A Strategic Analysis of the Role of Uncertainty in Electronic Waste Recovery System Economics: An Investigation of the IT and Appliance Industries

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Abstract

The volume of electronic waste is growing at an increasing rate. The extensive adoption of electronic products, the tendency of consumers to purchase multiple electronics, and the rapid obsolescence of products are contributing factors. More problematic than the growing volume of e-waste is where to put it. Environmental recovery is an option that is not often utilized, lagging far behind landfill disposal. Low collection volumes and uncertain valuations of recovered products make the economics of e-waste recovery unpredictable. Thus, firms see it as a costly endeavor. To make e-waste recovery more successful, firms must understand what aspects of the system affect profitability and how to mitigate the uncertainty around economic performance.

The economics of e-waste recovery in the IT and home appliance industries is examined through a mass flow and economic model, in which system parameters, such as product mix, retirement age, material compositions, and scrap commodity prices, and their uncertainties are incorporated. A series of sensitivity analyses reveals that the expected profit of a recovery system is highly dependent on product mix and product age. The original price (or quality) of incoming products is also a large determinant of a product's fate, i.e. recycling or reuse. In evaluating system performance under possible future scenarios, it is determined that the best option to improve profitability may be to promote the return of younger products, so that reuse activities can be better exploited.

However, implementing such a strategy in the IT industry could have detrimental effects on the energy savings currently achieved from environmental recovery. If consumers are not encouraged to buy used products, the early disposal of purchases will lead to a faster rate of production. In many cases, the energy saved by recycling and reuse cannot offset the energy of new manufacturing. Meanwhile, early recovery of appliances would still result in a net energy benefit, but the rate of recovery would have to increase to maintain the current level of energy savings achieved from recycling and reuse.

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1. Introduction

1.1. What is Electronic Waste?

Electronic waste, or e-waste, refers to electronic products that have been retired from use or discarded. Managing e-waste has become a serious problem as new sales and replacement rates of electronic products have increased. Sales of electronic products, most notably information technology and telecom (IT) equipment, have steadily increased over the past twenty years (Snapdata International Group 2008; U.S. Environmental Protection Agency 2008). The U.S. EPA states that the purchase rate has increased significantly in the past ten years alone. For example, over 10 million laptops were sold in the United States (U.S.) in 2002. Five years later, sales had tripled: over 30 million laptops were sold in 2007.

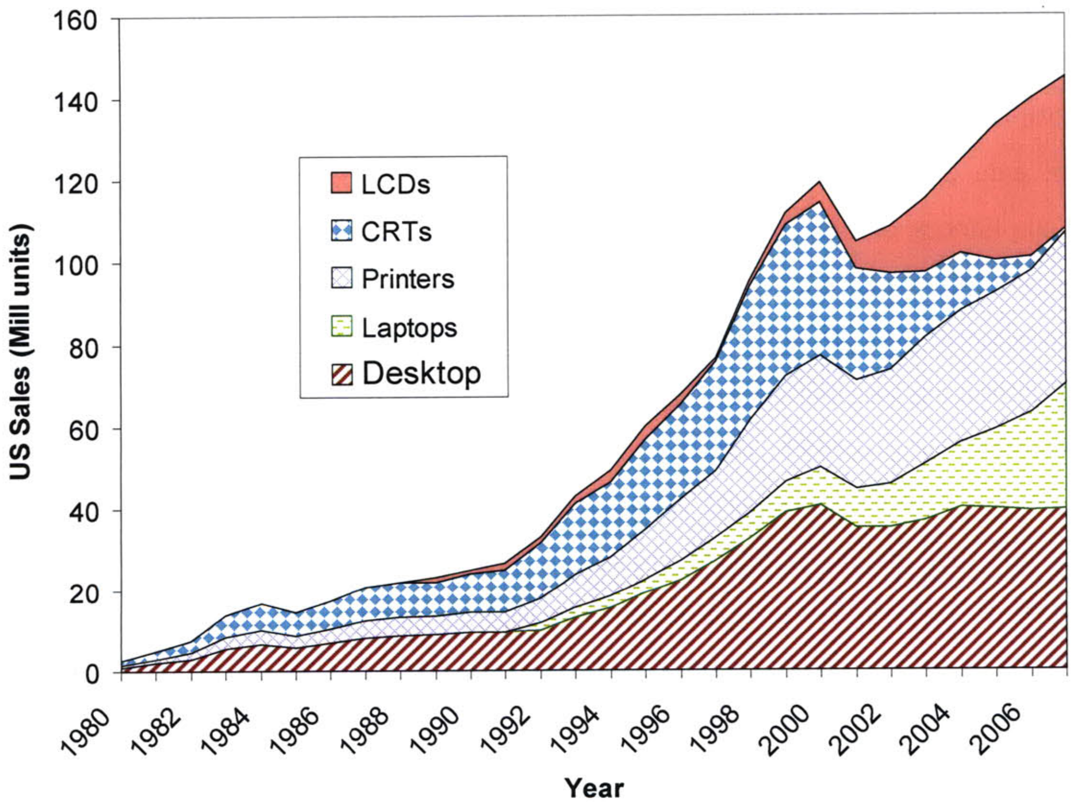

Figure 1: Sales of computer products have been growing at an increasingly faster rate (U.S. Environmental Protection Agency 2008).

This rate of growth reflects the fact that, for many people, computers have become a must-have component of everyday life and business. It also reflects the rate of technological obsolescence of IT products. As processor speed continues to improve rapidly, along with other vital features of the computer system, consumers have felt a need to upgrade their computers before they reach the end of their useful life. In the span of 20 years, computer processor speed has jumped from 16 MHz to 3.6 GHz; in the same time period, the average length of ownership has dropped from 8 years to 3 years (Babbitt et al. 2009; Intel 2009). Another reason for the rapid rate of growth in ownership is the fact that a significant portion of IT consumers own multiple computers simultaneously (Jackson et al. 2009). In 2006, 21% of European households owned more than one computer (Fogg et al. 2007).

Other electronic products with typically longer life cycles, namely household appliances, have also seen an increase in market penetration. In the last 20 years, the percent of U.S. homeowners owning a refrigerator, washer, dryer, and cooking range has increased from 48% to 71%; 99.9% of U.S. homes contain a refrigerator (Euromonitor International 2009). In the 7-year period from 2000 to 2007, total sales of home appliances in the U.S., including major appliances (e.g. refrigerators) and portable appliances (e.g. blenders), increased by almost 30% (Appliance 55th Annual Report 2008).

Recent data also implies that, similarly to IT products, consumers are beginning to replace their appliances before they reach end-of-life. 2000-2008 trend data about washing machine replacement reveals that there is a slowly growing movement among consumers to replace their washers at younger ages (The Stevenson Company 2010). In 2008, 26% of washers were replaced before six years of ownership as opposed to 14% in 2000. In fact, the number of consumers who buy new washers and dryers "just because" doubled from 5.3% and 6.2% respectively in 2000 to 9.2% and 12.9% respectively in 2009 (The Stevenson Company 2010). IBISWorld claims that in 2009, 25% of consumers bought new appliances for discretionary reasons (IBISWorld 2009b). Thus, because of increasing market penetration, multiple product ownership, and early product replacement, the volume of e-waste continues to grow.

1.2. Destinations of Electronic Waste

More problematic than the growing volume of e-waste is where to put it. There are four general fates for electronic products at their end of life (U.S. Environmental Protection Agency 2007):

1) *Reuse*: products are either refurbished for resale, given away for free, or stripped of functioning components that are then remanufactured and sold;
2) *Recycling*: products are dismantled and shredded for the recovery of raw materials;

3) *Disposal*: products are either sent to landfills or are incinerated; and
4) *Storage*: products are stored away in a garage or closet.

Although reuse and recycling are widely considered to be the more environmentally friendly treatment options for end-of-life products, e-waste is most frequently sent to landfills or stored before being sent to landfills (Huisman and Stevels 2006; U.S. Environmental Protection Agency 2008). The EPA estimates that, in 2005, 68% of e-waste in the United States was put in storage after first use, i.e. use by the original purchaser of the product. Meanwhile, 24% was diverted to landfills, and 8% to recyclers and reuse agents. Second or multiple use items were still largely diverted to landfills over recyclers and reuse agents at 75% to 23% (U.S. Environmental Protection Agency 2008).

Sometimes, products end up being exported to overseas facilities that conduct the activities listed above (U.S. Environmental Protection Agency 2007). There are varying estimates of the extent of exportation, but many authors consider it to be a major flow destination (Puckett et al. 2002; U.S. Government Accountability Office 2005; Widmer et al. 2005). There are two rationales for exportation. The first is to provide second-hand products to people in developing countries who typically cannot afford new products (Puckett et al. 2002). There are both altruistic and economic motivations for this, as the products are not given away for free. The second rationale, being purely economic, is to recycle products in countries whose labor costs are much lower than those in developed countries (Widmer et al. 2005). Concerns exist about exportation because some reports have shown that, although a limited reuse market exists in the importing countries, some products that arrive are of low quality or simply non-functioning (Puckett et al. 2002). Furthermore, the Basel Action Network has shown that the frequency and intensity of environmental and health problems due to exposure to the hazardous chemicals contained in e-waste have increased in those parts of the developing world where e-waste dumping is most prevalent (Puckett et al. 2002).

1.3. An Overview of E-waste Recovery Economics

So, the volume of e-waste is growing, and its destination can be environmentally harmful. Why are environmentally responsible end-of-life options less frequently used? The answer lies in the economics of e-waste disposal and how the stakeholders involved in disposal decisions react to the economics.

Consumers prefer disposal solutions that minimize their inconvenience, whether it is of their time or their money (Sodhi and Reimer 2001). Though green consumerism has begun to influence electronic product disposal decisions, the cheapest and simplest solutions are still to throw a product in the trash or in the closet.

Historically, original equipment manufacturers, or OEMs, and retailers have not had any incentive to encourage responsible e-waste disposal. As their economic goals are to increase revenue and reduce costs, product end-of-life has been a low priority. However, there are an increasing number of OEMs and retailers launching e-waste recovery programs to enhance corporate image and to promote corporate sustainability. These voluntary return programs vary in scope, implementation, and advertising, but they share the same goal: to increase the amount of e-waste diverted from landfills to recycling and reuse operations ("Recycling and Asset Recovery Services; Recycling; AT&T Reuse & Recycle; Hewlett Packard 2009).

Disinterested consumers, OEMs, and retailers lead to low collection volumes for recycling and reuse. Legislators are stakeholders who have tried to reverse this trend, for political and economic motives. By encouraging responsible disposal, they seek to protect citizen health and the environment and also speak for citizens who are concerned about these issues. Legislators also wish to decrease the strain on landfills across the U.S. and Europe (U.S. Environmental Protection Agency 2007). E-waste legislation is non-uniform in regions throughout the U.S. and Europe; a variety of financial and collection schemes exist. The European Union enacted the Waste Electrical and Electronic Equipment (WEEE) Directive in 2003, with implementation decisions to be made by each member state. Using the principle of extended producer responsibility, the WEEE Directive requires OEMs to physically and financially support the collection and treatment of e-waste for recycling and reuse (European Parliament and Council 2003). By 2010, 20 U.S. states had IT-specific e-waste laws, each with its own goals and implementation strategies (Electronics TakeBack Coalition 2010).

The economics of recovery processes also play a role in e-waste fate decisions. There are many commonalities among existing e-waste recovery systems. In the generic e-waste recovery system (see Figure 2), end-of-life (EOL) products are collected and sent to a dismantler (Neira et al. 2006; Huisman et al. 2007). The dismantler determines whether a product is more valuable resold or recycled. If the product has some retained use value, then it is sent to a refurbisher, reseller, or remanufacturer. Refurbishers and resellers prepare the entire product for resale, while remanufacturers remove and resell reusable components, such as video cards. If the product is more valuable recycled, it is dismantled into its various recoverable commodities. Hazardous components are usually sent away to specific waste-processing facilities. Valuable components are separated into their respective commodity streams by the dismantler or downstream recyclers. The separation process usually involves two or more shredders to create manageable-sized materials for further processing in a magnetic separator and an eddy current separator. Companies that perform precious metals recovery use additional machinery to achieve a high level of material segregation (Sodhi and Reimer 2001). Companies who receive large products, such as major appliances, take little care to finely separate commodities, as the most available commodities, such as steel, are easy to separate from the rest through the early processing stages (Ferrão and Amaral 2006). After commodity separation, the metal streams are sent to smelters and plastics to plastic refiners, incinerators, or landfills.

