categories using reason codes. These reason codes are further analyzed to forecast product returns. The computation part of this model uses a combination of two approaches namely extreme point approach and central tendency approach. Both the approaches are used separately for separate types of reason codes, and then results are added together. The extreme point approach is based on data envelopment analysis (DEA) as a first step combined with linear regression, while the central tendency approach uses a moving average. DEA is a non-parametric tool that is used to analyze performance indices. For certain types of returns, DEA evaluates relative ranks of products using 'single input and multiple outputs' model. Once this is completed, linear regression defines a correlation between relative ranks (predictor variable) and return quantities (response variable). For the remaining types of returns, we use a moving average of percent returns to estimate the central tendency. Thus, by combining two approaches for different types of returns, we have developed the model that can be used to forecast product returns for the consumer electronics industry.

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CHAPTER 1

INTRODUCTION

1.1 Overview

Reverse logistics plays the important role in a supply chain network of an organization. Nowadays, it is getting as much attention as it is given to the forward logistics. As a matter of fact, it is becoming a value added area of supply chain day by day. For enterprises, it has therefore become essential to manage the reverse flow of materials in an efficient way to gain competitive advantage (Meyer 1999). According to Andel (Andel 1997), for organizations it is a second chance to profit. One important aspect of reverse logistics is to have a correct and timely estimation of the reverse flow of the materials. Time series (intrinsic) and causal (extrinsic) are considered as some of the well known methods that are used for forecasting in forward logistics. Same techniques can be applied to the estimation of product returns in reverse logistics. The purpose of this research is to develop the methodology for forecasting product returns. The methodology is designed for the consumer electronics industry. It is needless to say that, increase in forecast accuracy leads to a better decision making in strategic, tactical and operational areas of an organization.

This dissertation is divided into five chapters. In the opening chapter, we will discuss the concepts, core processes and performance measures of reverse logistics.

We will then look at the workflow of the return process and see why there is a need to estimate product returns in the reverse supply chain network. Chapter two will include the literature review i.e. research work that has already been done or currently being studied by other researchers. In chapter three, we will talk about the methodology that is developed in this research for forecasting product returns. Data analysis and results will be discussed in chapter four and finally in chapter five, we will have concluding remarks and direction for further research.

1.2 Background

1.2.1 Concept of Reverse Logistics

The council of Logistics Management (CLM) defines the reverse logistics as "a process of planning, implementing and controlling raw materials, in process inventory and finished goods inventory from the point of consumption to the point of origin." Rogers et al (Rogers 2000) modified this definition as "a process of moving goods from their typical final destination for the purpose of capturing the value." The point of consumption or the final destination is typically an end consumer while the point of origin is a manufacturer or retailer in most cases. Some of key factors associated with reverse logistics are customer dissatisfaction, lost revenue, recovery cost and that makes it as an important aspect of a supply chain network. According to Rogers et al (Rogers 2000), $100 billion worth of goods are returned every year. Also, improperly handled returns erode 30-35% of potential profits. The impact by industry in reverse logistics varies from industry to industry. The magazine publishing industry is on top of the list followed by the book publishing industry. With this kind of magnitude, even the leading edge manufacturers and retailers have identified the importance of reverse logistics. According to Caldwell (Caldwell 1999), big companies like General Motors, Sears, 3M and handful of online retailers are seeing the clear benefits of reverse logistics. Some firms are beginning to benchmark their return operations and include reverse logistics as a part of management strategy (Beltran 2002). Two key components in reverse logistics i.e. recovery cost and lost revenue are usually not seen, however management understands that if they are controlled properly, they would result in the cost recovered and revenue. Following table shows some sample returns percentages by various industries.

Table 1.1 Sample Returns Percentage chart
(Adapted from “Going Backwards: Reverse Logistics Trends and Practices”, Rogers, D. et al, 2000)

Industry	**Percentage**
Magazine Publishing	50%
Book Publisher	20-30%
Book Distributors	10-20%
Greeting Cards	20-30%
Catalog Retailers	18-35%
Electronic Distributors	10-12%
Computer Manufacturers	10-20%
CD-ROMs	18-25%
Printers	4-8%

Table 1.1 - Continued

Mail Order Computer Manufacturers	2-5%
Mass Merchandisers	4-15%
Auto Industries (Parts)	4-6%
Consumer Electronics	4-5%
Household Chemicals	2-3%

Let us look at a simple scenario in reverse logistics, product return. Every one of us, one time or another, has been in a situation where we had to return a product in a store for one or more reasons. Most people simply call it a return. Has anyone thought about these returns? Where do they go from the store? How do retailers handle them? Does it have any value? Twenty years back, no one thought about all of these questions neither tried to answer them. However today, not only we know the answers to these questions but also we know that industries are trying to manage the entire return process efficiently across multiple channels. Getting a product back into supply chain and managing the reverse flow of the returned product in an efficient way, has become a value added activity. According to De Brito et al (De Brito 2002), managing a flow of returned products and the related information from the point of consumption to the point of origin is a process. It is called Reverse Logistics Management. This is a modified definition of reverse logistics that we have previously seen from Rogers et al (Rogers 2000). However, the phrase 'efficient management of information and material' is a key. To understand reverse logistics better, it is necessary to understand the core processes of reverse logistics. Typical stops in the journey of product returns are end consumers, retailers, distribution centers and manufacturers. In the next section, we will look at the core processes that are associated with reverse logistics. We will also see how the processes in reverse logistics are classified from the point of consumption to the point of origin. It all starts from an unhappy customer.

1.2.2 Core Processes of Reverse Logistics

In this section, we will discuss the core processes in reverse logistics network at high level. We know from the previous discussion that, high magnitude of the returns could consume extra labor, extra space, extra time and additional cost to retailers or manufacturers. If you have visited a large retailer after Christmas or holiday season, you would understand the complexity when retailers have to deal with receiving items, refund process, possibility of fraud just to name a few. The pile of return items is sitting in the store somewhere in the customer service area, waiting to begin their journey inside the reverse logistics channel. Once the product is returned, the retailer or manufacturer has to make the decision whether to make it as a part of forward logistics (by selling as refurbished or use in parts) or not to make it as a part of forward logistics (by making it as a scarp). By not making correct decision, retailers or manufacturers could be at risk of improper handling of this valuable inventory and losing revenue. Even though process is reversed, the goals are same as of those in forward logistics namely time, labor, space and cost efficiency. At the same time, complexity in the process is much higher in case of reverse logistics. As per the study carried out by

Daugherty et al (Daugherty 2005), to maintain the competitive advantage, organization should make the reverse logistics management as a value added activity.

Let us discuss the core processes in reverse logistics. We will begin with the point where the return goods enter the reverse logistics channel. This point typically is a customer service area inside a retail store. The following figure shows the core processes in the reverse logistics network for the consumer electronics industry.

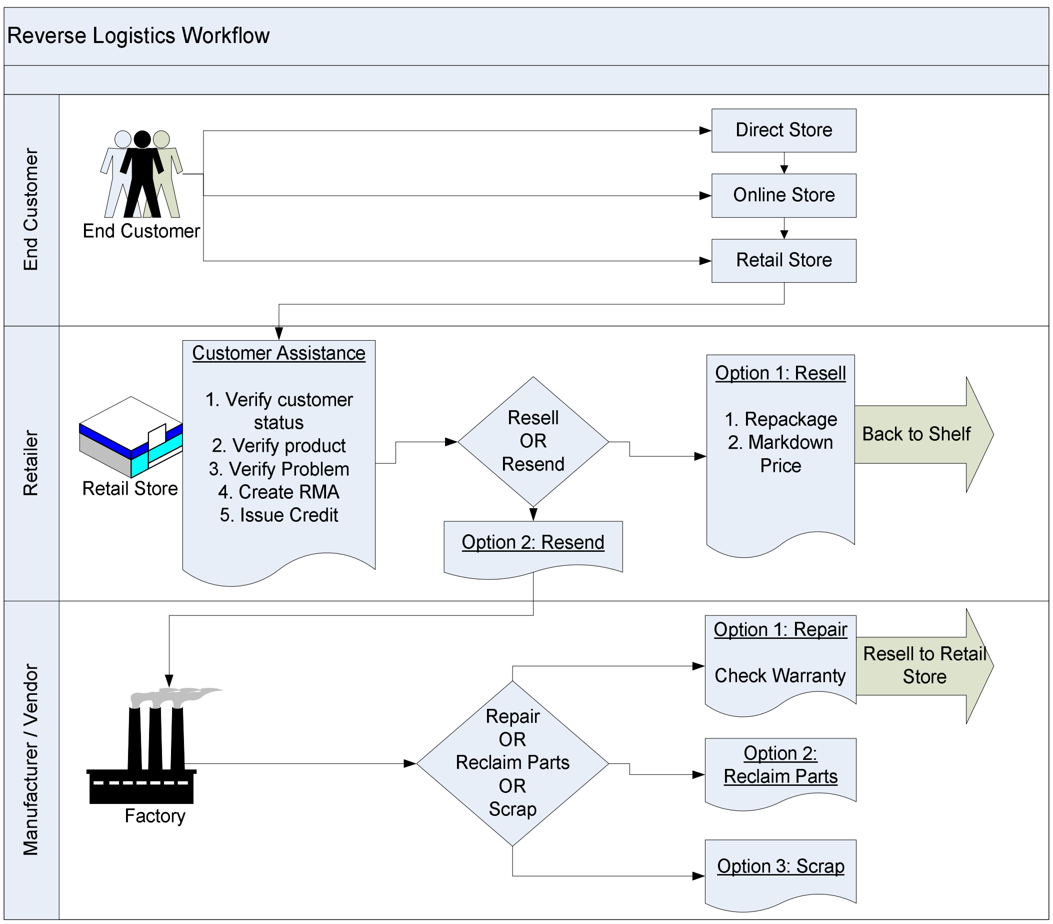

Figure 1.1 Core Processes in Reverse Logistics Network
(Adapted from “Reset: The parts support company” Solution Process)

The key players and the core processes in reverse logistics are explained in the following section:

1. End Customer:

   This is a point of consumption in forward supply chain and thus becomes a starting point for the return process or reverse supply chain. This player represents a typical customer who buys product.

2. Customer Service:

   An end customer returns a product in the store. The store can be typically classified into retail, direct or online store. The customer service is the location inside the retail store where the end customer goes to return the product. Customer service performs tasks like verification of customer status, checking condition of the product, verification of the problem, creation of return merchandise authorization (RMA) and issuing credit to the customer.

3. Retailer:

   This is the next stop in the system which is responsible for the managing product returns in the supply chain network. The customer service location as mentioned above could be a part of the retailer.

4. Resell or Resend:

   Once the product is received at the retailer's end, the decision has to be made if the product needs to be resold in the store or to be resent to the manufacturer. If it is to be reused then it should be resold as a refurbished product. The new packaging is required and price is required to be marked down. In some case if minor repairs are required, it is sent to a local repair depot owned by retailers. If retailers decide to send it back for major repairs or disposal, then it goes to the next player in the network and that is a manufacturer or vendor.

5. Manufacturer / Vendor:

   This is a point of origin in forward supply chain and thus becomes last stop for the return process. Once product is reached at this point, Manufacturer / Vendor have to make a decision if the product needs to be repaired or used in parts or scrapped.

6. Repair, Reclaim Parts or Scrap:

   Depending on the condition of the product, manufacturer / vendor needs to make the decision whether to repair or reclaim or scrap the returned product. If the returned product is repairable and sellable, it is repaired and sent back to the retailer. This is usually a preferred option. Sometime manufacturers / vendors decide to reclaim parts, meaning use some of the reusable parts of the product. E.g. in the case of the camera, circuit boards are typically reused or in case of the printers, cartridges are reused. The last option is to scrap or dispose of the product by sending it to landfill.

The table below shows some of the facts about reverse logistics. It shows the data about the initial value reclaimed, percent of new products returned and cost of reverse logistics as a percent of sales.

Table 1.2 Reverse Logistics fact sheet
(Adapted from "Aberdeen group research data")

Initial value reclaimed from returned product or parts	64.3%
Overall Reverse Logistics cost as a percent of sales	9.0%
New products returned for repair within warranty period	5.7%

The organizations view the entire process from strategic point of view. They want to turn this cost into profit (Blanchard 2007). At the same time they want it to be a customer friendly process. Organizations also view this process from strategic, tactical and operational levels. At the strategic level, organizations make decisions about designing the reverse logistics network to minimize the transportation cost, making return process customer friendly etc. At the tactical level, decisions regarding procurement of reusable parts are made. For example, circuit board inside the camera, whether to be purchased or reused. Also, decisions like capacity planning and disposal management are made at the tactical level (Toktay 2003). The operational level is where production planning, inventory management related decisions are made. For example, if a new product is being launched and an old product is being retuned at the same time, then how to manage the production and inventory planning. As per Van Hillegersberg et al (Van Hillegersberg 2001), same importance needs to be given to reverse logistics as it is given to forward logistics as far as planning process is concerned. These days, organizations hand over this job to third party vendors who have the specialized skills in this area. These third party vendors provide value added services such as end-to-end visibility, customized reporting, identifying customer product relationship matrix

(Richardson 2001). UPS, Genco Distribution System, USF Processor are some of the leading third party vendors that provide services in the area of reverse logistics. Software tools that are designed as per specific requirements in reverse logistics are also easily available these days (Tashman 1991), (Gooley 2001). Other than the software tools, some vendors have designs and maintains the reverse logistics network for their customers.

The other important aspect of any supply chain network is performance measures or key performance indices. Regardless of what technology organization is using, it is important for them to evaluate the overall performance of the reverse logistics network. Primarily, the performance indices are defined in terms of time, labor, space and cost. In the next section, we are going to see some of the performance measures defined for reverse logistics.

1.3 Performance Measures

As mentioned previously, even though the process is reversed, goals remain same as of those in forward logistics. They are time, labor, space and cost efficiency. In this section, we are going to discuss briefly about the key metrics of an organization in the area of reverse logistics. We know that, returns can occur any time (Ferguson 2005). It is happening every minute every day. The issue is, the process owners are not clearly recognized and data is not available easily to measure the performance of key indices. Due to this, identifying the performance measures in the reverse logistics channel has become difficult.

To measure the performance indices, we are going to use few techniques shown by Dr. Frazelle (Frazelle 2002). According to him, to understand the performance measures we need to understand activity profiles within any given process. Activity profiling is a systematic analysis of the activities in a given process. So, let us use the activity profiling technique to understand the performance measures in reverse logistics network. In the previous section, we saw core processes or activities in reverse logistics. The following table shows the activity profiles and profile component in reverse logistics channel based on the core processes or activities.

Table 1.3 Activity Profiling in Reverse Logistics
(Adapted from "Frazelle, E., "World-Class Warehousing and Material Handling", 2002")

Process / Activity	Key Question	Profile
Customer Return	Which product? Which customer?	Item Profile, Customer Profile, Season Profile
Verify product **Verify problem** **Issue Credit**	What is problem? Why return?	Return Reason, Supplier Profile
Repair / Refurbish/ Resend	Refurbish or send back to vendor?	Supplier Profile, Return Reason
Redistribution	How to re-label & re-package?	Carrier Profile

The performance measures and activity profiling have a close relationship with each other. Every activity in the channel is linked to a performance measure. We need to understand how resources are consumed in terms of labor, space, and material handling system when that particular activity is taking place.

Following tables shows the relationship between the activities and the performance measures. In the first column we have listed activities in reverse logistics and in rest of the columns we have noted key the performance measures of an organization.

Table 1.4 Performance Measure in Reverse Logistics

Activity/Measures	Financials	Productivity	Quality	Cycle Time	Utilization
Customer Return					
Product Inspection					
Repair / Refurbish				X	
Redistribution	X				

Financials, productivity, quality, cycle time and utilization are the key metrics in any industry. Let us see, how well do they fit in reverse logistics network. Consider the intersection of financials measure and redistribution activity. Here we need to ask ourselves a question, 'What is the shipping cost rather reshipping cost?' Next intersection is cycle time and repair / redistribution activity. Here we need to ask ourselves a question, 'How much cycle time is taken to repair or refurbish a product? Thus, 'reshipping cost' and 'cycle time to repair a product' are two performance measures evolved during the activity profiling. By using the same logic, one can come up with rest of the metrics for reverse logistics channel. The important thing to understand here is, in reverse logistics network, organizations are already dealing with unhappy customers, lost revenue and the recovery cost. Thus, every effort to show an improvement in the performance measures is adding a value. The above discussion was only intended to get an idea about the performance measures. We will not get into the details of performance measure, as it is not the objective of this research.

1.4 Problem Definition

So far we have seen what reverse logistics is; why it is a value added component; why management views it as a strategic tool. As per the study conducted by Reverse Logistics Executive Council (RLEC), 0.5% to 1% of America's GDP is attributed to the cost due to reverse logistics. It is such a big component of supply chain. Initial recognition in this area started in the late 90s. And now, day-by-day, industry practices are becoming sophisticated. Manufacturers and retailers are starting to understand the value of it. They are using end-to-end services from the third party vendors to get an edge over their competitors.

Let us pause for a minute, go back a little and think. Where does this all begin? Earlier we said that the point of origin in reverse logistics is an end consumer, when he/she brings a product back. Which makes sense, because input to the downstream processes is based on "what is coming back, how much is coming back and when is coming back". Meaning, if I am a manufacturer or a retailer and I am selling number of products, I would be interested in knowing the following. What are the chances that the sold product will be returned, what percentage of it will be retuned and when it will be returned. Thus, problem that we are going to solve here is the accurate estimation of the returned product. If we are able to estimate this quantity with reasonable accuracy, all our downstream processes (strategic, tactical and operational) will be positively impacted. Essentially we are talking about a robust forecasting methodology with a better forecast accuracy for product returns. In the next section, we will see why we need to forecast product returns.

1.4.1 Need for forecasting

In the previous section, we said that a manufacturer or a retailer would be interested in knowing that, what are the chances that the sold product will be returned, what percentage of it will be retuned and when it will be returned. Before we look at the forecasting methods, let us see how much return volume we are talking about.

The unsold returns, at end of their useful life, turn into waste. All returns need not be turned into waste; they may be resold as a refurbished product at reduced price before end of life. Waste in the consumer electronics industry is called as E-Waste. There are multiple reports available about the quantity of E-waste. According to the US Environment Protection Agency (EPA) 2.6 Million Tons of E-Waste generated in 2005 out of which only 12.6 % was recycled. The E-Waste includes millions of televisions, computers, laptops, camcorders etc. by household and also by businesses. If we speak in terms of dollars, $ 13.8 Billion worth of E-waste generated by the consumer electronics industry in 2007. This is 8 % of their revenue. Meaning, the return rate in the consumer electronics industry was nearly 8 % in 2007. In case of some electronics products it is observed to be between 11-20 %. This is huge. Now we know that why there is a need for accurate information about product returns.

Let us see, what methods are currently available other than forecasting? There is a Delphi method. This is interactive method where a panel of experts come together to answer the questions for likely outcome of the event in multiple sessions. They revise their answers after every round of discussion. Final round decides the likely outcome (Rowe 1999). There are other versions of Delphi method such as Policy Delphi and Argument Delphi. But we feel that, just by looking at the data, facts and argument, it may not be possible to achieve a desired level of accuracy.

Second option is forecasting, either time series or causal. There are certain quotes about forecasting. Such as, 'forecast is always wrong' or 'forecast only eliminates certain system errors' or 'forecasting is science but an art at the same time'. According to Samuelson (Samuelson 1996) five out of nine recessions on the Wall Street were predicted using forecasting. An accurate and robust forecasting method can give optimized results. But at the same time, it is important for any forecast model that parameters are chosen correctly (Box and Jenkins, 1976). Now question is causal or time series i.e. extrinsic or intrinsic forecasting? Past research by others in this area used the time series method of forecasting. We will see the details of those past studies in literature review chapter. This research is focused on the forecast model based on return reason codes (RC). For computation purpose, we will be using a combination of extrinsic (causal) and intrinsic (time series) method. Data envelopment analysis (DEA) will also be used as a part of causal forecasting method.

1.5 Dissertation Purpose

The purpose of this dissertation is to develop a methodology to forecast product returns for the consumer electronic industry using a combined approach of DEA/linear regression and a moving average. Typical return time (by which consumer can return the product to receive credit) in the consumer electronic industry is 15-30 days. This research primarily targets the products returned within this time period. As per survey conducted by Consumer Electronics Association (CEA), most of the product returns are observed in the initial period. Some of the other outcomes of this survey are:

1. The average rate of return in the consumer electronics industry has remained more or less constant at 8%
2. The return reasons have also remained constant in most of the cases, for example product did not have required features or it did not work right for them etc.
3. Consumers do visit websites related to the consumer electronics products to get familiar with different products and compare various products.
4. Males are more likely to return than females.

The methodology developed in this research is based on the combination of consumer behavior (return reason codes), extreme point approach and central tendency approach. It can be helpful for manufacturers and retailers in forecasting product returns. With timely and accurate information about product returns available to them, we believe that this methodology could be beneficial in building efficient design of reverse logistics network. For example, we have seen retailers carrying different products from different manufacturers and their prices vary from week to week. Once a retailer promotes one product (product A), it can impact not only sales rate of other product (product B) but also impact return quantity of the product B sold previously, provided product B is within the timeframe mentioned in the return policy. Retailers can estimate product returns (already sold) before they promote the other products. From the manufacturer's point of view, they need to know if competitor's product is impacting the returns of their own product and if they need to take any necessary actions. Timely and accurate estimation of return quantities will improve strategic, tactical and operational planning within the organization.

