Supply Chain Planning Decisions under Demand Uncertainty

by

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Abstract

Sales and operational planning that incorporates unconstrained demand forecasts has been expected to improve long term corporate profitability. Companies are considering such unconstrained demand forecasts in their decisions on investment in supply chain resources. However, demand forecasts are often associated with uncertainty. This research applies Monte Carlo simulation, value at risk and gain curve analysis, and real option analysis to investigate how the uncertainty of demands affects supply chain planning in order to make better supply chain investment decisions. This analytical framework was used to analyze the ocean shipping plans and inland trucking arrangements for Chiquita. Demands for Product A and front haul over a six-year period were simulated based upon forecasted distributions. The net income, revenue and costs as affected by ocean shipping plans were obtained by inputting the simulated demands to ocean shipping models. The major decision for Chiquita is whether to charter one large ship or two ships which provide approximately equivalent capacity. A large ship would save fuel costs. The plans for two smaller ships have the flexibility of using one ship only if future demand or price reactions warrant it. Using the analytical framework, a plan for two smaller ships is superior to that for one large ship because of significant real option value, particularly in the event of increases in fuel costs in the future. Chiquita's current inland trucking model, a mixed arrangement with a dedicated fleet and common carriers, seems to offer a good solution for the future needs. A model provided in this research offers a simple method to optimize the size of the dedicated fleet.

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Supply Chain Planning Decisions under Demand Uncertainty

1 Introduction

Unconstrained demand is the quantity of merchandise that could be sold if there were no supply chain or other constraints. Thus, unconstrained demand more accurately reflects the true level of customer demand and could be the starting point in all types of supply chain planning.

In matching supply with demand forecasts, business organizations may need to make long term investment in transportation, warehousing, manufacturing or other resources to develop necessary capacity to meet the demand. Resources might need to be acquired in advance because advance acquisition significantly reduces cost. In some situations, such resources might not be easily acquired on an as needed basis. Some supply chain resources, such as trucking and ocean shipping, can be obtained in a variety of ways. For example, trucking can be achieved through a dedicated fleet or common carrier or both.

One complication for supply chain planning is that demand forecasts are typically associated with uncertainty. Deterministic planning models can thus fail to manage the risk exposure. Therefore, decision makers need to consider the impact of the resource investment under uncertainty.

1.1 Supply Chain Planning under Demand Uncertainty, the Case Of Chiquita Brand International

Chiquita provides a good example of a business case. Chiquita (NYSE: CQB) is a major distributor of fresh and packaged produce in Europe and North America (*see, e.g.*, Lee and Po, 2007, for additional information about Chiquita and its supply chain operation). Many of its products are imported to the United States from tropical countries. While the company has a significant market share for Product A in the United States, it still has significant room to increase its market share. In addition, the overall market growth is small, but still significant. Therefore, Chiquita would like to understand the implications of expanding market share for its supply chain planning.

Chiquita has an extensive transportation and logistics operation that plays an important role in the overall operation of the company. Chiquita's logistics operation includes both ocean shipping and domestic trucking.

Fruits or other fresh products are either grown by Chiquita or purchased by Chiquita close to the farms that grow the products. These products are loaded into containers. These containers are transported to the port and loaded onto ocean ships destined for the United States. Chiquita operates ocean vessels with long term lease contracts, but it also leases other ships short term. When there is an excess of capacity, Chiquita may use its ships to transport goods of others to generate front-haul revenue. On south bound trips, Chiquita ships can also carry backhaul goods to generate additional revenue. These shipping related revenues can be a significant factor to reduce the overall costs of the shipping operation.

Once the ships arrived in a US port and containers unloaded, some Chiquita customers pick up products at the port and transport the products to their own facility. Other customers pay Chiquita to transport products to their facility. Ocean and surface transportation constitutes a significant part of Chiquita's supply chain operation. For inland trucking, Chiquita has the options of using common carriers. Chiquita has access to a large number of common carriers with varying availability and costs. Chiquita has also maintained a small dedicated fleet. Particularly for the dedicated fleet, Chiquita receives significant revenue through back haul. Therefore, the economics of Chiquita's supply chain, like those of many other companies, are quite complex.

In order to plan for market growth, Chiquita needs to understand the potential demands in the years ahead. However, future demands are affected by many factors and there are significant uncertainties associated with demand forecasts. Companies like Chiquita are interested in questions like these:

1) How can forecasts of true market potential, along with transportation capacity constraints, be used to make better supply chain investment decisions?
2) How might the estimated uncertainty of demand forecasts be incorporated into the investment decision process?
3) Do different types of supply chain investments (e.g., owned capacity versus carrier contracts) require different rules? and
4) What factors are important when driving this change within an organization?

1.2 Supply Chain Planning under Uncertainty

Because uncertainty is generally associated with many business activities, businesses in many industries have developed ways to cope with demand uncertainty in capacity planning. For example, businesses tend to seek outsourcing when there is a greater demand uncertainty. Outsourcing can, but does not always, provide greater flexibility and minimize the downside risks. This approach is in contrast with situations where there is significant supply uncertainty. Businesses with significant supply uncertainty tend to cope with it with vertical integration.

Many researchers have also investigated ways of incorporating demand uncertainty in supply chain planning.

Both scenario-based and distribution-based approaches have been used to analyze supply chain planning problems. The scenario-based approach models the outcome of each of the discrete scenarios based upon the probabilities of such scenarios' occurrences. In practice, the probabilities are often the decision maker's expectation that each of the scenarios will occur. The problem of the scenarios approach is that foreseeing all possible scenarios is often difficult if not impossible.

A related approach, stochastic programming has been studied for a variety of supply chain planning problems (*see*, Santoso et al., 2004 for a review). Stochastic programming is a mathematical linear, integer, mixed integer, or nonlinear programming with stochastic parameters. While in theory stochastic programming is well suited for capacity planning under uncertainty, the practical implementation is limited by the sheer size of possible scenarios in many real world situations (Santoso et al., 2004).

If the demand uncertainty (distribution of demands) is estimated with reasonable accuracy, Monte Carlo simulation can be an efficient way to understand how the demand uncertainty can affect engineering decision-making (de Neufville et al., 2006).

Cardin *et al.* (2007) proposed an engineering approach to extract value from uncertainty through engineering system design. The application of this approach to supply chain problems was noted by a research group (de Nuefville, 2005, presentation).

This approach identifies flexibility (or real option) in design. The model uses value assessment method to estimate the value of the flexibility or real option. Two primary financial measures, Net Present Value (NPV) and Value at Risk and Gain (VARG) curves, are analyzed. The NPV and VARG curve are analyzed using a Monte Carlo simulation. First, a design is analyzed using Monte Carlo simulation to generate NPV statistics and VARG curve without considering the flexibility or real option. The same systems are then analyzed again by incorporating the real option. The value of the real option is estimated by:

$$V_{Flexibility} = MAX[0, NPV_{Flex.} - NPV_{Non\text{-}Flex.}] \qquad \textbf{(Equation 1)}$$

This simple real option analysis can be performed with relatively straight forward spreadsheet simulation. In fact de Neufville et al. (2006) provided an example of this analytical approach in evaluating design options for a garage expansion under demand uncertainty.

1.3 Scope of the Research

The objective of the research is to address the questions Chiquita posed using the Monte Carlo simulation and the real option analysis approach outlined above. This research investigates whether analyzing the impact of unconstrained demands and transportation capacity using this analytical framework can facilitate better supply chain investment decision-making. The core of this analytical approach is the incorporation of the estimated uncertainty of demand forecasts. This research compares values of owned capacity versus those of common carriers which have more flexibility. Finally, we want to examine whether this analytical framework has broader implications for supply chain planning processes.

The Chiquita case provides a good test case to apply this analytical approach to real world supply chain investment decision-making. Another goal of this research is to develop a decision support tool to facilitate the adoption of this analytical approach by supply chain managers and planners at Chiquita and other companies.

1.4 Structure of the Thesis

The introduction of the thesis outlines the basic business questions this research addresses. It then reviews the relevant literature. The method section explains in greater details the generic analytical approach and the specific applications to Chiquita data. The results section presents the major results of this research projects. Specifically, it will address two major supply chain issues at Chiquita, ocean shipping plans and inland trucking plans for a particular geographic region. These results, and more importantly, the application of the analytical approach to real world supply chain decision-making, should be of interest to managers and supply chain planners in other companies and industries. Finally, the thesis draws conclusions, discusses their implications and highlights one area for future research.

2. Review of the Literature

This research focuses on examining supply chain investment decisions under demand uncertainty. A Monte Carlo simulation and real option analysis approach were used to study the characteristics of various supply chain designs. This review will provide a background on unconstrained demand, demand uncertainty, supply chain planning, real option analysis and Monte Carlo simulation.

2.1 Unconstrained Demand Forecast

Unconstrained demand is the true customer demand without any constraint that limits sales. One important constraint on demand is the capacity of the supply chain. Because sales can only be achieved within limitations of supply chain, sales forecast data may not reflect true demand, or unconstrained demand. If sales forecast data are used for supply chain planning without considering the true demand, supply chain issues that limit the demand to start with may not be understood. Therefore, unconstrained demand is often the starting point for supply chain planning (Lapide, 1998).

In a typical Sales and Operations Planning (S&OP) process, the first step is to produce a consensus based, unconstrained demand (Lapide, 2004; Grimson and Pyke, 2007). The unconstrained forecasts are often adjusted according to predicted responses to marketing plans. Forecasts of unconstrained demands are also affected by the S&OP planning process (Myer and Myer, 2004). Forecasts from different functions within a company can be different because of functional objectives, bias and other organizational issues (Myer and Myer, 2004; Olive and Watson, 2006). Therefore, it is important to prevent cross function divisions in the S&OP process (Slone *et al.*, 2007) and to provide the right incentives (Myer and Myer, 2004).

It is a major challenge for a supply chain to deliver the right product to the right customer at the right time for the right price all the time. Meeting the unconstrained demand, however, may not always be desirable. Revenues and margins may not increase, or even drop, in the pursuit of market share increase because of negative market price reaction. Demand management is the matching of demand with supply over time (Lapide, 2006). Over the long term, demand management involves matching customer service terms and conditions with the supply chain. In the medium term, demand management involves the development of both supply and demand plans. Traditionally, sales, marketing and customer service execute the demand plan, and supply chain related teams implement the supply plan.

2.2 Demand Uncertainty

Among the factors that detrimentally affect the performance of a supply chain, demand uncertainty can have the biggest impact, according to Yavuz (2007). Therefore, the author argued that the importance of an accurate demand forecast is underscored. Characterizing the demand uncertainty could be based upon historical data (Moe and Fader 2001). The traditional approach for estimating demand distribution basically calculates expected demand and standard deviation using historical data for the same product (Tyrus, *et al.*, 1999). The historical approach is, however, generally not applicable to fashion products that have short life cycle or new products. For products that do not have sufficient history, demand data from similar products may be used to estimate the demand variance.

When such historic data is lacking, expert opinions are often used to estimate the variance. Estimating standard deviations using expert option is, however, difficult because of the lack of good calibration among experts (Tyrus, *et al.*, 1999). Experts' direct estimate of variance can also be problematic because even experts with basic statistic training underestimate standard deviations.

In many contexts, the dispersion of expert opinion has been used to estimate the standard deviation. MacCormack and Verganti (2003), for example, used the variation among the experts as a measure of standard deviation in a software development process. Fisher *et al.* (1999) used a combination of historical data for similar products and dispersion of expert opinion to estimate the demand uncertainty of a fashion product. Gaur *et al.* (2007) took a more systematic approach to investigate whether variance of demand correlates with the dispersion of expert opinion on such demand. They also examined how dispersion of expert opinion can be used to estimate demand variance. Using about 25,000 historical observations spanning across 18 years, the authors found a positive correlation between standard deviation of demand forecast error and dispersion among expert opinions. They further proposed a method to estimate demand variance using forecasts from multiple experts and managers.

Gaur *et al.* (2007)'s explanation of the correlation between dispersion of forecasts among experts and the variance of demand forecast errors provides an insight into the causes of demand uncertainty. Demand uncertainty is the result of many complex processes. The dispersion among experts can be caused by, for example, experts' use of different information or focuses on different subsets of factors. In addition, the degree of the complexity of these processes could cause the disagreement among experts. The correlation between dispersion of expert opinion and demand variance not only is instructive in understanding demand uncertainty, but also provides a practical ways to estimate standard deviation of demand forecasts when appropriate, particularly for new products that do not have historical demand data.

2.3 Supply Chain Planning

Supply chain planning is often for the medium or long term. As Balachandran *et al.* (1997) pointed out, businesses may need to make long-term cost commitments to obtain resources, because such resources may not be economically acquired when needed. Because supply chain planning is performed before actual demand can be measured, the authors also highlight the importance of considering demand uncertainty in making supply chain investment decisions. While acknowledging that stochastic programming can be ideal for capacity planning problems, because of informational and computational complexities for larger organizations, the authors recommended simple rules that achieve reasonable approximations for such planning problem.

Kouvelis and Milner (2002) observed that companies take a variety of approaches to cope with demand uncertainty in capacity planning. In the electronic industry, greater demand uncertainty tends to encourage outsourcing, while greater supply uncertainty tends to encourage vertical integration and less out-sourcing.

Gupta and Maranas (2003) classify supply chain decision models based upon the time frames involved into three types: strategic, tactical and operational. Strategic or long-term planning models primarily deal with supply chain investment. Strategic decision models may identify timing, location and the amount of supply chain investment over a long period of 5 to 10 years (*see, also*, Sahinidis, Grossmann, Fornari, &

Chathrathi, 1989). Tactical planning models are useful for decisions that will have an impact in an intermediate time frame, such as 1 to 2 years. Tactical planning models have characteristics of strategic planning and operational planning models. Operational planning models are for short term, exact sequence of operational events such as manufacturing tasks.

2.4 Supply Chain Planning under Demand Uncertainty

There are many sources of uncertainty in today's complex supply chain and dynamic market place (Gupta and Maranas, 2003). The three categories of supply chain planning models correspond to the timeframes of how uncertainties affect supply chain. Short term uncertainty affects routine processing variations, rush orders, and equipment failure. Long term uncertainty includes raw material price, demand variations and others. Supply chain decisions based upon inaccurate estimates of long term uncertainty and misunderstanding its impact could result in a supply chain that is vulnerable to risks and unable to capture upside opportunities.

In their modeling of supply chain planning under demand uncertainty, Gupta and Maranas (2003) reviewed the approaches for decision-making under demand uncertainty. There are generally two major categories of methodology that have been used to analyze supply chain planning problems: scenario-based and distribution-based approaches. The scenario-based approach models the outcome of each of the discrete scenarios based upon the probabilities of such scenarios' occurrences. The distribution based approach leverages a probability function to represent uncertainty.