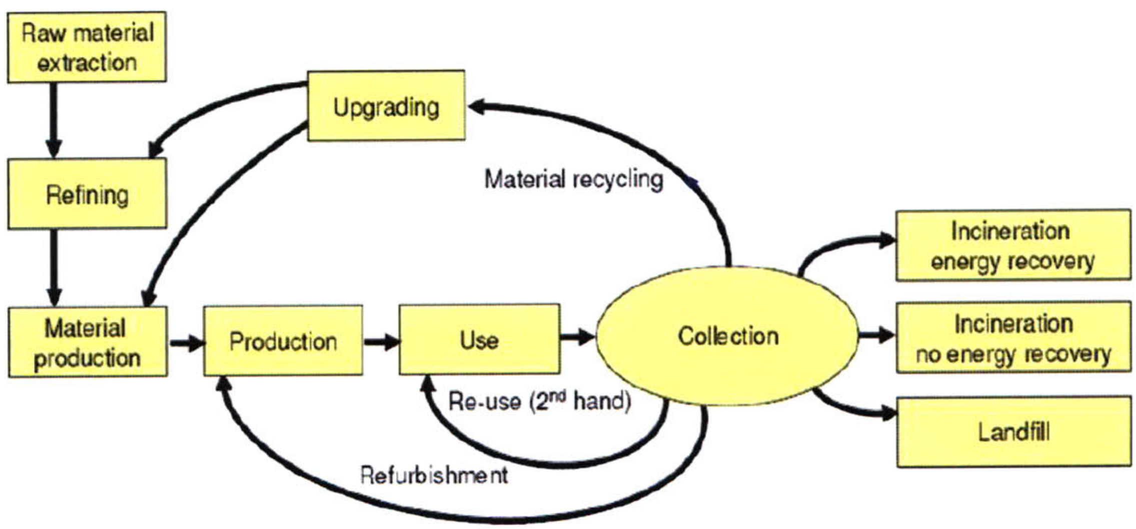

Figure 2: The end-of-life chain, reproduced from (Huisman et al. 2007)

Costs are incurred on every level of the chain. Collection, which may involve pickup from consumer homes or businesses, retail take-back, or other designs, involves management costs and transportation costs. Transportation costs are also incurred every time products are moved to another tier of processing. Labor costs for manual processing increase when hazardous materials have to be removed from devices and treated. Automated processing merely substitutes expensive labor with large and sophisticated machines, whose capital costs can be equally prohibitive (Walther et al. 2009).

The costs associated with recycling and reuse would not seem large if they were consistently outweighed by revenue generation. Instead, the revenue potential in e-waste recovery is currently low and uncertain because the volume of returns is low and quality is uncertain (Guide Jr. et al. 2003b; Geyer et al. 2007). As mentioned previously, the flow of obsolete products to recycling and reuse facilities is much lower than to disposal options, such as landfills (U.S. Environmental Protection Agency 2008). Without consistent high collection volumes, recyclers cannot generate stable revenues or exploit economies of scale to reduce costs. The low volume of products returned to a recovery system can be attributed to fluctuations in consumer participation and in the involvement of OEMs, retailers, and legislators.

In addition, uncertainty is a factor to revenue potential. Revenue is a function of the value of products that have arrived at a recovery facility. A product's fate, either reuse or recycling, is contingent on its retained use value and its scrap material value. (Guide Jr. et al. 2003b) notes that when remanufacturers receive products of unknown quality, their ability to sort through the products for those that are of acceptable quality for refurbishment is hindered. The cumulative time delays along the recovery chain, e.g. time before a consumer returns an obsolete product or time between collection and final processing, can greatly affect the use value of a product (Blackburn et al. 2004) too. For instance, because of their short life cycles, IT products have quick depreciation rates. In addition, a product's scrap material value is dependent on scrap commodity prices, which can be highly variable. For example, as illustrated in Figure 3, the price of copper-bearing scrap material has risen and fallen between \$500/ton and \$1500/ton in the past five years alone (Recycler's World 2009). Thus, even if the volume of returns were certain, the value of those returns and their commodities would remain uncertain.

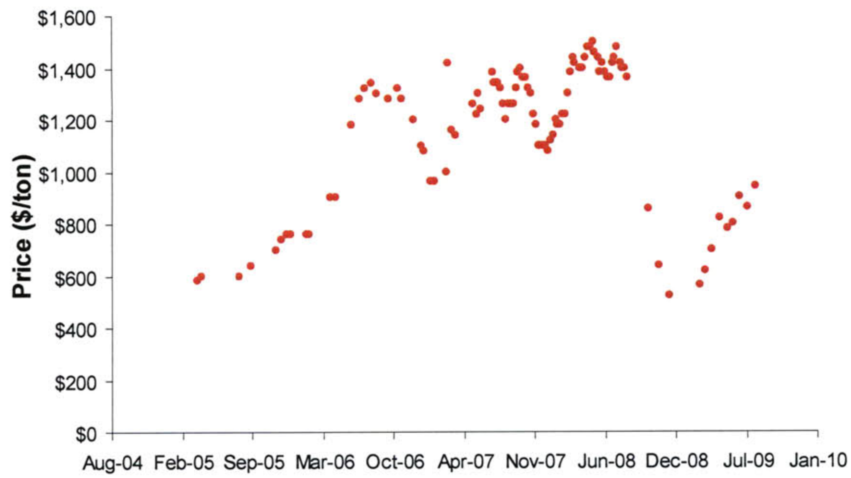

Figure 3: Recent fluctuation in the price of copper-bearing scrap

In summation, use and material values of recovered products are dependent on many product and market characteristics that cannot be predicted. These include product type and original quality, retirement age and current functionality, scrap commodity prices and consumer demand for used items. With little control over collection mix and market conditions, and thus the characteristics mentioned above, firms tend to see environmentally responsible e-waste recovery as a costly endeavor.

E-waste generation is growing, but not enough products are being recovered either for reuse and remanufacturing or for use as secondary materials in new production. Furthermore, e-waste can end up in regions where it is harmful to humans and the environment. For products that do get recovered, their incoming quality and outgoing value are often uncertain, potentially leading to net cost situations for recyclers and refurbishers.

Currently, legislation attempts to increase the volume of returns but not to greatly transform the economics of e-waste recovery. Firms engaged in e-waste recovery need economic incentives that are strong and reliable. (Frank R. Field et al. 1994) showed that the reason that automobile recovery became so prevalent by the 1970s, and continues to be so, is that it has strong economic incentives. Its consistent profitability, due to the large steel content in automobiles and the strong market demand for automobile commodities and parts, has led automobile firms and scrap dealers to foster automobile recovery. Because of this, an efficient automobile recycling industry that is also sustainable has developed. What is necessary to make e-waste recovery more profitable? What is necessary to make profit sustainable long-term?

1.4. Central Thesis Questions

To make e-waste recovery more profitable today and in the long-term, it is necessary to develop a deeper understanding of the mechanisms at play. It is also necessary to understand what tools are available to system managers so that they can minimize their risk of financial burden and what unforeseen effects may arise from business strategies that promote profitability. The objectives of this thesis can be summarized in three questions.

- **What characteristics of collection and the end-of-life markets affect the economic performance of an e-waste recovery system? *What are the effects of uncertainty in those characteristics on the expected economic performance?***

For firms who try to adhere to environmentally and socially responsible recovery, discovering ways to improve profitability is crucial. Whether these firms participate in an e-waste recovery system because of government mandate or because of a desire to buoy corporate image, the means of success are the same: increase revenue and minimize costs. However, the economic performance of an e-waste recovery system is affected by collection and market uncertainties. Returns are influenced by products that exist in the marketplace, who uses those products and how, and the value of the products at end-of-life. Thus, to develop successful system management policies, firms and other stakeholders must first understand the impact of uncertainty on the profitability of e-waste recovery systems.

- **Are there measures a firm can take to mitigate the effect of system uncertainties on economic performance? *What are the relative merits of these measures?***

Understanding what factors affect a system and how is only the first step. Afterwards, a firm must develop strategies to mitigate or enhance the effects. Which strategies are chosen becomes a decision based on implementation feasibility and level of system improvement relative to other measures.

- **What are the environmental impacts of the business strategies intended to promote economic performance?**

Strategies to improve system performance should not be evaluated purely from an economic standpoint; environmental effects should also be included (Huisman 2003). System success involves profit from returns as well as positive impact on total e-waste management. In other words, strategies should be evaluated for their ability to increase the flow of discarded products to responsible recycling and reuse options versus to landfills, storage, or exportation. One metric is mass diverted; another is avoided energy use because of the ability to use secondary materials in the production process.

Environmental impact should also be evaluated by studying the effect that strategies undertaken to improve the economics of e-waste recovery may have on purchase decisions. The relative number of new product purchases to used product purchases is of interest in such an evaluation.

1.5. Thesis Roadmap

In order to answer the previously mentioned thesis questions, the rest of this document is arranged into four sections. In Chapter 2, the thesis methodology is explained. This is followed by two sections of analysis. In the first section, Chapter 3, the economics and environmental outlook of IT e-waste recovery are examined. In Chapter 4, analysis turns to the appliance industry. E-waste management in the IT industry is currently unprofitable; as IT e-waste continues to grow at a fast rate, discovering methods to increase profitability is important. Meanwhile, e-waste management in the appliance industry is already profitable. However, innovations in product development and future legislative changes about disposal may decrease profitability. Lessons about managing e-waste recovery system characteristics can be learned in both cases.

In the last section, Chapter 5, conclusions are drawn about the possible futures of both industries. Recommendations are then made to promote economic and environmental sustainability of e-waste recovery in each industry.

2. METHODOLOGY

2.1. Literature Review

Many authors have investigated what drives the economics of e-waste recycling and how system design decisions affect economic outcomes. Some focused their analysis on the current state of existing collection and recovery infrastructures. Most of these case studies centered on the drivers of variation in e-waste system costs. For example, in a review of the implementation of the WEEE Directive in the European Union, it was shown that collection and administrative costs of various systems differed widely because of different collection and operational designs (Huisman et al. 2007; Sander et al. 2007). In another study, the collection, processing, and system management structures of different North American e-waste recovery systems were compared to investigate how system architecture affects cost distribution among the system's stakeholders (Gregory and Kirchain 2008). Again, it was shown that system design decisions influenced cost.

In a case study of Germany's e-waste recovery system, (Walther et al. 2009) expanded the scope of analysis to study the effects of transport and product scope decisions on the revenue potentials of both reuse and recycling operations. It was shown that by using bulk transport, in which functioning and broken products are mixed together, system managers prevented themselves from being able to sell products for reuse. However, total costs were higher for reuse activities.

Though case studies of existing systems are useful, (Dahmus et al. 2008) demonstrated that models can quickly quantify performance differences across a range of collection, processing, and system management configurations. For example, collection siting was shown to be a large contributor to collection volume variation (Dahmus et al. 2008; Dahmus et al. 2009).

Models have also been used to compare the impact of indirect and direct collection structures on a firm's profit potential (Savaskan and Wassenhove 2006). For example, when using a direct collection strategy, i.e. collecting EOL products directly from consumers, profits are greatly influenced by ability to realize economies of scale, i.e. large collection volumes.

In another study, the economic motivations of key recovery chain stakeholders, including consumers, recyclers, and smelters, were used to build separate objective functions that maximized the economic welfare of the particular stakeholder (Sodhi and Reimer 2001). The underlying premise was that the economics of recycling is driven by each actor behaving in his best interest, thereby affecting the options available to downstream actors who would like to do the same.

The above studies are useful in that they reveal the forces at work in e-waste recovery systems and lay the framework for how these forces interact. However, the studies generally consider deterministic states of the system and do not recognize the impact of uncertainty. It has been previously shown that considering uncertainty allows system designers or managers to better understand the influences on future system performance (de Neufville et al. 2004).

There have been a few authors who have examined the underlying components of e-waste recovery and how uncertain states of the system may drive system economic performance. In one study, an economic model showed that varying product quality (e.g. appearance and functionality) influenced recovery costs (Guide Jr. et al. 2003b). Yang and Williams used historic sales data and estimates of product lifespans to forecast trends in the retirement of computers in order to understand how future e-waste volumes should impact planning of recycling facility construction (Yang and Williams 2009).

In developing technical cost models to analyze the economics of the automobile recycling industry, Ferrão and Amaral specifically incorporated different vehicle material compositions and varying scrap metal prices to understand impact on profit (Ferrão and Amaral 2006).

Schaik and Reuter highlighted the importance of understanding uncertainty in automobile parameters when quantifying achievable recycling rates (van Schaik and Reuter 2004). Using a dynamic system model, they revealed the impact of the distribution of the lifetime of automobiles, time-varying vehicle weights, and time-varying material composition on achievable recycling targets.

In another study, the time-varying nature of product depreciation was studied as a factor that influences the environmental and economic performance of electronic products (Kondoh et al. 2008). Constructed as the weighted sum of physical and functional deterioration, the value depreciation over time of an electronic product was used as part of a performance analysis to identify improvement areas for material composition of computers and life cycle destinations.

Finally, (Kang and Schoenung 2006) used technical cost modeling to quantify the sensitivity of economic performance to a distribution of scrap metal prices, product resale values, and processing costs. Their study focused on the recycling and reuse of cathode ray tube (CRT) monitors and desktop personal computers (PCs). Material and labor costs were shown to be the most influential cost drivers, while collection fees and scrap metal prices were the most influential drivers of revenue.

Many authors have explicitly examined the environmental performance of e-waste recovery systems. (Dahmus et al. 2009) showed that recovery efficiency of metals and plastics from IT equipment can determine whether a recycling activity leads to a net energy savings or burden, when compared to the energy expended during collection. (Devoldere et al. 2006) and (Sahni et al. 2010) discuss how the benefits of reuse can be negated when a reused product is less energy efficient than a newer model. (Lu et al. 2006) compared the cost:benefit ratio of recycling laptops to the recycling rate, where the benefit was calculated as the change in life cycle impact of laptop disposal on human health, and ecosystem quality, and resource consumption. Finally, (Huisman 2003) developed the concept of QWERTY, or Quotes for environmentally Weighted RecyclabilTY, which attributes environmentally weighted recycling scores to the recycling of products instead of mass-based scores.

Though numerous, previous work has been limited in scope. It has primarily focused on costs or revenue alone, used average variable states to describe the system, characterized one uncertainty or one fate decision (recycling or reuse) at a time, or restricted analysis to one or two products. Some authors have included an analysis of the environmental effects of recovery; others have not. Much research has been done to understand the variation in system performance as a function of cost; little has included variation due to revenue uncertainty. Furthermore, few have recommended strategies that firms and other stakeholders can take to maximize profit potential with respect to uncertain system conditions.