However one may ask a question that, why are we focusing on the consumer electronics (CE) industry? What is so unique about it? The Consumer Electronics industry is big part of US economy. Consumer Electronics Associations (CEA) has mentioned in their recent study that this industry has generated $ 171 Billion in 2007 which is growth of 6% over its 2006 revenue of $ 161 Billion. The online spending is up by 5% from previous year and has a potential to grow more in future years (Oxman 2007). The table below shows some more facts about the CE industry and how it is contributing to US economy. It can be clearly seen that this industry is a big component of economy.

Table 1.5 Consumer Electronics Industry fact sheet
(Adapted from "Consumer Electronics Association 2008 Report")

Revenue 2007	$ 171 Billion
Growth Rate	6 - 8 %
Jobs Created / Labor Compensation	4.4 Million / $ 325 Billion
Tax Payment	$ 145 Billion
Total Contribution to US economy	4.6 %

In addition, the consumer electronics sector offers variety of products from televisions to VCRs to DVD players to camcorders to digital cameras to laptops to GPS. This industry has shown significant growth in last few years (Smith 2002). Not only it has a wide range of the products but also in each category it has a wide selection of specifications (Levine 2002). E.g. in a cellular phone category, we can find phones with the internet option, camera option, email options etc. The prices also vary from product to product and from retailer to retailer. This is typically observed in the consumer electronics industry. The other notable part about the consumer electronics industry is the product life cycle. It is usually 10-12 months. For most of the products, the product life cycle follows a typical path. This path is introduction phase, steady state and end of life. The steady state phase is about 80% of product life cycle. That means, during the life span of 10-12 months and approx. 80% of the time, products in the similar category and similar price range compete with each other.

Methodology developed in this research is for the consumer electronics industry and based on the combination of consumer behavior (return reason codes), extreme point approach and central tendency approach. We will discuss the detailed approach later in research methodology chapter. In the next chapter (chapter 2), we will look at some of the research ideas from the past by various researchers.

CHAPTER 2

LITERATUTRE REVIEW

2.1 Literature on Reverse Logistics

The initial idea of reverse logistics came forward in 1975. (Guiltinan et al 1975) At times, it was either called as reverse channel or reverse flow. Early work by Guiltinan and Nwokoye in this area focused on reuse of the goods like returnable bottles and set up the recycling centers with the help of manufacturers. The idea was to separate recycled materials from total waste using these recycling centers. According to them, reverse channel area had future growth. Today we can see that, the field of reverse logistics has grown very big and has a potential to grow still further. Later in the seventies, Ginter et al (Ginter 1978) carried out a research that also focused on the reverse channel, primarily in the municipal waste and waste management.

In the early eighties, area of reverse channel gained attention from many researchers. The research carried out by Lambert (Lambert 1982) was in the area of municipal waste management and movement of the waste materials. Christopher Witt (Witt 1986) and Murphy et al (Murphy 1989) were among the other researchers.

Reverse logistics gained major attention in the nineties. In 1992, study by Pohlen et al (Pohlen 1992) suggested that the flow of materials in reverse logistics is different from the material flow in forward logistics and needs to be studied separately.

Terrance Pohlen and M. Theodore Farris also suggested that this area is experiencing rapid growth and will have significant impact on the efficiency of the processes that handles recycled materials. Later in the nineties the council of Logistics Management (CLM) defined Reverse Logistics as "process of planning, implementing and controlling raw material, in process inventory and finished goods inventory from the point of consumption to the point of origin." Later many researchers modified this definition, but the gist remained same. Some researchers addressed reverse logistics as a closed loop supply chains. The goal of the closed loop supply chain is to close material flow, reduce waste and emission (Krikke et al 2001). Guide et al (Guide et al 2002) describe a reverse supply chain as "the series of activities required to retrieve a used product from a customer and either dispose of it or reuse it."

In the study conducted by Blackburn et al (Blackburn et al 2004), he suggested that the design of reverse supply chain should be structured based on the type of product returned. As recent as in 2006, the study has been carried out by S. Yellepeddi (Yellepeddi 2006) focusing on the performance evaluation of reverse supply chain. Also S. Rajagopalan (Rajagopalan 2006) studied efficient design of reverse supply chain. Both these studies were carried out for the consumer electronics industry. From the industry point of view, economic advantage is the motive whereas from researchers' point of view, efficient design of reverse logistics is the goal. Of course, if the researchers' view is effectively implemented, it can lead to the desired economic results. Earlier in this section we saw many researchers' referring to reverse logistics as a closed-loop supply chain. In the next section we will see what a closed loop supply chain is and the similarities between reverse logistics and a closed loop supply chain.

2.2 Closed Loop Supply Chain

In section 1.2.2, we saw the core processes inside reverse logistics network. The process starts when an end customer returns a product and it ends when it reaches a repair depot (repair or reclaim parts) or landfill (disposal). However when we compare reverse logistics with a closed loop supply chain, the picture becomes much broader. The process workflow from forward supply chain also should be incorporated. Meaning it should start when 1) demand is sensed; 2) demand is planned; 3) demand is fulfilled; 4) product return; 5) repair or reclaim parts or disposal. Following figure shows the closed loop supply chain.

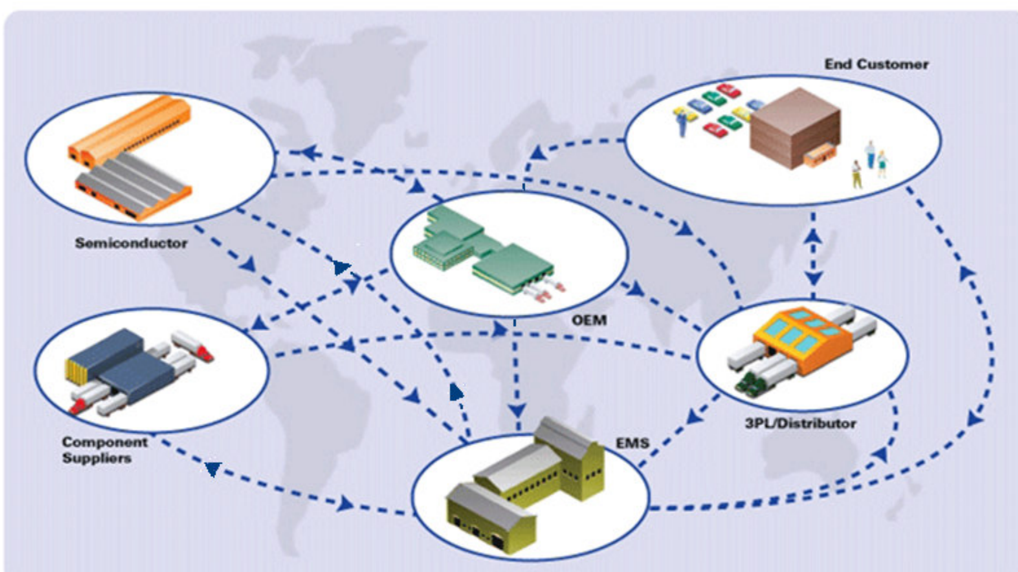

Figure 2.1 Closed Loop Supply Chain Network
(Adapted from “i2 Technologies Industry Solutions”)

The above diagram shows that how material flows in a closed loop supply chain network. It is developed for the semiconductor industries sector. There are six players in the network and they are performing different functions. An electronic Manufacturer Services (EMS) is the one who designs, tests, manufacturers, returns/repairs electronic components. Goal of EMS is to meet customers' diversified needs. The semiconductor industry understands this demand signal and through the optimized capacity planning and production planning, try to meet the promised date. Component manufacturer collaborates with their supplier and manage inventory as needed at desired locations. Original equipment manufacturer (OEM) is a company that sells the product of other company. OEM provides the environment and network to meet this demand with the help of third party logistics partner (3PL). The end consumer makes transaction at a retail location. The reverse flow starts from end consumer (product return) and flows through all these tiers of supply chain. It reaches the final destination, which is either repair or reclaim parts at repair deport or disposal in a landfill. It can be clearly seen that the process flow in reverse logistics and that in a closed-loop supply chain are quite similar including all stops. Also from section 2.1, it can be clearly seen that how the concept of reverse logistics was started in the late seventies and developed until now. Initially it started with the manufacturer, supplier and customer. Then player like 3PL/Distributor, OEM, repair depot, customer service center were added one by one and a single network of closed loop supply chain was developed.

Since the focus of this research is on the forecasting methodology for product returns, we will talk more about that. In the next section, we will explore the literature that has been studied by various researchers.

2.3 Evaluation of Current Forecast Models

In this section, we will discuss the return forecast models that have been studied in past. Then we will evaluate them. We have divided this section in two categories. The first part discusses the initial research carried out in the area of reverse logistics while the second part talks more about focused research in this area. The research study discussed in the first part, had their focus more on remanufacturing process. The research study discussed in the second part, had their focus more on forecasting models as opposed to remanufacturing. In the evaluation part, we will discuss briefly the basic methodology used in each forecast model. For the matter of fact there are very few examples that site the use of forecasting in reverse logistics channel.

2.3.1 Initial Research

The initial research that has been carried out in this area was very naive. It used the basic method of probability by proportion of cumulative returns to cumulative sales. Meaning, if a retailer sells X units of product over the period of time and Y is average of % of the product that comes back as returns, it is assumed assume that Y is probability of the product returns for future time bucket. For having higher forecast accuracy, we will need a robust method. We know that accurate forecast will lead to a better decision making in the strategic, tactical and operational areas of an organization.

The research carried out by Goh and Varaprasad (Goh & Varaprasad 1986) in the mid 80s, was among the initial efforts to study the statistical way of handling product returns. The research was carried out for soft drinks reusable containers. They used the historical data of four years, analyzed product demand and product returns for these products. The product life cycle parameters and basic time series techniques were used to develop this methodology. The main focus of this research was to study the effectiveness of recycling these containers and spread the cost over the container life cycle. This cost was expressed in terms of expected useful life, loss rate etc. The model estimated return probability by proportion of total product returns. The effort was concentrated towards inventory management and studying effectiveness of the recycling process of containers. In the late 80s, Kelle and Silver (Kelle & Silver 1989) carried out a research on reusable containers that are typically used in the industry to sell or store liquids. In the industry applications where these containers are sold, there is a chance that these containers are never returned because of loss or damage. In such cases, new containers are required. The research concentrated on forecasting return quantities of reusable containers to estimate net demand. Their research used the basic idea from the model developed by Goh and Varaprasad. Kelle and Silver used the estimate of return proportions for forecasting the demand of reusable containers. Then they calculated variability of this demand, which was dependent on various factors. The four different scenarios were considered to check the effect of various factors. Method 1 included the probability that all containers were returned. Method 2 used the more detailed information where each time bucket analyzed separately to find probability of returns in each time bucket. Method 3 was, method 2 plus conditional probabilities between each time bucket. Method 4 was method 2 plus aggregated return data. The model used probabilities of return events happening in the different time buckets after a product has been sold. This research also suggested that the model would behave more accurately if additional information about the individual item is available. In 1988, Panniset (Panniset 1988) explained importance of remanufacturing and suggested that the modifications in MRP systems are required to plan and control remanufacturing. Krupp (Krupp 1992) developed the model that suggested role of forecasting in the planning of replacement components. Srivastava and Guide (Srivastava & Guide 1997) were among the first researchers to introduce the idea of using intrinsic forecasting method (time series) for estimation of return quantities and rate of return. They developed a model that calculated the product recovery rate. Based on this recovery rate of the product, planning capacity is designed. They also showed the relationship between the product recovery rate, time for which product is in service and total sales for the product. In this research, efforts were concentrated on capacity planning. The forecasting method used in this model was based on simple time series methods. Later in 2000, Guide et al (Guide 2000) carried out a research on the management of recoverable manufacturing systems. Similar to the previous research, this research was also about the remanufacturing systems. It reiterated the fact that, the correct estimation of return quantity allows manufacturers to use these parts in manufacturing at the same time reducing the consumption of new materials. However, the task of estimation of return quantity is not easy due to available data and uncertainty of return time.

As mentioned previously, all of the above studies focused their efforts more on the remanufacturing or reusable systems. Their efforts were concentrated on capacity planning or cost effective design for the remanufacturing systems. In the next section, we are going to see the focused research in the area of forecasting product returns.

2.3.2 Focused Approach

Hess and Mayhew (Hess & Mayhew 1997) are recognized as amongst the first few researchers who actually developed a forecast model for estimating product returns. The direct marketing model developed by them is different from the traditional marketing model. In traditional marketing, buyer gets to see the product before he makes the purchasing decision as oppose to the direct marketing where buyer uses a medium such as catalog, brochure etc. As a result, there is a higher probability of returns as compared to that in the traditional purchasing. James Hess and Glenn Mayhew developed a statistical model where direct marketing companies can collect data from the returned products and use it to forecast the returns. In the direct marketing, data collection would be more accurate as compared to the data collection in traditional marketing. The model developed by Hess and Mayhew was called 'hazard rate model' that showed the effect of product category; price etc. on product returns. The two key questions in product returns that need to be answered are, 'when the product will be returned' (timing of the returns) and 'what are the chances that the product will be returned' (probability of return). In a simple linear regression method, they modeled 'time to return' based on the past returns and factors that affects these returns. The study showed that, when larger amount of money is at stake (higher price), then consumer is motivated to act more quickly if he wishes to return the product. Using the linear regression, it is possible to model the product price v/s product return time, and compute the time to return the product (Y) for a given price (X). To answer the second question i.e. probability of returns, it can be calculated as a return rate of the product. The logit model that considers the effect of different factors (product fit) on certain events (product returns), was used to answer this question. In the logit model, researchers introduced a variable called 'product fit' as a category. They defined dummy variable for product fit. It was shown that for some clothing items, product fit was unimportant as compared to others. For example, socks vs. suits. Logit model was designed to show impact of the product category and product fit on the product returns. According to Hess and Mayhew, both these models (regression and logit) consider the data for the products that have been returned and they do not consider data for the products that are not returned yet but will be returned eventually. The hazard model was used for the purpose. Basic idea of the hazard model was, event will eventually occur and timing of this event has some statistical distribution. Hazard rate is a ratio of probabilities. (Probability that return will occur to probability that return has not occurred yet) It is purely function of time e.g. return time has some probability distribution time function. If someone wants to use this model to see effect of various factors such as product category, price etc. on the event (returns) then multiply this time function by adjustment factor of other variables. In summary, this model calculates the probabilities of the two events such as 'return will occur' and 'return has not occurred yet'. The probabilities are calculated from the past data that has been categorized by effect of product category, price etc. According to the researchers, the effect of various factors such as product category, price etc. on the return quantities can be modeled using this model with one factor at a time.

In 2003, Toktay et al (Toktay 2003) studied the role of forecasting in managing product returns. The research was about the various factors that influence the return flow of the product. It also focused on ways of influencing the returns and their timing. For example, take back price to customer or trade in offers for the product can influence the timing of return. This way, one can be more accurate about the return quantities and timing. Three decision levels in the organization such as strategic, tactical and operational have been discussed. The strategic level is the level where decisions related to network design, product launch are made. The tactical level is the level where the decisions regarding the procurement, capacity planning and disposal management are made. And the operational level is the level where production planning, inventory management related decisions are made. This research focuses on the operational level i.e. uses forecast information of returned products at the operational level. The model calculates the forecast quantity as a function of past sales data. The forecast model that is used, is divided into two parts namely develop a return delay (if customer wishes to return the product, then the return period is influenced by certain factors) and the estimating parameters to forecast return quantity. In summary, this model suggests that, the factors that influence the returns (take back price, trade in offer etc) can be used to forecast returns.

At the Iowa State University, the research was carried out about using the forecast information about product returns to estimate the manufacturing capacity. For manufacturing companies, it is required to find an optimal manufacturing capacity for more profitability. This can be achieved by combining the reverse flow of materials with the forward flow in production lines. If we have the right estimate for product return quantities, it may be possible to use this information in the estimation of the manufacturing capacity. This research is about using information from early returns to predict future returns. Forecast quantity is calculated at time t0 (t0<t1). Then the manufacturing capacity was determined for returns at time t0. As time moves from t0 to t1, estimate new return quantity. Finally, expand the manufacturing capacity for return quantities at time t1. This research is different from others in a way that it uses information from early returns for calculating future return and uses this information for calculating the remanufacturing capacity. This model makes assumption that all products will be returned and no remanufacturing capacity is available at the beginning. It would be interesting to use the same model with some relaxed assumptions.

To summarize the above discussion, we saw various researchers tried to address the issue of the efficient design of reverse logistics. Some studied the problem via efficient remanufacturing facility design while some studied via early estimating the product return quantities. From the manufacturers or retailers point of view, latter holds the key. There are several ways of the cost reduction in the reverse channel. For example, reuse of the product parts in forward supply chain and recover the cost or adjust the manufacturing capacity as per future returns. However to address this issue from the beginning, if one can predict the returned quantities more accurately based on past sales, this information is more useful for manufacturers, retailers and distributors. Their decisions (reusing parts or adjusting manufacturing capacity) will be based on more accurate information. As we have seen in this section, forecasting the inbound flow in reverse supply chain is relatively new area and has not explored much yet. Even though there are number of articles or tools or software or improvement techniques available for forecasting in the forward supply chain (Tashman et al 1991), (Moon et al 1998), (Gooijer et al 2006), very few study material is available for forecasting product returns. Uncertain nature of return times and unpredictable consumer behavior are some of the key issues faced in forecasting product returns.

The methodology in this research is based on a combination of two approaches namely central tendency approach and extreme point approach. The central tendency approach uses a moving average whereas the extreme point approach is based on data envelopment analysis (DEA) as a first step combined with linear regression. We are familiar with regression analysis and moving average techniques. They are examples of a central tendency approach. However data envelopment analysis (DEA) is a relatively new technique. Data envelopment analysis (DEA) is a type of extreme point approach. It is used to measure and analyze the performance indices of similar entities. Data envelopment analysis (DEA) offers variety of models. It is also capable of assigning variable and fixed weight to inputs. In the next section, we will get familiar with data envelopment analysis.

2.4 Data Envelopment Analysis (DEA)

When we evaluate the performance or productivity of an entity, we usually define it terms of ratio of input to output. We usually refer to this ratio as efficiency or productivity. For example, for an organization, the revenue or profit is the output and cost parameter is the input. In case of labor efficiency, number of units produced per hour is the output while worker costs, machine costs, operating costs are various inputs. What if, we encounter with a situation where we have multiple outputs and a single input or vice-versa or what if we need to assign the weight to each input that we want to be considered in the calculation of output? Will a simple method of ratios work? We will definitely need a more sophisticated technique. Some of these problems can be answered with the method called data envelopment analysis or DEA. With DEA, similar products can be compared using the output that they produce or the input that they consume. With DEA, we can measure and analyze the performance indices of similar entities with single or multiple inputs and single or multiple outputs. DEA utilizes the mathematical programming which can handle multiple inputs, multiple outputs, weight assignment and what if scenarios at same time (Cooper 2006). It is a non-parametric technique based on the extreme point approach. It works great in the problem solving situations in economic and financial evaluations. It is frequently used in the manufacturing or retail environments. It is becoming an increasingly popular management tool for the decision making and also recognized as a valuable analytical research instrument. However the tool has certain weaknesses too.

Weaknesses of DEA:

- It is a non parametric technique.
- Input and outputs can have different units.
- Being non parametric techniques statistical hypothesis tests are difficult to perform.
- The solution is based on relative performance among the available data points and it may not necessarily be the theoretically best data point.

In this research, we are going to use DEA as a computational tool for comparing similar products. They are also called as decision making units or DMU. However DEA or extreme point approach is only one part of the computation. The other part is a central tendency approach. We are going to combine the two techniques for our purpose. Before we proceed further, let us look at briefly the use of DEA models in the past. In the mid nineties, Hollingsworth (Hollingsworth 1995) developed the DEA model where he compared the performance of the existing warehouse with the highly efficient warehouses. In 1996, Talluri et al (Talluri 1996) proposed a mathematical programming model that used combination of extension of DEA and integer programming. The purpose of this model was to improve poor performers in supply chain processes. In another study, Talluri et al (Talluri 2000) utilized cone ratio data and extension of DEA for the evaluation and selection of advanced manufacturing technology (AMT). Leem (Leem 2000) used DEA for the selection of modeling enterprise logistics network. Ross et al (Ross 2002) proposed the integrated benchmarking approach to distribution centers using DEA methodology. McGinnis et al

(McGinnis 2002) developed the internet based DEA model (iDEA), where the information about warehouses was recorded in terms of input and output. Inputs like space, labor, material handling system utilization and outputs like number of items picked, number of orders filled etc were used. Using this model, warehouse managers were able to compare their warehouse with the other efficient warehouses in the database. This model by McGinnis was somewhat similar to the DEA model developed by Hollingsworth in 1995. There are multiple examples like this that show effective use of DEA methodology in the performance evaluation process. It can be seen that, DEA was primarily used in the applications like logistics network selection or efficiency calculation of manufacturing or distribution facilities and comparing it against the efficient ones. In this research, we will be using DEA for comparing the similar products in the consumer electronics industry based on the specifications like product features, prices etc. Then we will use the results from DEA in the correlation analysis.