A related approach, stochastic programming has been studied for a variety of supply chain planning problems (*see*, Santoso *et al.*, 2004 for a review). Stochastic programming is mathematical linear, integer, mixed integer, or nonlinear programming with stochastic parameters. While in theory, stochastic programming is well suited for capacity planning under uncertainty, the practical implementation is limited by the sheer size of possible scenarios in many real world situations (Santoso *et al.*, 2004).

de Nuefville (2004) argued that, while engineers do consider risk and uncertainty, it will be beneficial for engineers to consider uncertainty using a different mindset and a different process. Professor de Nuefville defines uncertainty as "the entire distribution of possible outcomes." It is important to consider the both ends of the distribution, *i.e.*, good side (upside opportunities) and bad side of the distribution (risk). Therefore, de Nuefville distinguishes "uncertainty" from "risk" because uncertainty concerns with both sides of the distribution while risk emphasizes the down side. de Nuefville advocates a comprehensive approach to manage uncertainty in the planning and design of engineering systems. In addition to a shift from risk to uncertainty management, de Nuefville pointed out recent technological advances that make the comprehensive approach possible. He highlighted two particular areas of importance: "real options" and "robust design." Real option valuation methodologies are now widely available to estimate the value of flexibility in system design.

2.5 Real Option Valuation and Monte Carlo Simulation

Black, Scholes, and Merton (1973) established the foundation for modern options theory and have had a major impact in both financial and non-financial options. A real option is a right, but not obligation, to act on something at certain cost within or at a specific period of time (Wang, 2003). While real options are extensions of financial options and valuations of financial options provide insights into the value of real options, valuation of real options can be quite different from financial options. Wang (2003) reviewed major real option valuation approaches. Arbitrage-enforced real option valuation is close to the valuation of financial options. Black-Scholes' formula, dynamic programming with binomial tree and simulations can be used to value options enforced by arbitrage.

Simulation based valuation has also been used for real options that are not arbitrage enforced. A classic example of business application is Merck's use of simulation to evaluate real options in its drug discovery pipeline (Nichols, 1994). Monte Carlo simulation refers to simulations where repeated random sampling is used as inputs (Wang, 1994). In theory, Monte Carlo simulations can be very versatile and are limited by fewer assumptions than, for example, the Black-Scholes formulae. However, Monte Carlo simulations are based upon the understanding of the underlying distribution of random variables. Furthermore, Monte Carlo simulations are limited by so-called "curse of dimensionality" (Rust, 1997). Because Monte Carlo simulations use direct-sampling, the number of samples per variable needed to maintain accuracy increases exponentially with the number of variables. While it is straight-forward to add additional variables to simulations, a large number of variables can be computationally prohibitive.

One particularly useful approach to value flexibility is to use Monte Carlo simulation. If the distribution of the demands is estimated with reasonable accuracy, Monte Carlo simulation can be an efficient way to understand how the demand uncertainty can affect engineering decision-making (de Neufville et al., 2006).

Professor de Neufville's group at MIT has proposed a comprehensive value assessment methodology that is based upon Monte Carlo simulation and real option analysis. Use of financial metrics such as Net Present Value (NPV) and Value at Risk and Gain (VARG) curves is encouraged in this approach. But other metrics such as carbon emission can also be useful. The first step is to assess designs without flexibility. This can be done using deterministic inputs or design uncertainty such as demand and price. NPV calculation is performed using standard discounted cash flow analysis (DCF).

For each uncertainty variable, Monte Carlo simulation is used to obtain the expected NPV of the design as well as statistics such as standard deviation, and 90^{th} and 10^{th} percentile are obtained after *N* number of simulations. The third step is to identify flexibility or real option and then perform the simulations again to obtain another set of metrics. The improvement in mean NPV is the value of the real option.

2.6 Chiquita

Chiquita is a large distributor of fruits and other fresh produce. It is keen to understand how unconstrained demand forecasts can be used in its supply chain planning. In particular, the company is also interested in how unconstrained demand forecasts can be used to help make supply chain resource investments.

Chiquita's transportation network had been previously studied by Lee and Po (2007). Their study provided a detailed view of the transportation network at Chiquita. Chiquita uses trucks in dedicated fleets and from contract carriers. The trucks are used to front haul Chiquita's products as well as backhaul non-Chiquita goods to generate additional revenue. By focusing on the trucking part of the Chiquita's transportation network and applying mixed integer linear programming (MILP), the authors developed a model that, if adopted, can result in more profit for Chiquita. Their model can also be used to optimize the size of the dedicated fleets and common carriers. However, the MILP approach is deterministic in nature and does not take demand uncertainty into account.

While a dedicated fleet tends to cost less or provides back haul revenue opportunity, common carriers reduce the risk of demand uncertainty. Therefore, under demand uncertainty, there is value of not committing to resources that may turn out to be not necessary. This value is difficult to ascertain using a deterministic model. Zhelev (2004) analyzed the value of various trucking contract options and proposed real option as a flexible approach for transportation procurement.

3 Research Methods and Data

This research is to use Monte Carlo simulations, Value at Risk and Gain analysis, and real option (flexibility) analysis to understand the effects of demand uncertainty on supply chain investment and to compare different supply chain investment options that are available to decision makers and optimize parameters of supply chain designs. In addition, this methodology provides a practical way to value flexibility or real option in supply chain design.

Another goal of this research is to implement a readily available and easy to use computational approach to perform simulations, real option analysis and optimization. The computational approach should ideally be intuitive to supply chain decision makers and analysts who are not familiar with professional simulation and analytical tools. The computational models should be easily modified and adopted for different business situations.

3.1 Overall Generic Analytical and Optimization Approach

Figure 3 shows the overall process of the simulation analysis. This approach is adopted from the engineering system design process proposed by Cardin *et al.* (2007) which is also discussed in the Literature Review section above. The value assessment system developed by the Richard de Neufville group at MIT is useful for valuing flexibility or real options in system design. The value of such flexibility or real options is derived from its ability to handle uncertainties, such as demand uncertainty. This approach is also useful to understand how systems with complicated cost structures respond to uncertainties, as long as such uncertainties are reasonably characterized (such as the distribution of the future demand is estimated with reasonable accuracy).

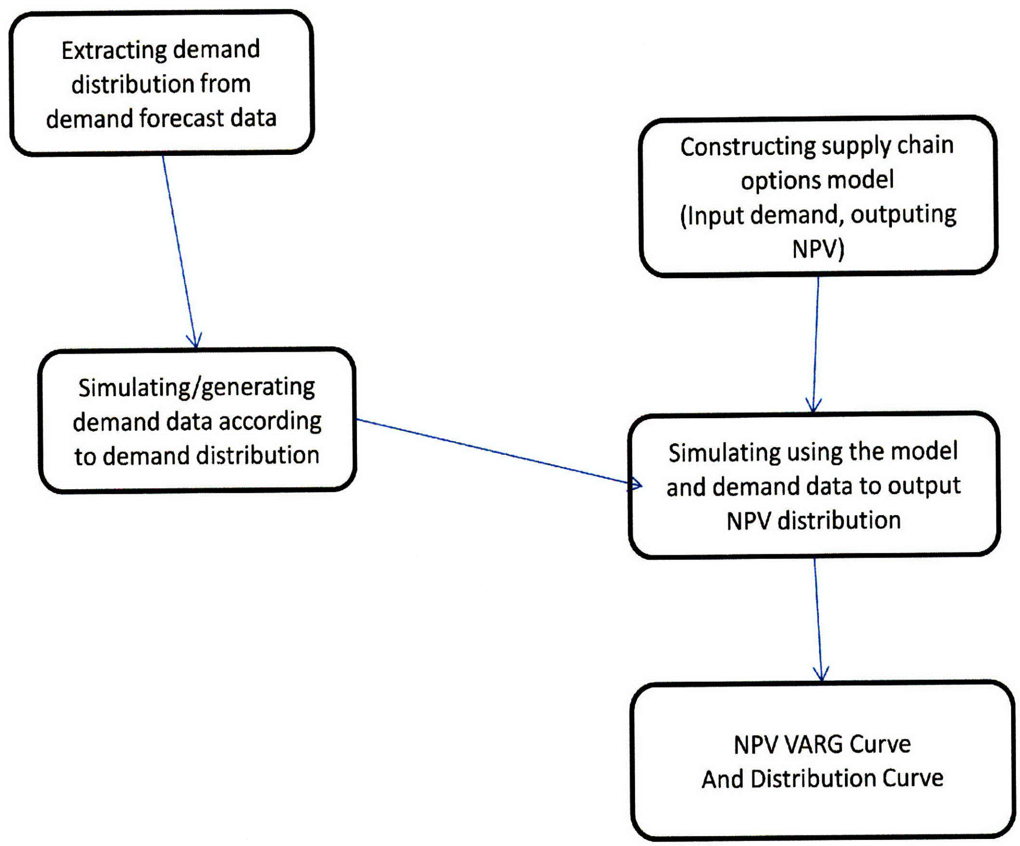

Figure 1. A Generic Monte Carlo Simulation Analysis Approach for Supply Chain Capacity Planning Under Demand Uncertainty

In this analysis, a variable of interest, such as unconstrained demand, is characterized based upon historical data and aggregated expert opinion. A distribution model is built based upon the forecast or expert opinion data. If the data can be fitted into a well understood distribution (such as a normal distribution), individual demands can be generated using many commercially available software tools including a spreadsheet. In Microsoft® Excel, a random demand that follows a normal distribution can be generated using the "NORMINV" function with the rand() function as one of the inputs. The other inputs are the mean and standard deviation of the expected demand distribution.

Figure 2 illustrates the actual analysis and optimization process using spreadsheets. Based upon unconstrained demand distribution estimates and different levels of simulation accuracy, spreadsheet simulations were used to generate a large number of demand data (N=2000 to N=10,000). The demand data were inputted into various supply chain design models to obtain parameters of interests, such as cost NPV distribution and VARG curve, net income NPV distribution and VARG curve. Some supply chain design parameters, such as the size of a dedicated fleet, were optimized using spreadsheet solver.

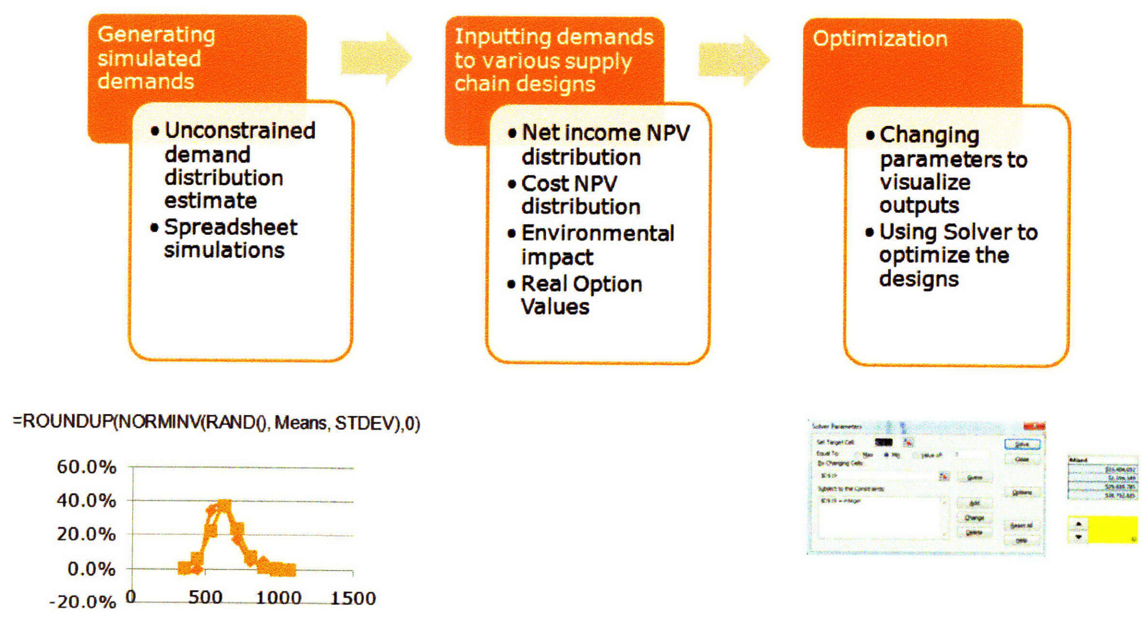

Figure 2. Spreadsheet Monte Carlo Simulation Analysis and Optimization of Supply Chain Decisions

3.2 Chiquita Supply Chain Decisions, Data and Assumptions

The generic approach as described above was used to analyze supply chain decisions using Chiquita data. The data presented in this thesis have been masked to maintain confidentiality in such a way that the masking process does not affect the overall conclusion of the research.

Shipping Plans. Chiquita was interested in comparing current ocean shipping plan versus three other potential ocean shipping plans in terms of costs and their potential impact on overall income derived from Fruit A. The shipping options are listed in Table 1.

Table 1. Ocean Shipping Plans and Their Capacity*

Name	Structure	Capacity, containers/week	Capacity for Fruit A, containers/week
Plan 1	Current small ship	490	425
Plan 2	Two small ship	990	925
Plan 3	One large ship	1000	935
Plan 4	One small ship and one Pallet ship	890	825

**Some Data in this thesis are masked to protect confidentiality of Chiquita Data.*

Plan 1 is the current shipping arrangement where Chiquita charters a ship to transport Fruit A from a foreign region to the United States. The current ship can carry 500 containers for each of its weekly trip. But, the capacity for Fruit A is limited to 425 containers per week because other transportation needs. Chiquita's ocean shipping operation also generates revenue by providing backhaul from the United States to the foreign region. The backhaul demand is considered to be relatively stable at about 435 containers per week. In addition, if there is an excess capacity in the ship, revenue can also be generated by providing front haul using the excess capacity in the Northbound trip. However, the front haul volume is limited by not only available space in the ship (excess capacity), but also the demands for the front haul.

Plans 2-4 all involve charting a new ship that needs to be built. Vessel building will take approximately three years so the models assume that the new ship will be commissioned in year 3. Other than the pallet ship, there is no capital investment from Chiquita other than a commitment to charter the chosen ship for at least three years (Chiquita does not own the vessel.) The time frame for the analysis is 6 years, which include the three years before the new ship can be used.

In addition to the options described above, there are 100 containers available in the market and can be rented. Such containers were assumed to cost $1900 per container per trip in our analyses.

Various costs associated with the shipping options are listed in Table 2 below. For each ship, there is the charting cost, port cost and fuel cost.