The first objective of this research is to incorporate all of the major parameters of e-waste recovery, and their uncertainties and interactions, into an analysis of recovery economics and to evaluate strategic decisions that may be made because of the economics. The second objective is to quantify the environmental impacts of these decisions.

2.2. Research Method

The goal of this work is to inform the financial planning of e-waste recovery systems. The analysis of economic performance is from the point of view of a recovery system manager, e.g. an OEM or municipality. A system can refer to a single recovery facility or a network of recovery facilities. Intermediate financial exchanges along the e-waste recovery value chain are not important. Instead, the system manager is concerned with overall revenue and cost streams.

Two industries, IT and appliances, are examined. Though their products have different life cycles, both industries share the goal of improving their e-waste management.

In order to study the economics of e-waste recovery, it was necessary to develop a mass flow and economic (MFE) model that adequately describes collection and fate determination processes. The model is built in such a way that product, collection, secondary market, and processing parameters, along with their uncertainties, drive the system's economic situation.

To identify the major profit drivers, a series of sensitivity analyses are conducted within the framework of the MFE model. The sensitivity analyses build upon each other, so that after each, another level of understanding about the dynamics of the system is achieved. The first tool that is used is Design of Experiments (DOE). Through DOE analysis, input variables that are key drivers of revenue variation are identified. This analysis is followed by single variable sensitivity analysis and Monte Carlo analysis; they are performed on distinct operating scenarios of the recovery system, which are created within the MFE model. Discrete operating scenarios are used because it is important to quantify the impact of uncertainty on e-waste recovery systems that exist in realistic contexts. Thus, the operating scenarios are chosen because of their link to actual data and their significance to future trends in both industries under investigation. With single variable sensitivity analysis and Monte Carlo analysis, the results of the DOE analysis are substantiated over a broader range of variable values. Furthermore, Monte Carlo analysis provides a way to compare the expected profit of distinct operating scenarios with respect to variable uncertainty. In the end, influential system characteristics are identified and the effect of their values and the uncertainty around them on the system's profit are quantified.

Once the behavior of the recovery system under uncertainty is evaluated and compared across discrete operating states of the recovery system, possible future states of the recovery system are examined. These future states are based on real trends in legislation and in the sales market. Based on the performance of the system in these states, alternative business strategies to maximize profit are developed and implemented in the MFE model. The aim of each strategy is to actively influence some aspect of the recovery system (e.g. collection mix) that has a dominant effect on profit. The effectiveness of the strategies in improving system profit is evaluated using similar sensitivity analyses as above.

Finally, the environmental impacts of the most profitable business strategies are evaluated to understand how improving economic performance of e-waste recovery may affect the environmental performance of e-waste recovery. This activity consists of using standard life cycle assessment techniques to calculate the energy saved due to the increase of the mass of materials diverted towards recovery after the implementation of a particular strategy.

Since analysis derived in the Mass Flow and Economic model is the backbone of this research, a detailed discussion of the model's structure is below. This is followed by a detailed description of the environmental analysis.

2.3. Mass Flow and Economic Model

The economic performance of an e-waste recovery system depends on variables that influence revenue potential and recovery cost. Previous authors have concluded that, to improve the economic performance, system managers need to control timing, quality, and quantity of returns (de Brito and Dekker 2003; Guide Jr. et al. 2003b). To do this, they must first understand product use, composition and deterioration. They must also understand the effect of sales market dynamics on collection mix and secondary market dynamics on end-of-life product valuation.

Meanwhile, the variation of recovery costs due to processing decisions and contextual circumstances must also be included. All of these variables can be grouped as the following system characteristics: *collection*, *product*, *secondary market*, and *EOL processing*. A mass flow and economic (MFE) model was developed to quantify the effect of system variables on the economic performance of a system.

2.3.1. Model Inputs

<u>*Collection Characteristics*</u>

What a recovery system collects and from where directly influence product characteristics and, subsequently, product value. Therefore, two important collection characteristics featured in the MFE model are *product mix* and *collection source*.

Product mix refers to the relative percentage by volume of the types of products that are collected by a recovery system. This is an uncertain parameter, largely influenced by the market share of products sold on the market. The type and quality of products available on the sales market, as well as the target consumers, influence the mix of returns and the timing of returns. Product mix is important because it dictates the assembly complexity and material composition of returns, which are key determinants of a product's embodied and material quality. Thus, product mix influences processing decisions. It should be noted that product mix can also be influenced by legislation that requires the environmental disposal of certain products.

Collection source refers to the type of customers from which the recovery system collects e-waste. If a recovery system is run by an OEM, returns largely come from the OEM's customer base. Broadly, customers can be categorized as residential or commercial. Within each category there are those who buy mass brand products versus high-end products or a mixture. As a result, collection source influences the quality of returns.

Within collection source, there is the distinction of collection *mode*. Mode refers to the method used to retrieve products at end-of-life. Depending on the system architecture, this may involve municipal collection, product mail-ins, or other methods of retrieval. Together, collection source and mode influence the timing of returns, thereby influencing their retirement age.

Product characteristics

Knowing the characteristics of incoming products helps recovery system managers determine their most profitable destinations. Important product characteristics captured in the MFE model are *manufacturer suggested retail price* (or *MSRP*), *age, functionality, depreciation, product weight,* and *material composition.*

MSRP is an indicator of the original quality of the components contained in the product and of the product's overall capabilities, or feature set. Since many OEMs group their products into distinct price segmentations, a similar distinction is made in the model. Thus, within each industry that is researched, one representative MSRP value is assigned to high-end product models, one to mid-range models, and one to low-end models. Some manufacturers in an industry might sell products across a wide range of MSRPs to capture as many consumers as possible. For example, mass consumer products tend to be cheaper and don't offer as many features as high-end products. Meanwhile, another manufacturer may choose to provide high-end products alone, serving a niche market.

Product users are the sole decision-makers in deciding when and how to retire a product. In making the retirement decision, they consider a myriad of issues, including convenience, product age, product functionality, product features, and the product's continued usefulness to their needs (U.S. Environmental Protection Agency 2008; Babbitt et al. 2009). As such, there is a high variability in the timing of end-of-life decisions made by product users, which influences the *age distribution* of returned products and their continued *functionality*, i.e. working status

(U.S. Environmental Protection Agency 2008; Babbitt et al. 2009). Product age and functionality directly influence the value of a product on the resale market (Guide Jr. and Wassenhove 2002; Guide Jr. et al. 2003b; Kondoh et al. 2008). Functionality determines whether a product can even be considered for reuse; age is an indicator of functionality and the technological obsolescence of a product. In the model, product retirement age is characterized by a probability distribution. There is a different age distribution for each type of collection mode for each product type as well. For example, IT products that are returned through retail take-back tend to be younger than those disposed of at community collection events (Guide Jr. and Wassenhove 2001). Functionality is also described as a probability function associated with product age.

Similar to functionality is a product's *depreciation* in value over time. As defined by the Bureau of Economic Analysis, depreciation represents the change in value of an asset because of aging, wear and tear, and obsolescence (Fraumeni 1997). Depreciation is a contributor to a product's resale value. In the MFE model, all items in a particular product category depreciate at the same rate, regardless of different initial qualities (which is represented by MSRP). There are a variety of ways to characterize depreciation. For the products explored in this research, empirical data suggest that product depreciation can be modeled as a logarithmic decay. In the MFE model, depreciation is represented by the following logarithmic decay function:

$$D = -R \ln x + C \qquad (1)$$

where D = retained value (% MSRP), R = depreciation rate, x = product age, and C = constant.

Material composition and product *weight* are useful indications of a product's material quality. Recycling value is a function of both product characteristics. Material composition and product weight also influence the type and number of processing techniques needed to sequester product commodities and are therefore integral to processing costs. Lastly, processing costs increase when a product contains hazardous materials that need specialized removal.

<u>Secondary Market Characteristics</u>

End-of-life product value is often determined by comparing the residual value of the whole product, the value of its individual components, and the value of its raw materials. However, all of these valuations are uncertain. In the model, whole product residual value, or *resale value*, is compared to *scrap material value*. Resale value, or the market value of used products, is a function of product type, age, MSRP, and consumer preference. It can be considered as a decay function. The resultant equation is:

$$V_{resale} = S * (-R \ln x + C) \qquad (2)$$

where V_{resale} = resale value, S = MSRP, R = depreciation rate, x = age (in years) and C = constant. Consumer preference comes into play when a product may still be functional and thus have value in an absolute sense but no longer has value on the resale market because it is technologically obsolete. Therefore, a threshold age at which a product no longer has resale value is incorporated into the version of the equation used in the model.

A further end-of-life uncertainty is the value of scrap materials on the secondary commodities market, which has a direct impact on the scrap, or recycling, value of EOL product components. Scrap material value varies because of uncertainty in product material compositions, weight, and secondary commodity prices. Long-term secondary commodity market prices are used to provide a framework for evaluating the effect of market fluctuations on recycling revenue potential. The resultant equation for product recycling value is thus:

$$V_{recyc} = m \sum_{1}^{N} p_i x_i \qquad (3)$$

where V_{recyc} = product scrap value, m = product weight, i = commodity, x = weight fraction of commodity, p = price of commodity, and N = number of commodities present in the product.

End-of-Life Processing Characteristics

Recovery costs differ according to the mode of recovery, the product mix, and the geographical and legislative context of the recovery system. For recycling, recovery activities include collection, transportation, sorting, dismantling and processing, waste disposal, and shipping of commodity streams to final destinations or further processing (Sodhi and Reimer 2001). Meanwhile, for reuse operations, dismantling and processing and waste disposal are not applicable activities, whereas refurbishing is (Walther et al. 2009).

2.3.2. Model Algorithm

The research scope covers recovery in the IT and appliance industries. For each industry, the model is populated with a list of prevalent products on the market, their material compositions, weights, MSRP ranges, depreciation rates, and retirement age distributions (linked to specific collection modes). Processing costs for reuse and recycling activities are also attributed to each product type. For example, dishwashers are prevalent products on the appliance market. Therefore, product and EOL processing characteristics associated with dishwashers are included in the MFE model for appliances.

Figure 4 depicts a schematic of the model algorithm.

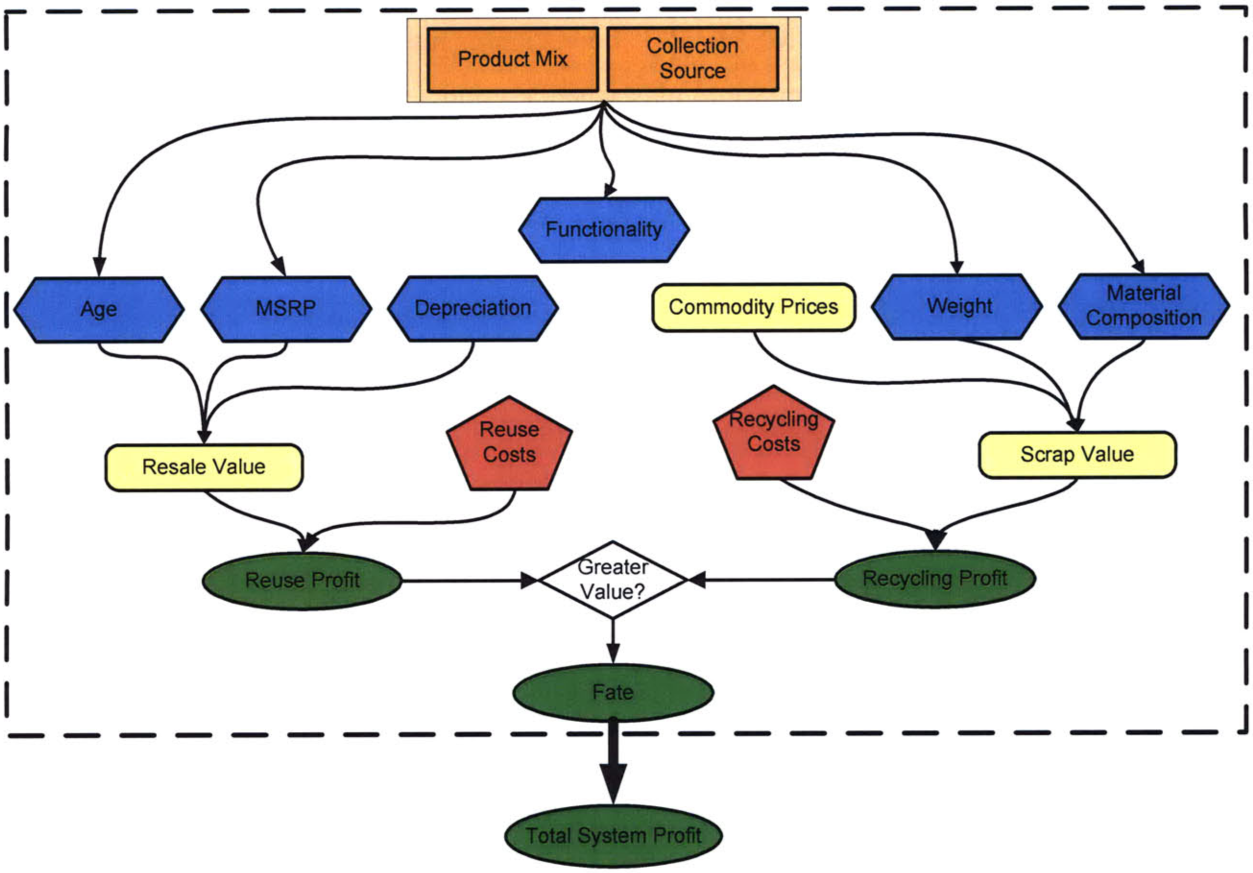

Figure 4: A depiction of the Mass Flow and Economic model algorithm. Rectangles = *collection* characteristics, hexagons = *product* characteristics, rounded squares = *secondary market* characteristics, and pentagons = *EOL processing* characteristics. Ovals = model calculations. Diamonds = decisions.