2.4.1 Single Input and Single Output DEA Model

DEA is a relatively new tool. It can provide multiple opportunities for a what-if analysis or decision making or collaboration. Whatever may be the application, the parameters and model selection is a key in DEA modeling. There are multiple models in DEA such as single input single output, multiple inputs single output, single input multiple outputs, CCR model, and BCC model. Let us look at the example of DEA with the single input and single output model. Table 2.1 shows 8 stores (A-H), number of employees working in each store, sales in each store. The data in last row is a number obtained by dividing 'sales' by 'number of employees' working in each store. For example, store A has 2 employees working in it and is selling 1 unit in a given time period. Thus, sales per employee for store A is 1 divide by 2 equals 0.5

Table 2.1 Single Input and Single Output DEA model
(Adapted from "Data Envelopment Analysis: A comprehensive text with models, applications, references and DEA solver software, 2006")

Store	**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**
Employee	2	3	3	4	5	5	6	8
Sale	1	3	2	3	4	2	3	5
Sale/Employee	0.5	1	0.667	0.75	0.8	0.4	0.5	0.625

Now, we will plot the data from above table into graphical format. Figure 2.2 shows graphical representation of above table. The numbers of employees are plotted on the horizontal (X) axis. The sales by each store are plotted on the vertical (Y) axis. In the DEA analysis, numbers of stores are called as decision making units or DMUs. They are also called 'producers'. The DEA solution primarily considers the efficiency line rather than regression line.

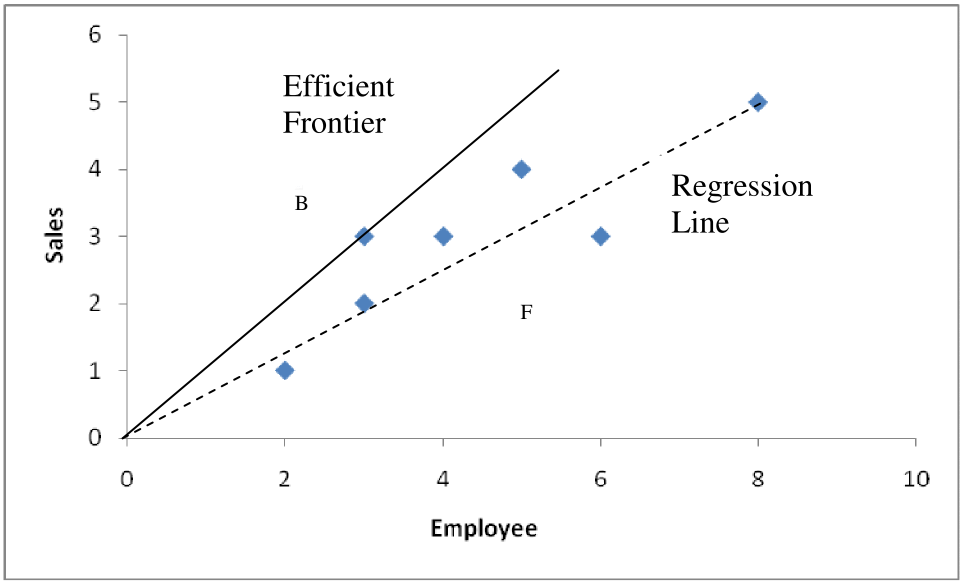

Figure 2.2 Comparisons of Branch Stores
(Adapted from "Data Envelopment Analysis: A comprehensive text with models, applications, references and DEA solver software, 2006")

The graphical solution plots all decision making units (producers). The points on the efficiency frontier are considered as the points with the highest efficiency. If we were to plot a regression line for the same data set, then it would look like the dotted line as shown in figure 2.2. The tool works somewhat similar to simplex method (used for solving linear programming problems). It can be clearly seen that the store B is the highest efficiency store. The 'sales per employee ratio' for store B is higher than any other store. Other points or stores are measured relative to the highest efficiency point using following formula:

$$0 \leq (\text{Sales per employee of other stores / Sales per employee of B}) \leq 1$$

If we calculate the efficiencies for all the stores, they would be as shown in the following table.

Table 2.2 Store Efficiency calculations
(Adapted from "Data Envelopment Analysis: A comprehensive text with models, applications, references and DEA solver software, 2006")

Store	**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**
Efficiency	0.5	1	0.667	0.75	0.8	0.4	0.5	0.625

Now, we have calculated efficiencies for all the stores. Next step is to make the inefficient store as efficient one. For example, let us consider store F. Task is to make the store F as efficient as the store B. The store B has 3 employees and making sale of 3 units, whereas the store F has 5 employees and selling 2 units. Please see following figure for the improvement method of store F.

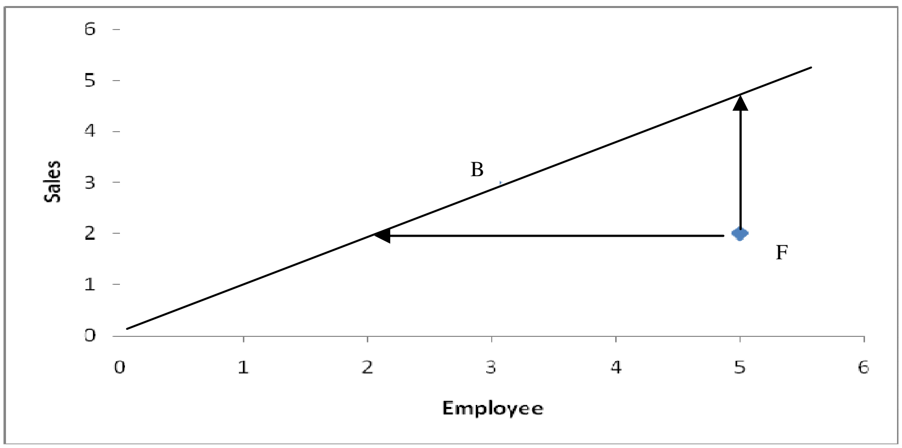

Figure 2.3 Improvement Method for Stores
(Adapted from "Data Envelopment Analysis: A comprehensive text with models, applications, references and DEA solver software, 2006")

The store F can be made efficient in two ways i.e. either by increasing the sales to 5 units or by reducing number of employee in the store to 2. In both the cases, the efficiency of store F will be 5/5 or 2/2 = 1. Hence it will become as efficient as the store B. Thus using DEA, we can compare efficiencies of DMUs and apply the improvement techniques. The other part of the DEA methodology is weight assignment. In the next section, we will see fixed and variable weight assignment in DEA model.

2.4.2 Weight Distribution in DEA

The example that we saw above was single input and single output model in DEA. What if, we have a case where we have to deal with the single input and multiple outputs or multiple input and single output? One way to solve this problem is to assign the pre-selected weights to various inputs or outputs. This is called fixed weight. However it raises the questions like, if fixed weight assignment is the correct way to compute efficiency? Will it give the same results if we were to assign the variable weights to various inputs or outputs? DEA uses the variable weight method while assigning weights to the various inputs or outputs. The weights are assigned based on the input data that is fed to a DEA model. At the same time, weights are chosen in such a manner that every decision making unit (DMU) is assigned with the best set of weights. The general rules that DEA follows in weight assignment are as follows:

1. All data and all weights are positive
2. Resulting ratio of input to output must be between zero and one

The concept of weight assignment will be clearer with the following example. Following table shows the example of multiple inputs and single output mode.

Table 2.3 Weight Assignment in CCR model
(Adapted from "Data Envelopment Analysis: A comprehensive text with models, applications, references and DEA solver software, 2006")

Store		**A**	**B**	**C**	**D**	**E**	**F**
Input	x1	4	7	8	4	3	9
	x2	3	3	2	4	2	1
Output	y	1	1	1	1	1	1

Please note that the output value is unitized to 1 for each store. Let us say, v1 is the weight assigned to input x1, v2 is the weight assigned to input x2 and u is the weight assigned to output y. If we wish to solve this linear program for the store A, then

max $\theta = u$

subject to $4v1 + 3v2 = 1$

$u \leq 4v1 + 3v2$ (A)

$u \leq 7v1 + 3v2$ (B)

$u \leq 8v1 + 3v2$ (C)

$u \leq 4v1 + 4v2$ (D)

$u \leq 3v1 + 2v2$ (E)

$u \leq 9v1 + 1v2$ (F)

If we wish to solve this linear program for the store B, then

max $\theta = u$

subject to $7v1 + 3v2 = 1$

$u \le 4v1 + 3v2$ (A)

$u \le 7v1 + 3v2$ (B)

$u \le 8v1 + 3v2$ (C)

$u \le 4v1 + 4v2$ (D)

$u \le 3v1 + 2v2$ (E)

$u \le 9v1 + 1v2$ (F)

For every store, similar equation can be formed which can be solved by DEA solver to find out the values of v1, v2 & u.

Data Envelopment Analysis is a relatively new tool and we wanted to spend considerable amount of time on it to explain its methodology, weight assignment and problem solving techniques. The model that we will be using in this research is a single input and multiple outputs model and we will be using DEA solver to find out the optimal solution.

To summarize, in this chapter we reviewed the literature on reverse logistics. We saw the similarities between reverse logistics and a closed loop supply chain. We also looked at the work done by early and recent researchers in the area of reverse logistics. We analyzed them separately by initial research or focused research and evaluated them. Then, we turned our focus on data envelopment analysis (DEA). We briefly discussed different models within DEA, weight assignment and problem solving techniques in DEA.

In the next chapter, we are going to discuss the methodology in this research. This methodology is developed to forecast product returns using reason codes based forecasting approach. This methodology is developed for the consumer electronics industry. We will see how product returns can be analyzed using reason codes in the consumer electronics industry and how our model can be used to forecast them.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Establishing Goals

In today's rapidly changing and global environment, every organization is trying to find new ways to increase revenue, profit margins and free cash flow. In all operational areas of organization, new solutions are being implemented for continuous improvement. As mentioned before, reverse logistics is one of those areas where organizations are seeking innovative solutions. More researchers are focused in this area. Estimation of product returns is a first step in reverse logistics. If we are able to estimate product returns with reasonable accuracy, all our downstream processes (strategic, tactical and operational) will be positively impacted.

One of the several ways of reducing inventory in the channel is to improve forecast accuracy. However, to improve forecast accuracy, a robust forecast method is required. Consider an example of a consumer electronics manufacturer, who uses all the techniques to reduce inventory in the channel and wish to place right products at right place and right time. However, in today's competitive consumer electronics market, consumers are looking for the latest and the greatest technology in the products at affordable prices. Consumers buy a product today and if they find a better one tomorrow, they exchange it with the product that is offering a better price and features.

Manufacturers and their retail partners constantly have to deal with this shift in the demand and at the same time they have to deal with the returned products. The existing solutions may not effectively address this type of consumer behavior, product competitiveness and forecasts product returns accurately.

The goal of this research is to develop a forecast model that can be used in the estimation of product returns based on the consumer behavior and product competitiveness. This model is developed for the consumer electronics industry. The model considers situations like, 'customer returns a product when better options are available'. In other words, we are trying to translate consumer behavior into meaningful data that can be fed to the model to forecast product returns. In addition, typical scenarios like, 'customer returns without exchange' or 'customer returns defective item' are also considered. We believe that, the consumer electronics industry is dynamic in nature, has variety of products with variety of specifications. Hence, consumer electronics products would be a good fit for our forecast model. We also believe that, the use of this forecast model would change the viewpoint of forecasting product returns and increase the forecast accuracy.

3.2 Role of Return Reasons

As mentioned before, the methodology in this research is based on return reason codes (RC). Reason codes are simply the customized codes associated with a return reason and fed back into the point of sales (POS) system at the time of return. Reason code based forecasting is a unique part of this research. In this section, we will see what reason codes are and how they are classified into different categories.

The terminology of return reason code was originally defined by the U.S. Department of Treasury for financial management services and was more popular in case of the transactions associated with the financial institutions. They established reason codes for every Automated Clearing House (A.C.H.) transaction that is returned. For example, R01 is the reason code for "Insufficient Funds", R02 is the reason code for "Account Closed" etc. However, this coding is becoming increasingly popular at the point of sales systems at retail locations. Manufacturers like HP, IBM are offering the flexible POS systems with the capabilities to enter a customized reason code at the time of return. These codes are different from the codes classified for the financial institutions and they vary from retailer to retailer.

We know that, product returns can occur any time (Ferguson 2005). It is happening every minute every day. It is happening now. Earlier in the chapter 2, we saw the core processes in reverse logistics channel. However, to understand the return reason codes better, consider the following scenario. Whenever we return any merchandise back in the store, the common question that is asked by the store clerk is, 'what is wrong with the product?' Sometimes we know the specific answer such as, 'product is defective' or 'product is damaged' or 'not delivered on time' or sometime we just say, 'did not like the product' or 'like to exchange it with some other product'. Listed below are some of the popular return reasons. These return reasons are customized and vary from retailer to retailer. They can be found with the customized codes (built-in POS system) in the store clerk's computer.

Return Reasons:

1. Product is defective
2. Damaged product delivered (In case of online purchases)
3. Return without any reason
4. Product does not have desired features
5. Did not like the product (operation wise)
6. Product is not worth the price (exchange it with different product)

Look at the reasons 1 & 2, where product was defective. Reason 2 would be mainly applicable in case of online purchases. In both these cases, product will be covered under warranty and will be replaced by retailers. Product being defective has very small percentage of total returns. Reason 3 is the case where customer simply does not need the product and wishes to return it without any reason. Reasons 4, 5, 6 essentially tell us that the customer is aware of other products in the market which may be less expensive and/or may have better features than the existing product. In other words, some other product in the market (competitor's product) is better than the purchased product. In all of these cases (4, 5 & 6), customer is likely to exchange the product. If customer does not exchange the current product with a different one, we can treat it same as the return category 3 and store it under return reason 3 in POS system. Please note that, the list of return reasons discussed above may vary from industry to industry. For our purpose, we have tried to capture as many 'return reasons' as possible. These return reasons are usually observed in the consumer electronics industry. We suggest that, the return reasons to be set up in POS system as per individual needs.

Now, with the available data, we need to analyze how many times a store faces with different return reasons and what is the amount of returns against each reason. Before we do that, we need to classify them and assign them with a reason code, so that they can be easily set up and identified in POS system.

3.2.1 Classification of Reason Codes

We saw return reasons (1-6) in the above section. To simplify them and for the purpose of our research, we are going to group these return reasons by category. For example we can group 1 & 2 together. We can treat 3 separately and again group 4, 5 & 6 together. Now we need to assign them with a customized reason codes (RC). Following table shows the classification of reason codes based on return reasons. Please note that these reason codes are generated only for the purpose of this research. We suggest that, reason codes to be set up in POS system as per individual needs

Table 3.1 Classification of Reason Codes

Reason Codes	**Return Reason Description**	**% Returns**
RC1	• Product is defective or Delivered damaged	5%
RC2	• Return without any reason	27%
RC3	• Product does not have desired features • Product is not worth the price	68%

The percentage numbers in the % returns columns are based upon the study conducted for the CE industry. They attributed 5 % of the returns to the actually defective products, 27 % of the returns to the buyers' remorse and remaining 68 % to the customers' expectations about the product. Now that we have classified the reason codes, next step is to analyze return the data pattern for every reason code. Then, the return data will be fed to the forecast model by reason code category to generate return forecast.

3.3 Development of Methodology

The approach in this forecasting model is based on reason codes. We saw the customized reason codes in previous section. Every reason code (RC1, RC2 or RC3) has a different return reason behind it. Thus, if we plot the return data for every reason code separately, it will follow a different distribution. Our goal is to form and analyze the return data pattern for every reason code. Once we understand the data pattern for each reason code, we can apply appropriate method to predict the future. Before we proceed any further, we need to make some assumptions about the product being analyzed, return policy etc. The assumptions are as follows:

- The consumer electronics product that will be considered for this research is a digital camcorder (Mini DV type). This product is among the most popular consumer electronics products (Based on the reports by CEA, CNET & IEEE Consumer Electronics Society).
- This product is manufactured by several vendors and available in various price ranges. For our purpose, we will consider five different camcorders. The price range considered is between US$ 200.00 – US$300.00

- Being a popular consumer product and being available with variety of features, we believe that this product can represent a typical class of the consumer electronic products and will be a good fit for our model.
- Prices and the specifications data about the product will be primarily applicable in case of reason code RC3. The reason codes RC1 and RC2 will not require product price and the product specification data.
- For the purpose of this research, we are focusing on only in-store purchases. Online or catalog purchases are excluded.
- The planning cycle is assumed to be weekly (Monday – Sunday) with most of the demand falling over weekends (Friday & Saturday). The current week is considered as Week 0. (See Figure 3.1)
- The assumption about the merchandise return policy is as follows. Any item purchased in the store can be returned within fourteen (14) days or 2 weeks from the data of purchase to receive full credit. This period is termed as the 'return period' for our purpose.

Following figure shows the planning week representation. The current week is considered as Week 0. Monday is considered as the first day of the planning week while Sunday is the last day of the weekly planning cycle.

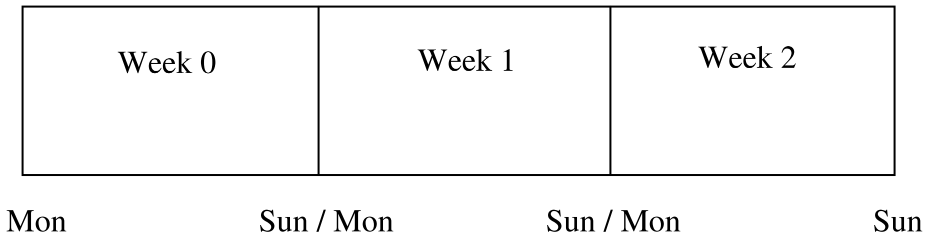

Figure 3.1 Planning Week Representation

3.3.1 Reason Code RC1: Analysis and Solution

In the section 3.2.1, we saw the classification of reason codes (table 3.1) and different descriptions for reason codes. We assigned reason code RC1 for those types of returns that fall under description of ‘defective or damaged product.’ In this section, we will analyze the returns falling under this category and apply appropriate statistical forecasting solution.

Look at the following scenario. A consumer purchased a digital camcorder. After reaching home, he found out that the product he purchased was defective. What do you think he would do? He would immediately (or at least in a day or two) go back to the store and get the defective piece exchanged with a non defective one. Since he is within his return period (14 days), the store is happy to exchange it. The store clerk would take the defective camcorder back, scan it in his POS system as a return and check the reason code RC1. In this scenario (RC1), how do you think the pattern of return data would be? Since nobody would like to sit with a defective product for longer period of time, the maximum returns will occur in week 0, moderate returns in week 1 and very few returns will occur in week 2. Clearly, this is an exponential data pattern. See figure 3.2

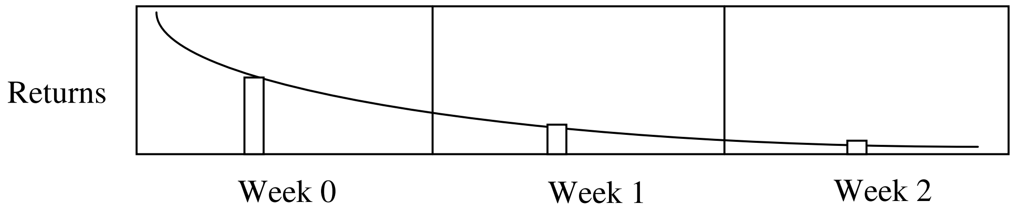

Figure 3.2 Return Data Pattern for Reason Code RC1 – Part 1

Now assume that, Week 0 has passed and we are into Week 1. We have new sales happening in Week 1, so will be the new returns. Since we are still dealing with the reason code RC1, the return data pattern will be same i.e. exponential. See figure 3.3

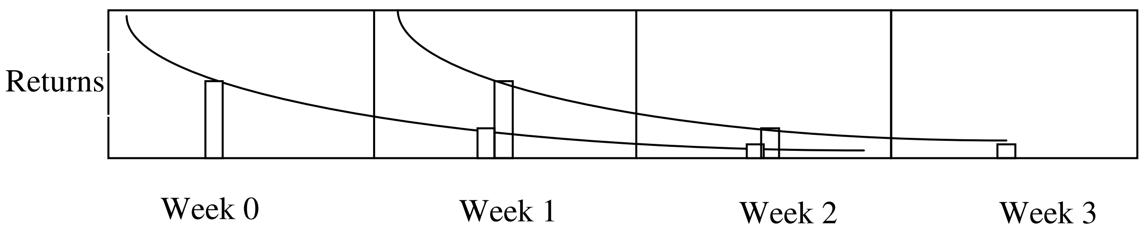

Figure 3.3 Return Data Pattern for Reason Code RC1 – Part 2

Now assume that, Week 1 has passed and we are into Week 2. We have new sales happening in Week 2, so will be the new returns. Since we are still dealing with the reason code RC1, the return data pattern will be same i.e. exponential. See figure 3.4

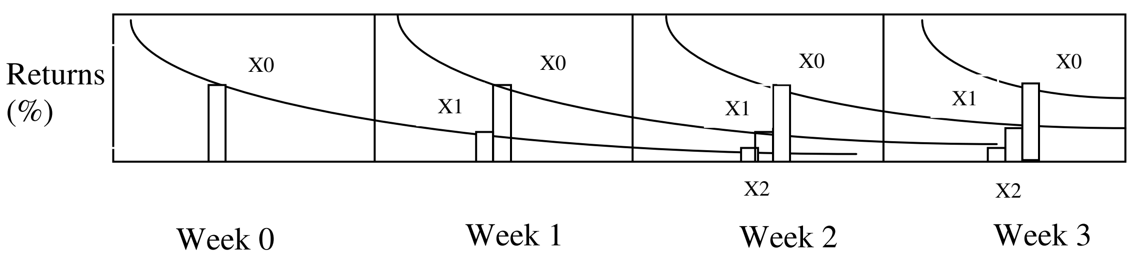

Figure 3.4 Return Data Pattern for Reason Code RC1 – Part 3

Please note that, the consumer's return period is 14 days. Thus, if a consumer purchased a product in Week 0, it needs to be returned by Week 2 to receive credit. And if consumer purchased a product in Week 1, it needs to be returned by Week 3, so on and so forth. In other words, since our return period is two weeks or fourteen days, in any given week, a retailer is dealing with the returns from the current week and past two weeks of sales as shown in figure 3.4. Let us further analyze product returns under RC1. For our convenience we will use following terminology (depending on time of return):

X_0 = Week 0 returns in % = Returns in Week 0 / Sales in Week 0

X_1 = Week 1 returns in % = Returns in Week 1 / Sales in Week 0

X_2 = Week 2 returns in % = Returns in Week 2 / Sales in Week 0

Thus for any given week, we will see returns from the current week's sales and past two weeks' sales i.e. Week 0 returns, Week 1 returns, Week 2 returns. Please note that, we are still under reason code RC1. From figure 3.4, it is clear that, all Week 0 returns will always be higher, Week 1 returns will be moderate and Week 2 returns will be low. Meaning, all the camcorders purchased today, if found defective, will have the maximum returns in this week, moderate returns in the next week and low returns in the week after. Usually, in the consumer electronics industry, the percent of defective product is very low. Recent study shows that only 5 % of the consumer electronics products are genuinely malfunctioning. Rest of the time they do not meet customer expectation (Arar 2008). For example, if a store sells 200 camcorders today, based on

8% of return rate (average in CE industry), it will receive 16 camcorders back, out of which only 1 (rounded) camcorder will be actually defective, which is a very small quantity. And it is very likely that it will be received in Week 0 or at least in early in Week 1. Now, we are going to group all Week 0, Week 1 and Week 2 returns. But instead of using the return volume, we will be using returns as a percent of the sales volume.