Table 2. Costs Associated with Shipping Plans

	Options			
	1	**2**	**3**	**4***
Weekly Cost to Charter Old Ship	$90,000	$90,000	$0	$90,000
Weekly Cost to Charter New Ship	$0	$90,000	$210,577	$104,519
Weekly Port Cost	$58,750	$58,750	$58,750	$58,750
Weekly Fuel Cost	$300,000	$600,000	$570,000	$600,000
Total	$448,750	$868,750	$838,077	$882,644

**There is a one-time capital investment for option 4 (Pallet Ship at Year 2, the third year). Data presented may have been masked to protect confidentiality.*

These weekly costs are calculated based upon annual costs. Other than fuel costs, the other costs are committed for at least three years and cannot be avoided even if a ship does not travel that week.

Trucking Plans. Chiquita is also interested in comparing two trucking plans: common carrier and a dedicated fleet.

Table 3 compares the basic properties of the two options.

Table 3. Comparison of Common Carriers and a Dedicated Fleet

	Common Carrier	Dedicated Fleet
Variable cost, per container	$900	$1,006
Fixed Cost, per truck/per week	$0	$ 1,425
per commercial trips,	$0	$100
Back haul contributing margin, per container	$140	$1,000

The \$1006 variable cost per container for the dedicated fleet includes the variable cost for both front haul and backhaul, whereas the \$900 variable cost for common carrier only covers the front haul cost. The contributing margin is a lot higher for dedicated fleet (\$1000 vs. \$140) because the variable cost per container has already covered the costs of making round trips.

It is worth noting that about 45% of the Fruit A requires trucking, the rest (55%) is picked up at the ports by customers.

Unconstrained Demands. Chiquita's unconstrained demand forecasts for Fruit A were used as the basis to generate a demand forecast table (Appendix 1. Demand Forecast and Price Reaction Table, data masked to preserve confidentiality). The uncertainty of the unconstrained demand is expressed in the form of confidence of achieving (*See, e.g.,* year 5 demand forecast in Table 4). Appendix 1 also lists the projected price reaction for the corresponding weekly container level. By taking market share from competitors, Chiquita expects that there will be a negative market price reaction, either because it is a method of expanding market share or because of competitive reactions. For example, in year 5, if Chiquita were to increase sales from 422 to 617 containers per week, it expects the price of the Chiquita Bananas will drop by about 10%. Conversely, a reduced number of containers of Fruit A to the market can generally increase the price of Fruit A.

Table 4. Exemplary Demand Forecast Distribution

	Weekly Containers	Confidence of Achieving	Price Reaction
Year 5	325	100.0%	15.0%
	422	100.0%	0.0%
	520	100.0%	-5.0%
	617	90.0%	-10.0%
	715	65.0%	-15.0%
	812	25.0%	-20.0%
	910	10.0%	-25.0%
	1007	0.0%	-50.0%

For ocean shipping front haul, the demand is above 50 containers and fewer than 120 containers. The confidence of achieving various levels of weekly front haul containers for ocean shipping is listed in Table 5.

Table 5. Front Haul Demand Forecast

Weekly Loads	*Confidence of Achieving*
50	100%
75	65%
100	25%
120	0%

3.3 Spreadsheet Simulation

Because the increasing power of personal computers and the ubiquity of spreadsheet software such as the Microsoft® Excel, supply chain decision analysts and decision makers have increasingly employed spreadsheet analysis to understand business issues and optimize solutions. In this study, all simulation and other analysis were conducted using Microsoft® Excel with a desktop computer equipped with an Intel®

Core Quad CPU and 3 Gbytes RAM or a portable computer equipped with a Pentium 1.6-GHz Core 2 Duo L7500 process and 2 Gbytes of RAM. The models and simulations were carried out with the simple spreadsheet layouts.

While Microsoft® Excel and other spreadsheet software products offer advanced functions, this research program intended to use the basic functions so that the resulting spreadsheets can be easily modified by those with basic spreadsheet knowledge.

Initially, the Excel® data tables were extensively used for simulations in initial versions. However, as the complexity increases, the performance of data tables became a significant hurdle. In addition, the current data tables in Excel® can only return a single value. Therefore, data tables were replaced with simple sheets.

3.4 Unconstrained Demand Probabilistic Distribution Models

The confidence of achieving provided by Chiquita was interpreted as the probability of achieving the particular level or lower. For example, confidence of achieving 527 containers per week is 50% in year 0. This was interpreted to mean that the probability of achieving 527 containers or lower is 50%. Therefore, the cumulative probability of achieving a particular demand equals to:

$$P_{achieving}^{Cumulative} = 1 - P_{confidence} \qquad \textbf{(Equation 2)}$$

Assuming unconstrained demand follows a normal distribution, the means of the demand forecasts were calculated using weighted average:

$$\mu = \sum_{0}^{n} P_{achieving} \cdot d \qquad \textbf{(Equation 3)}$$

where μ is the mean of the demand forecasts for a particular year; $P_{achieving}$ is the probability of achieving a particular demand and d is the forecasted demand. The standard deviation is calculated using:

$$\sigma = \sqrt{\sum P_{achieving} \cdot (d - \mu)^2} \qquad \textbf{(Equation 4)}$$

The means and standard deviations were used to generate 2,000-10,000 random normally distributed demands using the NORMINV() and RAND() functions (in Microsoft® Excel 2007). Instead of using data tables, each demand cell was coded with the NORMINV functions.

3.5 Ocean Shipping Spreadsheet Models

Shipping and trucking models were constructed according to traditional discount cash flow (DCF) analysis approach. Some of the inputs to shipping models are shown in Figure 3.

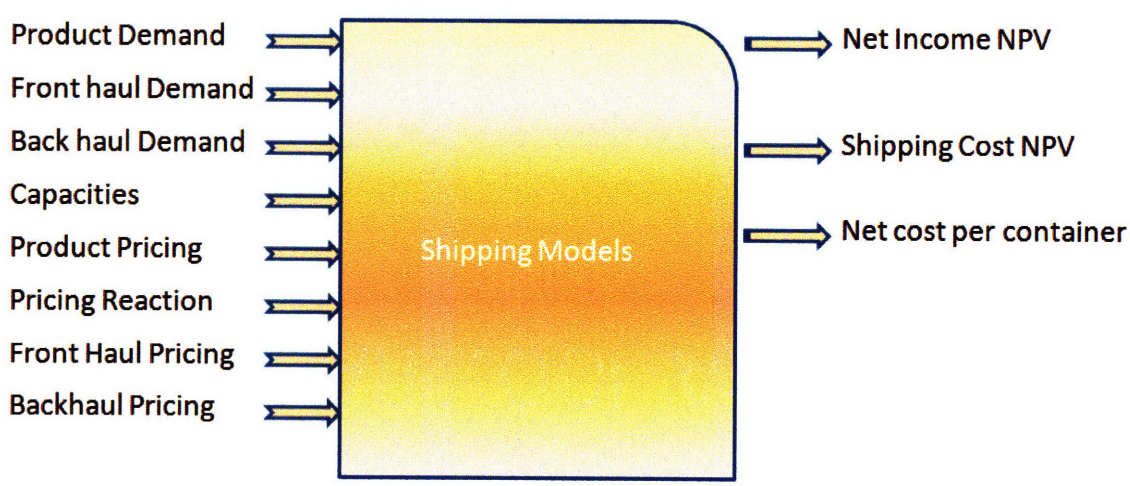

Figure 3. Inputs and outputs of shipping models

In the spreadsheets, all inputs are in cells colored yellow. Product demand inputs were in the format of discrete demand estimate numbers (weekly number of containers) and confidence of achieving these demand estimates (General Data Entries Sheet). These numbers were then used to calculate means and standard deviation as described in Section 3.2 above. The spreadsheets were hard coded to use normal distributions because normal distributions worked pretty well with the Chiquita data supplied. However, if other distributions are desired, the simulation can be easily adopted to use other distributions such as the log normal distribution.

In this particular implementation, demands for each of the six years considered were assumed to be independent. For example, if demand for year 2 was relatively high, demand for year 3 was not assumed to be high. Instead, demand for year 3 was generated completely independent of year 2. This was decided after consultation with Chiquita. However, if correlated demands were desired, it can be easily implemented. A user can generate a matrix of correlated random numbers using methods such as Cholesky decomposition (Haugh, 2004).

The simulated demands were limited to a specified level in the spreadsheet using the function *min*(demand, max demand served). The default for the spreadsheet was to set the maximum demand served value at 2000 containers per week. Because it is higher than any demand that had been observed, the default was in fact no limitation. The maximum demand served, however, can be adjusted to optimize net income. In the spreadsheet, the maximum_demands_served for the six years were made adjustable with Excel Spinner Controls. These cells were also optimized using Microsoft® Excel Solver to maximize net income.

It is straight forward to add additional random variables for Monte Carlo simulation. A user can simply insert columns in the Demand Simulation sheet and code the columns to generate numbers using a desired distribution. The resulting simulation results can be used as inputs for the models. For example, demand for front haul was simulated using the same approach as for product A demand. When there is excess capacity, Chiquita's ships could carry front hauls to generate revenue. The front haul demand data were also inputted in the General Data Entries Sheet in the format of discrete demand estimates and the confidence of achieving these demands. The calculation of means and standard deviation was similar to that of Product A demands. In the same sheet for inputting demand estimate data, a series of graphics were displayed so the accuracy of simulation can be easily visualized.

A generic cost model for a supply chain option includes fixed costs, semi-fixed costs and variable costs. It may also include conditions and flexibility (real options). For example, a shipping approach may allow renting container spaces that do not require prior commitment. In another example, as in the shipping Plan 2 described above, there is the flexibility of using one ship versus two ships if demand is low or there is oversupply in the market .

Individual cost NPVs can be estimated using the following generic equation:

$$CostNPV=\sum\frac{C_{variable}\bullet Min(d_{Capacity}, D_{Unconstraied})+C_{fixed}-(P_{Backhaul}\bullet D_{Backhaul}+P_{Fronthaul}\bullet d_{Fronthaul})}{(1+WACC)^{i}}$$

(Equation 5)

where C is the cost; D is the demand, $WACC$ is the discount rate (typically a weighted average cost of the capital for a company or the project), d is the capacity limit,

P is the price ($/container) that can be charged for back haul or front haul, $d_{Fronthaul}$ is the constrained front haul (limited by available capacity) and i is the period. The cost NPV number can be misleading when the number of container shipped is different among different shipping plans. For example, Plan 1 (one small ship) has maximal capacity of 425 containers per week for product A. Considering commercially available capacity (100 containers per week) that can be rented, the total capacity for Plan 1 is 525 containers per week. In contrast, Plan 2 or 3 have 1025 and 1035 containers per week, respectively. Therefore, Plan 1 is likely to have a lower cost NPV because of its lower number of containers shipped, not necessarily because of better performance.
As one way to compensate the difference in capacity, the costs per container shipped for the various shipping plans were calculated.

If the price is a function of the demand, *e.g.*, there is a typically negative price reaction to increased volume, the overall net income from product sales excluding shipping cost should be considered. Total revenue NPV can be estimated using the following equation:

$$\mathrm{Re}\,venueNPV = \sum \frac{P(Min(d_{Capacity}, D_{Unconstrained})) \bullet Min(d_{Capacity}, D_{Unconstrained})}{(1+WACC)^i}$$

(Equation 6)

where $P(D)$ is the price that is dependent upon the supply. The net income NPV can be calculated by subtracting cost from the revenue:

$$NetincomeNPV = \mathrm{Re}\,venueNPV - CostNPV$$ **(Equation 7)**

In the Excel implementation, shipping costs were treated as occupying one row in either variable or fixed costs. Figure 4, Figure 5, Figure 6 and Figure 7 show the cost tables of the various shipping plans.

SHIPPING PLAN (SP) 1: Existing Ship Only

			Year					
			0	1	2	3	4	5
Variable Cost per container								
	1	Cost to rent per container	$1,900	$1,900	$1,900	$1,900	$1,900	$1,900
	2	Other costs	$0	$0	$0	$0	$0	$0
		Total	$1,900	$1,900	$1,900	$1,900	$1,900	$1,900
Fixed Cost								
	1	Weekly Cost to Charter Old Ship	$90,000	$90,000	$90,000	$90,000	$90,000	$90,000
	2	Weekly Cost to Charter New Ship	$0	$0	$0	$0	$0	$0
	3	Weekly Port Cost	$58,750	$58,750	$58,750	$58,750	$58,750	$58,750
	4	Weekly Fuel Cost	$300,000	$300,000	$300,000	$300,000	$300,000	$300,000
	5	Other costs	$0	$0	$0	$0	$0	$0
		Total	$448,750	$448,750	$448,750	$448,750	$448,750	$448,750

Figure 4. Cost Model of Shipping Plan 1

SHIPPING PLAN 2: Two Small Ships

			Year					
			0	1	2	3	4	5
Variable Cost per container								
	1	Cost to rent per container	$1,900	$1,900	$1,900	$1,900	$1,900	$1,900
	2	Other costs	$0	$0	$0	$0	$0	$0
		Total	$1,900	$1,900	$1,900	$1,900	$1,900	$1,900
Fixed Cost								
	1	Weekly Cost to Charter Old Ship	$90,000	$90,000	$90,000	$90,000	$90,000	$90,000
	2	Weekly Cost to Charter New Ship	$0	$0	$0	$90,000	$90,000	$90,000
	3	Weekly Port Cost	$58,750	$58,750	$58,750	$88,750	$88,750	$88,750
	4	Weekly Fuel Cost	$300,000	$300,000	$300,000	$600,000	$600,000	$600,000
	5	Other costs	$0	$0	$0	$0	$0	$0
		Total	$448,750	$448,750	$448,750	$868,750	$868,750	$868,750

Figure 5. Shipping Cost Model in Excel for Shipping Plan 2 (Two Small Ships)

SHIPPING PLAN 3: New large Ship							
		Year					
		0	1	2	3	4	5
Variable Cost per container							
1	Cost to rent per container	$1,900	$1,900	$1,900	$1,900	$1,900	$1,900
2	Other costs	$0	$0	$0	$0	$0	$0
	Total	$1,900	$1,900	$1,900	$1,900	$1,900	$1,900
Fixed Cost							
1	Weekly Cost to Charter Old Ship	$90,000	$90,000	$90,000	$0	$0	$0
2	Weekly Cost to Charter New Ship	$0	$0	$0	$209,327	$209,327	$209,327
3	Weekly Port Cost	$58,750	$58,750	$58,750	$58,750	$58,750	$58,750
4	Weekly Fuel Cost	$300,000	$300,000	$300,000	$570,000	$570,000	$570,000
5	Other costs	$0	$0	$0	$0	$0	$0
	Total	$448,750	$448,750	$448,750	$838,077	$838,077	$838,077

Figure 6. Cost Model in Excel for Shipping Plan 3 (One large ship)

SHIPPING PLAN 4: Pallet Ship							
		Year					
		0	1	2	3	4	5
Variable Cost per container							
1	Cost to rent per container	$1,900	$1,900	$1,900	$1,900	$1,900	$1,900
2	Other costs	$0	$0	$0	$0	$0	$0
	Total	$1,900	$1,900	$1,900	$1,900	$1,900	$1,900
Fixed Cost							
1	Weekly Cost to Charter Old Ship	$90,000	$90,000	$90,000	$90,000	$90,000	$91,250
2	Weekly Cost to Charter New Ship	$0	$0	$0	$104,519	$104,519	$104,519
3	Weekly Port Cost	$58,750	$58,750	$58,750	$88,125	$88,125	$88,125
4	Weekly Fuel Cost	$300,000	$300,000	$300,000	$600,000	$600,000	$600,000
	Capital Investment, per week	$0	$0	$38,462	$0	$0	$0
5	Other costs	$0	$0	$0	$0	$0	$0
	Total	$448,750	$448,750	$487,212	$882,644	$882,644	$883,894

Figure 7. Shipping Cost Model in Excel for Ocean Shipping Plan 4 (a Small Ship plus a Pallet Ship)

Ocean shipping Plans 2 and 4 have the flexibility of using one ocean ship instead of two. The value of flexibility like this can be estimated using real option analysis. The value of a real option was estimated according to de Neufville et al. (2006).