When collection sources and product mix are specified, the parameters of the recovery system's operating scenario are characterized. The total number of returns and the percentage of returns at each price segment (e.g. low-end models versus high-end models) are also necessary to characterize the scenario under analysis. Product mix and the total number of returns are used to calculate the number of returns of a particular product type. The number of returns of each product type is subdivided into groups according to product age, price segment, and functionality. Fate decisions are then determined for each group. All non-functional products immediately enter the recycling stream. For functioning products, a comparison is made between potential reuse profit and potential recycling profit. Age distribution, MSRP, product depreciation rate, and reuse processing costs are used to determine potential reuse profit. Material composition, commodity price, product weight, and recycling processing costs are used to determine the potential recycling profit of a group.

The comparison between the two potential profits also includes a bias factor to reflect the decision process as made in reality (Rockhold 2008). This bias factor represents the tendency of recovery system managers to include more than just numerical comparison when making fate decisions, thereby slightly favoring one fate over the other. For example, if a net cost is calculated for both the potential reuse and potential recycling profits of a product group, the fate of the group will be recycling even if the reuse fate is a smaller cost. This is because the reuse fate only generates a net cost if the group provides no resale revenue. Since there is no resale value, the product can never be sold on the reuse market and would end up recycled anyway. Thus, this fate delay is pre-empted by forcing the recycling fate to be chosen through use of a bias factor. Each product type has its own bias factor. The decision criterion for functioning products in a given subgroup of a given product type is thus:

$$\text{If } V_{recyc} < V_{resale}(1+r) \rightarrow \text{Fate = reuse; else Fate = recycling}$$

where r = bias factor. Upon comparison of the two potential profits, the group's fate is determined. This process continues until a fate has been determined for every group in every product type. Finally, the profit and volume of products in each fate stream are calculated as well as the recovery system's total profit.

2.4. Environmental Analysis

After a series of sensitivity analyses and an evaluation of the economic performance of potential recovery strategies, an environmental analysis is conducted. The environmental analysis consists of estimating the long-term effect that the new policies might have on the mass flow of obsolete products to different end-of-life fates. As the total flow is bounded by the available stock of retired products, the analysis focuses on changes to the relative EOL flows within the system. The activities involved in e-waste management can be pictured as in Figure 5 below. A consumer can make one of three replacement purchase decisions: (a) purchase a new product, (b) purchase a used product, or (c) do not replace. This decision is not only influenced by consumer preference but also by decisions made previously by other consumers when disposing their products. Therefore, the availability of new products made from secondary materials and of refurbished products on the used product market are directly linked to the number of products disposed of through e-waste recovery.

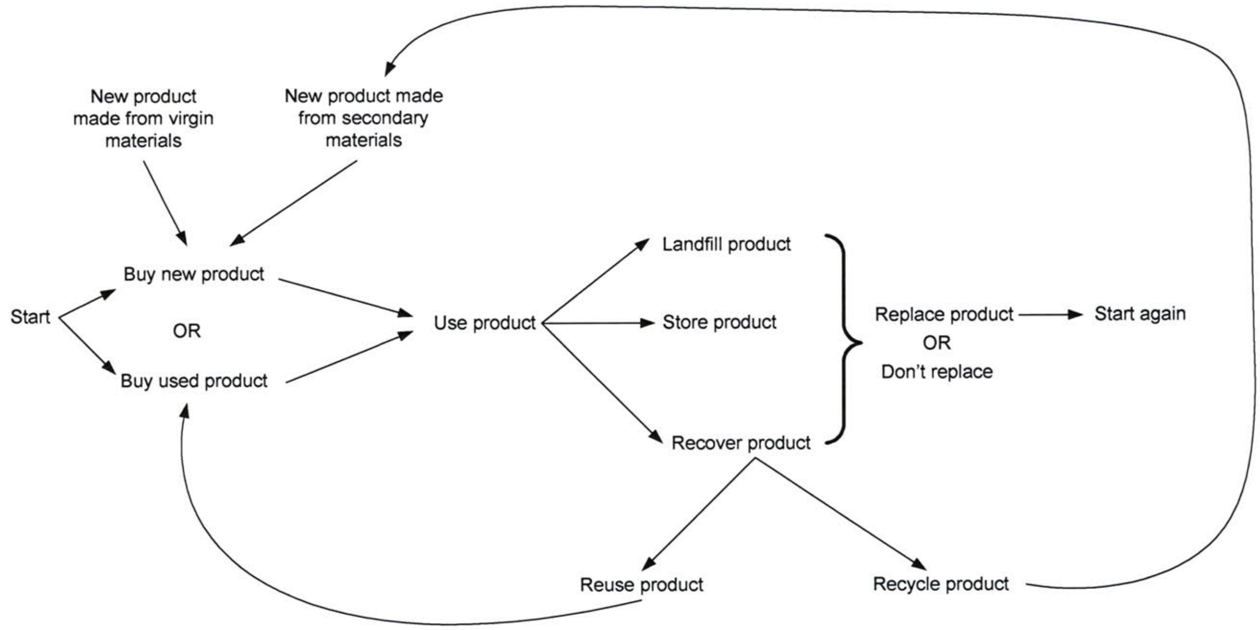

Figure 5: A diagram relating e-waste decisions to purchase decisions.

The scope of the analysis covers energy used in new product manufacturing, from virgin and recycled materials, and energy used in product reuse. The life cycle activities of each are displayed in Figure 6.

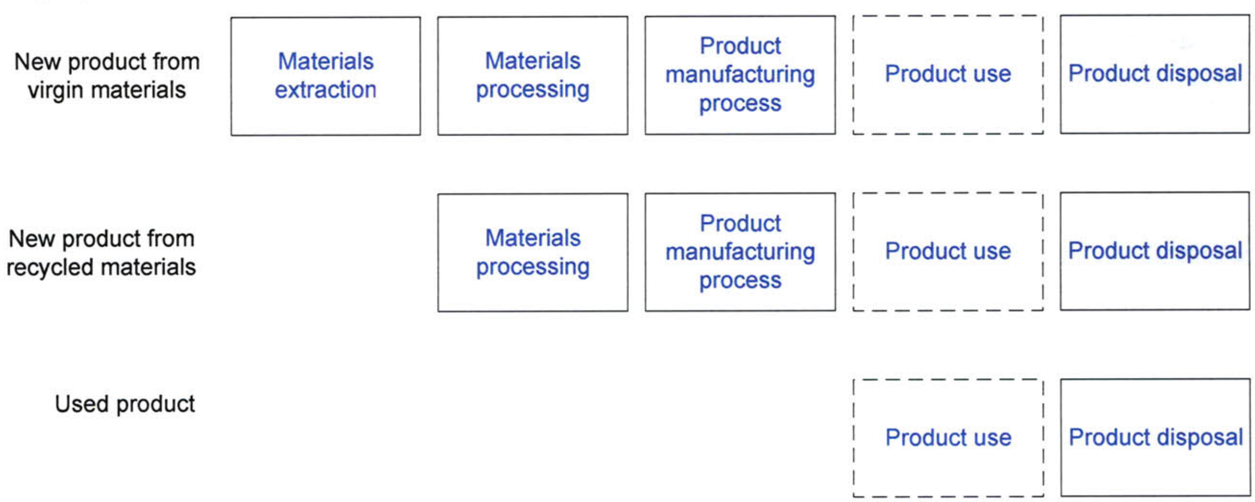

Figure 6: Reusing a product avoids the energy of all production processes.

Equations used in the analysis are shown in Table I (variable descriptions are in Table II). Potential energy savings or burdens are calculated with a focus on energy expended during production. Energy in the use phase is ignored because it is assumed that the same amount of energy will be used whether the product is new or used, though in reality there may be periodic energy efficiency gains from one iteration of a product to another. Energy used in the EOL phase is also ignored because it is often inconsequential when compared to production energy (Swiss Center for Life Cycle Inventories 2010). Energy savings are calculated for one purchase cycle. Then, a long-term look at energy savings is taken in order to investigate the impact of different replacement frequencies on energy usage. The analysis also assumes a constant population over the fixed time horizon. Two recovery scenarios are compared: (a) recycling is the only option and (b) recycling and reuse are viable options.

Table I: Equations used in environmental analysis of e-waste recovery strategies

$$N = n_{buy\_new} + n_{buy\_used}$$

$$n_{buy\_new} = n_{primary\_mfg} + n_{secondary\_mfg}$$

$$n_{buy\_used} = n_{reuse} = N * \Pr(reuse) * \Pr(recovery)$$

$$n_{secondary\_mfg} = n_{recycle} = N * (1 - \Pr(reuse)) * \Pr(recovery)$$

$$\Pr(reuse) = \Pr(functioning) * D_{used\_products}$$

$$E_{life\_cycle} = n_{primary\_mfg} * E_{primary\_mfg} + n_{secondary\_mfg} * E_{secondary\_mfg} + n_{buy\_used} * E_{buy\_used}$$

$$E_{primary\_mfg} = E_{virgin\_materials} + E_{mfg\_process}$$

$$E_{secondary\_mfg} = E_{secondary\_materials} + E_{mfg\_process}$$

$$E_{buy\_used} = 0$$

$$E_{Total} = E_{life\_cycle} * \frac{T}{\mu_{retirement}}$$

Table II: Description of variables used in environmental impact equations

Variable	Description
N	Original number of laptops sold
n_{buy_new}	Number of new replacement purchases
n_{buy_used}	Number of used replacement purchases
$n_{primary\_mfg}$	New replacement purchases that originate from virgin materials
$n_{secondary\_mfg}$	New replacement purchases that originate from secondary/recycled materials
n_{reuse}	Number of recovered products that get reused
$n_{recycle}$	Number of recovered products that get recycled
Pr(recovery)	Probability that an end-of-life product will be sent for recovery
Pr(functioning)	Probability that a recovered product is still functioning
Pr(reuse)	Probability that a recovered product will be eligible for reuse
$D_{used\_products}$	Market demand for used products
E_{life_cycle}	Total energy used in one replacement iteration of N laptops
$E_{primary\_mfg}$	Energy used to manufacture a laptop from virgin materials
$E_{secondary\_mfg}$	Energy used to manufacture a laptop from secondary materials
E_{buy_used}	Energy used to sell a used laptop
$E_{virgin\_materials}$	Energy used to procure and process virgin materials for laptop production
$E_{\_secondary\_materials}$	Energy used to process secondary materials for laptop production
$E_{mfg\_process}$	Energy used to form and assemble components into a new laptop
T	Total time horizon over which a number of product replacement iterations are made
$\mu_{retirement}$	Mean age of product retirement
E_{total}	Total energy used over the number of product replacement iterations that occur in time T

3. Analysis: The Economics of IT E-waste Recovery

In this chapter, the economics of IT e-waste recovery in the United States is examined. In Section 3.1, inputs in the IT mass flow and economic model are described. This is followed by a baseline analysis of the current state of IT e-waste recovery in Section 3.2. Uncertainty analysis is presented in Sections 3.2 through 3.5, with each section of analysis building upon the previous one. These sections are followed by an evaluation in Section 3.6 of strategies that a recovery system manager might implement given the results of the previous system analysis. The environmental impacts of the most viable strategies are evaluated in Section 3.7. Finally, concluding statements are made in Section 3.8.

3.1. Data collection for the MFE Model

As mentioned in Chapter 2.3, the critical variables in the performance of an e-waste recovery system can be grouped as *collection*, *product*, *secondary market*, and *EOL processing* characteristics.

3.1.1. Collection Characteristics

Two important collection characteristics featured in the MFE model are *product mix* and *collection source*. Product mix refers to the types of IT products that are available for return. As this is largely a function of the products that are available on the sales market, the following analysis includes desktop PCs, laptop computers, multifunctional peripherals (e.g. printers), CRT monitors, and liquid crystal display (LCD) monitors. The trend in sales of each product category was shown in Figure 1.

The collection sources considered in this analysis are business (B2B) customers and residential (B2C) customers. B2B customers represent businesses that buy or lease IT equipment from one or more IT firms. The two primary modes of collection from B2B customers are end of lease and asset recovery (de Brito and Dekker 2003). End of lease returns occur when the business customer's contract agreement for using particular IT equipment ends. Lease agreements are typically three or four years long (Rashid 2009). Asset recovery returns refer to IT equipment that was previously purchased by the business customer and is now being retired.

Meanwhile, B2C customers represent residential consumers who buy IT equipment from retail stores, online, or through other distribution channels (de Brito and Dekker 2003). Though there are many different collection modes with regards to B2C customers, just two are featured in the model. The first refers to municipal collection, in which the municipality picks up retired

IT equipment directly from consumers' homes or from local collection points. Drop-offs at community events are also included in this category. The second collection mode refers to retail take-back strategies, in which the customer returns obsolete equipment to retail stores either through a buy-back, trade-in, or free program. Returns through municipal collection tend to be much older and have a higher probability of not functioning as compared to those through retail take-back (Guide Jr. et al. 2003b).

3.1.2. Product Characteristics

Important product characteristics captured in the MFE model are *MSRP, age, functionality, depreciation, material composition,* and *product weight*.