Table 3.2 Grouping of Returns Percentage – RC1

Weeks / %	Wk_0	Wk_1	Wk_2	Wk_3	Wk_4	…	Wk_{n-2}	Wk_{n-1}	Wk_n
Week 0 returns	X_0	X_0	X_0	X_0	X_0	…	X_0	X_0	X_0
Week 1 returns	-	X_1	X_1	X_1	X_1	…	X_1	X_1	X_1
Week 2 returns	-	-	X_2	X_2	X_2	…	X_2	X_2	X_2

Since, the large % of RC1 type returns are happening in Week 0, all X_0 in all weeks in the above table will have value in the same ballpark. Similarly, all X_1 & X_2 in all weeks in the above table will have values in the same ballpark. Meaning, there is a small shift in the values of all X_0, X_1 and X_2. Moving average (MA) is the method typically used when estimating small shift in the values (Neter 2004). Deviation up to 2 sigma can be easily picked up using a moving average method. Thus, for reason code RC1, for each of the % returns i.e. Week 0, Week 1 & Week 2 returns, the ‘4 week moving average’ method is chosen for forecasting product returns.

3.3.2 Reason Code RC2: Analysis and Solution

Now, let us move on to the next reason code i.e. RC2. The description for this reason code is "Return without any reason". The consumer neither wants to exchange nor is the product defective. Meaning, the consumer just wants to return the product within return period to receive credit.

Look at the following scenario. Consumer purchased a digital camcorder. After reaching home, he/she realized that he does not need the camcorder for whatever reasons. What do you think he/she would do? Since his/her money is at stake, he/she would immediately (or at least in a day or two) go back to the store and return it. The store clerk would take the camcorder back, scan it in his POS system as a return and check the reason code RC2. In this scenario (RC2), how do you think return data pattern would be? Study by Hess et al (Hess & Mayhew 1997) showed that, the price is a key indicator in this case. Customer would act more quickly if a large amount of money is at stake. Since, the camcorder costs are quiet large, the consumer is motivated to return it more quickly. Similar to the reason code RC1, in this case also, the maximum returns will occur in week 0, moderate returns in week 1 and very few returns in week 2. Similar to the RC1 type, this is also an exponential data pattern. See figure 3.5

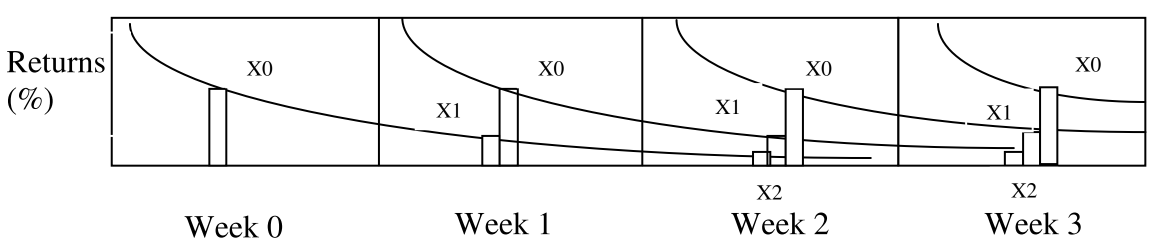

Figure 3.5 Return Data Pattern for Reason Code RC2

Please note that, since RC2 return data pattern is exactly similar to that of RC1, we have combined part 1, part 2 and part 3 together in the above figure instead of showing them separately (Fig 3.2, Fig 3.3 and Fig 3.4). Since, the return data pattern is same as before, we can make the same assumptions about Week 0, Week 1 and Week 2 returns. In any give week, we will have returns from the current week's sales and the past two weeks' of sales i.e. Week 0 returns, Week 1 returns, Week 2 returns. From figure 3.5, it is clear that, all Week 0 returns will always be higher, Week 1 returns will be moderate and Week 2 returns will be low due to the price factor. Now, we are going to group all Week 0, Week 1 and Week 2 returns. However, instead of using the return volume, we will use them as a percent of the sales volume.

Table 3.3 Grouping of Returns Percentage – RC2

Weeks / %	Wk_0	Wk_1	Wk_2	Wk_3	Wk_4	…	Wk_{n-2}	Wk_{n-1}	Wk_n
Week 0 returns	X_0	X_0	X_0	X_0	X_0	…	X_0	X_0	X_0
Week 1 returns	-	X_1	X_1	X_1	X_1	…	X_1	X_1	X_1
Week 2 returns	-	-	X_2	X_2	X_2	…	X_2	X_2	X_2

Since, large % of the RC2 returns are happening in Week 0, all X_0 in all weeks in the above table, will have values in the same ballpark. Similarly, all X_1 & X_2 in all weeks in the above table will have value in the same ballpark. Meaning, there is a small shift in the values of all X_0, X_1 and X_2. Moving average (MA) is the method typically used when estimating small shift in the values (Neter 2004). Deviation up to 2 sigma can be easily picked up using a moving average method. Thus, under reason code RC2, for each of the returns i.e. Week 0, Week 1 & Week 2 returns, the '4 Week Moving Average' method is chosen for forecasting product returns.

3.3.3 Reason Code RC3: Analysis

The last reason code in our list is RC3. The description for this reason code says that (from customer's perspective) the product does not have desired features or did not like the product (operation wise) or the product is not worth the price (exchange it with different product). In other words, customer's expectation fell short about this product either in terms of features or in terms of operations or in terms of the price. Customer did not see any value in this product or from his point of view, the amount of money he/she spent on the product, he/she could have gotten a better deal. So he wants to exchange it with something else that he thinks is a good deal. Remember, RC3 is the case only if; a customer exchanges the product with some other product. If he does not exchange, it should be entered under RC2 in POS system assuming that the customer is not a serious buyer.

Look at the following scenario. A consumer goes to the store to purchase a digital camcorder. Let us say, there is a special price being offered on one of the camcorders. These weekly special prices or promotions or catalog advertisements are sponsored by the manufacturers and published by the retailers in their weekly catalogs. Typically, it is observed that the product that is on promotion or advertised in the store catalog (at reduced price), sells the most. Some consumers are brand loyal and may or may not choose the advertised or promoted product if it is not one of their preferred brands. Thus, after looking at available options of camcorders in his/her price range, he/she buys the camcorder that is on promotion.

Now, if the consumer is a serious buyer, under what circumstances he/she would exchange this product? (unless it is a defective product, which has been discussed under reason code RC1). If consumer thinks that, the product does not have desired specifications or not easy to operate, he/she may want to exchange it. In the case of a product like camcorder, some of the consumer complaints could be, low zoom level, small screen size or heavier in weight etc. Or if the consumer thinks that he/she should have spent less money on the product to get the same features, he/she may want to exchange it. In other words, after purchase, the consumer compares the product that he/she bought with some other products. If, he/she feels that the other product has better features or offered at a better price, he/she is likely to exchange the current product with the other product. Meaning, some combination of price and features about the other product attracts the consumer. As seen in the table 3.1, 68 % of total returns are attributed to this type, which is a big chunk. On one side, the consumer exchanges the product and gets what he/she wants, while on the other side, a retailer is stuck with the returned product that he needs to sell as a refurbished item before the end of its useful life. The reason code RC3 identifies these types of returns. They depend on two factors: (1) what products are competing with the product that consumer purchased and (2) what are their specifications and what prices are they offered at.

Study shows that, a typical consumer on an average spends about the 4-5 hours initially after purchasing a product to understand its features. Another study shows that, in the consumer electronics industry, most of its demand falls over the weekend i.e. Friday, Saturday and Sunday. Based on the above two studies, what is a likely distribution of the return data under RC3 reason code? Marketing research shows that, most of the RC3 type returns; fall in Week 1 for the product that was purchased in Week 0. This is because, once a customer purchases a product in Week 0 (demand falling over the weekend of Week 0), he/she will spend some hours initially to understand the product. If he/she wishes to exchange it with another product, he/she is likely to do so in Week 1. Moderate exchanges will occur in Week 0 and Week 2. In that case, the return data pattern under RC3 reason code will be similar to a normally distributed data and will look like as shown in the following figure.

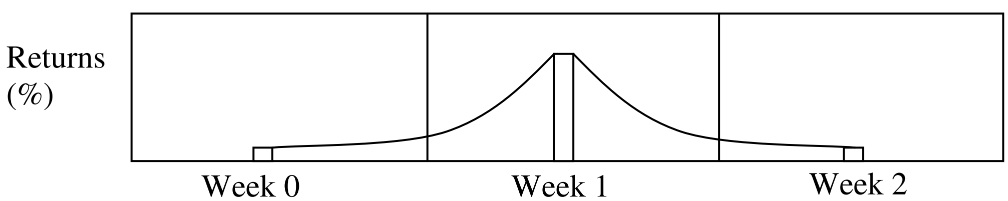

Figure 3.6 Return Data Pattern for Reason Code RC3 – Part 1

Now assume that, Week 0 has passed and we are into Week 1. We have new sales happening in Week 1, so will be the new returns. However, the return data pattern will be same i.e. similar to a normally distributed data as shown in the following figure.

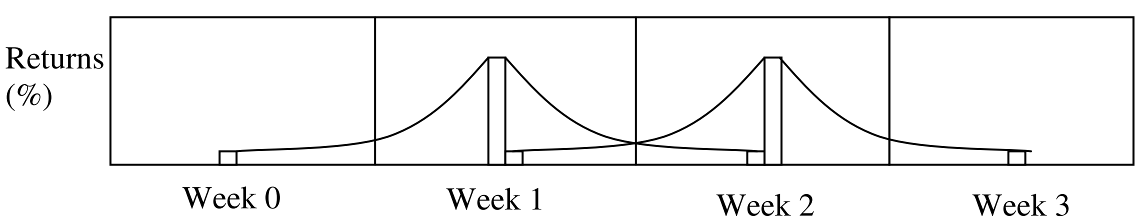

Figure 3.7 Return Data Pattern for Reason Code RC3 – Part 2

Now assume that, Week 1 has passed and we are into Week 2. We have new sales happening in Week 2, so will be the new returns. However, the return data pattern will be same i.e. similar to a normally distributed data as shown in the following figure.

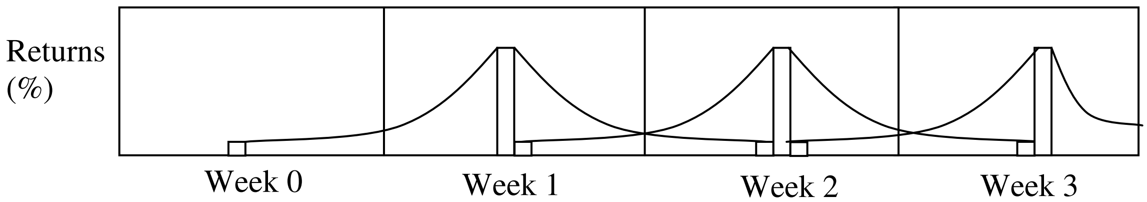

Figure 3.8 Return Data Pattern for Reason Code RC3 – Part 3

Please note that, the return period is 14 days. Thus, if the consumer purchased a product in Week 0, it needs to be exchanged by Week 2 to receive credit. And if consumer purchased a product in Week 1, it needs to be returned by Week 3, so on and so forth. Thus, based on these assumptions, under RC3 reason code, the maximum probability of exchanging the product will fall in 'Purchase Week + 1' i.e. for Week 0 sales, the maximum exchanges will occur in Week 1, for Week 1 sales, the maximum exchanges will occur in Week 2, for Week 2 sales, the maximum exchanges will occur in Week 3 so on and so forth. As stated previously, these exchanges will be based on two factors: (1) what products are competing with the product that the consumer purchased and (2) what are their specifications and what prices are they offered at. Thus, to forecast product returns under RC3 reason code, we need to identify the similar and competing products in the similar price range and create some kind of a matrix for the product specifications & prices. Once that is completed, we have to correlate the RC3 return data with the results of this matrix. Result of this matrix is nothing but the rank analysis of similar and competing products in the similar price range. It is seen that, even if a customer exchanges the product, he/she is likely to stay in the same price range. To understand the methodology for the RC3 returns, first we need to look at some of the facts about product life cycle and the promotional activities (price reductions) in the consumer electronics industry.

3.3.3.1 Product Life Cycle and Promotions Facts

In the consumer electronics (CE) industry, manufacturers and retailers typically perform the product life cycle and promotions planning together. The product life cycle planning follows a typical path. This path includes an introduction phase, a steady state and end of life. A steady state phase is about 80% of the product life cycle. That means, during the life span of 10-12 months, for approx. 80% of the time, the products in the similar category and similar price range compete with each other. About the promotions planning, depending on the financial support from manufacturers, the retailers plan the promotions and advertise in their weekly catalogs, television or radio ads or store flyers. The promotional activities are planned well ahead of time i.e. about 8-10 weeks ahead of the actual promotional time period to prepare the stores for the promotional activities such as inventory stocking, setting up reduced pricing in the system, display unit positioning etc. Events like ‘Black Friday’ and ‘Christmas’ are the biggest and planned almost 4-5 months in advanced. Some more facts about the CE industry and product life cycle planning are listed below.

1. Trends in the CE industry show that, manufacturers and retailers not only offer promotions in the holiday season, but throughout the year at periodic intervals. It has been observed that, typical promotional calendar months are May (Memorial

Day, Graduation Period), July (Independence Day), September (Labor Day), November (Thanksgiving Day), December (Christmas), February (Super bowl). Following figure shows the sales trend by month in CE industries. The above-mentioned months can be clearly seen as high selling months.

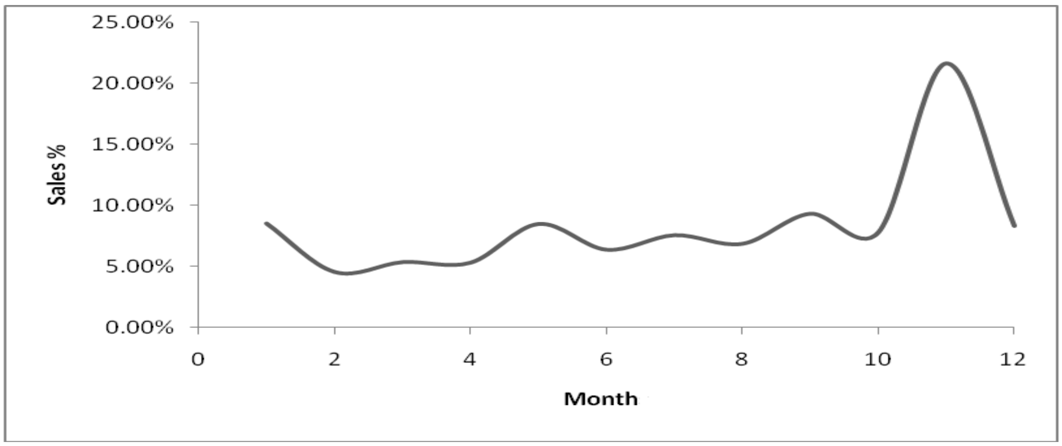

Figure 3.9 Sales Trend by months in CE Industry
(Adapted from Market Research Reports)

2. Some manufacturers (small players) participate only during the biggest holiday events such as Black Friday and Christmas
3. In 2007, a big retail giant actually promoted one of the featured CE products a week prior to the thanksgiving shopping day. Black Friday deals were actually available a week in advance to get an edge over their competitors.
4. Product returns observed in CE industry are directly proportional to the sales in past weeks i.e. high sales high returns and vice versa. Retail stores are typically seen dealing with the high returns after holiday season.

In the literature survey chapter, we saw few forecast models developed for forecasting product returns. None of those models were specially designed for the CE industry. If we wish to apply them for forecasting product returns in CE industry, they may not effectively address the issue for the following reasons:

- 68% of the returns in the CE industry are due to the fact that the consumers' expectations are not met. Today's consumer is in the search of products that offer better specification and price both.
- Promoting a product in the CE industry is not limited to the holiday season. CE manufacturers and retailers also promote and offer discounts throughout the year depending on their needs.
- Even though the returns are based on the past sales, just by computing probability of return quantity may not be enough because the returns are also impacted by the promotional activities of competitors' products. For example, if we have 10% return rate in May 2007 on product A, it may not be the same in May 2008, because the promotional activities of competing products could be different in May 2007 as compared to those in May 2008.

3.3.4 Reason Code RC3: Solution

In the previous section, we saw that the RC3 type product returns follow a normal distribution pattern and returns under this category depend either on the competing products and the combined effect of specifications and prices of the competing products. Thus, the first step towards solving this problem is to identify the competing products in the similar price range and form a matrix for product specifications & prices. Second step is to correlate RC3 return data with the results of this matrix.

For the purpose of identifying the competing products in the similar price range and forming a matrix for product specifications & prices, we perform the following steps:

1. Select 5 Camcorders from 5 different vendors for the analysis
2. Create a Specifications and Prices chart for these 5 Camcorders from first (product launch) week to the current week.

One of these 5 Camcorders should be the product for which forecast to be computed and rests of them should be the competitor's products. The typical specifications of the camcorders that interest consumers are price, screen size, zoom level, resolution etc. The key product parameters need to be considered when we compare different camcorders. The comparison chart for 5 camcorders is shown in the following table. Please note that these five camcorder models are chosen randomly from different models in the consumer electronics market.

Table 3.4 Product Specifications and Price Comparison chart
(The price and specifications data is manipulated)

Week 0	**Specifications**						
Model Name	Price	Screen	Digital Still Resolution	Weight	Optical Zoom	Digital Zoom	Line of Resolution
V-GS85	$270	Mini DV	0.68 mp	1 lbs	32x	1000x	480
C-D173	$300	Mini DV	0.68 mp	0.76 lbs	34x	1200x	400
CR HC28	$280	Mini DV	N/A	0.87 lbs	20x	800x	500
RD 770US	$250	Mini DV	0.68 mp	0.9 lbs	34x	800x	520
RZ 830	$280	Mini DV	0.8 mp	0.84 lbs	35x	1000x	N/A

During the product lifecycle, only parameter that is going to change from week to week is the price of a camcorder. The price changes because every manufacturer wishes to promote their product and offers price discount that is implemented by retailers. We created above table for week 0. Similarly, we need to do the same exercise for remaining weeks or until the week where latest return data is available. Like the above table, we will have multiple tables available, one for every week. Once we have this data available for all the weeks, we have to model it in the DEA solver. As seen in chapter 2, DEA is a non-parametric tool that is used to analyze performance indices. It based on extreme point approach.

3.3.4.1 Rank Analysis with DEA – CCR Model

Previously in chapter 2, we discussed data envelopment analysis (DEA) tool. We also looked at one of the basic DEA model (Single Input Single Output). Now we are going to use a different DEA model called CCR model. The purpose of this model is also same i.e. analyze the performance indices or compare multiple items based on their input and output parameters. This model was initially introduced by Charnes, Cooper and Rhodes in 1978. The entities in the DEA modeling are called decision making units (DMU). In the DEA model, DMU converts input into output and its performance is evaluated. DEA solver is a software tool that is used to find the solution for CCR or any other DEA model. In our case, a camcorder is a decision making unit with one input and multiple outputs. There are certain requirements that are required to be fulfilled about the input data for CCR model. They are as follows:

1. Input data is required to be positive and needed for all inputs.
2. Smaller input amounts are preferable.
3. The measurement units of different inputs and outputs need not be same.
4. Numbers of DMUs are greater than three times number of inputs plus output.

After stating the assumption about the input data, let us feed input and output data to CCR model. We have 5 DMUs (camcorders). The outputs for these DMUs are taken from table 3.4 defined in the previous section. Following will be the outputs:

Y1: Digital Still Resolution

Y2: Optical Zoom

Y3: Digital Zoom

Y4: Lines of Resolution

The input that we are going to consider for the CCR model is 'Price'. We are going to unitize the price under the 'constant return to scale' assumption. Hence, the outputs will be normalized to the value for getting the input of $1. Following is the input:

X1: Price

New output values for the unitized input for Week 0 data looks as follows. This data will be fed into DEA solver engine to find the optimized solution.