3.6 Inland Trucking Spreadsheet Models

Inland trucking Plan 1 uses common carriers only. There are a number of common carriers available in the market with varying availability and prices. The variability of prices could, for example, be simulated like the demands. In this research, we did not simulate these additional variables. Instead, we used the average cost of common carriers per container, which is approximately $900 per container. There was no fixed cost. It was assumed that 40% of the Product A containers from ocean ship(s) were transported by inland trucking by Chiquita. The rest of the containers were picked up by customers.

Inland trucking Plan 2 uses a dedicated fleet only. A dedicated fleet has fixed costs and variable costs. The fixed fleet cost depends upon the number of trucks needed. Dedicated fleet trucks on average can transport 3.6 containers per week. The maximum number of containers to be trucked per week was about 440 (maximum demand x 40%) in the six year period and therefore, the number of trucks in the dedicated fleet to ensure 100% availability was 440/3.6 = 127 trucks. While this large size of dedicated fleet can ensure the availability, it has too much excess capacity. In a practical implementation, the size of dedicated fleet is likely to be smaller. If demand exceeds the capacity of the fleet, it is likely that Chiquita will use common carriers to provide the capacity needed. Trucking Plan 3 is a combination of a dedicated fleet and common carriers. The size of the dedicated fleet was allowed to be adjusted using a spinner on the trucking summary sheet. This parameter was also optimized using Microsoft® Excel Solver.

4 Results

The goal of the research is to provide computational models that help companies like Chiquita to visualize the effect of various demand uncertainty on supply chain investment options. The models were based upon computational simulation of demands and evaluation of the various supply chain plans under the simulated demands. Various outputs, such as net income, costs, and cost per container, were analyzed using Value at Risk and Gain Curves.

4.1 Demand Models

Figure 8 shows the simulated demand distributions versus demand distribution inputs. The figure shows that the simulated demands generally follow closely with the data input. Figure 9 shows the corresponding cumulative distribution functions (CDFs).

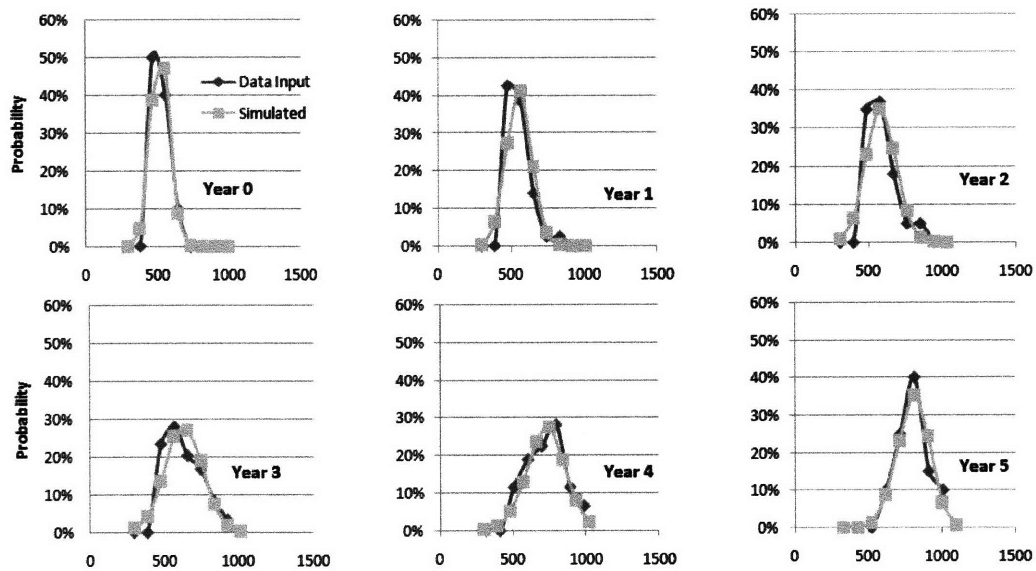

Figure 8. Simulated and Inputted Demand Distribution

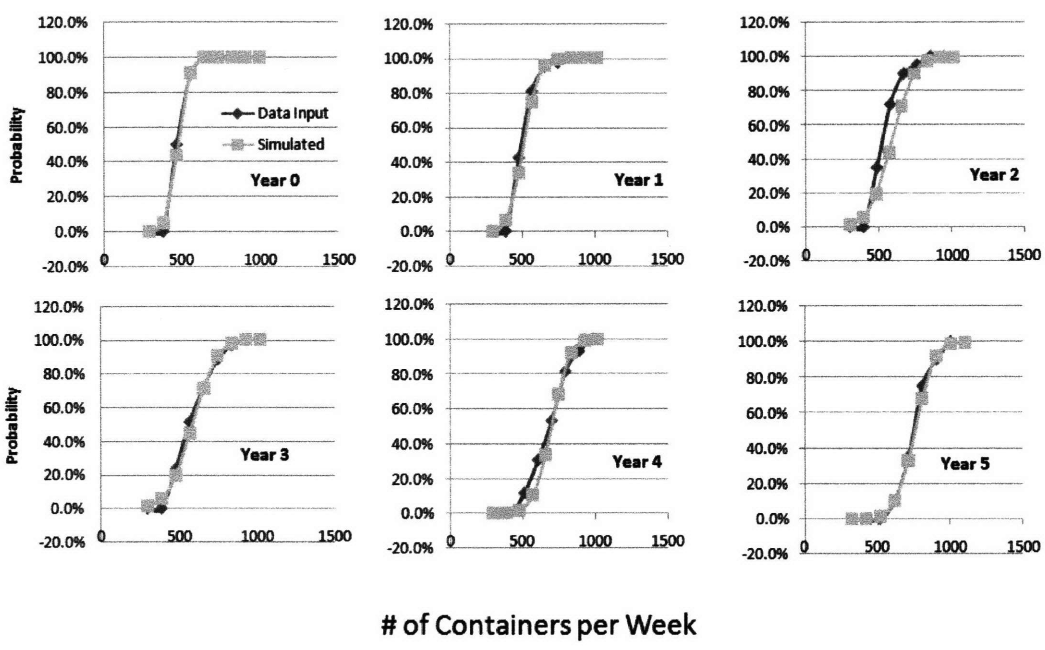

Figure 9. Simulated and Inputted Demand CDFs

The CDF curves seem less prone to variations caused by random errors. As can be seen, the simulated demands generally match with the inputted data.

While most of the analyses were performed with the assumption that the demand distributions for each year are not correlated, the spreadsheets implemented one version of the correlated random numbers. Table 6 shows the correlation of resulting simulated demands.

Table 6. Correlations of Demands between Years

Year 1	*Year 2*	*Year 3*	*Year 4*	*Year 5*
0.602995	0.587098	0.605379	0.601242	0.584586

4.2 Costs of Ocean Shipping

Total costs of various ocean shipping plans (NPV basis) are listed in Table 7. Revenues generated via ocean shipping, *i.e.*, front haul and backhaul, are deducted from the costs. Plan 1 has the lowest cost NPV. However, Plan 1, a single ship with available capacity of 525 containers per week, does not meet the demand in a significant number of the cases.

Table 7. Ocean Shipping Costs

	Plan 1	Plan 2	Plan 2 with Real Option	Plan 3	Plan 4	Option 4 with Real Option
	Old Ship	*New Small Ship + Old Ship*	New Small Ship+Old Ship	*New Large Ship*	*Pallet Ship+ Old Ship*	*Pallet Ship+ Old Ship*
NPV	$2,757,121	$18,314,143	$15,697,018	$15,235,092	$23,821,882	19,893,865
STDEV	$7,614,438	$7,462,545	$7,984,378	$7,438,848	$8,038,016	8,211,118
MIN	($26,903,747)	($11,997,645)	($14,013,277)	($14,947,005)	($8,033,136)	(11,075,708)
MAX	$15,836,690	$38,058,814	$36,001,010	$34,573,207	$45,902,171	40,821,002
90 percentile	$12,477,490	$27,656,468	$25,845,156	$24,508,740	$33,727,951	$30,278,101
10 percentile	($7,538,447)	$8,382,222	$5,027,245	$5,408,472	$13,259,734	$8,848,513

Table 8 shows the projected weekly overcapacity for the current ship. The red numbers in parenthesis indicate that the demand forecast exceeds the capacity of the ship. This capacity does not include the 100 containers that could be available from commercial container leases. In almost all years, the current ship would not be able to meet the expected demand in the majority of cases (particularly years 3, 4 and 5).

Table 8. Projected Weekly Overcapacity for Current Ship

	Years					
	0	1	2	3	4	5
Mean	(50)	(86)	(114)	(159)	(249)	(334)
STEV	59	83	101	124	130	106
Min	(216)	(410)	(428)	(500)	(562)	(583)
Max	144	178	203	233	278	(6)

Shipping Plans 2, 3, and 4 (*See*, Table 9, Table 10 and Table 11, respectively) generally meet the capacity demands in years 3, 4 and 5. Since the new ships will be available in year 3, the numbers for the first three years are the same for all shipping plans.

Table 9. Projected Weekly Overcapacity for Ocean Shipping Plan 2

	Years					
	0	1	2	3	4	5
Mean	(50)	(86)	(114)	341	251	166
STEV	59	83	101	124	130	106
Min	(216)	(410)	(428)	0	(62)	(83)
Max	144	178	203	733	778	494

Table 10. Projected Weekly Overcapacity for Ocean Shipping Plan 3

	Years					
	0	1	2	3	4	5
Mean	(50)	(86)	(114)	351	261	176
STEV	59	83	101	124	130	106
Min	(216)	(410)	(428)	10	(52)	(73)
Max	144	178	203	743	788	504

Table 11. Projected Weekly Overcapacity for Ocean Shipping Plan 4

	Years					
	0	1	2	3	4	5
Mean	(50)	(86)	(114)	241	151	66
STEV	59	83	101	124	130	106
Min	(216)	(410)	(428)	(100)	(162)	(183)
Max	144	178	203	633	678	394

Ocean shipping Plans 2-4 have the maximum capacity of 1025, 1035, and 925 containers per week, respectively, and they have the capacity to meet the majority of the simulated demands. Plan 3 has the largest capacity, but the cost is the lowest among the new shipping plans at $15 million versus $18 million and $24 million for Plan 2 and 4, respectively. Both Plan 2 and Plan 4 offer the flexibility (real option) of using one ship if the demand becomes known at the beginning of the year, instead of two ships. This real option significantly reduces the costs for Plans 2 and 4 by approximately $2.6 million (Plan 2) and $3.9 million (Plan 4), respectively. In this analysis, the decision to use one ship versus two ships was made based upon which alternative generates the higher net income. Because of contractual commitments, even if only one of the two ships is used for that year, Chiquita will still need to pay charter costs and port costs. Therefore, the savings from using one ship is primarily through savings in fuel consumption.

Figure 10 shows the distribution of cost NPVs for the ocean shipping plans. Because the ocean ship costs, such as fuel, port and chartering costs, are basically fixed and do not vary, the variations in overall costs are caused by the need for renting additional containers and variations in revenues generated by front haul and backhaul. The demand for front haul is randomly distributed and is simulated in this analysis. Back haul demand is proportional to the number of containers front haul shipped per week. The cost of Plan 1 is much lower than these of other plans. This is primarily due to capacity limitation.

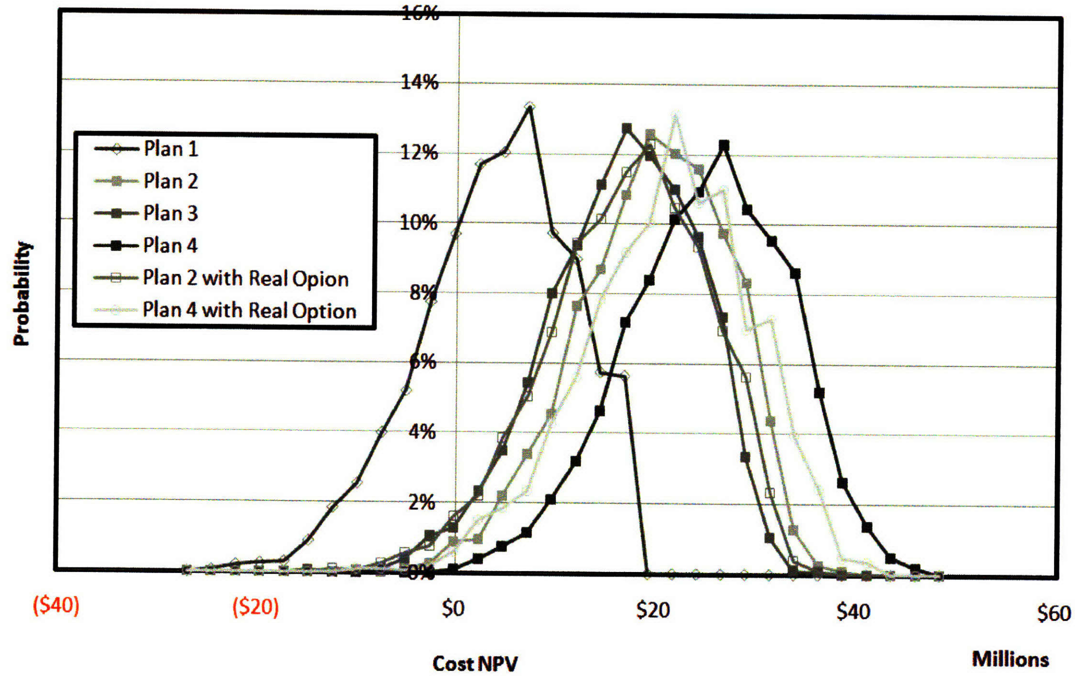

Figure 10. Cost Distribution

Otherwise, cost distributions generally follow a similar pattern. Plan 4, without real option, has the highest cost. The flexibility of using one ship reduces costs for both Plan 2 and Plan 4. Considering the flexibility, Plan 2 with real option has the lowest costs among the three potential ocean shipping plans. Figure 11 shows the cumulative probability distribution functions of various ocean shipping plans. In addition, back haul and front haul shipping income is approximately the same for all the plans.