As mentioned earlier, MSRP is a useful indicator of initial product quality. In the MFE model, three representative MSRPs are attributed to the following price segmentations for each product type: low-end, mid-range, and high-end. Without primary data on price segmentations, data were collected on the range of MSRPs of different products as sold from 2002 through 2008 (The Orion Blue Book 2009). In order to obtain a reasonable representation of products, a sample size greater than 30 was used for each product type, except CRT monitors, where 17 samples were used. Data collection was focused on Dell and HP computers and monitors because they have consistently held greater than a combined 50% market share over the last 10 years (Euromonitor International 2009). Data were collected on HP and Lexmark printers for similar reasons; HP alone has held over 45% market share over ten years (Euromonitor International 2009). Printer data collection was also focused on inkjet and laser jet printers because of their consistent popularity (Snapdata International Group 2002). After statistical analysis, low-end, mid-range, and high-end MSRPs were attributed to the different products (using the 10^{th}, 50^{th}, and 90^{th} percentiles respectively), as listed in Table III. Though prices have gradually decreased over time (IBISWorld 2009a), especially for printers, it is assumed that the price ranges have remained constant and that only the relative sales at each price point have changed over time.

Table III: Price segmentation of different IT products, based on data collected from (The Orion Blue Book 2009)

Price Point	**Laptops (n = 62)**	**Desktops (n = 63)**	**Printers (n = 48)**	**CRT Monitors (n = 17)**	**LCD Monitors (n = 35)**
Low-end (10^{th} percentile)	\$999	\$500	\$63	\$199	\$298
Mid-range (50^{th} percentile)	\$1891	\$938	\$208	\$299	\$469
High-end (90^{th} percentile)	\$3010	\$2759	\$1537	\$588	\$1559

Data were collected about the retirement ages of the aforementioned IT products in the residential and commercial markets (U.S. Environmental Protection Agency 2007; Babbitt et al. 2009). Gamma distributions were used to model the age distribution of the product streams because these distributions have shape and scale parameters that can effectively capture the possible range of collection stream characteristics. The gamma distribution is of the form

$$f(x;\alpha,\beta) = \frac{1}{\beta\Gamma(\alpha)}\left(\frac{x}{\beta}\right)^{\alpha-1} e^{-\frac{x}{\beta}} \text{ for } x > 0;\ \alpha,\ \beta > 0 \quad (4)$$

where x = random variable (here, age), α = shape parameter, β = scale parameter, and Γ = the gamma distribution. Age distributions of retirement that occurs after a product's first service life were used to characterize end of lease retirements of printers and monitors because end of lease retirements occur after first use of a product (U.S. Environmental Protection Agency 2007; Rashid 2009). Empirical data collected by (Babbitt et al. 2009) on the current retirement ages of desktops and laptops used by academic institutions were used to characterize end of lease retirement of desktops and laptops. The means of the end of lease distributions were shifted slightly older to represent asset recovery returns, based on discussion with industry experts (Rashid 2009). Retirements that occur after a product's second service life were used to characterize municipal pick-up retirements because the second service life takes into account storage and/or long-term use (U.S. Environmental Protection Agency 2007). The means of the distributions were shifted slightly younger to represent retail take-back returns because products returned to retailers are generally younger and of better quality than those disposed through local municipalities (Guide Jr. et al. 2003b). On a relative scale, the distributional means (in years of age) of the aforementioned collection modes can be represented as:

$$\mu_{\text{End-of-Lease}} < \mu_{\text{Asset Recovery}} < \mu_{\text{Retail Take-back}} < \mu_{\text{Municipal Pick-up}}.$$

Figure 7 depicts product retirement distributions as related to collection mode. Though the distributions continue beyond 8 years, which is why the cumulatively probabilities displayed below may not add up to 100%, most returns are 8 years or younger. This is why the graphs terminate at 8 years.

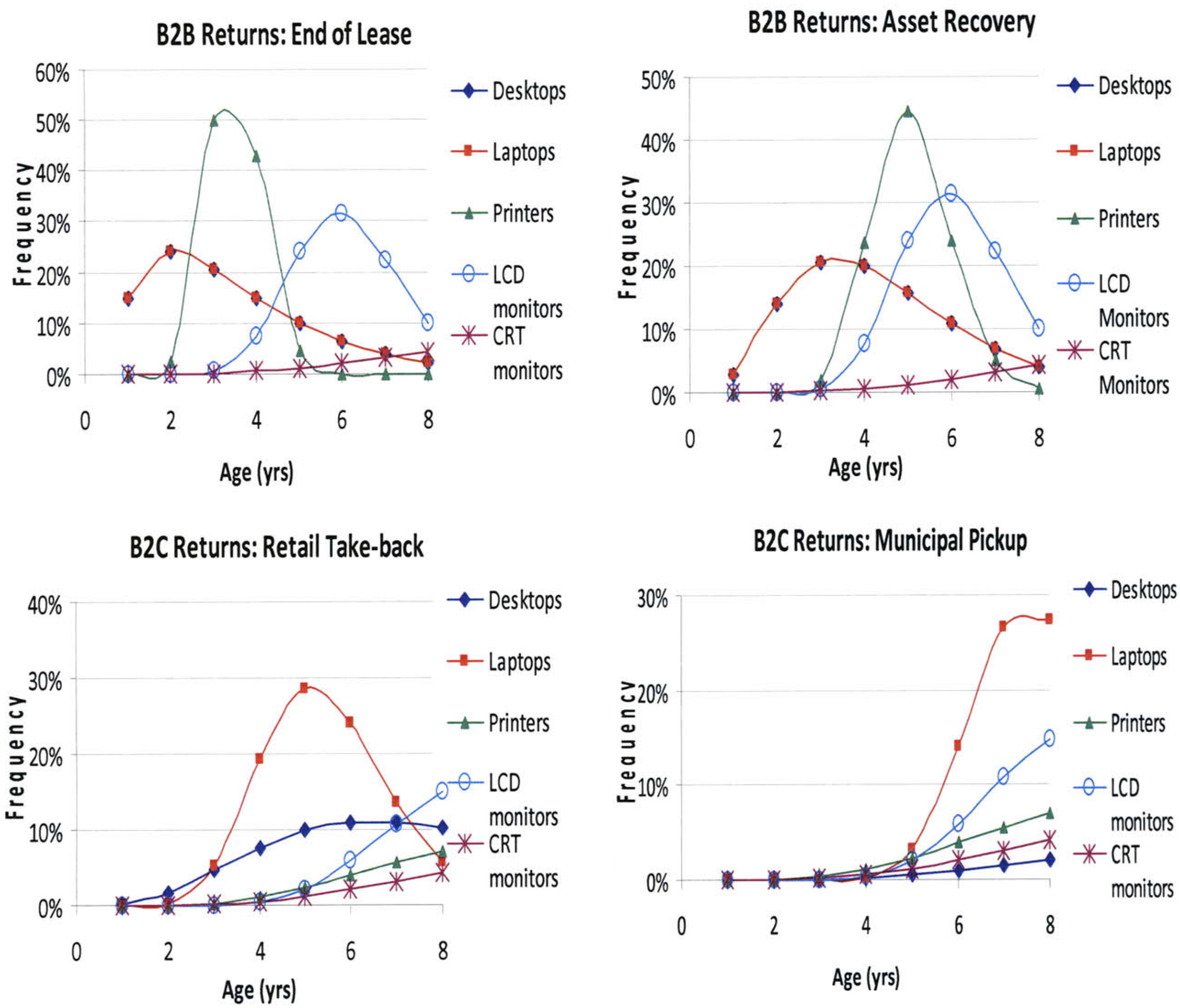

Figure 7: Retirement age distributions. B2B customers tend to return younger products than B2C customers. In both B2B collection modes, laptops and desktops share the same retirement age distributions.

No quantitative data exist on the relationship between the continued functionality of an IT product and its age, but industry experts anecdotally correlate the two (Rashid 2009). Thus, it was assumed that the functionality drops linearly with age, at a rate of 10% a year (see Figure 8).

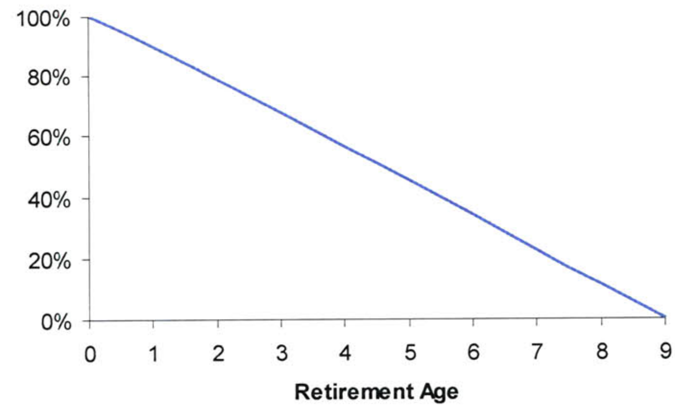

Figure 8: It is estimated that the probability that a one-year-old product is still functional is 0.90.

Depreciation represents the change in value of an asset because of aging, wear and tear, and obsolescence (Fraumeni 1997). Depreciation is a contributor to a product's resale value and is represented by Equation (1). The time-varying depreciation of each product type was compiled from resale data collected from (The Orion Blue Book 2009) for sale years 2002 through 2008, the same data set used to create representative MSRPs. CRT sales dropped precipitously after 2002, such that no CRT monitors younger than five years exist on the resale market (The Orion Blue Book 2009). As mentioned earlier, data collection was focused on Dell and HP computers and monitors and HP and Lexmark printers because of their market dominance. The assumption that depreciation is primarily a function of product type alone was correct; products within a particular category generally depreciate at the same rate regardless of MSRP. The largest deviation from the age-based estimates was 4%. The depreciation curves are displayed in Figure 9. Details of the procedure to build the decay functions are located in Appendix C.

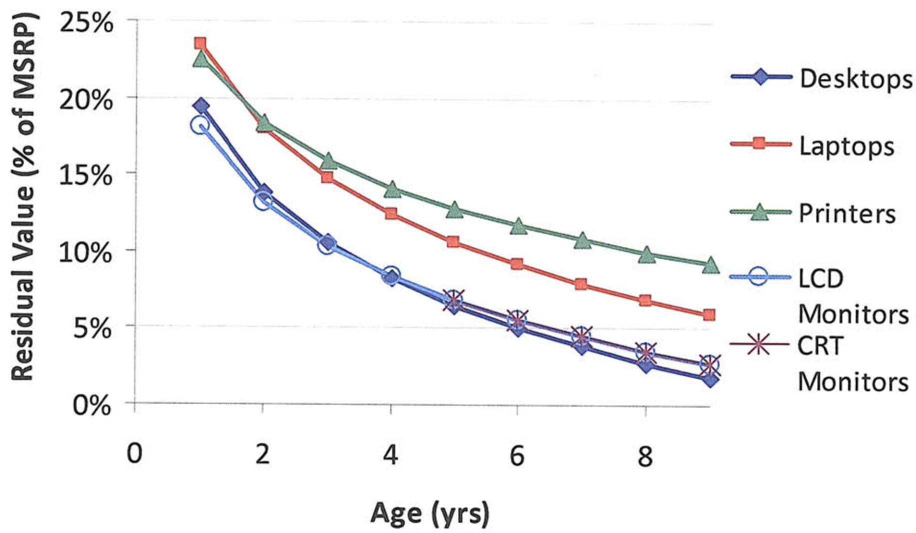

Figure 9: Calculation of the time-varying depreciation of IT products. In the first year after purchase, all products lose over 75% of their value.

Product weight and material composition are important to scrap material value. There is much variation in the estimated material composition of products reported in the literature. Furthermore, recyclers tend not to think about outgoing material streams on a product-level basis but by grouping recovered products as high-value and low-value e-waste. From visits to recycling facilities and a review of pertinent literature, the statistical average material composition of each product type was calculated (Miyamoto et al. 1998; Environmental Product Declaration 2001; Huisman 2003; Kuehr and Williams 2003; California Department of Toxic Substances Control 2004; Hikwama 2005; Lu et al. 2006; Musson et al. 2006; Huisman et al. 2007; U.S. Environmental Protection Agency 2007; Lee and Cooper 2008). Figure 10 is a summary of the material compositions; a more detailed list of materials can be found in Appendix B. As the figure below illustrates, desktop PCs are over 70% metals-based while laptops have high concentrations of metals and plastics.

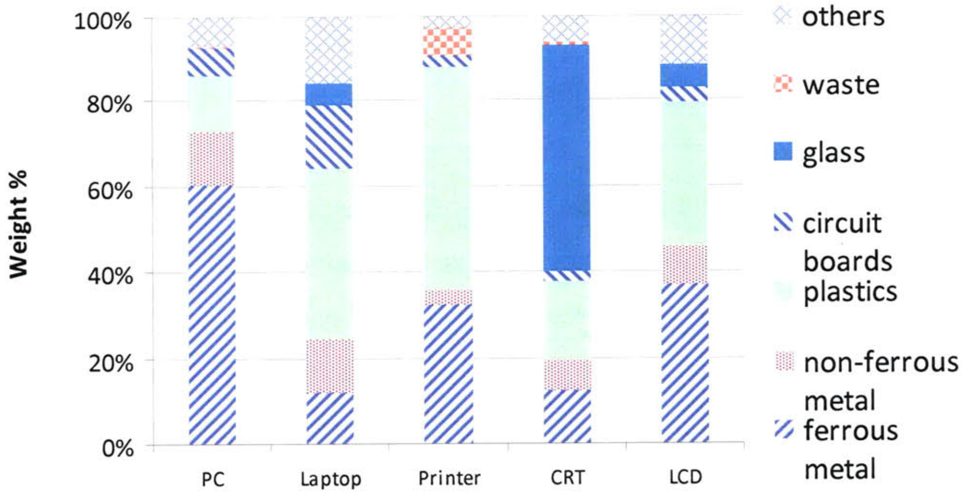

Figure 10: Material compositions of different IT products. Desktop PCs are primarily steel-based while printers are primarily plastics-based. The references on which the compositions are based are listed in the text.