Table 3.5 Input Data for DEA Solver

Week0	**V-GS85**	**C-D173**	**CRHC28**	**RD770US**	**RZ-830**
Y1: Digital Still Resolution	0.0025	0.0023	0	0.0027	0.0029
Y2: Optical Zoom	0.1185	0.1133	0.0714	0.1360	0.1250
Y3: Digital Zoom	3.7037	4.0000	2.8571	3.2	3.5714
Y4: Line of Resolution	1.7778	1.3333	1.7857	2.080	0
X1: Price	1	1	1	1	1

We need to do the same exercise for remaining weeks or until the week where latest return data is available. Now that we have created the input data for DEA solver, we will run the DEA solver to get results. In this case, product rank is an output of DEA solver. The ranks given by DEA solver are summarized in the following table.

Table 3.6 DEA Ranks Summary

Week 0	**V-GS85**	**C-D173**	**CR-HC28**	**RD-770US**	**RZ-830**
Rank	4	3	5	1	2

Thus, based on the CCR model and input data, camcorder model RD-770 US has been ranked as number 1 for week 0 followed by RZ-830, C-D173, G-GS85 and CR-HC28. We need to do the same exercise for remaining weeks or until the week where latest return data is available. It is interesting to note that the camcorder that was ranked number 1 by DEA was also at the lowest price in Week 0. Of course, brand loyal consumer may view this differently. Since the prices are changing continuously (week to week), unitized input data will also change and so will the ranks of the camcorders. Let us assume that customer purchased this particular camcorder model RD-770 US in Week 0.

Now assume that, RD-770 US promotion is over in Week 1, price has gone back to \$ 270. And now other manufacturer decided to promote their product C-D173. They decided to reduce the price from \$ 300 to \$ 270 in Week 1. We created exact same input data as created in Table 3.5 for the new prices and ran the DEA solver engine. The new results showed that C-D173 is now Rank 1 and RD-770 US has dropped to Rank 2. What percentage of the consumers (serious buyers and within return period) who purchased RD-770 US model in Week 0 will bring it back and replace it with C-D173 model? Due to the attractive pricing on C-D173 camcorder (or due to drop in rank for RD-770 US), some consumers may want to exchange the RD-770 US or some may want to keep RD-770 Camcorder and wait for Week 2.

Now assume that in Week 2, promotion is over for model C-D173, price has gone back to \$ 300. And now another manufacturer decided to promote their product RZ-830. They decided to reduce the price from \$ 280 to \$ 255 for one week. We created exact same input data as in Table 3.5 for these new prices and ran the DEA solver engine. The new results showed that RZ-830 is now Rank 1 and C-D173 has dropped to Rank 3. What percentage of consumers (serious buyers and within return period) who purchased the RD-770 US in Week 0 will bring it back and replace it with the model RZ-830? Or if someone purchased C-D173 in Week 1, will he/she exchange it with RZ-830 in Week 2 or will he/she keep his product? In simple words, if a manufacturer is not competitive in the market, will there be increase in the product returns? The solution that we are going to propose for RC3 type returns has the answer to this question.

3.3.4.2 Rank Vs Percent Returns: Correlation Matrix

The potential solution for RC3 type returns can be formed with a correlation method. It is one of the most common and useful statistical tool to show how strong are the two variables related. It is a method to find the association or relationship between two variables. Once the relationship is established, it will allow us to predict the change in one variable with the change in other. The outcome of the correlation analysis is known as a 'correlation coefficient' and its value ranges from -1 to +1 depending on the relationship between two variables. If a 'correlation coefficient' is positive, it means that as one variable gets larger the other gets larger too. If a 'correlation coefficient' is negative, it means that as one gets larger, the other gets smaller and if there is no relationship between two variables, value of the 'correlation coefficient' is close to 0.

In our case, the two variables are rank and percentage returns. Based on the existing data, we need to monitor the percentage returns with the changing ranks of the product. It is very likely that less competitiveness of the product will result in lower rank and will eventually result in higher percent returns. Following table shows the correlation between rank and percent returns under RC3 reason codes.

Table 3.7 Ranks and Percent Returns Correlation – RC3

Week 0	**V-GS85**	**C-D173**	**CR-HC28**	**RD-770US**	**RZ-830**
Rank	4	3	5	1	2
% Returns	X1	X2	X3	X4	X5
Week 1	**V-GS85**	**C-D173**	**CR-HC28**	**RD-770US**	**RZ-830**
Rank	4	1	5	2	3
% Returns	Y1	Y2	Y3	Y4	Y5
Week 2	**V-GS85**	**C-D173**	**CR-HC28**	**RD-770US**	**RZ-830**
Rank	4	3	5	2	1
% Returns	Z1	Z2	Z3	Z4	Z5
….	….	….	….	….	….
….	….	….	….	….	….
….	….	….	….	….	….
Week n	**V-GS85**	**C-D173**	**CR-HC28**	**RD-770US**	**RZ-830**
Rank	4	3	5	2	1
% Returns	N1	N2	N3	N4	N5

Please note that, the week n is the current week or a week until the latest return data is available. Once we find the correlation between the two variables namely rank and percent returns, for the future weeks we can predict the returns using linear regression method. (Since manufacturers/retailers know promotional prices in advance and ranks in future weeks can be estimated ahead of time). For example, in table 3.7

rank of the model RD-770US changes from 1 to 2 or rank of the model C-D173 changes from 3 to 1 to 3. We need to note the changes in percent returns data for those weeks. Say, we have established a correlation between rank and percent returns based on the past data. Now, in four weeks from today, there is a promotional price being offered on one of the products. Based on our DEA – CCR model, we can estimate the ranks of all similar products in that week. Then, based on the correlation and linear regression analysis between ranks and percent returns, we can forecast product returns.

To summarize, in this chapter we saw the development of forecasting methodology that can be used to estimate product returns for the consumer electronics industry. In the model development process, we saw the reason codes and their role in product returns. We classified them into different categories such as RC1, RC1 and RC3. After classification of reason codes, we analyzed them separately. For the RC1 & RC2 reason codes, we analyzed the data pattern and then applied a moving average method to forecast RC1 & RC2 type product returns. For the third type of product returns i.e. RC3, based on the market research data, we said that it depends on the price, specifications and the promotional activities of competing products. We then performed a rank analysis with DEA (extreme point approach) and used a correlation/linear regression method between product ranks and percent returns to forecast RC3 type product returns. In the next chapter, we will look at the simulated data, apply the forecasting methodology and analyze results.

CHAPTER 4

DATA ANALYSIS AND RESULTS

4.1 Data Analysis

In the previous chapter, we saw different types of product returns that are seen in the Consumer Electronics industry. We classified these returns under different reason codes namely RC1, RC2 and RC3. We also suggested potential solutions for each type of product return. For RC1 and RC2 type returns, we chose a moving average method whereas for RC3 type returns we selected a combination of DEA and correlation/linear regression. Our next goal is to collect the input data, apply the forecasting methodology and analyze results. The question is, 'what is the input data in this case?' There are three different categories of product returns. So what kind of input data do we need for analysis? Is it sales data or is it returns data or is it percent returns data?

When we developed the forecasting model in the previous chapter, we used percent returns data. We will use the same (percent return data) for the data analysis. Additionally, for RC3 type returns, we will also need product specifications data for DEA model to be able to compute product ranks. Since the actual industry sales and returns data is hard to get due to its sensitive nature, we will have to generate the input data by a simulation method. We have seen previously that, all three types of product returns follow specific probabilistic distributions (normal or exponential).

Thus, depending on the return data distribution (exponential in the case of RC1 and RC2 and normal in the case of RC3) we will generate the input data set for each type of return by simulation. To summarize, for RC1 and RC2 type product returns, we will generate percent returns data using an exponential distribution and for RC3 type product returns we will generate percent returns data using a normal distribution. Additionally for RC3 type returns, we will use product specification data for rank analysis. Then we will apply the proposed forecasting solution to this data to achieve results. Finally, we will combine the results (by all reason codes) and analyze them.

4.1.1 Input data and results for RC1

In section 3.3.1 (Reason Code RC1: Analysis and Solution), we saw the product return scenario under RC1 reason code. Consumers under this reason code received a defective product. Based on the product return scenario, we concluded that the maximum returns will occur in week 0, moderate returns in week 1 and very few will occur in week 2. In this case, percent return data would be exponentially distributed. An exponential distribution is a type of a continuous probability distribution and commonly used. The probability density function (pdf) for an exponentially distributed data is defined as follows.

$$f(T) = \lambda e^{-\lambda T}$$

$$T \geq 0, \lambda \geq 0$$

Where λ = Constant Failure Rate. In our case λ is ‘Return Rate.’

Based on the market research data, an average product return rate for the Consumer Electronics Product is approx. 8-10%. For simplicity, let us choose 10 % for our analysis. Similar study shows that, 5% of product returns are attributed to the RC1 type returns (see table 3.1 Classification of Reason Codes). Thus, overall 0.5% (10 % x 5 %) of total weekly sales is likely to be returned due to defective or malfunctioning products over next two week period. For example, if a retailer has sold 2000 camcorders in a week, out of which 200 (10%) are likely to be returned within next 14 days then, 10 (5%) are likely to be defective or malfunctioning. As seen previously, the return data will be spread over two weeks and will follow an exponential distribution i.e. the highest return rate will be observed in Week 0, moderate in Week 1 and lowest in Week 2. Please note that, the return period is two weeks (14 days). Based on the exponential distribution function and using random number generation functionality in Microsoft excel, we simulated the percent return data (Appendix A) for RC1 type returns between 0.4 % – 0.6 %. Data in the table below is a snapshot of the data generated in Appendix A. Appendix A shows the complete simulated data for RC1 type returns for 52 weeks.

Table 4.1 Percent Returns Data and Moving Average for RC1

Week	Wk0	Wk1	Wk2	Wk3	......	Wk52	Wk53	Wk54	4MA
Week 0 Returns (%)	0.329287	0.333526	0.358131	0.317322	......	0.336685			**0.340%**
Week 1 Returns (%)		0.180717	0.179418	0.102606	......	0.066121	0.076489		**0.119%**
Week 2 Returns (%)			0.099179	0.096517	......	0.066369	0.013484	0.017377	**0.048%**

Now notice that, in Table 4.1 there is a small shift in the values for Week 0 % returns and Week 1 % returns and Week 2 % returns. Whenever there is a small shift in the values, typically a moving average (MA) method is used. A time window (3MA, 4MA or 5 MA) can be chosen based on individual's needs. We will use 4MA for RC1 type returns. 4 week moving average is computed in the last column (titles 4 MA) of the above table 4.1.

Let us say forecast for camcorder model C-D173 for next week is 2300. We can say that, assuming retailer sells 2300 units in week 0 of this camcorder, 0.340% will be returned in Week 0, 0.119% in Week 1 and 0.048% in Week 2 under RC1. Or in other words total 0.507% (0.340 + 0.118 + 0.047) of the camcorders i.e. 12 (rounded) will be returned by end of the Week 2 that was purchased in Week 0.

In any forecast model, more data points give a better picture of the history. Thus, as we move forward in time and as more percent returns data is available, the 4 week moving average is recomputed and the forecast model gets refined.

4.1.2 Input data and results for RC2

In section 3.3.2 (Reason Code RC2: Analysis and Solution), we saw the product return scenario under RC2 reason code. A consumer under this reason code, returns the product without any reason i.e. product is in working condition however the consumer would like to return it within the return period without an exchange. Based on the product return scenario, we concluded that the maximum returns will occur in week 0; moderate returns in week 1 and very few will occur in week 2 and percent returns data would be exponentially distributed. An exponential distribution is a type of continuous probability distribution and commonly used. The probability density function (pdf) for an exponentially distributed data is defined as follows.

$$f(T) = \lambda e^{-\lambda T}$$

$$T \geq 0, \lambda \geq 0$$

Where λ = Constant Failure Rate. In our case λ is 'Product Return Rate.'

Based on the market research data, an average product return rate for the Consumer Electronics Product is approx. 8-10%. For simplicity let us choose 10 % for our analysis. Similar study shows that, 27% of the product returns are attributed to the RC2 type returns (see table 3.1 Classification of Reason Codes). Thus, overall 2.7% (10 % x 27 %) of total weekly sales is likely to be returned without an exchange (these products are non defective). For example, if retailer has sold 2000 camcorders in a week, out of which 200 (10%) are likely to be returned within next 14 days then, 54 (27%) are likely to be returned without an exchange. As seen previously, the return data will be spread over two weeks and will follow an exponential distribution i.e. the highest return rate will be observed in Week 0, moderate in Week 1 and lowest in Week 2. Please note that, the return period is two weeks (14 days). Based on the exponential distribution function and using random number generation functionality in Microsoft excel, we simulated the percent return data (Appendix B) for the RC2 type returns between 2.2 % – 3.2 %. Data in the table below is a snapshot of the data set in Appendix B. Appendix B shows the complete simulated data for the RC2 type returns for 52 weeks.

Table 4.2 Percent Returns Data and Moving Average for RC2

Week	**Wk0**	**Wk1**	**Wk2**	**Wk3**	......	**Wk52**	**Wk53**	**Wk54**	**4MA**
Week 0 Returns (%)	2.449645	2.693172	2.774344	2.052125	......	2.114193			**2.377%**
Week 1 Returns (%)		0.273882	0.360855	0.394717	......	0.275153	0.182441		**0.260%**
Week 2 Returns (%)			0.030621	0.04835	......	0.018867	0.030856	0.015744	**0.030%**

Now notice that, in Table 4.2 there is a small shift in the values for Week 0 % returns and Week 1 % returns and Week 2 % returns. Whenever there is a small shift in the values, typically a moving average (MA) method is used. A time window (3MA or 4MA or 5 MA) can be chosen based on individual's needs. We will use 4MA for the RC1 returns. 4 week moving average is computed in the last column (titled 4MA) of the table 4.2.

Let us say forecast for camcorder model C-D173 for next week is 2300. We can say that assuming a retailer sells 2300 units in week 0 of this camcorder, 2.377% will be returned in Week 0, 0.260% in Week 1 and 0.030% in Week 2 under RC2. Or in other words total 2.667% (2.377 + 0.260 + 0.030) of the camcorders i.e. 62 (rounded) will be returned by end of the Week 2 that was purchased in Week 0.

To reiterate the previous statement, in any forecast model, more data points give a better picture of the history. Thus, as we move forward in time and as more percent returns data is available, the 4 month moving average is recomputed and the forecast model gets refined.

4.1.3 Input data and results for RC3

In section 3.3.3 (Reason Code RC3: Analysis), we saw the product return scenario under RC3 reason code. Under this reason code, a consumer returns a product and exchanges it with competitor's product because his expectations about that product fall short. In other words, the customer did not see any value in this product or he/she feels that, the amount of money he/she spent on the product, he/she could have gotten better deal. Therefore, he/she wants to exchange it with something else (similar product offered by competitor) that he thinks is a good deal. Please note that, RC3 is the case only if a customer exchanges the product with some other product. As seen in the table 3.1, 68 % of the total returns are attributed to this (RC3) type. These types of consumers are serious buyers, well informed about the product specifications and prices offered by retailers. Based on the product return scenario, we concluded that, most of the RC3 type returns fall in Week 1, moderate returns in week 0 and week 2 for the product purchased in Week 0. This is because a customer purchases a product in Week 0. As per the market research data, demand falls over the weekend of Week 0 and the customer spends some hours initially to understand the product. Thus, if he/she wishes to exchange it with another product, he/she is likely to do so in Week 1. That is why most of the RC3 type returns fall in Week 1. Thus, return data would be normally distributed. It is defined in term of mean (μ) and standard deviation (σ). The probability density function (pdf) for normally distributed data is defined as follows.

$$P(x) = 1 / (\sigma \sqrt{2\pi}) * \exp^{-\{sqr\,(x-\mu)/sqr\,(2\sigma)\}}$$

Where μ = Mean and σ = Standard Deviation

Based on the market research data, the average product return rate for Consumer Electronics Product is approx. 8-10%. For simplicity, let us choose 10 % for our analysis. Similar study shows that 68% of returns are attributed to the RC3 type returns (see table 3.1 Classification of Reason Codes). Thus, overall 6.8% (10 % x 68 %) of total weekly sales are likely to be returned with exchanges. For example, if retailer has sold 2000 camcorders in a week, out of which 200 (10%) are likely to be returned within next 14 days then, 136 (68%) are likely to be returned with exchange. As seen previously, return data will be spread over two weeks and will follow a normal distribution i.e. the highest return rate will be observed in Week 1 and moderate return rate in week 0 and week 2. Please note that, return period is two weeks (14 days). Based on the normal distribution function and using random number generation functionality in Microsoft excel, we simulated the percent return data (Appendix C) for RC3 type returns between 6.2 % – 7.5 %. For RC3 type product returns, in addition to percent returns data, we will also need product specifications (spec & price) data for DEA-CCR model to be able to compute the product ranks. Once product ranks are computed using DEA, they will be used in a correlation analysis. Correlation analysis will be performed to find a relationship (coefficient of correlation) between ranks and percent returns as shown in the table below. It is a snapshot of the data set in Appendix C. Appendix C shows the complete simulated percent returns data, product specifications, input data for DEA model, rank calculation and correlation/regression analysis for RC3 type returns for 52 weeks.

Table 4.3 Ranks and Percent Returns Correlation for RC3

	Rank of C-D173	**% Returns for C-D173**
Week 0	3	7.09%
Week 1	1	6.62%
Week 2	3	7.18%
Week 3	1	6.79%
…	…	…
…	…	…
…	…	…
Week 51	2	6.82%
Week 52	2	6.82%

Table 4.3 Continued

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.841830757
R Square	0.708679023
Adjusted R Square	0.702966847
Standard Error	0.001671515
Observations	53

	Coefficients
Intercept	0.062416589
X Variable 1	0.003295126

The value of coefficient of correlation ‘R’ is 0.8418 which indicates a strong correlation. Value of R^2 is 0.7086. It means that 70.86% of the times, relationship between product ranks and percent returns can be explained and 29.14% of the times it is unexplained. Using slope and intercept information from regression analysis, we can forecast product returns. For example, a consumer purchased model C-D173 at $250 (promotional price) in current week (week 0). Next week (week 1), promotion for C-D173 is over and price for C-D173 is going to be $280 and some other camcorder (competitor’s model) is going to be on promotion. The price information in future weeks is available to retailers and manufacturers ahead of time. Since the price for C-D173 has gone up; it is likely that its rank among similar product will drop. Based on the price and product specifications metrics, we will compute product ranks in week 1 using a DEA-CCR model. Let us say, the product rank in week 1 among similar and competing products turns out to be 4. From correlation and regression analysis we have

X variable as 0.0032 and intercept as 0.0624. Thus Y= 0.0032(4) + 0.0624 = 0.0752 or 7.52 % of the C-D173 camcorder models sold in week 0 are likely to be returned with exchanges in week 1. Let us say, forecast for C-D173 camcorder is 2300 in week 0. Thus, 7.52 % or 173 (rounded) will be exchanged in week 1.

In any forecast model, more data points give a better picture of the history. Thus, as we move forward in time, more percent return data is available, product ranks are computed based on changes in product prices, the coefficient of correlation is calculated and forecast model is refined.

4.2 Interpretation of Results

Now that we have seen the input data and results, we need to interpret and summarize these results for all types of returns i.e. RC1, RC2 and RC3. The RC1 & RC2 type returns were computed using a moving average method while the RC3 type returns were estimated using a combination of DEA & regression analysis. The total returns will be a simple addition of returns computed in each return type by week. For example, let us say forecast for the camcorder model C-D173 is 2300 in week 0 and return period is 14 days (2 weeks). Product returns will occur in week 0, week 1 and week 2. In all three weeks, the returns will be observed by all three types i.e. RC1, RC2 and RC3. We also concluded that, for RC1 & RC2 types, the maximum returns will occur in week 0, moderate in week 1 and very few in week 2. Whereas for RC3 type, the maximum returns will occur in week 1 and moderate returns will occur in week 0 and week 2.

Since the actual industry data was not available due to its sensitive nature, we assumed that, each return type would follow a certain type of probabilistic distribution. We suggested that, RC1 & RC2 returns would follow an exponential distribution whereas the RC3 returns would follow a normal distribution. Assuming these probabilistic distributions and return period of 14 days (2 weeks), we simulated the data as shown in appendices A, B and C for one of the camcorder model i.e. C-D173. To summarize the results based on this simulated data, we will forecast product returns for C-D173 in each category by week and add the results as shown in the following table.