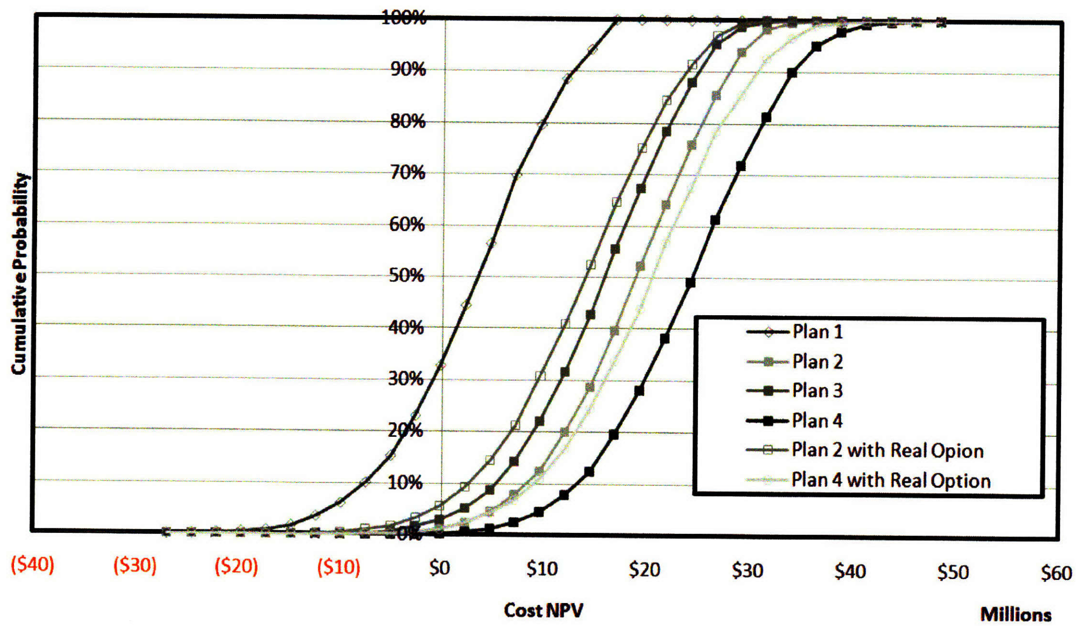

Figure 11. Cumulative Distribution Function of Various Ocean Shipping Plans

Because the shipping capacities of the different ocean shipping plans are different, it is worth examining the shipping cost per container (Table 12). Plan 1 has the lowest expected average shipping cost at just $19 per container. The very low cost number and negative values indicate that the revenue generated in ocean shipping exceeds the costs, where the ocean shipping operation is profitable. The second lowest cost per container is achieved with Plan 3 with an expected cost per container at about $114. The option to use a single ship instead of two reduces the expected average shipping costs significantly for Plan 2 and Plan 4. But even with real options, Plan 2 and Plan 4 still have higher costs per container. This is expected. While the flexibility of using one ship reduces cost and improves net income (*see*, section below), at least in some cases, using one ship reduces the number of containers shipped.

Table 12. Shipping Cost Per Container

	Plan 1	Plan 2	Plan 2 with Real Option	Plan 3	Plan 4	Option 4 with Real Option
	Old Ship	*New Small Ship + Old Ship*	New Small Ship+Old Ship	*New Large Ship*	*Pallet Ship+ Old Ship*	*Pallet Ship+ Old Ship*
Cost per container	$19	$139	$114	$114	$180	$147
STDEV	$73	$67	$70	$67	$67	$69
MIN	-$327	-$160	-$195	-$185	-$124	-$153
MAX	$128	$342	$251	$293	$382	$290

Plan 1 has the lowest shipping cost primarily because of back haul. International ocean back haul volume was fixed at 435 containers per week. Additional back haul capacities in Plans 2 to 4 were not utilized. If this assumption is changed, the costs for different ocean shipping plans, particularly for Plans 2 to 4, will likely change.

Table 13 shows the number of containers shipped per year for all the plans. During the first three years, all the plans have the same number of containers shipped, simply because the new plans will not be providing additional capacity until year 3. It is worth noting that Plan 2 with one ship option only reduced the annual mean of containers shipped in year 5 from 39449 to 39236, with a difference of 213 containers in the entire year. This indicates that the one ship option was not used frequently. In year 3, the mean of container shipped for Plan 2 is 30359. Option to use one ship reduces the mean to 28,824, with a difference of 1,535 containers per year. The difference here may reflect the fact the forecasted demand mean is higher in year 5 versus that in year 3. When demand is lower, it is more likely that using a single ship saves cost and improves net income. If the demand is higher, two ships, particularly one single larger ship will perform better.

Table 13. Total Number of Containers Shipped per Year

		Years					
		0	1	2	3	4	5
Plan 1	Mean	24,341	25,175	25,545	25,962	26,859	27,279
	Stdev	2,545	2,765	2,812	2,749	1,577	216
	Min	14,612	12,844	11,544	9,984	7,644	22,412
	Max	27,300	27,300	27,300	27,300	27,300	27,300
Plan 2	Mean	24,341	25,175	25,545	30,359	35,048	39,449
	Stdev	2,545	2,765	2,812	6,465	6,742	5,504
	Min	14,612	12,844	11,544	9,984	7,644	22,412
	Max	27,300	27,300	27,300	48,100	51,324	52,416
Plan 2 with one ship option	Mean	24,341	25,175	25,545	28,824	33,942	39,236
	Stdev	2,545	2,765	2,812	5,257	6,146	5,484
	Min	14,612	12,844	11,544	9,984	7,644	22,412
	Max	27,300	27,300	27,300	38,740	46,228	52,312
Plan 3	Mean	24,341	25,175	25,545	30,359	35,048	39,449
	Stdev	2,545	2,765	2,812	6,465	6,742	5,504
	Min	14,612	12,844	11,544	9,984	7,644	22,412
	Max	27,300	27,300	27,300	48,100	51,324	52,416
Plan 4	Mean	24,341	25,175	25,545	30,359	35,002	39,346
	Stdev	2,545	2,765	2,812	6,465	6,644	5,309
	Min	14,612	12,844	11,544	9,984	7,644	22,412
	Max	27,300	27,300	27,300	48,100	48,100	48,100
Plan 4 with one ship option	Mean	24,341	25,175	25,545	28,824	33,839	39,346
	Stdev	2,545	2,765	2,812	5,257	6,100	5,309
	Min	14,612	12,844	11,544	9,984	7,644	22,412
	Max	27,300	27,300	27,300	38,740	45,656	48,100

4.3 Net Income of Ocean Shipping

While Chiquita desires to expand its market share for Product A, it needs to consider the price reactions. Figure 12 shows the forecasted price reactions (% of price increase) versus weekly number of containers of product A sold in the market.

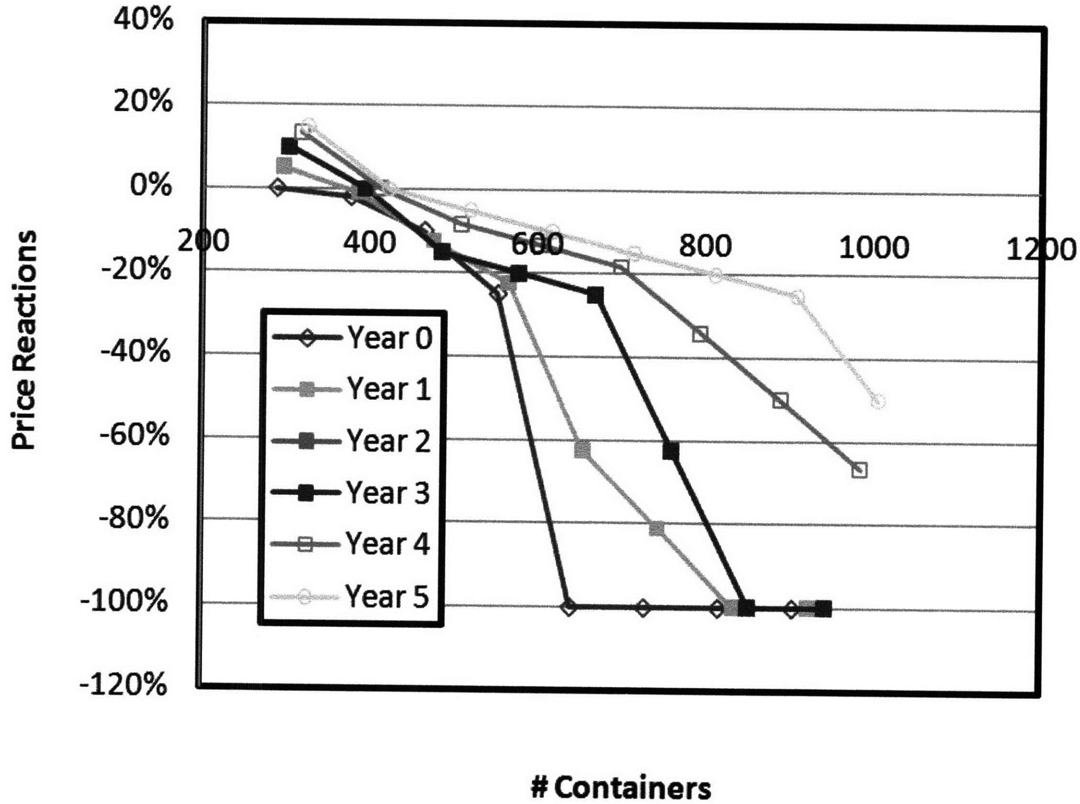

Figure 12. Forecasted Price Reaction to Chiquita's Sales of Product A in the Relevant Market

In some cases, the price reaction can be dramatic, *i.e.* "crash and burn" (treated as -100% in this research). Even a moderate increase in market share can result in significant price reduction. Therefore, it is important to consider price reaction in supply chain planning. In this research, we assumed that the product A gross margin excluding ocean shipping is 20%. Therefore, the net income is: revenue*20% - shipping cost. Table 14 summarizes the net income of various ocean shipping plans. Among the four plans, Plan 3 has the largest net income at $212.0 million versus, $209.9, $208.9, and $203.5 million for Plans 1, 2, and 4, respectively.

Table 14. Net Income NPV Comparison

	Plan 1	Plan 2	Plan 2 with Real Option	Plan 3	Plan 4	Plan 4 with Real Option
	Old Ship	*New Small Ship + Old Ship*	New Small Ship+Old Ship	*New Large Ship*	*Pallet Ship+ Old Ship*	*Pallet Ship+ Old Ship*
NPV	$209,942,775	$208,930,448	$211,999,500	$212,009,498	$203,484,006	$206,972,069
STDEV	$2,951,803	$8,373,504	$6,142,011	$8,348,666	$8,661,524	$5,838,046
MIN	$195,646,424	$174,434,031	$190,490,223	$177,750,156	$161,898,121	$187,552,655
MAX	$220,056,496	$232,397,110	$232,397,110	$235,671,041	$226,213,837	$226,213,837
Option Value	$0	$0	$3,069,052	$0	$0	$3,488,064
90 percentile	$213,814,377	$219,040,602	$220,061,402	$222,073,475	$214,010,274	$214,896,299
10 percentile	$206,685,834	$198,455,491	$204,155,089	$201,438,461	$192,925,095	$199,482,785

However, both Plans 2 and 3 offer the flexibility of using one ship only at years 3, 4, and 5 if the estimated net income is higher with using one ship. This can happen in cases where the actual demand does not warrant the two ships. It can also happen because of negative price reaction if too much Product A is entered into the market. Plan 3 does not have this option.

When the flexibility or real option is considered, Plan 2's expected net income ($212.0 million) is the same as Plan 3. Plan 4 with real option also improves expected net income significantly, but it is still lower than Plan 3. The value of the real option for Plan 2 is approximately $3.1 million. At 90 percentile, Plan 3 is at $222 million versus the $220 million for Plan 2 with real option, indicating the Plan 3 may be better at capturing upside potential (lower cost per container if the actual demand is high in years 3-5). At 10 percentile, Plan 2 with real option ($204 million) is higher than that with Plan 3 ($201 million), which shows that Plan 2 with real option is better at minimizing the risk of lower net income. Overall, Plan 2 with real option has a smaller standard deviation than Plan 3.

Figure 13 shows net income distribution and Figure 14 is the Cumulative Distribution Function (CDF) or Value at Risk and Gain VARG curve of the same comparison.