It was discovered that average product weights have changed less than 1% over the past ten years (U.S. Environmental Protection Agency 2008). This is despite the increasing popularity of light and small laptops and printers (Jackson et al. 2009). Thus, an average product weight for each product type sold from 2000 to 2007 is used:

Table IV: Average product weights, based on data in (U.S. Environmental Protection Agency 2008)

Product	Weight (kg)
Desktop PC	10.1
Laptop	3.0
Printer	7.8
LCD Monitor	11.2
CRT Monitor	23.1

3.1.3. Secondary Market Characteristics

The current analysis compares whole product residual value, or simply resale value, to scrap material value. 2009 fair market values of used IT products were collected for each type of product, ranging from those sold in 2002 through 2008, in order to compute resale value decay curves (The Orion Blue Book 2009). Once product depreciation rates were calculated, as described in Section 3.1.2, MSRPs were added so that resale value could be calculated. Though depreciation rate is independent of MSRP, resale value is not. In other words, all laptops will depreciate at the same rate, but a high-end laptop will command a greater resale price than a low-end model of the same sales year. The equation for resale value is shown below.

$$V_{resale} = S*(-R\ln x + C) \text{ for } 1 \leq x \leq x_L$$

$$V_{resale} = 0 \text{ for } x > x_L \qquad (5)$$

where V_{resale} = resale value, S = MSRP, R = rate constant, x = age, C = initial value, and x_L = cut-off age at which resale viability ends. A cut-off age is incorporated into the description of resale value because according to industry experts, IT products lose total residual value on the U.S. market after four or five years, depending on the particular product (Rockhold 2008). Desktops and laptops are characterized as being viable for reuse for five years, while printers and LCD monitors are only viable for four years. One will notice in Figure 11 below that CRTs are represented as having no resale value. Earlier it was mentioned that no CRTs have been sold in the past five years. Therefore, according to information from industry experts, existing CRT monitors from previous sales years no longer have resale value on the U.S. market (Rockhold 2008). When validated against actual resale data in (The Orion Blue Book 2009), the constructed resale curves for products between one and five years old have an average error of 15%. Figure 11 depicts the depreciation portion of the resale value equation, taking into account the constraint that products no longer have resale value after age four or five. Figure 12 displays the full resale value curve for desktop computers at different price points. For example, a low-end desktop, with original MSRP of $500, is worth $100 after one year of use.

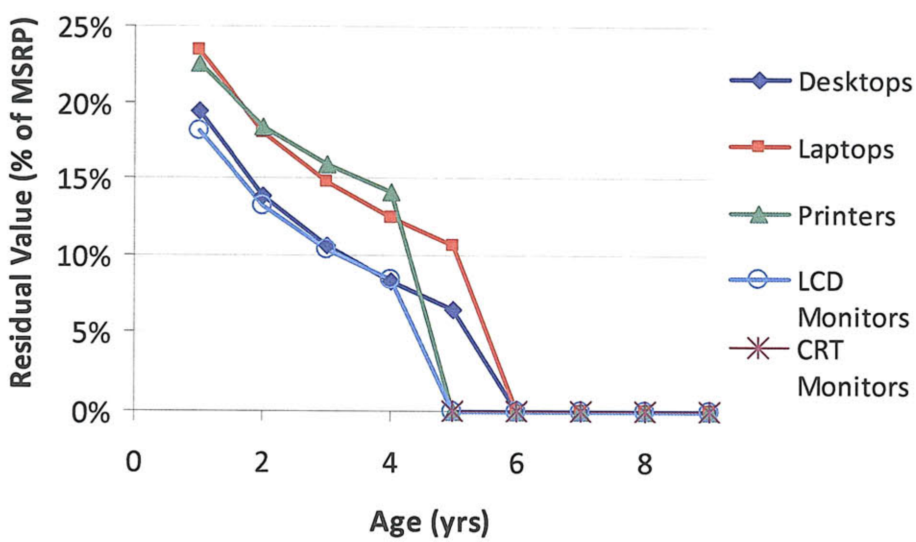

Figure 11: Product depreciation rates (with cut-off ages) where depreciation is shown as a percentage of MSRP. The cut-off age for the resale of printers and LCDs is four years; it is five years for desktops and laptops.

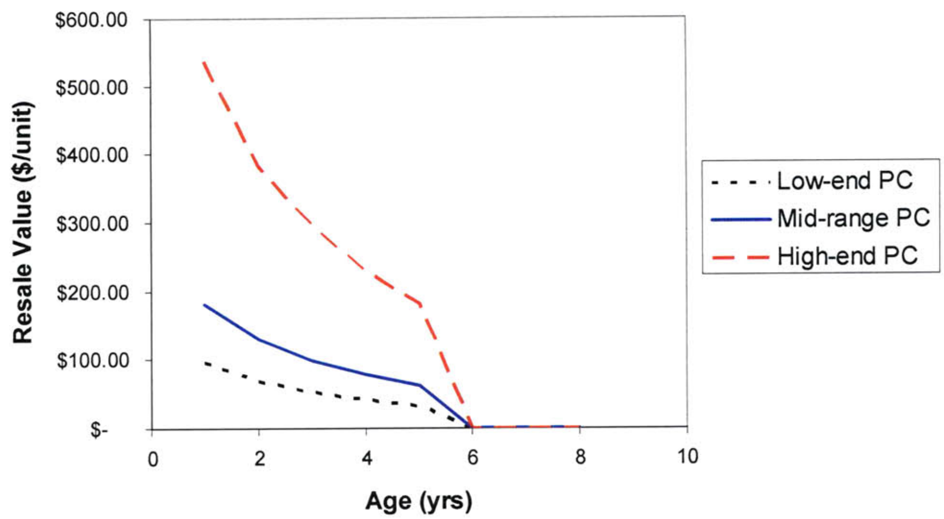

Figure 12: Resale value versus product age for different desktop PCs. Though adhering to the same decay rate, the resale values of desktop PCs differ because of their original MSRPs, which are indicators of their contained features and initial quality.

Figure 13 illustrates the differences in resale value of mid-range IT products at four years of age. Laptops have the greatest resale value by far at $235 per laptop.

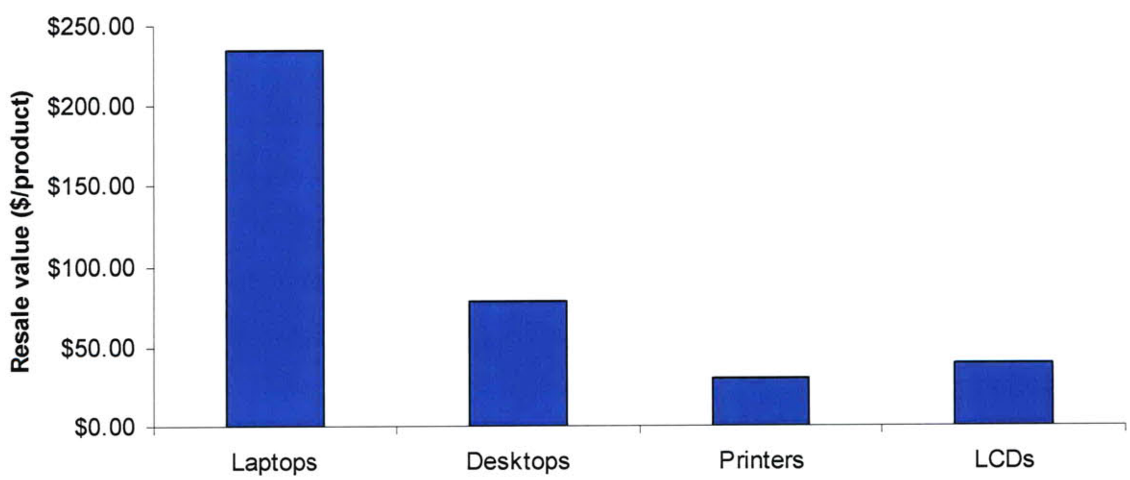

Figure 13: The resale value of different mid-range products that were purchased four years ago.

To compute scrap material values, data were collected on product material compositions and weights, which were shown earlier, and secondary commodity prices. Long-term commodity prices provide a framework for evaluating the effect of market fluctuations on recycling revenue. Monthly prices were collected for the time period April 2005 to August 2009 from the online Recycler's Exchange, a "membership based worldwide information exchange for those companies and individuals who buy/sell/trade [recyclable] commodities" (Recycler's World

2009). The commodities and their prices were vetted with industry experts for their plausibility and relation to actual outgoing streams at recycler facilities (Grant 2009; Rosner 2009; Ryan 2009). Monthly prices prior to 2005 were difficult to obtain.

The commodity industry has seen a great deal of volatility in recent years. As Figure 14 shows, some commodities experienced a large swing in value during the four-year period, whereas others remained relatively constant.

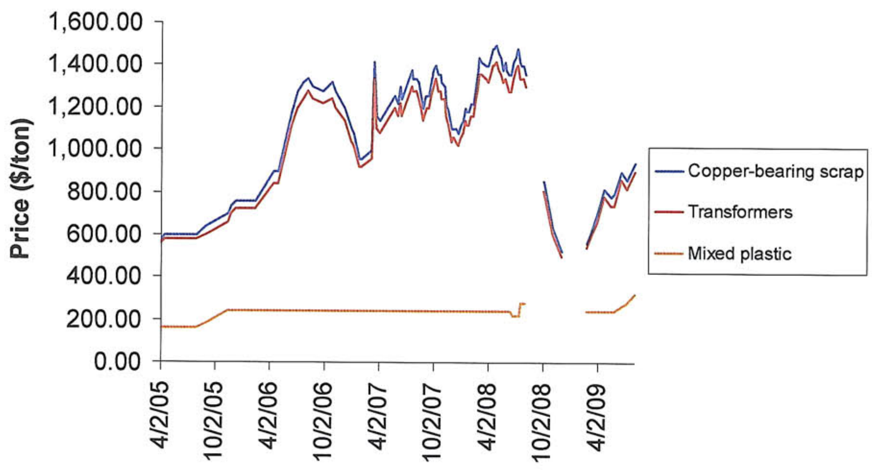

Figure 14: Scrap commodity prices from 2005 through 2009. Breaks in trend-lines indicate missing data points.

Using the mean monthly price and percent standard deviation over the four-year period, three market conditions are constructed for each commodity value: Poor (-2σ from the mean), Average, and Good, or Favorable, (+2σ from the mean). In this way, the effect of the highs and lows of the market on the valuation of a returned product's recyclable content can be analyzed. Some critical commodities and their associated prices are listed in Table V (see Appendix E for a full list of commodity prices).

Table V: Secondary commodity prices, as collected from (The Orion Blue Book 2009)

Outgoing Commodity	Market Prices ($/kg) Poor	Avg	Good	% variation
Mixed or irony Al	$ 0.26	$ 0.49	$ 0.73	23%
100% Al	$ 0.39	$ 0.75	$ 1.11	24%
Mixed plastic	$ 0.22	$ 0.26	$ 0.31	8%
ABS plastic	$ 0.18	$ 0.37	$ 0.55	25%
High grade CBs	$ 1.81	$ 3.12	$ 4.43	21%
Low grade CBs	$ 0.07	$ 0.13	$ 0.19	22%
Copper	$ 1.71	$ 4.63	$ 7.56	32%
Copper-bearing (incl. wires)	$ 0.68	$ 1.27	$ 1.86	23%
Steel	$ 0.08	$ 0.25	$ 0.41	33%
Stainless steel	$ 0.67	$ 2.20	$ 3.73	35%
Grade B steel	$ 0.08	$ 0.22	$ 0.36	32%
Waste	$ (0.12)	$ (0.12)	$ (0.12)	0%
Glass	$ (0.20)	$ (0.20)	$ (0.20)	0%

Finally, product scrap material value can be calculated according to Equation 3, reproduced below:

$$V_{recyc} = m\sum_{1}^{N} p_i x_i$$

where V_{recyc} = product scrap value, m = product mass, i = commodity, x = weight fraction of commodity, p = price of commodity, and N = number of recoverable commodities in the product. As Figure 15 shows, even though laptop computers contain a high concentration of valuable commodities (including circuit board waste), their low weight results in low overall scrap value. Somewhat surprising is the fact that CRT monitors, which recyclers consider the greatest burden in e-waste recycling, have positive scrap material value. The value of the contained metals clearly outweighs the negative value of the glass[1].

[1] In this particular exercise, only material value, i.e. gross revenue from material composition of products, was considered. Once recovery costs are included, CRT monitors present a net cost.