Table 4.4 Summarized Results

		Actuals					
	Wk	Wk -6	Wk -5	Wk -4	Wk -3	Wk -2	Wk -1
	POS Sales	2,405	2,461	3,738	3,433	2,211	2,119
RC1	**Week 0 Returns (%)**	0.334%	0.340%	0.337%	0.363%	0.324%	0.337%
	Week 1 Returns (%)	0.074%	0.080%	0.178%	0.155%	0.066%	0.076%
	Week 2 Returns (%)	0.016%	0.019%	0.094%	0.066%	0.013%	0.017%
RC2	**Week 0 Returns (%)**	2.550%	2.405%	2.739%	2.203%	2.454%	2.114%
	Week 1 Returns (%)	0.307%	0.260%	0.380%	0.204%	0.275%	0.182%
	Week 2 Returns (%)	0.037%	0.028%	0.053%	0.019%	0.031%	0.016%
RC3	**Rank**	2	1	1	2	2	2
	Week 1 Returns (%)	7.039%	6.723%	6.636%	6.767%	6.824%	6.820%

RC1	**4MA of Week 0 Returns (%)**	0.340%
	4MA of Week 1 Returns (%)	0.119%
	4MA of Week 2 Returns (%)	0.048%
RC2	**4MA of Week 0 Returns (%)**	2.377%
	4MA of Week 1 Returns (%)	0.260%
	4MA of Week 2 Returns (%)	0.030%
RC3	**Intercept**	0.0624
	X Variable	0.0032

Table 4.4 Continued

		Forecast					
Wk		Wk 0	Wk 1	Wk 2	Wk 3	Wk 4	Wk 5
Sales Forecast		2,300	2,470	2,655	2,260	2,515	2,345
4MA of Week 0 Returns (%)	0.340%						
4MA of Week 1 Returns (%)	0.119%						
4MA of Week 2 Returns (%)	0.048%						
Week 0 Return Forecast		8	8	9	8	9	8
Week 1 Return Forecast			3	3	3	3	3
Week 2 Return Forecast				1	1	1	1
4MA of Week 0 Returns (%)	2.377%						
4MA of Week 1 Returns (%)	0.260%						
4MA of Week 2 Returns (%)	0.030%						
Week 0 Return Forecast		55	59	63	54	60	56
Week 1 Return Forecast			6	6	7	6	7
Week 2 Return Forecast				1	1	1	1
Intercept	0.0624						
X Variable	0.0032						
Rank		3	4	2	5	5	5
Week 1 Return (%)		7.201%	7.521%	6.881%	7.841%	7.841%	7.841%
Week 1 Return Forecast		153	173	170	208	177	197
Total Return Forecast		216	249	253	282	257	273

Typically, we receive the actual data (POS sales) from company's data warehousing system. In our case, we have simulated the data assuming certain probabilistic distributions. Once historical data is available, % returns are computed for each (RC1, RC2 and RC3) category. Additionally, product ranks are computed for RC3 type returns based on the product price and specifications data.

For RC1 and RC2 type returns, based on percent returns data, 4 week moving average (4 MA) is computed. And for RC3 type returns, based on percent returns and ranks, correlation/linear regression analysis is performed. The intercept and X variable are required to be obtained as a result of the correlation/linear regression analysis.

Once all this data is computed, for each type, the return forecast is calculated as explained in section 4.1 (4.1.1, 4.1.2 and 4.1.3). Finally, all return forecast numbers are added to obtain total return forecast.

4.3 Guidelines for Alternate Scenarios

In the previous section 4.2, we saw the input data, data analysis and computation of returns forecast for RC1, RC2 and RC3 returns. We mentioned that, since the industry data was not available due to its sensitive nature, we had to simulate the input data assuming certain probabilistic distributions. Our analysis is based on the simulated data. Even though these assumptions are made based on the market research data, obvious questions that can be asked are, 'what if the probability distribution is different?' 'What if the product ranks computed are different from the way CE industry views them?' 'What if there are more types of returns in addition to RC1, RC2 and RC3?' 'What if there is a seasonal pattern in return data?' Let us look at these scenarios one by one. These scenarios can also be used as implementation guidelines.

First scenario i.e. 'what if the probability distribution is different in reality?' We assumed the input data for RC1 and RC2 returns to be exponential and for RC3 to be normal. Think yourself as a consumer and dealing with RC1 type product return. You received a malfunctioning product from a retail shop. You have two weeks to return the product. Would you return it right away or would you wait until end of the return period? Obviously, you would want to return it right away and get the product that is in working condition. Similarly, in case of RC2 scenario, you as a consumer dealing with a product that you purchased but you are not sure if you are going to keep it or not.

When large amount of money is at stake, you would want to return it right away. Thus in both RC1 & RC2 scenarios, the maximum returns will occur in week 0 of the purchase, moderate returns in week 1 and few returns in week 2, which is a exponential distribution.

Now, consider the RC3 scenario. During the return period of two weeks, if you are happy with the product, you would keep it. If you are not happy with the product you would exchange it with another product. As explained in section 4.1.3, the maximum returns in this case would occur in week 1 and moderate returns would occur in week 0 and week 2, which is a normal distribution.

In reality, the input data (% return data) could follow any other distribution. If different probability distribution is observed, the alternate solution can be developed using guidelines from this methodology.

Now let us look at the second scenario, 'What if the product ranks computed are different from the way CE industry views them?' Our rank computation method uses DEA tool and is based on the metrics of product price and product features. Some folks may have different views about computing product ranks. They may compute the ranks using only price factor (say the lowest price) or only product features (say the highest zoom level in case of camcorder) or using product popularity (the highest selling). The rank computation may vary from product to product or retailer to retailer or manufacturer to manufacturer. Methods other than DEA can be used to compute product ranks. One thing to remember in this case is that, we have to compute product ranks based on the factors that makes the most business sense and relates closely to product returns. These factors could vary from product to product and time to time. Rank computation method should be based on the individual's requirements.

The third scenario is, 'What if there are more types of returns in addition to RC1, RC2 and RC3?' We believe that RC1, RC2 and RC3 types cover most of the product returns scenarios in the consumer electronics industry. If different types of returns are observed then planners need to analyze the return type, factors contributing to each return type, consumer behavior and return data pattern by time buckets. Then suggest the appropriate solution for it.

The last scenario is, 'What if there is a seasonal pattern in return data?' Product returns data that we have considered for our analysis is percent returns instead of actual return volumes. Thus, any minor seasonal patterns in the data can be overcome by percent returns. However, there may be some situations where seasonality will required to be considered even though we are using percent returns. This would be another opportunity to develop an alternate solution. Typically, the best industry practices compute a baseline forecast and then impose the seasonality pattern on top of it. The industry guidelines on computing a seasonal forecast can be employed in this case to address the seasonality pattern and to develop an alternate solution.

One thing to remember for any forecast model is, 'more data points give the planner a better picture about the parameters selection'. As we move forward in time, more percent return data is available. All parameters (4 week moving average, product ranks, and coefficient of correlation) are computed every week and the forecast model gets refined.

4.4 Model Comparison

One more important aspect of a new methodology is to compare the new methodology with one of the existing forecast models that are used in the industry or previously proposed by different researchers. By doing so, we will know the issues that we have addressed in this model that were not effectively addressed previously.

The models currently used for forecasting the product returns in the Consumer Electronics (CE) industry are mainly of time series types. They analyze the historical returns data and apply time series techniques such as single exponential, double exponential, moving average, croston's etc. These techniques are typically built inside automated software. The Market research for the CE industry shows that the promotional/seasonal activities and the consumer behavior (refer section 3.3.3.1) change from month to month and year over year. Thus, traditional time series methods may not be sufficient and a more robust method is required to forecast product returns in the CE industry.

Let us look at one of the forecasting models proposed previously. In the literature survey chapter (section 2.3.2), we discussed some of the approaches for forecasting product returns. We believe that, these proposed models discussed in literature survey, may not effectively address the typical scenarios in the CE industry. In one of the proposed model, return time is computed using a regression analysis. It assumed that the higher price would allow quick returns (if more money is at stake, then consumer would return it sooner rather than later). In the same model, return probability is computed assuming that consumers will reject a poor fit for more expensive items.

We believe that this model may not effectively address the product returns in the CE industry. For example, RC2 return type can be modeled using the regression analysis, assuming 'more money at stake, quick return time' logic. However, RC1 and RC3 (especially RC3) product returns may not be effectively modeled using this model due to the consumer behavior, promotional/seasonal activities, product competitiveness in the CE industry.

We know that, the CE industry offers variety of products in variety of specifications. At the same time, the product life cycle, promotional/seasonal activities, consumer buying and the return data patterns that are observed for the CE products are unique and differ from the products in other industries. It requires a forecast model that would effectively address the return scenarios based on the above-mentioned factors. We believe that, the model proposed in this research would be a close fit model to forecast product returns for the CE industry.

CHAPTER 5

CONCLUSION

5.1 Summary

In this research, a new forecasting methodology is developed for the Consumer Electronics (CE) industry to forecast product returns. CE retailers and manufacturers can use this model for forecasting the product returns. This forecast model is based on reason codes. Reason codes (RC) are simply customized codes entered into the point of sales system when the product is returned. Reason code based forecasting is a unique part of this research. We believe that, this methodology can effectively translate consumer behavior into meaningful data that can be fed into the model to forecast product returns.

Product returns observed in the CE industry are categorized into three different categories namely RC1, RC2 and RC3. They each effectively address different product return scenarios for the CE products. The computation part of the model uses a combination of two approaches, extreme point approach and central tendency approach. The extreme point approach uses 'data envelopment analysis (DEA)' in the initial step combined with correlation/linear regression whereas the central tendency approach uses a moving average method. The moving average method is chosen for

RC1 and RC2 type product returns whereas a combination of data envelopment analysis and linear regression is chosen for the RC3 type product returns. Results are then added together to compute total forecast.

The product that we have considered for our analysis is a digital camcorder. Since actual industry data was not available for product returns and product prices due to its sensitive nature, we simulated the input data (percent returns, product price and product specification data). The complete set of simulated data is as shown in Appendices A, B and C for RC1, RC2 and RC3 type returns respectively. The snapshot of the data is shown in Tables 4.1, 4.2, 4.3. Summarized results are in table 4.4. The questions related to the alternate scenarios have also been addressed. These scenarios can be used as the implementation guidelines by users.

5.2 Contributions

This study provides several contributions to the body of knowledge in the field of reverse supply chain. CE Retailers and manufacturers can effectively use this methodology to forecast product returns.

The first contribution of this methodology is a new way of forecasting product returns i.e. reason codes based forecasting. Also, this methodology integrates extreme point approach and central tendency approach. As seen previously, the existing models may not effectively forecast product returns and address the consumer behavior with respect to the product competitiveness in the CE industry. There is a need for new forecasting approach to forecast product returns for the CE industry. With a robust forecast model, all downstream processes (strategic, tactical and operational) will be positively impacted.

Secondly, this methodology can effectively address and cover different product return scenarios. The RC1, RC2 and RC3 return types cover most of the return scenarios that are observed today. The RC1 scenario addresses the returns for defective products, the RC2 scenario addresses the returns without exchanges and the RC3 type focuses on the returns with exchanges. Any other return scenario that users (retailers and manufacturers) wishes to model, can be modeled using guidelines shown in this methodology. Also, this methodology can be extended to the other industries as well.

Finally, this methodology shows a new way of translating the consumer behavior into meaningful data. This data can be fed to the model to forecast product returns. When a consumer returns a product in a store, the reason codes (customized code designed for point of sales system) can be captured. These codes can be categorized based on users' requirements. The reason codes reflect the consumer behavior under different return scenarios. Returns data attributed to each reason code can be analyzed and used to forecast the product returns.

5.3 Future Research

The forecast model developed in this research was primarily for the Consumer Electronics (CE) industry. The area where future research can be performed is an extension of this forecast model to other industries. In the industries like book publishing/distribution, clothing merchandise and auto parts industries, the return rate is considerably high. The methodology in this research can be extrapolated to develop the forecast model to forecast product returns for these industries. As mentioned in the ‘guideline for alternate scenarios’ section, future research can also be done to develop alternate solutions for different probabilistic distributions. Using these guidelines this model can be expanded to include more types of returns.

We previously said that, timely and accurate product returns forecast would positively impact the downstream processes (strategic, tactical and operational). Let us see, how accurate and timely forecast can impact the strategic and tactical level planning. The strategic planning within the organization is a much broader term and typically includes long term planning such as a new product introduction. Timely and accurate information about product returns can have significant impact on the new product introduction. The impact on the product launch strategy using product returns forecast would be an interesting area to research.

The tactical planning typically includes capacity planning, disposal management etc. Early information about product returns can definitely make impact on the capacity planning, design of the disposal facilities, logistics network etc. Especially, within the disposal management, modifications of the disposal facilities due to early forecast information can be studied. The capacity planning to handle the unexpected returns can also be an interesting topic to explore.

APPENDIX A

SIMLUATED INPUT DATA FOR REASON CODE RC1

Overview:

Since the actual industry sales data is hard to get due to its sensitive nature, we will generate the input data by the simulation method. When we looked at the return scenario for RC1 type returns, we concluded that it follows an exponential distribution. Thus, assuming that data pattern is exponentially distributed, we have generated the input data for RC1 type product returns.

Based on the market research data, the average product return rate for Consumer Electronics Product is approx. 8-10%. For simplicity, let us choose 10 % for our analysis. The similar study shows that, 5% of the returns are attributed to the RC1 type (see table 3.1 Classification of Reason Codes). Thus, overall 0.5% (10 % x 5 %) of total weekly sales is likely to be returned due to defective or malfunctioning products over next two week period. Based on the exponential distribution function and using random number generation functionality in Microsoft excel, we simulated percent return data set for RC1 type returns between 0.4 % – 0.6 %. The probability density function (pdf) for exponentially distributed data is defined as follows.

$$f(T) = \lambda e^{-\lambda T}$$

$$T \geq 0, \lambda \geq 0$$

Where λ = Constant Failure Rate. In our case λ is 'Product Return Rate.'

The return data generated is between 0.4 % – 0.6 %. Since the return period is two weeks, each % returns should be spread over two weeks and exponentially distributed. From figure 3.4 (Return Data Pattern for Reason Code RC1) and table 3.2 (Grouping of Returns Percentage) we know that the part of the percent returns falls in week 0, part of it falls in week 1 and part of it falls in week 2 for the product that is purchased in Week 0. We compute the return forecast for one product at a time. Thus we have generated input data (% returns) for one of the camcorders models (C-D173) under RC1 type supporting the above-mentioned requirements.

Table A.1 Percent Return data for RC1

Week	Wk0	Wk1	Wk2	Wk3	Wk4	Wk5	Wk6	Wk7
Week 0 Returns (%)	0.329287	0.333526	0.358131	0.317322	0.366297	0.34761	0.309151	0.367879
Week 1 Returns (%)		0.180717	0.179418	0.102606	0.183079	0.147443	0.172618	0.183796
Week 2 Returns (%)			0.099179	0.096517	0.029397	0.105627	0.05935	0.085719

Week	Wk8	Wk9	Wk10	Wk11	Wk12	Wk13	Wk14	Wk15
Week 0 Returns (%)	0.361433	0.342845	0.309151	0.346087	0.354291	0.3293	0.364488	0.351794
Week 1 Returns (%)	0.135335	0.108862	0.175437	0.183796	0.173589	0.0966	0.180717	0.152703
Week 2 Returns (%)	0.109271	0.049787	0.032788	0.089772	0.109271	0.0871	0.026314	0.0992

Week	Wk16	Wk17	Wk18	Wk19	Wk20	Wk21	Wk22	Wk23
Week 0 Returns (%)	0.364132	0.360335	0.350462	0.367577	0.362589	0.36719	0.355099	0.351755
Week 1 Returns (%)	0.169532	0.115298	0.160298	0.170588	0.140743	0.111416	0.143435	0.097748
Week 2 Returns (%)	0.063975	0.081699	0.036507	0.07131	0.083034	0.053889	0.034236	0.05603

Week	Wk24	Wk25	Wk26	Wk27	Wk28	Wk29	Wk30	Wk31
Week 0 Returns (%)	0.362023	0.367861	0.355888	0.360181	0.365913	0.355099	0.349059	0.367807
Week 1 Returns (%)	0.093031	0.110135	0.136689	0.09895	0.106336	0.148769	0.097748	0.08959
Week 2 Returns (%)	0.026907	0.024605	0.033505	0.05079	0.027512	0.031394	0.060485	0.026907

Week	Wk32	Wk33	Wk34	Wk35	Wk36	Wk37	Wk38	Wk39
Week 0 Returns (%)	0.347178	0.339065	0.355426	0.360181	0.344242	0.337449	0.367435	0.340338
Week 1 Returns (%)	0.132629	0.087343	0.078743	0.166221	0.106336	0.084044	0.077201	0.128579
Week 2 Returns (%)	0.022994	0.047825	0.021974	0.018287	0.077736	0.031394	0.020519	0.017662

Week	Wk40	Wk41	Wk42	Wk43	Wk44	Wk45	Wk46	Wk47
Week 0 Returns (%)	0.332442	0.35652	0.335363	0.323034	0.341176	0.330147	0.326631	0.333574
Week 1 Returns (%)	0.079993	0.072709	0.165073	0.07528	0.06522	0.080834	0.070777	0.067954
Week 2 Returns (%)	0.044995	0.018802	0.015902	0.076431	0.016898	0.013168	0.019152	0.015173

Week	Wk48	Wk49	Wk50	Wk51	Wk52	Wk53	Wk54	Wk55
Week 0 Returns (%)	0.340127	0.337467	0.363303	0.324242	0.336685			
Week 1 Returns (%)	0.07369	0.079784	0.177944	0.155281	0.066121	0.076489		
Week 2 Returns (%)	0.014138	0.016279	0.018715	0.093828	0.066369	0.013484	0.017377	

Note: Since the returns fall over next two weeks, for any given week please add numbers diagonally. For example for Wk 0 add 0.3292 + 0.1807 + 0.0991 = 0.6091

Note: When adding the % returns number to compute moving average, please add them in straight row. For example for Week 0 % returns add 0.3292 + 0.3335 + 0.3581 +…. + 0.3362. And 4 Week MA will be average of last 4 weeks for each row.

Now notice that, in Table A.1 there is a small shift in the values for Week 0 % returns and Week 1 % returns and Week 2 % returns. Whenever there is a small shift in the values, typically a moving average (MA) method is used. Time window (3MA or 4MA or 5 MA) can be chosen based on individual's needs. We will use 4MA for RC1 returns.

Table A.2 4MA of Percent Returns for RC1

	Wk0	Wk1	Wk2
4MA of Week 0 Returns (%)	0.340%		
4MA of Week 1 Returns (%)		0.119%	
4MA of Week 2 Returns (%)			0.048%

Let us say, sales forecast for C-D173 camcorder model for next week is 2300, we can say that assuming the retailer sells 2300 units of this camcorder, 0.340% will be returned in Week 0, 0.119% in Week 1 and 0.048% in Week 2 under RC1. Or in other words, total 0.507% (0.340 + 0.119 + 0.048) of the camcorders i.e. 12 (rounded) will be returned by end of the Week 2, that were purchased in Week 0.

In any forecast model, more data points give a better picture of the history. Thus, as we move forward in time and as more percent return data is available, 4 month moving average is recomputed and the forecast model gets refined.

APPENDIX B

SIMLUATED INPUT DATA FOR REASON CODE RC2

Overview:

Since the actual industry sales data is hard to get due to its sensitive nature, we will generate the input data by the simulation method. When we looked at the return scenario for RC2 type returns, we concluded that it follows an exponential distribution. Thus, assuming that, the data pattern is exponentially distributed, we have generated the input data for RC2 type product returns.

Based on the market research, the average product return rate for the Consumer Electronics Product is approx. 8-10%. For simplicity let us choose 10 % for our analysis. The similar study shows that, 27% of returns are attributed to the RC2 types of product returns (see table 3.1 Classification of Reason Codes). Thus, overall 2.7% (10 % x 27 %) of total weekly sales are likely to be returned without an exchange. Based on the exponential distribution function and using random number generation functionality in Microsoft excel, we simulated the percent return data set for RC2 type returns between 2.2 % – 3.2 %. The probability density function (pdf) for exponentially distributed data is defined as follows.

$$f(T) = \lambda e^{-\lambda T}$$

$$T \geq 0, \lambda \geq 0$$

Where λ = Constant Failure Rate. In our case λ is 'Product Return Rate.'

The return data generated is between 2.2 % – 3.2 %. Since the return period is two weeks, each % returns should be spread over two weeks and exponentially distributed. From figure 3.5 (Return Data Pattern for Reason Code RC2) and table 3.3 (Grouping of Returns Percentage) we know that the part of the percent returns falls in week 0, part of it falls in week 1 and part of it falls in week 2 for the product that is purchased in Week 0. We compute the return forecast for one product at a time. Thus we have generated input data (% returns) for one of the camcorders models (C-D173) under RC2 type supporting the above-mentioned requirements.