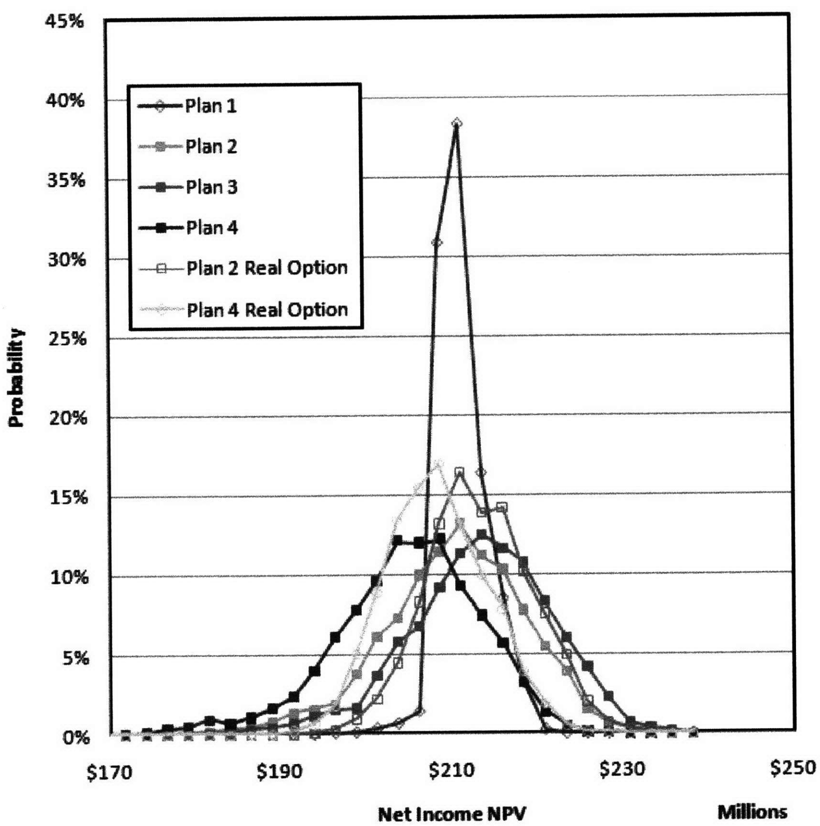

Figure 13. Distribution of Net Income NPV

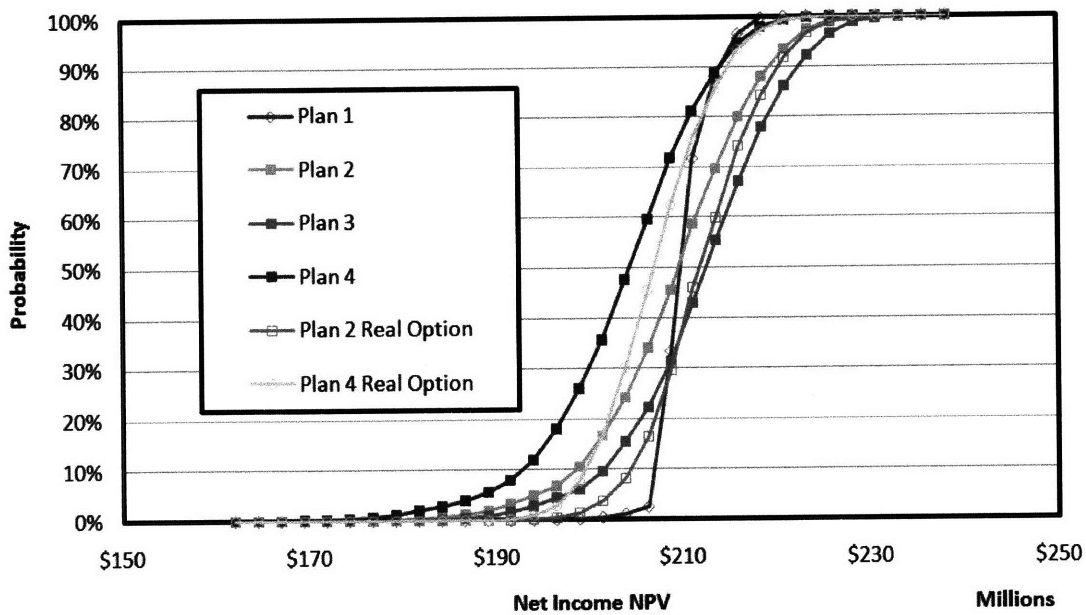

Figure 14. Net Income Risk and Gain Curve

Net income for Plan 1 has a sharp distribution centered on its mean of $210 million (NPV over six years). Figure 15 are histograms of the same data as in Figure 13. Plan 2 has the sharpest distribution. Plans 2, 3 and 4 share similar distribution patterns, while Plan 3 has the highest expected net income and Plan 4 has the lowest. The option to use one ship makes the distributions of both Plan 2 and 5 sharper.

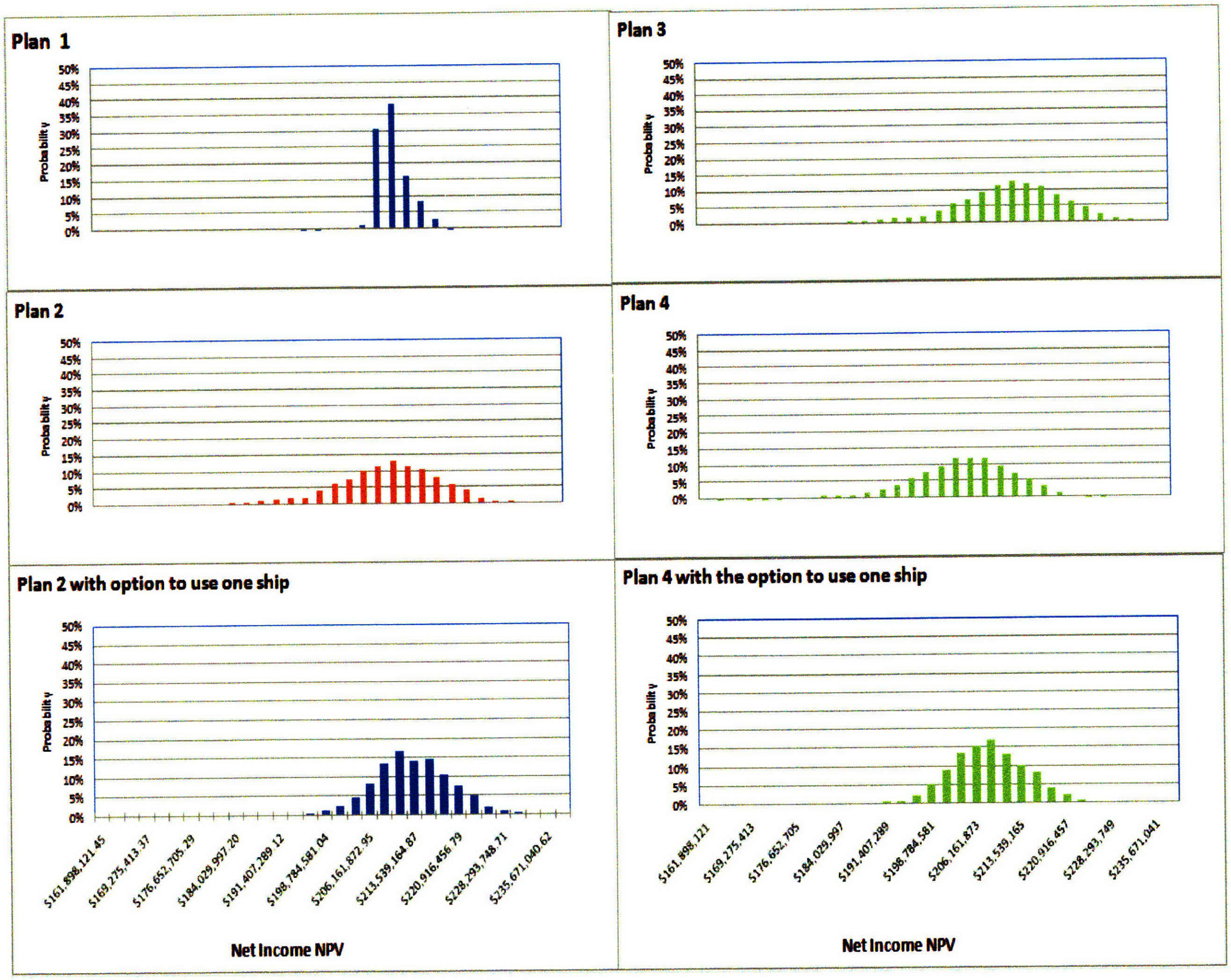

Figure 15. Histogram of Net Income Distribution

Figure 16 focuses on the VARG comparison of Plan 2, Plan 2 with real option, and Plan 3.

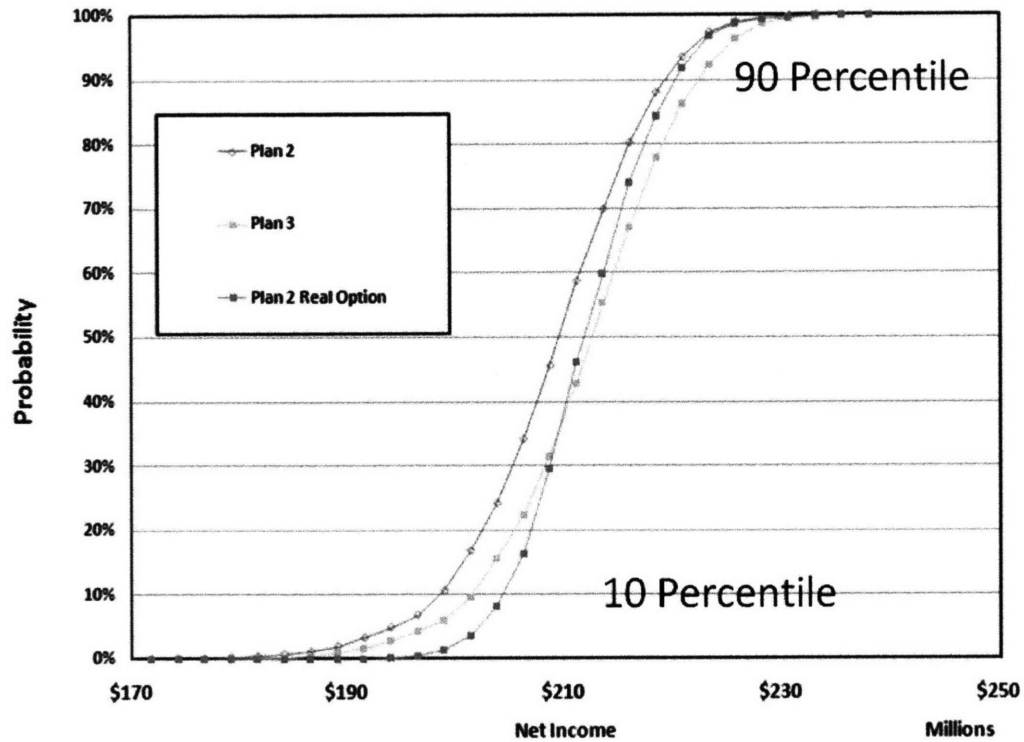

Figure 16. VARG curve for Ocean Shipping Plans 2 and 3

The real option significantly shifted the VARG curve of Plan 2 to the right, particularly at the lower end, which improves net income. Comparing with Plan 2, the net income of Plan 2 with real option reduced the low end risk.

The distribution of the net income shows the same pattern (see Figure 17). The option to use one ship shifts the distribution to the right, thus increases the mean.

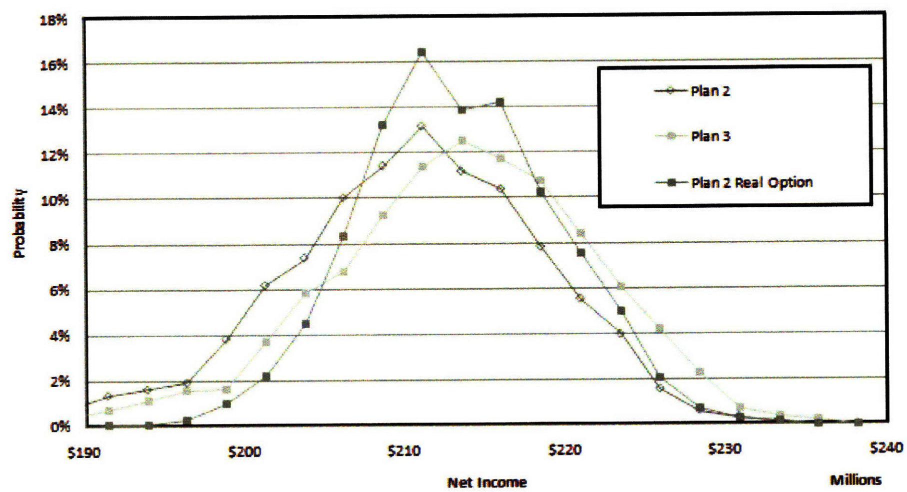

Figure 17. Distribution of Net Income for Plans 2 and 3

Part of the improvement of net income by real options in Plan 2 and 4 was primarily due to reduction in shipping costs. This is because the expected revenues for Plans 2 and Plan 3 with real option were lower than those of Plans 2 and 3 without real option. In other words, the real option improved net income. This can happen despite a reduction in revenue.

Table 15 lists the revenue of various shipping plans. Plan 1 has the lowest revenue. This is expected because Plan 1 is severely limited in its capacity, particularly in years 3-5. Appendix 4 lists the annual revenue data.

Table 15. Product A Revenue

	Plan 1	Plan 2	Plan 2 with Real Option	Plan 3	Plan 4	Plan 4 with Real Option
	Old Ship	*New Small Ship + Old Ship*	New Small Ship + Old Ship	*New Large Ship*	*Pallet Ship+ Old Ship*	*Pallet Ship+ Old Ship*
NPV	$1,063,499,480	$1,136,222,952	$1,138,482,588	$1,136,222,952	$1,136,529,440	$1,138,541,508
STDEV	$31,531,571	$41,533,472	$39,463,188	$41,533,472	$41,110,755	$39,170,692
MIN	$863,773,637	$902,865,746	$903,031,174	$902,865,746	$902,865,746	$903,031,174
MAX	$1,112,103,488	$1,240,250,309	$1,240,250,309	$1,240,250,309	$1,240,250,309	$1,240,250,309

Figure 18 shows the distribution of revenue of the different ocean shipping plans. Plan 1's revenue distribution is skewed around $1.1 billion (over six years). This is caused by the capacity limitation. Plans 2 and 3 generate exactly the same amount of revenue simply because their shipping capacities are basically the same and we use the same simulated demands to test all the Shipping Plans. Plan 4 has slightly lower revenue because it has a lower capacity.

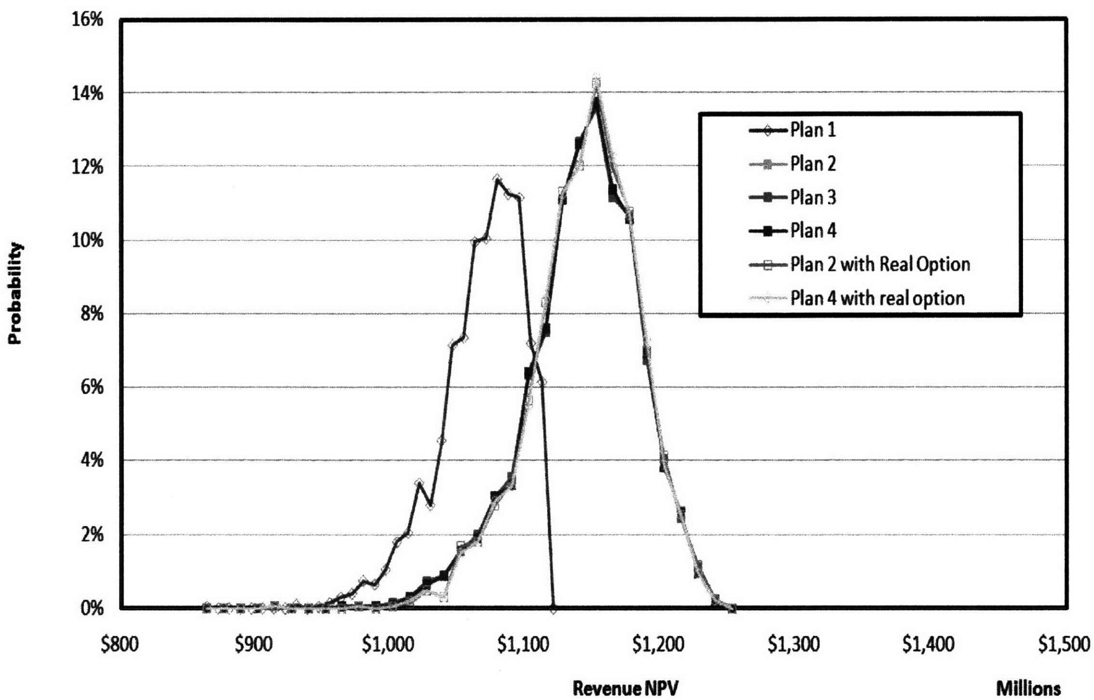

Figure 18. Revenue Distribution

The option to use one ship increases the overall revenue. Figure 19 shows the VARG curve for revenues. The flexibility shifts the VARG curve to the right and increases revenues.