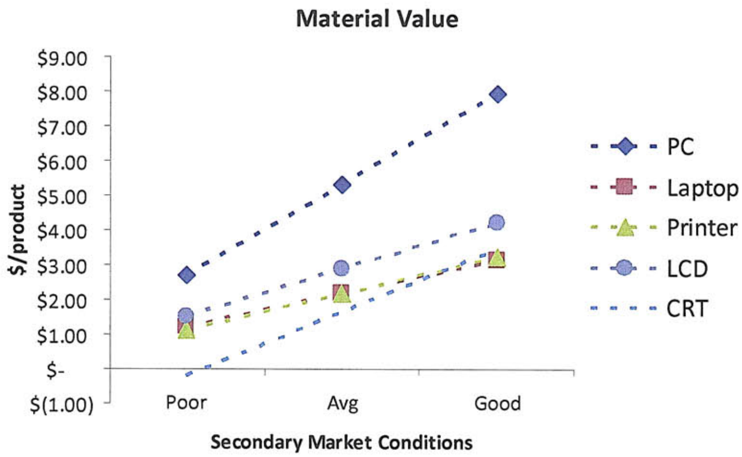

Figure 15: Recycling value of IT products under different market conditions.

In comparing Figure 13 and Figure 15, it is interesting to note the large difference between resale value and scrap value. While a five year old, low-end desktop is worth $40 on the used product market, its material content is worth only $8 in a favorable secondary market.

3.1.4. Processing Characteristics

Literature sources were used to build a range of costs for both reuse and recycling activities (Boon et al. 2001; Hainault et al. 2001; Northeast Recycling Council 2002; Caudill 2003; Future Energy Solutions 2003; U.S. Environmental Protection Agency 2004; Product Stewardship Institute 2005; Sepanski et al. 2005; Northwest Product Stewardship Council 2006; Huisman et al. 2007; Electronics TakeBack Coalition 2008; California Department of Resources Recycling and Recovery 2009; Californians Against Waste 2009; Maine's Department of Environmental Protection 2009; Nat'l Electronics Recycling Infrastructure Clearinghouse 2009; Walther et al. 2009). Costs found in the literature described particular steps in the EOL chain, such as collection, or covered the entire recycling process (see Appendix F). As such, very few could be distinguished as pertaining to a particular product. Therefore, judgment was used to adjust costs by product type to account for differences in processing difficulty, including labor-intensive steps for hazardous material removal (see Table VI for a list of average recovery costs). For example, CRT monitors require hazardous component removal, so their recycling processes are more costly. Meanwhile, in refurbishing desktops and laptops, extra cost is added because of data-wiping activities and potential replacement of non-functioning components (Grant 2009; Rashid 2009; Rosner 2009; Ryan 2009).

Table VI: Average processing costs (does not include revenue generated from scrap). References used are listed in the text.

	Costs ($/kg)	
Product	Processing for Reuse	Processing for Recycling
Desktop PCs	$0.36	$0.74
Laptops	$0.34	$0.74
Printers	$0.35	$0.74
CRT monitors	$0.34	$0.81
LCD monitors	$0.33	$0.78

3.2. Baseline Analysis

The following baseline scenario demonstrates the usefulness of the MFE model in understanding the economics of IT recovery. It was imagined that a recovery system receives 1,000,000 IT products annually. 50% of returns are from residential customers; the other 50% from commercial customers. The mix of products from B2C customers is defined according to the recent trend in IT sales and product retirement profiles, as described in Sections 3.1.1 and 3.1.2. Therefore, it is assumed that 32% of the retired product volume is CRT monitors, 30% desktops, 24% printers, 9% laptops, and 5% LCD monitors. In this scenario, all of the B2C returns originate from municipal pick-up. The mix of products from business customers is loosely based on data from an OEM who operates an e-waste recovery system. Thus, the B2B product mix is 40% desktops, 30% CRTs, 15% laptops, 10% LCD monitors, and 5% printers. It is also assumed that all of the B2B returns are end of lease products. From the MSRP data previously collected, it can be roughly estimated that the sales distribution of products is 50% low-end, 25% mid-range and 25% high-end models. This distribution was confirmed as a reasonable estimate by industry experts (Rockhold 2008). In the analysis, it is assumed that the scrap commodity market is operating under average conditions. Following the model algorithm as outlined in Section 2.3.2 and using the previously defined age distributions, depreciation curves, scrap value calculations, and other system parameters, the profit of the system is calculated.

The recovery system makes an average of $1.99/kg and $25.97/product. In total, profit is $26M.

Figure 16 illustrates that most of the incoming products, 82% exactly, are recycled. Approximately one-third of incoming desktops are reused, while no monitors are reused. In Figure 17, a comparison is made between contribution to total system profit and contribution to inflow mass by product type. Though laptops represent only 9% of the incoming mass, they contribute over 50% of the system profit. Figure 18 illustrates why; a B2B laptop is worth almost \$100/kg resold and a B2C laptop is worth \$60/kg resold. Laptops are by far the most lucrative products to collect on a per mass basis; per mass, they are over three times more profitable than the next profitable product, desktops. Meanwhile, CRTs represent 55% of the mass and almost all of the system cost. Figure 19 shows that CRTs cost over \$0.65/kg to process. Other illustrative graphs can be found in Appendix G.

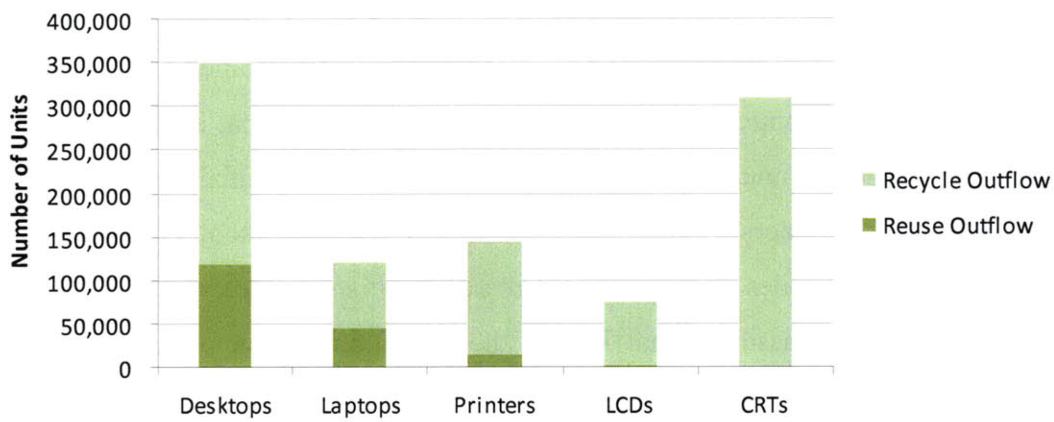

Figure 16: An illustration of the number of products that meet each fate.

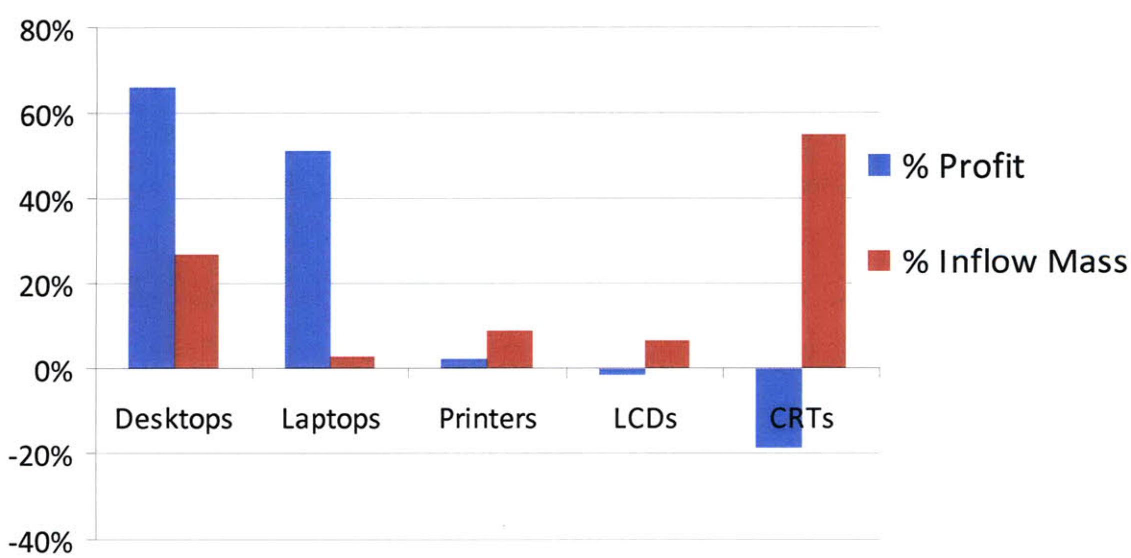

Figure 17: Product contribution to total profit. A negative percent contribution to profit represents a net cost.

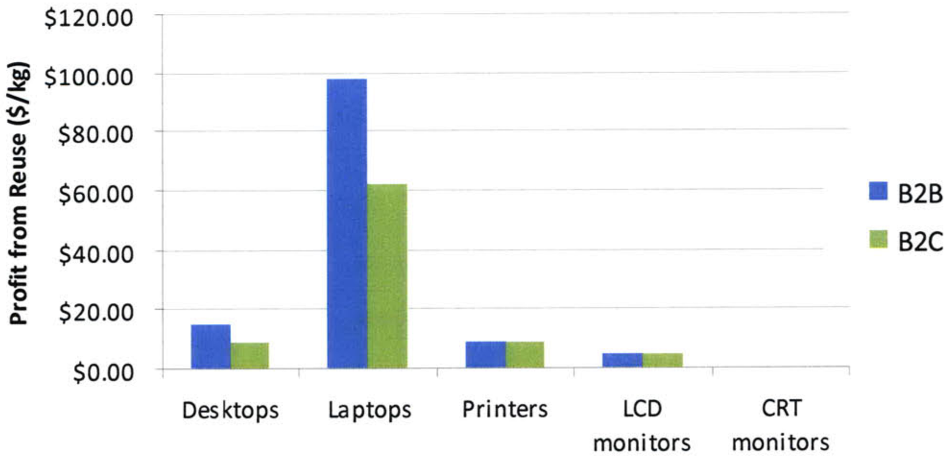

Figure 18: Profit from reuse. In the reuse stream, laptops are the most profitable products on a per-mass basis. No CRTs are eligible for reuse. B2B returns generate more profit because they are younger.

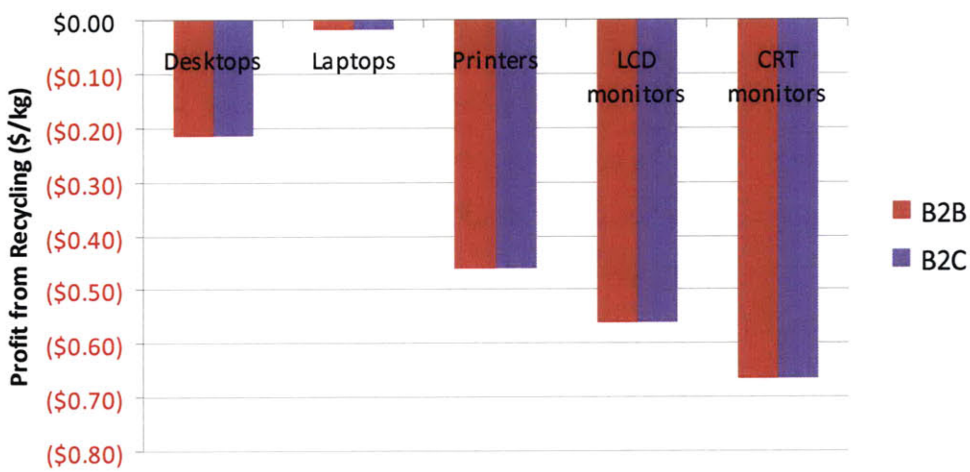

Figure 19: Profit from recycling. In this scenario, there is no profit from recycling. Collection source doesn't matter in recycling, because recycling profit is based on material composition of the product.

3.3. DOE Analysis

The Design of Experiments (DOE) method of statistical analysis was used to identify which system variables produce the largest variation in revenue potential. The analysis was conducted using JMP® software. Since the intent was to detect variable influence on revenue, the analysis was conducted in a zero cost environment.

DOE analysis is a method that allows one to screen important variables without using intense computation. It provides a way to quickly gain directional insight about the effect of independent variables on a response variable and thereby know where to focus further analysis. A $2^{6-1}{}_{V}$ screening design was used; the experimental matrix is shown in Table VII.

Table VII: Experimental design for DOE analysis

Factor	Units	- Level	+ Level
Retirement Age	Years	Mean age = 7, σ = 1	Mean age = 2, σ = 1
Product Mix	% by return volume	66% Low Value	66% High Value
Sales Price	U.S. Dollars	50% low-end products	50% high-end products
Depreciation Rate	% depreciation	Double current rate	Current rate
Commodity Prices	U.S. Dollars	Poor market	Favorable market
Return Volume	Number of products	100,000	3,000,000

To understand the effect of retirement age, the negative level was set such that within each product type, the mean age of returns was 7 years old, with a standard deviation of 1 year. The gamma distribution was used to represent each age distribution. Meanwhile, the positive level was set at a mean age of 2 years old, with a standard deviation of 1 year.

As for product mix, 66% Low Value refers to a return amount that is 66% monitors by volume, evenly split between LCD and CRT monitors. The remaining 34% is evenly split among laptops, PCs, and printers. Monitors are considered low-value e-waste because they contain less complex circuit boards and a higher concentration of undesirable commodities, such as glass. 66% High Value refers to a return amount that is 33% laptops and 33% desktops. The remaining 34% is evenly split between printers and monitors.

To investigate the impact of original sales price, or MSRP, DOE levels were set to describe the volume of returns at different price points in each product category. For instance, the negative level setting means that 50% of laptop returns are low-end models, 25% are mid-range, and 25% are high-end models. This ratio exists for every product category. The positive level setting means that 50% of returns are high-end models, 25% are mid-range, and 25% are low-end.