Table B.1 Percent Return data for RC2

Week	Wk0	Wk1	Wk2	Wk3	Wk4	Wk5	Wk6	Wk7
Week 0 Returns (%)	2.449645	2.693172	2.774344	2.052125	2.464305	2.686406	2.42704	2.639066
Week 1 Returns (%)		0.273882	0.360855	0.394717	0.168449	0.278569	0.358153	0.266781
Week 2 Returns (%)			0.030621	0.04835	0.056158	0.013827	0.03149	0.047749

Week	Wk8	Wk9	Wk10	Wk11	Wk12	Wk13	Wk14	Wk15
Week 0 Returns (%)	2.571585	2.7473	2.67964	2.733771	2.440329	2.7202	2.612046	2.586409
Week 1 Returns (%)	0.33974	0.314907	0.38313	0.355469	0.37745	0.2709	0.371844	0.329603
Week 2 Returns (%)	0.029325	0.043736	0.038562	0.05343	0.047155	0.0521	0.030081	0.0508

Week	Wk16	Wk17	Wk18	Wk19	Wk20	Wk21	Wk22	Wk23
Week 0 Returns (%)	2.713472	2.437669	2.767586	2.597199	2.709412	2.639066	2.450977	2.279947
Week 1 Returns (%)	0.320226	0.369069	0.270101	0.391792	0.324144	0.367413	0.33974	0.274305
Week 2 Returns (%)	0.041591	0.039647	0.050198	0.029928	0.055464	0.040455	0.049824	0.043736

Week	Wk24	Wk25	Wk26	Wk27	Wk28	Wk29	Wk30	Wk31
Week 0 Returns (%)	2.591803	2.319002	2.605296	2.531234	2.635011	2.504409	2.305953	2.632308
Week 1 Returns (%)	0.224059	0.32218	0.234837	0.327112	0.300805	0.338202	0.291724	0.231192
Week 2 Returns (%)	0.030699	0.022019	0.040049	0.023781	0.041071	0.035747	0.043408	0.033981

Week	Wk32	Wk33	Wk34	Wk35	Wk36	Wk37	Wk38	Wk39
Week 0 Returns (%)	2.177231	2.411122	2.626903	2.44432	2.151903	2.076832	2.41775	2.679911
Week 1 Returns (%)	0.33718	0.197514	0.26187	0.335144	0.272196	0.191351	0.173921	0.263906
Week 2 Returns (%)	0.023179	0.04319	0.017918	0.028441	0.042758	0.030311	0.017015	0.014565

Week	Wk40	Wk41	Wk42	Wk43	Wk44	Wk45	Wk46	Wk47
Week 0 Returns (%)	2.33208	2.164549	2.708059	2.691819	2.241175	2.739183	2.423057	2.550049
Week 1 Returns (%)	0.355576	0.238535	0.19441	0.366863	0.360313	0.213739	0.379713	0.265545
Week 2 Returns (%)	0.028806	0.047179	0.024398	0.017461	0.049699	0.04823	0.020384	0.052637

Week	Wk48	Wk49	Wk50	Wk51	Wk52	Wk53	Wk54	Wk55
Week 0 Returns (%)	2.4045	2.739183	2.202704	2.453641	2.114193			
Week 1 Returns (%)	0.307313	0.259848	0.379713	0.203862	0.275153	0.182441		
Week 2 Returns (%)	0.029101	0.037035	0.028081	0.052637	0.018867	0.030856	0.015744	

Note: Since the returns fall over next two weeks, for any given week please add numbers diagonally. For example for Wk 0 add 2.4496 + 0.2738 + 0.0306 = 2.7541

Note: When adding the % returns number to compute the moving average, please add them in straight row. For example for Week 0 % returns add 2.4496 + 2.6931 + 2.7743 +…. + 2.1141. And 4 Week MA will be average of last 4 weeks for each row.

Now notice that, in Table B.1 there is a small shift in the values for Week 0 % returns and Week 1 % returns and Week 2 % returns. Whenever there is a small shift in the values, typically a moving average (MA) method is used. Time window (3MA or 4MA or 5 MA) can be chosen based on individual's needs. We will use 4MA for RC2 returns.

Table B.2 4MA of Percent Returns for RC2

	Wk0	Wk1	Wk2
4MA of Week 0 Returns (%)	2.377%		
4MA of Week 1 Returns (%)		0.260%	
4MA of Week 2 Returns (%)			0.030%

Let us say sales forecast for C-D173 camcorder model for next week is 2300, we can say that assuming the retailer sells 2300 units of this camcorder, 2.377% will be returned in Week 0, 0.260% in Week 1 and 0.030% in Week 2 under RC2. Or in other words, total 2.667% (2.377 + 0.260 + 0.030) of the camcorders i.e. 62 (rounded) will be returned by end of the Week 2 that were purchased in Week 0.

In any forecast model, more data points give a better picture of the history. Thus, as we move forward in time and as more percent return data is available, 4 four month moving average is recomputed and the forecast model gets refined.

APPENDIX C

SIMLUATED INPUT DATA FOR REASON CODE RC3

Overview:

Since the actual industry sales data is hard to get due to its sensitive nature, we will generate the input data by the simulation method. When we looked at the return scenario for RC3 type returns, we concluded that it follows a normal distribution. Thus, assuming that the data pattern is exponentially distributed, we have generated the input data for RC3 type product returns.

Based on the market research data, the average product return rate for the Consumer Electronics Product is approx. 8-10%. For simplicity let us choose 10 % for our analysis. The similar study shows that 68% of returns are attributed to the RC3 types of product returns (see table 3.1 Classification of Reason Codes). Thus, overall 6.8% (10 % x 68 %) of total weekly sales is likely to be returned because consumer wishes to exchange the product. Based on the normal distribution function and using random number generation functionality in Microsoft excel, we simulated the percent return data set for RC3 type product returns between 6.2 % – 7.5 %. The probability density function (pdf) for normally distributed data is defined as follows.

$$P(x) = 1 / (\sigma \sqrt{2\pi}) * \exp^{-\{sqr\ (x-\mu)/sqr\ (2\sigma)\}}$$

Where μ = Mean and σ = Standard Deviation

The return data generated is between 6.2 % – 7.5 %. Since the return period is two weeks, each % returns should be spread over two weeks and normally distributed. From figure 3.8 (Return Data Pattern for Reason Code RC3) we know that the part of the percent returns falls in week 0, part of it falls in week 1 and part of it falls in week 2 for the product that is purchased in Week 0. We compute the return forecast for one product at a time. Thus, we have generated the input data (% returns) for one of the camcorder models (C-D173) under RC3 type supporting the above requirements.

Table C.1 Percent Return data for RC3

Week	Wk0	Wk1	Wk2	Wk3	Wk4	Wk5	Wk6	Wk7
Week 0 Returns (%)	1.0560	1.0776	1.1719	1.0722	1.0631	1.0365	1.0347	1.1898
Week 1 Returns (%)		4.7218	4.5018	4.8393	4.6269	4.7910	4.3920	4.4746
Week 2 Returns (%)			1.3155	1.0408	1.1698	1.0923	1.0957	1.2084

Week	Wk8	Wk9	Wk10	Wk11	Wk12	Wk13	Wk14	Wk15
Week 0 Returns (%)	1.1832	1.0297	1.0542	1.1554	1.0841	1.0260	1.1650	1.1758
Week 1 Returns (%)	4.6017	4.5902	4.9867	4.2983	4.9046	4.6028	4.8312	4.8435
Week 2 Returns (%)	1.4139	1.0168	1.0392	1.4478	1.4738	1.4977	1.0029	1.2998

Week	Wk16	Wk17	Wk18	Wk19	Wk20	Wk21	Wk22	Wk23
Week 0 Returns (%)	1.1198	1.1039	1.0783	1.0626	1.1410	1.1604	1.1210	1.1347
Week 1 Returns (%)	4.8435	4.9922	4.6215	4.8218	4.7675	4.0428	4.5329	4.1277
Week 2 Returns (%)	1.4720	1.3700	1.2314	1.1994	1.3325	1.3980	1.4572	1.0049

Week	Wk24	Wk25	Wk26	Wk27	Wk28	Wk29	Wk30	Wk31
Week 0 Returns (%)	1.0514	1.5941	1.0876	1.1426	1.1702	1.0123	1.1003	1.1037
Week 1 Returns (%)	4.6085	4.4885	4.0256	4.9508	4.8618	4.6804	4.2376	4.2965
Week 2 Returns (%)	1.1655	1.3835	1.0468	1.0047	1.3380	1.2154	1.2087	1.3324

Week	Wk32	Wk33	Wk34	Wk35	Wk36	Wk37	Wk38	Wk39
Week 0 Returns (%)	1.0267	1.0120	1.1220	1.0927	1.0166	1.1837	1.0046	1.0548
Week 1 Returns (%)	4.0243	4.0610	4.0896	4.3399	4.6358	4.1742	4.6970	4.3979
Week 2 Returns (%)	1.4051	1.4596	1.3713	1.4627	1.2740	1.0055	1.1670	1.1911

Week	Wk40	Wk41	Wk42	Wk43	Wk44	Wk45	Wk46	Wk47
Week 0 Returns (%)	1.0517	1.1462	1.1928	1.1205	1.0517	1.0507	1.0093	1.0252
Week 1 Returns (%)	4.6574	4.8721	4.9658	4.8419	4.3537	4.8721	4.1247	4.7034
Week 2 Returns (%)	1.1596	1.0200	1.1611	1.4305	1.1041	1.4728	1.1611	1.4784

Week	Wk48	Wk49	Wk50	Wk51	Wk52	Wk53	Wk54	Wk55
Week 0 Returns (%)	1.1285	1.0722	1.0583	1.0148	1.0153			
Week 1 Returns (%)	4.8723	4.4086	4.0803	4.4944	4.6511	4.6446		
Week 2 Returns (%)	1.3769	1.1415	1.1858	1.4834	1.2139	1.1579	1.1596	

Note: Since the returns fall over next two weeks, for any given week, please add numbers diagonally. For example for Wk 0 we will add 1.0560 + 4.7218 + 1.3155 = 7.0933%. Thus, 7.0933% of the products are likely to be returned (exchanged) within next 14 days that are purchased in Wk 0. Similarly, for Wk1 6.6202 % (1.0776 + 4.5018 + 1.0408) of the products are likely to be returned (exchanged) within next 14 days that are purchased in Wk 1 and so on and so forth. The following table shows the aggregated % returns by week for C-D173 model.

Table C.2 Aggregated Percent Return data for RC3

Week	Wk 0	Wk 1	Wk 2	Wk 3	Wk 4	Wk 5	Wk 6	Wk 7	Wk 8
% Returns	7.09%	6.62%	7.18%	6.79%	6.95%	6.64%	6.92%	6.81%	6.81%

Week	Wk 9	Wk 10	Wk 11	Wk 12	Wk 13	Wk 14	Wk 15	Wk 16	Wk 17
% Returns	7.46%	6.83%	7.56%	6.69%	7.16%	7.48%	7.39%	7.34%	6.92%

Week	Wk 18	Wk 19	Wk 20	Wk 21	Wk 22	Wk 23	Wk 24	Wk 25	Wk 26
% Returns	7.23%	7.23%	6.64%	6.70%	6.41%	7.13%	6.59%	6.62%	7.38%

Week	Wk 27	Wk 28	Wk 29	Wk 30	Wk 31	Wk 32	Wk 33	Wk 34	Wk 35
% Returns	7.22%	7.06%	6.58%	6.80%	6.59%	6.46%	6.56%	6.74%	6.73%

Week	Wk 36	Wk 37	Wk 38	Wk 39	Wk 40	Wk 41	Wk 42	Wk 43	Wk 44
% Returns	6.36%	7.07%	6.56%	6.73%	7.09%	7.54%	7.14%	6.95%	7.09%

Week	Wk 45	Wk 46	Wk 47	Wk 48	Wk 49	Wk 50	Wk 51	Wk 52	Wk 53
% Returns	6.65%	7.09%	7.04%	6.72%	6.64%	6.77%	6.82%	6.82%	

For RC3 type product returns, in addition to the percent return data, we are also going to need the product specification and price data as an input to DEA model to compute product ranks. The following section of this appendix shows the product specification data. We have simulated the product specification and price data. The following table shows the camcorder specifications data.

Table C.3 Product Specification Data

	Type	Screen	Dig. Still Resolution	Weight	Opt. Zoom	Dig. Zoom	Line of Resolution	Record Speed
V-GS85	Mini DV	2.7" LCD	0.68 mp	1 lbs	32x	1000x	480	Lp, Sp
C-D173	Mini DV	2.7" LCD	0.68mp	0.76 lbs	34x	1200x	400	N/A
CR-HC28	Mini DV	2.5" LCD	N/A	0.875 lbs	20x	800x	500	Sp, Lp
RD-770 US	Mini DV	2.7" LCD	0.68 mp	0.9 lbs	34x	800x	520	Sp, Lp
RZ-830	Mini DV	2.7" LCD	0.8 mp	0.84 lbs	35x	1000x	N/A	N/A

Note: In section 3.3.4.1 (Rank Analysis with DEA – CCR Model), we specified the number of decision making units (DMUs) required for DEA-CCR model. The requirement states that the numbers of DMUs should be greater than three times the number of inputs plus outputs. In our case, we have 1 input and 4 outputs, total 5. Thus, number of DMUs should be greater 15 (5*3). To satisfy this requirement, we created 15 dummy camcorder models (DMUs) with dummy data. Thus, we have 5 actuals plus 15 dummy, total 20 DMUs, which satisfies the condition for required number of DMUs. For simplicity purpose, we have not shown data for dummy camcorders.

The following table shows product price data for 52 weeks.

Table C.4 Product Price Data

	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Week 0	$270.00	$300.00	$280.00	$250.00	$280.00
Week 1	$270.00	$280.00	$280.00	$250.00	$280.00
Week 2	$280.00	$300.00	$266.00	$253.00	$273.00
Week 3	$300.00	$300.00	$260.00	$280.00	$300.00
Week 4	$300.00	$300.00	$280.00	$253.00	$300.00
Week 5	$285.00	$280.00	$280.00	$253.00	$300.00
Week 6	$300.00	$280.00	$250.00	$253.00	$255.00
Week 7	$290.00	$280.00	$250.00	$280.00	$280.00
Week 8	$290.00	$280.00	$250.00	$280.00	$280.00
Week 9	$280.00	$300.00	$245.00	$250.00	$240.00
Week 10	$300.00	$300.00	$250.00	$280.00	$280.00
Week 11	$285.00	$280.00	$237.00	$244.00	$230.00
Week 12	$247.00	$245.00	$250.00	$244.00	$236.00
Week 13	$270.00	$300.00	$280.00	$250.00	$280.00
Week 14	$280.00	$300.00	$266.00	$253.00	$273.00
Week 15	$280.00	$300.00	$266.00	$253.00	$273.00
Week 16	$280.00	$300.00	$245.00	$250.00	$240.00
Week 17	$300.00	$300.00	$250.00	$280.00	$280.00
Week 18	$285.00	$280.00	$237.00	$244.00	$230.00
Week 19	$285.00	$280.00	$237.00	$244.00	$230.00
Week 20	$300.00	$280.00	$250.00	$253.00	$255.00
Week 21	$300.00	$280.00	$250.00	$250.00	$255.00
Week 22	$290.00	$280.00	$250.00	$280.00	$280.00
Week 23	$280.00	$300.00	$245.00	$250.00	$240.00
Week 24	$300.00	$280.00	$250.00	$253.00	$255.00
Week 25	$300.00	$280.00	$250.00	$250.00	$255.00
Week 26	$280.00	$300.00	$245.00	$250.00	$240.00
Week 27	$280.00	$300.00	$245.00	$250.00	$240.00
Week 28	$280.00	$300.00	$245.00	$250.00	$240.00
Week 29	$300.00	$280.00	$250.00	$253.00	$255.00
Week 30	$300.00	$280.00	$250.00	$250.00	$255.00

Table C.4 Continued

	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Week 31	$290.00	$280.00	$250.00	$280.00	$280.00
Week 32	$290.00	$280.00	$250.00	$280.00	$280.00
Week 33	$247.00	$245.00	$250.00	$244.00	$236.00
Week 34	$300.00	$280.00	$250.00	$253.00	$255.00
Week 35	$300.00	$280.00	$250.00	$250.00	$255.00
Week 36	$270.00	$280.00	$280.00	$250.00	$280.00
Week 37	$280.00	$300.00	$266.00	$253.00	$273.00
Week 38	$300.00	$300.00	$260.00	$280.00	$300.00
Week 39	$300.00	$300.00	$280.00	$253.00	$300.00
Week 40	$280.00	$300.00	$266.00	$253.00	$273.00
Week 41	$280.00	$300.00	$266.00	$253.00	$273.00
Week 42	$280.00	$300.00	$266.00	$253.00	$273.00
Week 43	$300.00	$280.00	$250.00	$253.00	$255.00
Week 44	$300.00	$280.00	$250.00	$253.00	$255.00
Week 45	$270.00	$280.00	$280.00	$250.00	$280.00
Week 46	$300.00	$300.00	$250.00	$280.00	$280.00
Week 47	$300.00	$300.00	$250.00	$280.00	$280.00
Week 48	$247.00	$245.00	$250.00	$244.00	$236.00
Week 49	$247.00	$245.00	$250.00	$244.00	$236.00
Week 50	$300.00	$280.00	$250.00	$253.00	$255.00
Week 51	$300.00	$300.00	$250.00	$280.00	$280.00
Week 52	$300.00	$300.00	$280.00	$253.00	$300.00

Now to compute product ranks, DEA tool requires an input file. This input file is created based on the combination of product specifications and prices. As explained in Table 3.5 (Input Data for DEA Solver), below we have created the input data based on the product specifications and price data for DEA-CCR model.

Table C.5 Input Data for DEA-CCR Model

Week 0	**V-GS85**	**C-D173**	**CR-HC28**	**RD-770 US**	**RZ-830**
Y1: Digital Still Resolution	0.0025	0.0023	0	0.0027	0.0029
Y2: Optical Zoom	0.1185	0.1133	0.0714	0.136	0.125
Y3: Digital Zoom	3.7037	4	2.8571	3.2	3.5714
Y4: Line of Resolution	1.7778	1.3333	1.7857	2.08	0
X1: Price	1	1	1	1	1
Week 1	**V-GS85**	**C-D173**	**CR-HC28**	**RD-770 US**	**RZ-830**
Y1: Digital Still Resolution	0.0025	0.0024	0	0.0027	0.0029
Y2: Optical Zoom	0.1185	0.1214	0.0714	0.136	0.125
Y3: Digital Zoom	3.7037	4.2857	2.8571	3.2	3.5714
Y4: Line of Resolution	1.7778	1.4286	1.7857	2.08	0
X1: Price	1	1	1	1	1
Week 2	**V-GS85**	**C-D173**	**CR-HC28**	**RD-770 US**	**RZ-830**
Y1: Digital Still Resolution	0.0024	0.0023	0	0.0027	0.0029
Y2: Optical Zoom	0.1143	0.1133	0.0752	0.1344	0.1282
Y3: Digital Zoom	3.5714	4	3.0075	3.1621	3.663
Y4: Line of Resolution	1.7143	1.3333	1.8797	2.0553	0
X1: Price	1	1	1	1	1
Week 3	**V-GS85**	**C-D173**	**CR-HC28**	**RD-770 US**	**RZ-830**
Y1: Digital Still Resolution	0.0023	0.0023	0	0.0024	0.0027
Y2: Optical Zoom	0.1067	0.1133	0.0769	0.1214	0.1167
Y3: Digital Zoom	3.3333	4	3.0769	2.8571	3.3333
Y4: Lines of Resolution	1.6	1.3333	1.9231	1.8571	0
X1: Price	1	1	1	1	1

Table C.5 Continued

Week 4	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0023	0.0023	0	0.0027	0.0027
Y2: Optical Zoom	0.1067	0.1133	0.0714	0.1344	0.1167
Y3: Digital Zoom	3.3333	4	2.8571	3.1621	3.3333
Y4: Lines of Resolution	1.6	1.3333	1.7857	2.0553	0
X1: Price	1	1	1	1	1

Week 5	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0024	0.0024	0	0.0027	0.0027
Y2: Optical Zoom	0.1123	0.1214	0.0714	0.1344	0.1167
Y3: Digital Zoom	3.5088	4.2857	2.8571	3.1621	3.3333
Y4: Lines of Resolution	1.6842	1.4286	1.7857	2.0553	0
X1: Price	1	1	1	1	1

Week 6	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0023	0.0024	0	0.0027	0.0031
Y2: Optical Zoom	0.1067	0.1214	0.08	0.1344	0.1373
Y3: Digital Zoom	3.3333	4.2857	3.2	3.1621	3.9216
Y4: Lines of Resolution	1.6	1.4286	2	2.0553	0
X1: Price	1	1	1	1	1

Week 7	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0023	0.0024	0	0.0024	0.0029
Y2: Optical Zoom	0.1103	0.1214	0.08	0.1214	0.1251
Y3: Digital Zoom	3.4483	4.2857	3.2	2.8571	3.5714
Y4: Lines of Resolution	1.6552	1.4286	2	1.8571	0
X1: Price	1	1	1	1	1

Week 8	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0023	0.0024	0	0.0024	0.0029
Y2: Optical Zoom	0.1103	0.1214	0.08	0.1214	0.1251
Y3: Digital Zoom	3.4483	4.2857	3.2	2.8571	3.5714
Y4: Lines of Resolution	1.6552	1.4286	2	1.8571	0
X1: Price	1	1	1	1	1

Week 9	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0024	0.0023	0	0.0027	0.0033
Y2: Optical Zoom	0.1143	0.1133	0.0816	0.136	0.1458
Y3: Digital Zoom	3.5714	4	3.2653	3.2	4.1667
Y4: Lines of Resolution	1.7143	1.3333	2.0408	2.08	0
X1: Price	1	1	1	1	1

Table C.5 Continued

Week 10	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0023	0.0023	0	0.0024	0.0029
Y2: Optical Zoom	0.1067	0.1133	0.08	0.1214	0.1251
Y3: Digital Zoom	3.3333	4	3.2	2.8571	3.5714
Y4: Lines of Resolution	1.6	1.3333	2	1.8571	0
X1: Price	1	1	1	1	1

Week 11	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0024	0.0024	0	0.0028	0.0035
Y2: Optical Zoom	0.1123	0.1214	0.0844	0.1393	0.1522
Y3: Digital Zoom	3.5088	4.2857	3.3755	3.2787	4.3478
Y4: Lines of Resolution	1.6842	1.4286	2.1097	2.1311	0
X1: Price	1	1	1	1	1

Week 12	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0028	0.0028	0	0.0028	0.0034
Y2: Optical Zoom	0.1296	0.1388	0.08	0.1393	0.1483
Y3: Digital Zoom	4.0486	4.898	3.2	3.2787	4.2373
Y4: Lines of Resolution	1.9433	1.6327	2	2.1311	0
X1: Price	1	1	1	1	1