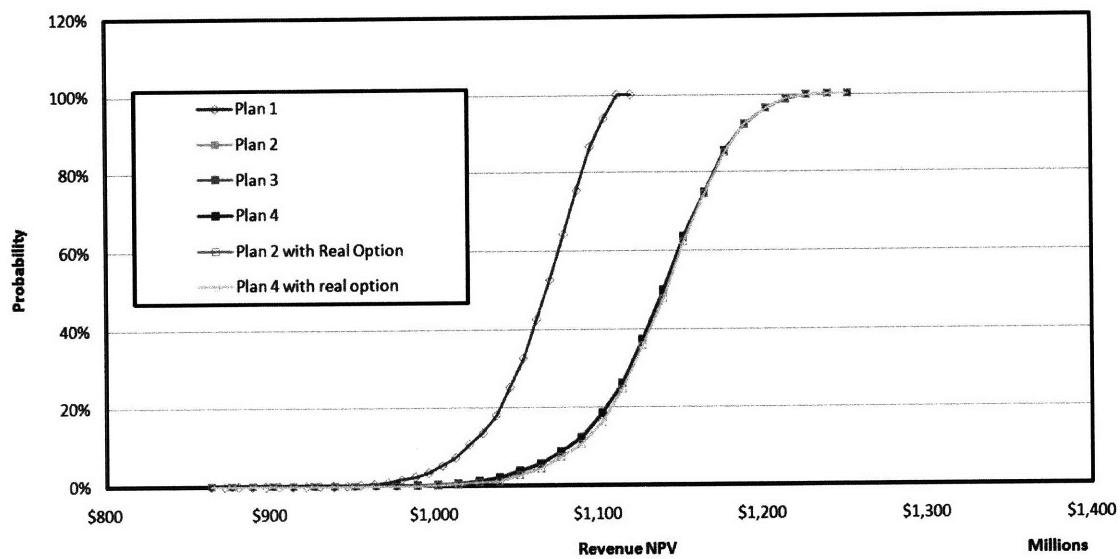

Figure 19. Cumulative Distribution Function of Revenues from Different Shipping Plans

4.4 Ocean Shipping Optimization

Chiquita can also optimize the net income by potentially limiting the amount of Product A supplied to the market place. This can be performed by using the Excel Solver. In addition, by changing the volume cap cells in the ocean shipping summary sheet, one can also observe the changes in net income values.

By both the Solver or manual method (adjusting spinners), the optimized net incomes for shipping Plan 3 can be improved to $223 million by limiting the number of containers supplied to the market. Plan 2 with real option can achieve 222 million (Table 16).

Table 16. Net Income for Shipping Plans Optimized

for Plan 2 with Real Option and Plan 3

	Plan 1	Plan 2	Plan 2 with Real Option	Plan 3	Plan 4	Plan 4 with Real Option
	Old Ship	New Small Ship + Old Ship	New Small Ship+Old Ship	New Large Ship	Pallet Ship+ Old Ship	Pallet Ship+ Old Ship
NPV	$217,306,481	$220,207,609	$222,555,477	$223,263,421	$214,696,023	$217,249,471
STDEV	$1,978,276	$6,278,353	$4,702,421	$6,317,783	$6,107,446	$4,318,249
MIN	$199,658,474	$182,510,367	$194,619,511	$185,459,727	$179,572,798	$191,681,943
MAX	$223,041,584	$237,284,308	$237,284,308	$240,233,668	$229,567,943	$229,567,943
Option Value	$0	$0	$2,347,867	$0	$0	$2,553,448
90 percentile	$219,595,665	$227,804,634	$228,391,590	$230,928,904	$222,380,200	$222,782,038
10 percentile	$215,403,430	$211,957,829	$216,364,143	$214,929,368	$206,491,440	$211,858,327

The optimized shipped container limitations are listed in Figure 20. For years 0 to 2, the limitations are at 461, 464 and 464 containers per week, respectively. This is mainly due to the high rental cost per container, much higher than the average cost by Chiquita's own ship. In addition, the rented containers do not generate any shipping revenue. The optimization tried to minimize the need for container rental.

Optimization

	Demand Served, containers/week					
	Years					
	0	1	2	3	4	5
Volume Cap, containers	461	464	464	827	890	883

Figure 20. Optimized Amount of Product A to be Supplied to the Market

4.5 The Effect of Fuel Cost

One of the biggest downside risks for ocean shipping is the increase in fuel costs (Andel, 2007). Therefore, we conducted a sensitivity analysis with regard to fuel cost increases. Figure 21 shows that fuel cost has a major negative impact on net income. The ability to use one ship in Plan 2 significantly slows the decline. The value of the real option increases significantly as fuel cost increases (Figure 22). Therefore, Plan 2 with the ability to use one ship can be a good choice if Chiquita expects that there is significant risk of higher fuel cost in the future.

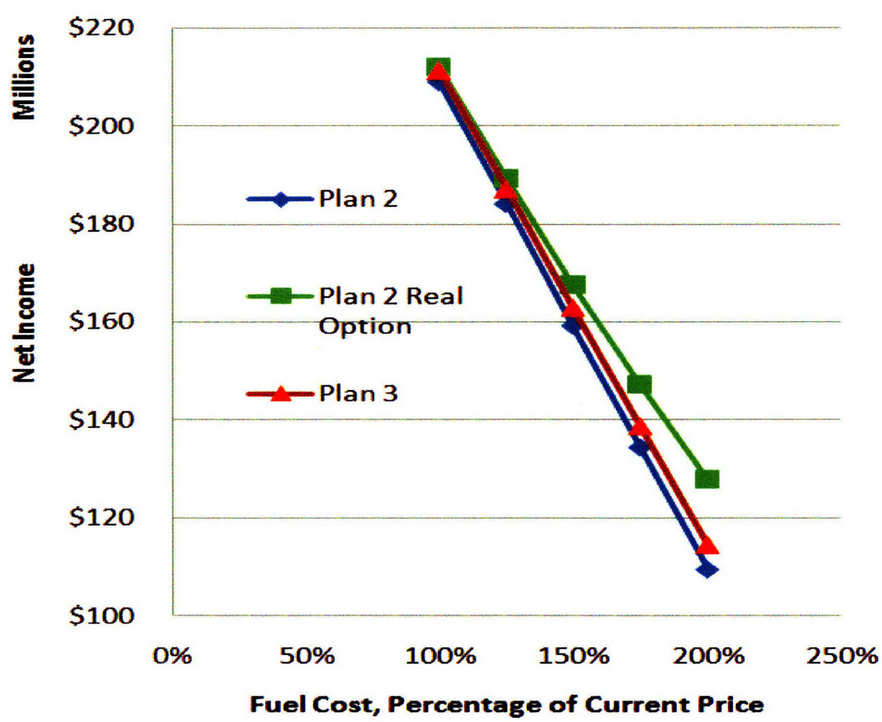

Figure 21. Effect of Fuel Cost on Net Income

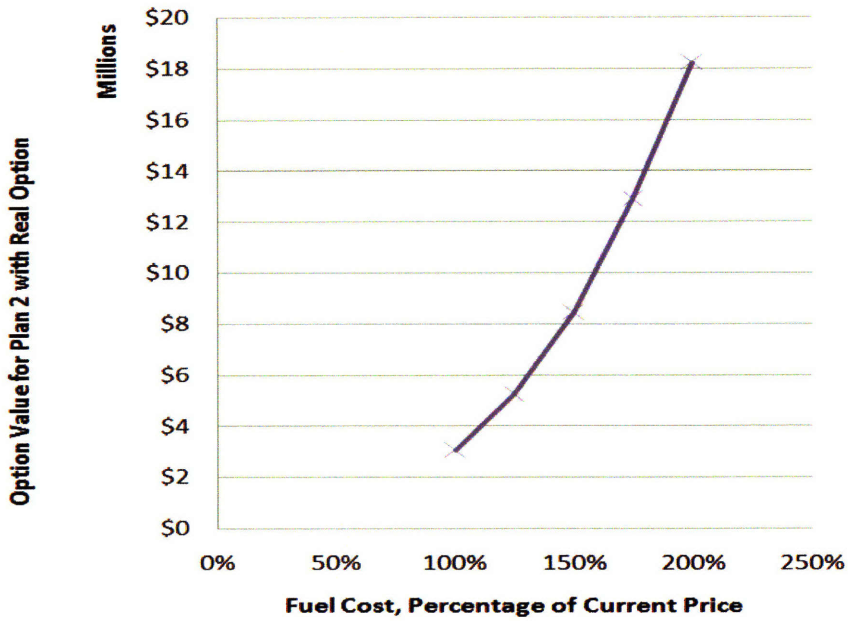

Figure 22. Effect of Fuel Cost on Option Value of Plan 2

4.6 Costs of Inland Trucking

The distribution patterns of the costs of common carrier and dedicated fleet are very similar. It is worth noting that in the dedicated fleet only option, the size of the dedicated fleet is quite large in order to ensure availability. Reducing the size of the dedicated fleet could decrease its fixed costs.

Table 17. Costs of Inland Trucking

	Dedicated Fleet	Common Carrier	Mixed
Cost NPV	$39,538,930	$43,322,180	$32,084,449
STDEV	$1,993,021	$2,406,276	$1,884,097
MIN	$29,970,989	$31,770,316	$23,784,051
MAX	$45,691,511	$50,750,505	$38,436,919

The last column of Table 17 shows the costs of a mixed arrangement. In this mixed arrangement, Chiquita would maintain a small dedicated fleet, but will use common carriers if the dedicated fleet could not meet the need. In the spreadsheet implementation, the size of the fleet is adjustable using spinners. It can also be optimized using the Microsoft® Excel Solver. The results shown in Table 17, Figure 23 and Figure 24 were obtained after the dedicated fleet size is optimized at the capacity of transporting 75 containers per week. Using an average of 3.6 containers transported per truck per week, the dedicated fleet size should be about 21 trucks.

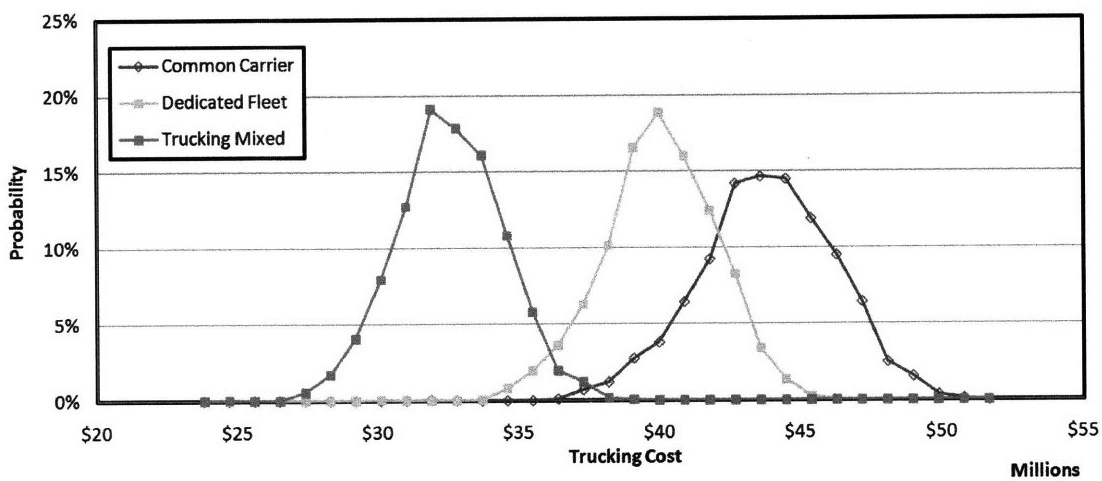

Figure 23. Distribution of Trucking Costs

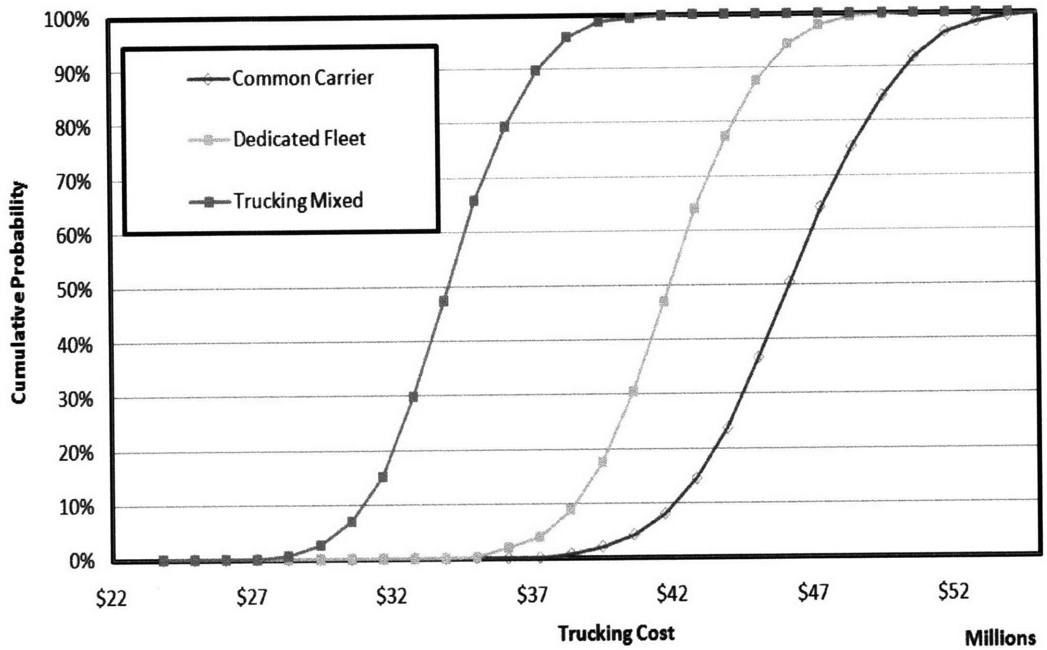

Figure 24. Cumulative Distribution Function of Trucking Costs

5 Conclusion

Monte Carlo simulation, value at risk and gain analysis, and real option analysis were used to compare four ocean shipping plans and two trucking plans. The analyses were conducted with Microsoft® Excel without advanced tools or specialized add-ins, which can be quickly adopted by supply chain managers and analysts.