Week 13	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0025	0.0023	0	0.0027	0.0029
Y2: Optical Zoom	0.1185	0.1133	0.0714	0.136	0.125
Y3: Digital Zoom	3.7037	4	2.8571	3.2	3.5714
Y4: Line of Resolution	1.7778	1.3333	1.7857	2.08	0
X1: Price	1	1	1	1	1

Week 14	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0024	0.0023	0	0.0027	0.0029
Y2: Optical Zoom	0.1143	0.1133	0.0752	0.1344	0.1282
Y3: Digital Zoom	3.5714	4	3.0075	3.1621	3.663
Y4: Line of Resolution	1.7143	1.3333	1.8797	2.0553	0
X1: Price	1	1	1	1	1

Week 15	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0024	0.0023	0	0.0027	0.0029
Y2: Optical Zoom	0.1143	0.1133	0.0752	0.1344	0.1282
Y3: Digital Zoom	3.5714	4	3.0075	3.1621	3.663
Y4: Line of Resolution	1.7143	1.3333	1.8797	2.0553	0
X1: Price	1	1	1	1	1

Table C.5 Continued

Week 16	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0024	0.0023	0	0.0027	0.0033
Y2: Optical Zoom	0.1143	0.1133	0.0816	0.136	0.1458
Y3: Digital Zoom	3.5714	4	3.2653	3.2	4.1667
Y4: Lines of Resolution	1.7143	1.3333	2.0408	2.08	0
X1: Price	1	1	1	1	1

Week 17	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0023	0.0023	0	0.0024	0.0029
Y2: Optical Zoom	0.1067	0.1133	0.08	0.1214	0.1251
Y3: Digital Zoom	3.3333	4	3.2	2.8571	3.5714
Y4: Lines of Resolution	1.6	1.3333	2	1.8571	0
X1: Price	1	1	1	1	1

Week 18	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0024	0.0024	0	0.0028	0.0035
Y2: Optical Zoom	0.1123	0.1214	0.0844	0.1393	0.1522
Y3: Digital Zoom	3.5088	4.2857	3.3755	3.2787	4.3478
Y4: Lines of Resolution	1.6842	1.4286	2.1097	2.1311	0
X1: Price	1	1	1	1	1

Week 19	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0024	0.0024	0	0.0028	0.0035
Y2: Optical Zoom	0.1123	0.1214	0.0844	0.1393	0.1522
Y3: Digital Zoom	3.5088	4.2857	3.3755	3.2787	4.3478
Y4: Lines of Resolution	1.6842	1.4286	2.1097	2.1311	0
X1: Price	1	1	1	1	1

Week 20	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0023	0.0024	0	0.0027	0.0031
Y2: Optical Zoom	0.1067	0.1214	0.08	0.1344	0.1373
Y3: Digital Zoom	3.3333	4.2857	3.2	3.1621	3.9216
Y4: Lines of Resolution	1.6	1.4286	2	2.0553	0
X1: Price	1	1	1	1	1

Week 21	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0023	0.0024	0	0.0027	0.0031
Y2: Optical Zoom	0.1067	0.1214	0.08	0.136	0.1373
Y3: Digital Zoom	3.3333	4.2857	3.2	3.2	3.9216
Y4: Lines of Resolution	1.6	1.4286	2	2.08	0
X1: Price	1	1	1	1	1

Table C.5 Continued

Week 22	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0023	0.0024	0	0.0024	0.0029
Y2: Optical Zoom	0.1103	0.1214	0.08	0.1214	0.1251
Y3: Digital Zoom	3.4483	4.2857	3.2	2.8571	3.5714
Y4: Lines of Resolution	1.6552	1.4286	2	1.8571	0
X1: Price	1	1	1	1	1

Week 23	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0024	0.0023	0	0.0027	0.0033
Y2: Optical Zoom	0.1143	0.1133	0.0816	0.136	0.1458
Y3: Digital Zoom	3.5714	4	3.2653	3.2	4.1667
Y4: Lines of Resolution	1.7143	1.3333	2.0408	2.08	0
X1: Price	1	1	1	1	1

Week 24	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0023	0.0024	0	0.0027	0.0031
Y2: Optical Zoom	0.1067	0.1214	0.08	0.1344	0.1373
Y3: Digital Zoom	3.3333	4.2857	3.2	3.1621	3.9216
Y4: Lines of Resolution	1.6	1.4286	2	2.0553	0
X1: Price	1	1	1	1	1

Week 25	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0023	0.0024	0	0.0027	0.0031
Y2: Optical Zoom	0.1067	0.1214	0.08	0.136	0.1373
Y3: Digital Zoom	3.3333	4.2857	3.2	3.2	3.9216
Y4: Lines of Resolution	1.6	1.4286	2	2.08	0
X1: Price	1	1	1	1	1

Week 26	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0024	0.0023	0	0.0027	0.0033
Y2: Optical Zoom	0.1143	0.1133	0.0816	0.136	0.1458
Y3: Digital Zoom	3.5714	4	3.2653	3.2	4.1667
Y4: Lines of Resolution	1.7143	1.3333	2.0408	2.08	0
X1: Price	1	1	1	1	1

Week 27	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0024	0.0023	0	0.0027	0.0033
Y2: Optical Zoom	0.1143	0.1133	0.0816	0.136	0.1458
Y3: Digital Zoom	3.5714	4	3.2653	3.2	4.1667
Y4: Lines of Resolution	1.7143	1.3333	2.0408	2.08	0
X1: Price	1	1	1	1	1

Table C.5 Continued

Week 28	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0024	0.0023	0	0.0027	0.0033
Y2: Optical Zoom	0.1143	0.1133	0.0816	0.136	0.1458
Y3: Digital Zoom	3.5714	4	3.2653	3.2	4.1667
Y4: Lines of Resolution	1.7143	1.3333	2.0408	2.08	0
X1: Price	1	1	1	1	1

Week 29	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0023	0.0024	0	0.0027	0.0031
Y2: Optical Zoom	0.1067	0.1214	0.08	0.1344	0.1373
Y3: Digital Zoom	3.3333	4.2857	3.2	3.1621	3.9216
Y4: Lines of Resolution	1.6	1.4286	2	2.0553	0
X1: Price	1	1	1	1	1

Week 30	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0023	0.0024	0	0.0027	0.0031
Y2: Optical Zoom	0.1067	0.1214	0.08	0.136	0.1373
Y3: Digital Zoom	3.3333	4.2857	3.2	3.2	3.9216
Y4: Lines of Resolution	1.6	1.4286	2	2.08	0
X1: Price	1	1	1	1	1

Week 31	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0023	0.0024	0	0.0024	0.0029
Y2: Optical Zoom	0.1103	0.1214	0.08	0.1214	0.1251
Y3: Digital Zoom	3.4483	4.2857	3.2	2.8571	3.5714
Y4: Lines of Resolution	1.6552	1.4286	2	1.8571	0
X1: Price	1	1	1	1	1

Week 32	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0023	0.0024	0	0.0024	0.0029
Y2: Optical Zoom	0.1103	0.1214	0.08	0.1214	0.1251
Y3: Digital Zoom	3.4483	4.2857	3.2	2.8571	3.5714
Y4: Lines of Resolution	1.6552	1.4286	2	1.8571	0
X1: Price	1	1	1	1	1

Week 33	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0028	0.0028	0	0.0028	0.0034
Y2: Optical Zoom	0.1296	0.1388	0.08	0.1393	0.1483
Y3: Digital Zoom	4.0486	4.898	3.2	3.2787	4.2373
Y4: Lines of Resolution	1.9433	1.6327	2	2.1311	0
X1: Price	1	1	1	1	1

Table C.5 Continued

Week 34	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0023	0.0024	0	0.0027	0.0031
Y2: Optical Zoom	0.1067	0.1214	0.08	0.1344	0.1373
Y3: Digital Zoom	3.3333	4.2857	3.2	3.1621	3.9216
Y4: Lines of Resolution	1.6	1.4286	2	2.0553	0
X1: Price	1	1	1	1	1

Week 35	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0023	0.0024	0	0.0027	0.0031
Y2: Optical Zoom	0.1067	0.1214	0.08	0.136	0.1373
Y3: Digital Zoom	3.3333	4.2857	3.2	3.2	3.9216
Y4: Lines of Resolution	1.6	1.4286	2	2.08	0
X1: Price	1	1	1	1	1

Week 36	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0025	0.0024	0	0.0027	0.0029
Y2: Optical Zoom	0.1185	0.1214	0.0714	0.136	0.125
Y3: Digital Zoom	3.7037	4.2857	2.8571	3.2	3.5714
Y4: Line of Resolution	1.7778	1.4286	1.7857	2.08	0
X1: Price	1	1	1	1	1

Week 37	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0024	0.0023	0	0.0027	0.0029
Y2: Optical Zoom	0.1143	0.1133	0.0752	0.1344	0.1282
Y3: Digital Zoom	3.5714	4	3.0075	3.1621	3.663
Y4: Line of Resolution	1.7143	1.3333	1.8797	2.0553	0
X1: Price	1	1	1	1	1

Week 38	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0023	0.0023	0	0.0024	0.0027
Y2: Optical Zoom	0.1067	0.1133	0.0769	0.1214	0.1167
Y3: Digital Zoom	3.3333	4	3.0769	2.8571	3.3333
Y4: Lines of Resolution	1.6	1.3333	1.9231	1.8571	0
X1: Price	1	1	1	1	1

Week 39	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0023	0.0023	0	0.0027	0.0027
Y2: Optical Zoom	0.1067	0.1133	0.0714	0.1344	0.1167
Y3: Digital Zoom	3.3333	4	2.8571	3.1621	3.3333
Y4: Lines of Resolution	1.6	1.3333	1.7857	2.0553	0
X1: Price	1	1	1	1	1

Table C.5 Continued

Week 40	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0024	0.0023	0	0.0027	0.0029
Y2: Optical Zoom	0.1143	0.1133	0.0752	0.1344	0.1282
Y3: Digital Zoom	3.5714	4	3.0075	3.1621	3.663
Y4: Line of Resolution	1.7143	1.3333	1.8797	2.0553	0
X1: Price	1	1	1	1	1
Week 41	**V-GS85**	**C-D173**	**CR-HC28**	**RD-770 US**	**RZ-830**
Y1: Digital Still Resolution	0.0024	0.0023	0	0.0027	0.0029
Y2: Optical Zoom	0.1143	0.1133	0.0752	0.1344	0.1282
Y3: Digital Zoom	3.5714	4	3.0075	3.1621	3.663
Y4: Line of Resolution	1.7143	1.3333	1.8797	2.0553	0
X1: Price	1	1	1	1	1
Week 42	**V-GS85**	**C-D173**	**CR-HC28**	**RD-770 US**	**RZ-830**
Y1: Digital Still Resolution	0.0024	0.0023	0	0.0027	0.0029
Y2: Optical Zoom	0.1143	0.1133	0.0752	0.1344	0.1282
Y3: Digital Zoom	3.5714	4	3.0075	3.1621	3.663
Y4: Line of Resolution	1.7143	1.3333	1.8797	2.0553	0
X1: Price	1	1	1	1	1
Week 43	**V-GS85**	**C-D173**	**CR-HC28**	**RD-770 US**	**RZ-830**
Y1: Digital Still Resolution	0.0023	0.0024	0	0.0027	0.0031
Y2: Optical Zoom	0.1067	0.1214	0.08	0.1344	0.1373
Y3: Digital Zoom	3.3333	4.2857	3.2	3.1621	3.9216
Y4: Lines of Resolution	1.6	1.4286	2	2.0553	0
X1: Price	1	1	1	1	1
Week 44	**V-GS85**	**C-D173**	**CR-HC28**	**RD-770 US**	**RZ-830**
Y1: Digital Still Resolution	0.0023	0.0024	0	0.0027	0.0031
Y2: Optical Zoom	0.1067	0.1214	0.08	0.1344	0.1373
Y3: Digital Zoom	3.3333	4.2857	3.2	3.1621	3.9216
Y4: Lines of Resolution	1.6	1.4286	2	2.0553	0
X1: Price	1	1	1	1	1
Week 45	**V-GS85**	**C-D173**	**CR-HC28**	**RD-770 US**	**RZ-830**
Y1: Digital Still Resolution	0.0025	0.0024	0	0.0027	0.0029
Y2: Optical Zoom	0.1185	0.1214	0.0714	0.136	0.125
Y3: Digital Zoom	3.7037	4.2857	2.8571	3.2	3.5714
Y4: Line of Resolution	1.7778	1.4286	1.7857	2.08	0
X1: Price	1	1	1	1	1

Table C.5 Continued

Week 46	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0023	0.0023	0	0.0024	0.0029
Y2: Optical Zoom	0.1067	0.1133	0.08	0.1214	0.1251
Y3: Digital Zoom	3.3333	4	3.2	2.8571	3.5714
Y4: Lines of Resolution	1.6	1.3333	2	1.8571	0
X1: Price	1	1	1	1	1

Week 47	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0023	0.0023	0	0.0024	0.0029
Y2: Optical Zoom	0.1067	0.1133	0.08	0.1214	0.1251
Y3: Digital Zoom	3.3333	4	3.2	2.8571	3.5714
Y4: Lines of Resolution	1.6	1.3333	2	1.8571	0
X1: Price	1	1	1	1	1

Week 48	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0028	0.0028	0	0.0028	0.0034
Y2: Optical Zoom	0.1296	0.1388	0.08	0.1393	0.1483
Y3: Digital Zoom	4.0486	4.898	3.2	3.2787	4.2373
Y4: Lines of Resolution	1.9433	1.6327	2	2.1311	0
X1: Price	1	1	1	1	1

Week 49	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0028	0.0028	0	0.0028	0.0034
Y2: Optical Zoom	0.1296	0.1388	0.08	0.1393	0.1483
Y3: Digital Zoom	4.0486	4.898	3.2	3.2787	4.2373
Y4: Lines of Resolution	1.9433	1.6327	2	2.1311	0
X1: Price	1	1	1	1	1

Week 50	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0023	0.0024	0	0.0027	0.0031
Y2: Optical Zoom	0.1067	0.1214	0.08	0.1344	0.1373
Y3: Digital Zoom	3.3333	4.2857	3.2	3.1621	3.9216
Y4: Lines of Resolution	1.6	1.4286	2	2.0553	0
X1: Price	1	1	1	1	1

Week 51	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0023	0.0023	0	0.0024	0.0029
Y2: Optical Zoom	0.1067	0.1133	0.08	0.1214	0.1251
Y3: Digital Zoom	3.3333	4	3.2	2.8571	3.5714
Y4: Lines of Resolution	1.6	1.3333	2	1.8571	0
X1: Price	1	1	1	1	1

Table C.5 Continued

Week 52	V-GS85	C-D173	CR-HC28	RD-770 US	RZ-830
Y1: Digital Still Resolution	0.0023	0.0023	0	0.0027	0.0027
Y2: Optical Zoom	0.1067	0.1133	0.0714	0.1344	0.1167
Y3: Digital Zoom	3.3333	4	2.8571	3.1621	3.3333
Y4: Lines of Resolution	1.6	1.3333	1.7857	2.0553	0
X1: Price	1	1	1	1	1

The above input data is fed to DEA-CCR model to compute product ranks. Below is the rank output of DEA-CCR model. Ranks are computed using DEA-Solver.

Table C.6 Rank Output of DEA-CCR model

	V-GS85	C-D173	CR-HC28	RD-770US	RZ-830
Week 0	4	3	5	1	2
Week 1	4	1	5	2	3
Week 2	4	3	5	2	1
Week 3	4	1	5	3	2
Week 4	4	2	5	1	3
Week 5	4	1	5	2	3
Week 6	4	2	5	3	1
Week 7	4	1	5	3	2
Week 8	4	1	5	3	2
Week 9	4	3	5	2	1
Week 10	4	2	5	3	1
Week 11	4	3	5	2	1
Week 12	4	1	5	3	1
Week 13	4	3	5	1	2
Week 14	4	3	5	2	1
Week 15	4	3	5	2	1
Week 16	4	3	5	2	1
Week 17	4	2	5	3	1
Week 18	4	3	5	2	1
Week 19	4	3	5	2	1
Week 20	4	2	5	3	1

Table C.6 Continued

	V-GS85	C-D173	CR-HC28	RD-770US	RZ-830
Week 21	4	2	5	3	1
Week 22	4	1	5	3	2
Week 23	4	3	5	2	1
Week 24	4	2	5	3	1
Week 25	4	2	5	3	1
Week 26	4	3	5	2	1
Week 27	4	3	5	2	1
Week 28	4	3	5	2	1
Week 29	4	2	5	3	1
Week 30	4	2	5	3	1
Week 31	4	1	5	3	2
Week 32	4	1	5	3	2
Week 33	4	1	5	3	1
Week 34	4	2	5	3	1
Week 35	4	2	5	3	1
Week 36	4	1	5	2	3
Week 37	4	3	5	2	1
Week 38	4	1	5	3	2
Week 39	4	2	5	1	3
Week 40	4	3	5	2	1
Week 41	4	3	5	2	1
Week 42	4	3	5	2	1
Week 43	4	2	5	3	1
Week 44	4	2	5	3	1
Week 45	4	1	5	2	3
Week 46	4	2	5	3	1
Week 47	4	2	5	3	1
Week 48	4	1	5	3	1
Week 49	4	1	5	3	1
Week 50	4	2	5	3	1
Week 51	4	2	5	3	1
Week 52	4	2	5	1	3

The correlation analysis will be performed to find a correlation between ranks and percent product returns. Since we generated % return data for C-D173, for correlation analysis we will use product ranks of C-D173 model and correlate with the aggregated percent returns generated previously (Table C.2) in this appendix.

Table C.7 Correlation between Rank and Percent Returns

	Rank of C-D173	% Returns (RC3 type) for C-D173
Week 0	3	7.09%
Week 1	1	6.62%
Week 2	3	7.18%
Week 3	1	6.79%
Week 4	2	6.95%
Week 5	1	6.64%
Week 6	2	6.92%
Week 7	1	6.81%
Week 8	1	6.81%
Week 9	3	7.46%
Week 10	2	6.83%
Week 11	3	7.56%
Week 12	1	6.69%
Week 13	3	7.16%
Week 14	3	7.48%
Week 15	3	7.39%
Week 16	3	7.34%
Week 17	2	6.92%
Week 18	3	7.23%
Week 19	3	7.23%
Week 20	2	6.64%
Week 21	2	6.70%
Week 22	1	6.41%
Week 23	3	7.13%
Week 24	2	6.59%
Week 25	2	6.62%
Week 26	3	7.38%

Table C.7 Continued

	Rank of C-D173	% Returns (RC3 type) for C-D173
Week 27	3	7.22%
Week 28	3	7.06%
Week 29	2	6.58%
Week 30	2	6.80%
Week 31	1	6.59%
Week 32	1	6.46%
Week 33	1	6.56%
Week 34	2	6.74%
Week 35	2	6.73%
Week 36	1	6.36%
Week 37	3	7.07%
Week 38	1	6.56%
Week 39	2	6.73%
Week 40	2	7.09%
Week 41	3	7.54%
Week 42	3	7.14%
Week 43	2	6.95%
Week 44	2	7.09%
Week 45	1	6.65%
Week 46	2	7.09%
Week 47	2	7.04%
Week 48	1	6.72%
Week 49	1	6.64%
Week 50	2	6.77%
Week 51	2	6.82%
Week 52	2	6.82%

The results of the correlation analysis between the product ranks and percent returns are as follows.

Table C.8 Correlation Analysis

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.841830757
R Square	0.708679023
Adjusted R Square	0.702966847
Standard Error	0.001671515
Observations	53

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.000346632	0.000346632	124.0646336	2.87722E-15
Residual	51	0.000142492	2.79396E-06		
Total	52	0.000489124			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.062416589	0.000645075	96.75861954	1.81913E-59	0.061121547	0.063711632	0.061121547	0.063711632
X Variable 1	0.003295126	0.000295834	11.13843048	2.87722E-15	0.002701215	0.003889038	0.002701215	0.003889038

The value of coefficient of correlation R is 0.8418, indicating a strong correlation. The value of R^2 is 0.7086. This means that, 70.86% of the times, relationship between product ranks and percent returns can be explained and 29.14% of the times it is unexplained. Using the slope and intercept information from the regression analysis, we can forecast product returns. For example, a consumer purchased C-D173 at $250 (promotional price) in the current week (week 0). Next week, (week 1) promotion for C-D173 is over and the price for C-D173 is going to be $280 and some other camcorder (competitor's model) is going to be on promotion. The price information in future is available to retailers and manufacturers ahead of time. Since the price for C-D173 has gone up, it is likely that its rank among the similar products will drop. Based on the price and product specifications metrics, we will compute product rank in week 1 using a DEA-CCR model. Let us say, the rank in week 1 among the similar and competing product turns out to be 4. From correlation/linear regression analysis we have X variable as 0.0032 and an intercept of 0.0624. Thus, Y= 0.0032(4) + 0.0624 = 0.0752 or 7.52 % of the C-D173 camcorders sold in week 0 are likely to be returned in week 1. Let us say forecast for C-D173 camcorder model for next week is 2300 in week 0. Thus, 7.52 % or 173 (rounded) of the C-D173 camcorder model will be returned in week 1.

In any forecast model, more data points give a better picture of the history. Thus, as we move forward in time, more percent return data is available, the product ranks are computed based on the changes in product prices, the coefficient of correlation is recalculated and the forecast model gets refined.

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