5.1 Chiquita's Ocean Shipping Plans

Chiquita's ocean shipping plans for the future are basically a choice between two ships (with flexibility of using only one ship) and one large ship. These types of problems are ideally suited to the Monte Carlo simulation and the real option analysis approach. Traditional discount cash flow analysis, without considering real options, will likely penalize the flexible option (in Chiquita's case, Plan 2 and Plan 4). The simulation result shows that Plan 2 with real option is preferred. The specific outcome, however, is highly dependent upon the data input. The economics of the shipping plans are particularly sensitive to fuel costs. In the current models, it is assumed that by using a large ship, fuel costs can be reduced by 10%. The demand distributions also have a major impact on the economics of shipping cost. A large standard deviation of the demands (high uncertainty) may make the real option more valuable.

The analytical tool provided in this research can also be useful for supply chain planners and managers to understand the role of price reaction and the complex cost structure of ocean shipping plans. For example, by changing limitations on the number of containers, the response of net income distribution can be observed and the optimal demand to be served can be obtained.

5.2 Chiquita's Inland Trucking Plan

Chiquita's inland trucking needs is likely to be met with the current trucking arrangement with a dedicated fleet of about 21 trucks and common carriers. This result is highly dependent upon the current cost data. If, for example, common carrier transportation costs increase, it may justify an increase in the size of dedicated fleet. Again, the tool provided in this research should help companies like Chiquita to understand the implications.

While the models in this research are structured according to Chiquita's data, the general approach and the spreadsheet can be useful for those who want to compare different supply chain options under demand uncertainty.

5.3 Incorporating Demand Uncertainty in Supply Chain Investment Decision-making and Optimization

One core question of this research project is how estimated uncertainty of demand forecasts can be incorporated into the supply chain investment decision process. The result of this research illustrates that the Monte Carlo simulation, real option analysis and Value at Risk and Gain analysis approach developed by Professor de Neufville's group at MIT can be an effective approach. Simulated demands according to the estimated uncertainty can be readily generated using spreadsheets that managers are familiar with. These simulated demands can be inputted to supply chain models to obtain output variables of interests, such as net income, costs and carbon emissions. Value at Risk and Gain curves (VARG) provide a graphic view of how these output variables behave. Supply chain designs and plans can be compared using VARG curves. Real options in the systems could be identified and their effects on the interested variables can be examined using this approach. Some parameters can be optimized based upon the simulation results as well.

Success of this approach in businesses will likely depend upon how managers of different functions view risk and uncertainty and whether they seek to actively manage uncertainty. Many of the parameters, particularly demand distributions, are estimated with many assumptions. To make this approach truly effective, various corporate functions will need to collaborate extensively.

5.4 Areas for Future Research

For future research, it will be helpful to simulate correlated demands over the years. In such simulations, if year 0 has a higher demand, it is more likely that subsequent years will have a higher demand. The spreadsheet for this research project has a built-in method to generate correlated demands. But, the method needs to be tested to confirm it is valid.

If demands over time are correlated, there is an opportunity to take advantage of this information in decision-making. For example, if demand in year 3 is very low, a decision can be made to use one ship in subsequent years because the correlated demand in subsequent years will likely be low as well.

Another area for future research is to incorporate other components of the supply chain planning such as ripening, distribution centers and even the cost of goods and other sales and marketing data.

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Appendices

Appendix 1. Demand Forecast and Price Reaction Table

	Weekly Container	Confidence of Achieving	Price Reaction
Year 0	288	100.0%	0.0%
	377	99.9%	-2.0%
	465	50.0%	-10.0%
	553	10.0%	-25.0%
	641	0.0%	-100.0%
	730	0.0%	-100.0%
	818	0.0%	-100.0%
	906	0.0%	-100.0%
Year 1	295	100.0%	5.0%
	385	100.0%	-1.0%
	475	57.5%	-12.5%
	565	19.0%	-22.5%
	656	5.0%	-62.5%
	746	2.5%	-81.3%
	836	0.0%	-100.0%
	926	0.0%	-100.0%
Year 2	302	100.0%	10.0%
	394	100.0%	0.0%
	486	65.0%	-15.0%
	578	28.0%	-20.0%
	670	10.0%	-25.0%
	762	5.0%	-62.5%
	854	0.0%	-100.0%
	946	0.0%	-100.0%
Year 3	295	100.0%	11.7%
	385	100.0%	0.0%
	475	76.7%	-11.7%
	565	48.7%	-16.7%
	656	28.3%	-21.7%
	746	11.7%	-48.3%

	836	3.3%	-75.0%
	926	0.0%	-100.0%
Year 4	317	100.0%	13.3%
	413	100.0%	0.0%
	508	88.3%	-8.3%
	604	69.3%	-13.3%
	700	46.7%	-18.3%
	795	18.3%	-34.2%
	891	6.7%	-50.0%
	986	0.0%	-66.7%
Year 5	325	100.0%	15.0%
	422	100.0%	0.0%
	520	100.0%	-5.0%
	617	90.0%	-10.0%
	715	65.0%	-15.0%
	812	25.0%	-20.0%
	910	10.0%	-25.0%
	1007	0.0%	-50.0%

Appendix 2. Annual Ocean Shipping Cost

		Years					
		0	1	2	3	4	5
Plan 1	Mean	($1,847,335)	($256,758)	$489,247	$1,275,334	$2,744,357	$3,466,518
	Stdev	$4,312,617	$4,613,409	$4,455,146	$4,189,679	$2,530,332	$410,588
	Min	($13,669,760)	($13,251,160)	($13,071,760)	($13,131,560)	($12,952,160)	($5,781,360)
	Max	$3,505,840	$3,505,840	$3,505,840	$3,505,840	$3,505,840	$3,505,840
Plan 2	Mean	($1,847,335)	($256,758)	$489,247	$10,459,264	$10,813,806	$11,283,884
	Stdev	$4,312,617	$4,613,409	$4,455,146	$1,209,301	$1,867,366	$2,431,939
	Min	($13,669,760)	($13,251,160)	($13,071,760)	$6,794,840	$6,794,840	$6,794,840
	Max	$3,505,840	$3,505,840	$3,505,840	$15,465,840	$21,591,440	$23,666,240
Plan 2 with one ship option	Mean	($1,847,335)	($256,758)	$489,247	$7,763,410	$9,720,156	$11,140,162
	Stdev	$4,312,617	$4,613,409	$4,455,146	$4,385,771	$2,873,189	$2,190,459
	Min	($13,669,760)	($13,251,160)	($13,071,760)	($6,891,560)	($6,712,160)	$458,640
	Max	$3,505,840	$3,505,840	$3,505,840	$13,671,840	$14,090,440	$23,468,640
Plan 3	Mean	($1,847,335)	($256,758)	$489,247	$8,851,856	$9,151,566	$9,541,765
	Stdev	$4,312,617	$4,613,409	$4,455,146	$1,187,853	$1,724,975	$2,224,874
	Min	($13,669,760)	($13,251,160)	($13,071,760)	$5,199,840	$5,199,840	$5,199,840
	Max	$3,505,840	$3,505,840	$3,505,840	$13,272,840	$19,008,440	$21,083,240
Plan 4	Mean	($1,847,335)	($256,758)	$2,489,247	$11,542,875	$12,868,088	$14,840,743
	Stdev	$4,312,617	$4,613,409	$4,455,146	$2,048,348	$3,753,799	$4,744,068
	Min	($13,669,760)	($13,251,160)	($11,071,760)	$7,756,540	$7,517,340	$8,060,740
	Max	$3,505,840	$3,505,840	$5,505,840	$26,068,340	$26,068,340	$26,133,340
Plan 4 with one ship option	Mean	($1,847,335)	($256,758)	$2,489,247	$8,271,607	$10,232,969	$14,758,393
	Stdev	$4,312,617	$4,613,409	$4,455,146	$4,222,884	$2,887,657	$4,826,288
	Min	($13,669,760)	($13,251,160)	($11,071,760)	($6,169,060)	($5,989,660)	$1,181,140
	Max	$3,505,840	$3,505,840	$5,505,840	$13,138,540	$14,812,940	$26,133,340

Appendix 3. Annual Net Income

		Years					
		0	1	2	3	4	5
Plan 1	Mean	$46,707,989	$46,413,858	$46,146,483	$45,897,874	$45,740,033	$46,707,989
	Stdev	$1,633,873	$1,659,493	$1,587,424	$923,255	$160,068	$1,633,873
	Min	$37,734,736	$33,156,136	$30,817,384	$27,612,936	$45,732,440	$37,734,736
	Max	$49,906,422	$49,906,422	$49,906,422	$49,906,422	$49,899,774	$49,906,422
Plan 2	Mean	$47,301,703	$46,261,572	$45,312,175	$38,649,312	$46,301,142	$55,309,816
	Stdev	$1,826,276	$2,640,841	$3,594,074	$7,308,679	$6,774,944	$5,220,641
	Min	$39,603,408	$39,021,705	$35,469,554	$8,632,260	$7,815,413	$28,854,592
	Max	$49,906,422	$50,892,244	$53,391,707	$52,822,286	$59,376,398	$63,215,922
Plan 2 with one ship option	Mean	$47,301,703	$46,261,572	$45,312,175	$42,146,569	$47,262,129	$55,412,783
	Stdev	$1,826,276	$2,640,841	$3,594,074	$3,116,099	$4,902,607	$4,798,711
	Min	$39,603,408	$39,021,705	$35,469,554	$24,577,384	$21,372,936	$39,492,440
	Max	$49,906,422	$50,892,244	$53,391,707	$52,822,286	$59,376,398	$63,215,922
Plan 3	Mean	$47,301,703	$46,261,572	$45,312,175	$40,256,721	$47,963,381	$57,051,936
	Stdev	$1,826,276	$2,640,841	$3,594,074	$7,263,412	$6,682,007	$5,278,541
	Min	$39,603,408	$39,021,705	$35,469,554	$10,825,260	$9,410,413	$31,437,592
	Max	$49,906,422	$50,892,244	$53,391,707	$54,417,286	$60,971,398	$65,408,922
Plan 4	Mean	$47,301,703	$46,261,572	$43,312,175	$37,565,702	$44,286,250	$51,821,383
	Stdev	$1,826,276	$2,640,841	$3,594,074	$8,219,264	$7,511,388	$3,551,663
	Min	$39,603,408	$39,021,705	$33,469,554	($1,970,240)	$7,092,913	$33,085,508
	Max	$49,906,422	$50,892,244	$51,391,707	$49,409,712	$54,475,666	$57,348,521
Plan 4 with one ship option	Mean	$47,301,703	$46,261,572	$43,312,175	$41,410,704	$45,617,263	$51,834,188
	Stdev	$1,826,276	$2,640,841	$3,594,074	$3,079,748	$4,946,743	$3,504,768
	Min	$39,603,408	$39,021,705	$33,469,554	$23,854,884	$20,650,436	$38,769,940
	Max	$49,906,422	$50,892,244	$51,391,707	$49,409,712	$54,475,666	$57,348,521

Appendix 4. Annual Revenue

		Years					
		0	1	2	3	4	5
Plan 1	Mean	$227,271,838	$232,256,154	$234,515,524	$237,109,084	$243,211,155	$246,032,754
	Stdev	$16,529,089	$18,518,852	$19,533,005	$19,628,898	$10,973,245	$1,519,487
	Min	$146,412,240	$128,696,880	$115,670,880	$100,039,680	$76,592,880	$220,076,875
	Max	$246,191,400	$246,191,400	$246,191,400	$246,191,400	$246,191,400	$246,191,400
Plan 2	Mean	$227,271,838	$230,024,069	$229,007,110	$245,542,883	$285,574,736	$332,968,502
	Stdev	$16,529,089	$14,357,792	$12,676,499	$34,998,071	$29,919,747	$27,225,815
	Min	$146,412,240	$135,131,724	$127,237,968	$108,897,360	$86,805,264	$224,568,240
	Max	$246,191,400	$245,019,060	$253,225,440	$304,070,260	$338,285,220	$393,124,680
Plan 2 with one ship option	Mean	$227,271,838	$230,024,069	$229,007,110	$249,549,895	$284,911,426	$332,764,720
	Stdev	$16,529,089	$14,357,792	$12,676,499	$29,424,545	$31,339,941	$27,840,256
	Min	$146,412,240	$135,131,724	$127,237,968	$100,039,680	$76,592,880	$220,076,875
	Max	$246,191,400	$245,019,060	$253,225,440	$304,070,260	$338,285,220	$393,124,680
Plan 3	Mean	$227,271,838	$230,024,069	$229,007,110	$245,542,883	$285,574,736	$332,968,502
	Stdev	$16,529,089	$14,357,792	$12,676,499	$34,998,071	$29,919,747	$27,225,815
	Min	$146,412,240	$135,131,724	$127,237,968	$108,897,360	$86,805,264	$224,568,240
	Max	$246,191,400	$245,019,060	$253,225,440	$304,070,260	$338,285,220	$393,124,680
Plan 4	Mean	$227,271,838	$230,024,069	$229,007,110	$245,542,883	$285,771,689	$333,310,630
	Stdev	$16,529,089	$14,357,792	$12,676,499	$34,998,071	$29,187,892	$25,857,929
	Min	$146,412,240	$135,131,724	$127,237,968	$108,897,360	$86,805,264	$224,568,240
	Max	$246,191,400	$245,019,060	$253,225,440	$304,070,260	$338,285,220	$378,900,288
Plan 4 with one ship option	Mean	$227,271,838	$230,024,069	$229,007,110	$249,533,813	$284,599,440	$333,246,357
	Stdev	$16,529,089	$14,357,792	$12,676,499	$29,417,581	$31,441,284	$26,088,603
	Min	$146,412,240	$135,131,724	$127,237,968	$100,039,680	$76,592,880	$220,076,875
	Max	$246,191,400	$245,019,060	$253,225,440	$304,070,260	$338,285,220	$378,900,288