For depreciation rate, two situations are considered. At the negative level setting, products depreciate at the individual rates that were seen currently on the used market. At the positive level setting, these rates have been doubled. It was believed that this was a wide enough range because the decay function changes dramatically. For example, instead of desktops maintaining residual value through five years of age, they would only maintain it through three years (see Figure 20).

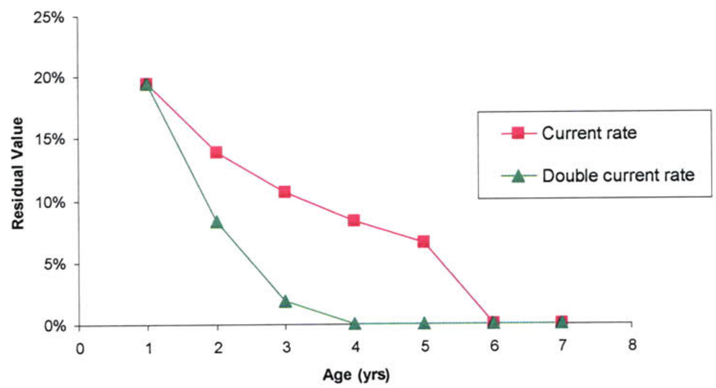

Figure 20: The two levels of desktop resale value considered. Doubling the depreciation rate causes an early loss of resale value.

Finally, to investigate the effect of commodity prices on revenue potential, levels were set such that all prices were either two standard deviations below or two standard deviations above their average price. Finally, total return volume was also varied from 100,000 products to 3,000,000.

The analysis revealed that product age was by far the most influential factor on revenue per unit mass ($/kg) (see Table VIII and Figure 21). The average revenue generated by scenarios involving young returns was $12.05/kg; for older returns it was $0.49/kg. As shown previously, resale value can be substantially greater than scrap value if a product is retired at a time when it still retains most of its usefulness. As this analysis shows, when the mean age of returned products is two years, the products still have significant value on the used product market. According to Table VIII, moving from collecting all old returns to all young returns increases gross revenue by $11.40/kg. The interaction between age and product mix is also influential on revenue. Young, high value returns have a large positive effect on gross revenue. This confirms anecdotal evidence that the most important returns are young laptops and desktops.

Table VIII: Results of the first DOE analysis. The table depicts only the parameters that were found to be statistically significant (p-value < 0.05).

Summary of Fit		Analysis of Variance		
R^2	0.994477	Source	DF	F Ratio
R^2 adj	0.982879	Model	21	85.7427
RMSE	0.975836	Error	10	Prob > F
Mean of Response	6.271563	C. Total	31	<.0001
Observations	32			

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	6.271563	0.172505	36.36	<.0001
Age	5.782813	0.172505	33.52	<.0001
Mix	2.994063	0.172505	17.36	<.0001
Age*Mix	2.787813	0.172505	16.16	<.0001
Sales Price	1.015313	0.172505	5.89	0.0002
Age*Sales Price	0.985313	0.172505	5.71	0.0002
Depreciation Rate	0.755938	0.172505	4.38	0.0014
Age*Depreciation	0.674688	0.172505	3.91	0.0029
Mix*Sales Price	0.452813	0.172505	2.62	0.0254

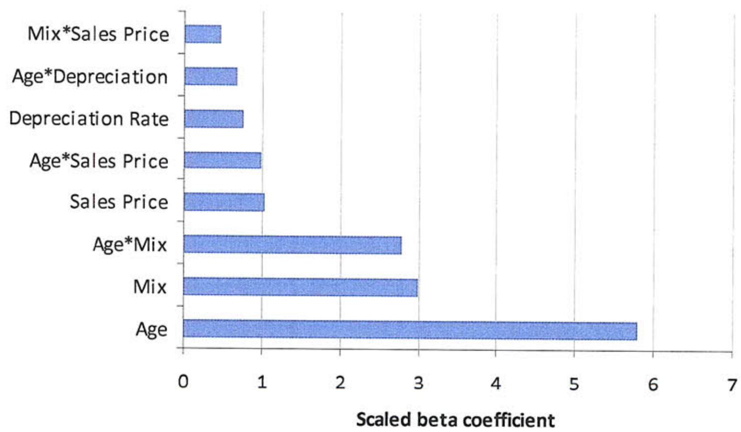

Figure 21: A Pareto chart of the factors that were found to be statistically significant, using DOE analysis. A scaled beta coefficient is the normalized estimate of the half-effect of a parameter on the dependent variable (e.g. revenue).

A second analysis was completed to determine which factors become important when a firm finds itself dealing primarily with young returns versus old returns. In real-life, firms who recover products from B2B customers tend to recover much younger products than firms who recover products from B2C customers. As such, their economic outlooks are very different and are likely to be affected by different system components.

In the second analysis, performed using two separate 2^4 full factorial designs (return volume was excluded as a factor), product mix was determined to be a large source of variation in revenue for both scenarios. It was the largest source of revenue variation for younger returns, followed by depreciation rate and sales price (see Table IX and Figure 22). In fact, product mix has more than double the impact on revenue potential as product depreciation does (beta coefficient = 4.39). The use value of laptops and desktop PCs, being the most complex IT products, greatly outweighs that of monitors.

Table IX: Results of DOE analysis on the factors that influence revenue for younger returns. The table depicts only the parameters found to be statistically significant (p-value < 0.05).

Summary of Fit		Analysis of Variance		
R^2	1	Source	DF	F Ratio
R^2 adj	0.999999	Model	14	1239274
RMSE	0.005	Error	1	Prob > F
Mean of Response	9.15625	C. Total	15	0.0007
Observations	16			
Sorted Parameter Estimates				
Term	Estimate	Std Error	t Ratio	Prob>|t|
Mix	4.39	0.00125	3512	0.0002
Depreciation Rate	2.00125	0.00125	1601	0.0004
Sales Price	1.51625	0.00125	1213	0.0005
Depreciation*Mix	0.975	0.00125	780	0.0008
Sales Price*Mix	0.665	0.00125	532	0.0012
Depreciation*Sales Price	0.33625	0.00125	269	0.0024

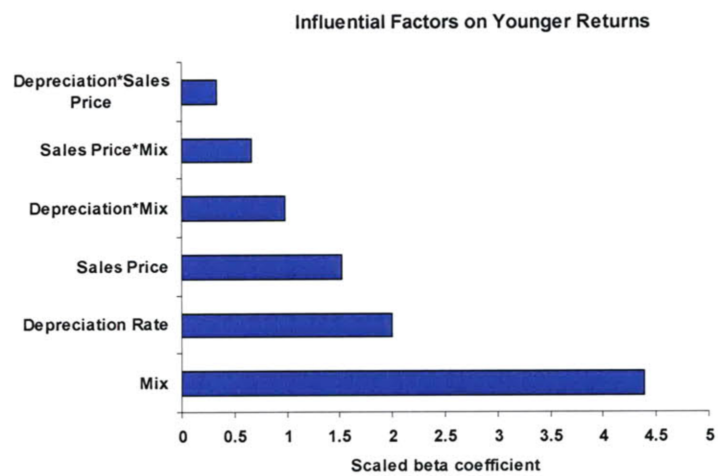

Figure 22: Product mix is the most important factor for a firm that receives younger returns.

Meanwhile, product mix was second to commodity prices in its effect on revenue for old returns (see Table X and Figure 23). Old returns only provide recycling value so it is not surprising that commodity prices become the most important factor as they directly influence scrap material value (beta coefficient = 0.15).

Table X: Results of DOE analysis on the factors that influence revenue for older returns. The table depicts only the parameters found to be statistically significant (p-value < 0.05).

Summary of Fit		Analysis of Variance		
R^2	0.999988	Source	DF	F Ratio
R^2 adj	0.999824	Model	14	6075.286
RMSE	0.0025	Error	1	Prob > F
Mean of Response	0.295625	C. Total	15	0.0101
Observations	16			

Sorted Parameter Estimates				
Term	Estimate	Std Error	t Ratio	Prob>|t|
Commodity Prices	0.146875	0.000625	235	0.0027
Mix	0.099375	0.000625	159	0.004
Commodity Prices*Mix	0.033125	0.000625	53	0.012
Depreciation	0.021875	0.000625	35	0.0182
Depreciation*Mix	0.013125	0.000625	21	0.0303

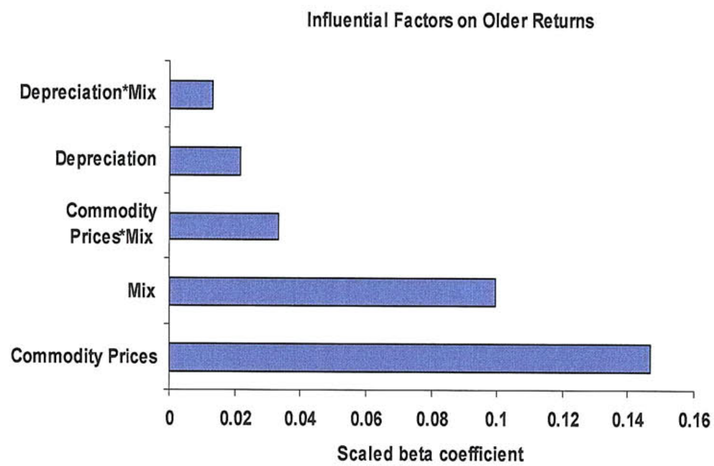

Figure 23: Results of DOE analysis of the most influential factors on revenue potential for a firm that receives older returns

What is also interesting about the results is that interactions proved to be important. For example, the interaction between depreciation and product mix is statistically significant in predicting revenue in a young-age return scenario. If the depreciation is slow and the product mix is high-value, then the recovery system should realize higher revenues. Meanwhile, the interaction between commodity prices and product mix is significant in an old-age return scenario. Their interaction changes gross revenue by $0.06/kg, which is significant when a firm operates around break-even conditions.

3.4. Scenario-based Sensitivity Analysis

DOE analysis is useful for quickly identifying the most influential variables in a system. However it is limited because it forces the variables into binary states. Other tools are necessary for quantifying sensitivity of revenue to a range of variable states. The following analyses are single variable sensitivities of a recovery system that operates in particular contexts.

The revenue that an e-waste recovery system generates depends on the collection sources it relies on for returns, as dictated by legislation or simply by the market segment in which a firm operates. For example, of the 20 U.S. states that have IT-specific e-waste legislation, all require take-back of monitors and laptops; only four require take-back of printers (Electronics TakeBack Coalition 2010). In addition, many IT manufacturers, such as HP or Dell, sell to B2B and B2C customers, and can thus rely on both customer bases for returns. It was already shown that collection source often influences age of returns. DOE analysis revealed the large impact that age has on revenue potential. In addition, product mix was shown to be vital to revenue potential. Thus, six collection scenarios were considered in the investigation of revenue sensitivity to changes in these key system variables.

Table XI: Six collection scenarios considered for analysis

100% B2B High Value Mix	Even 50% High Value Mix	100% B2C High Value Mix
100% B2B Low Value Mix	Even 50% Low Value Mix	100% B2C Low Value Mix

The scenarios differ by collection source, a proxy for age of returns, and product mix. "100% B2B" means that returns are sourced solely from commercial customers through end of lease; in other words, returned products tend to be young and still functioning. "100% B2C" means that returns are sourced solely from residential consumers through municipal pick-up or community events; returns tend to be older. "Even 50%" means an equal number of returns are sourced from both customer bases. Many firms find themselves operating somewhere along this spectrum (Rockhold 2008).

Product mix directly influences reuse and recycling value. In the scenarios, "High Value" describes a product mix of returns in which desktop PCs and laptops comprise 66% of the returns, by return volume. "Low Value" mix describes a mix of returns in which CRT and LCD monitors comprise 66% of the returns, by volume. Product age profiles for each consumer source were shown earlier in Figure 7.

The following analyses are executed under zero cost conditions. This was considered reasonable because, although processing costs are not constant, they are similar across products and are therefore insignificant. A constant return volume is also assumed; only the relative return share of each product type changes.

Before testing sensitivities, it is useful to understand how the economic performance of the six scenarios differs under average conditions. In the following table, it is assumed that all returns are mid-range models and that the scrap commodity market is behaving at average conditions. As the table below depicts, both product mix and collection source have substantial impact on total profit.

Table XII: The recovery system's profit in different operating scenarios. It changes dramatically depending on product mix and collection source.

	100% B2B	Even 50%	100% B2C
High Value Mix	$9.46/kg	$4.64/kg	-$0.17/kg
Low Value Mix	$1.75/kg	$0.62/kg	-$0.52/kg

3.4.1. Sensitivity to Commodity Prices

DOE analysis revealed that aside from product age and mix, commodity prices, depreciation rate, and price points are important determinants of revenue. The first analysis in this section focuses on what effect fluctuations in scrap commodity prices may have on the revenue of a firm operating in each scenario.

In this analysis, it is assumed that the market of available returns consists of 50% low-end products, 25% mid-range, and 25% high-end products. This sales distribution is based on discussions with industry experts (Rockhold 2008). It is also assumed that each product type is depreciating at the current rate compiled from data. The reference point for the following analysis is a time when all commodity prices are at their mean values. When this occurs, product scrap values are also at their mean values. A multiplier is used to move prices below or above this condition. For example, if the multiplier is increased by 25%, then all commodity prices increase by 25% and the scrap value of each product type increases by 25%. The following graph illustrates what happens to the scrap value of each product type as the commodity multiplier changes. The results are similar to the previous description of poor and favorable market conditions.

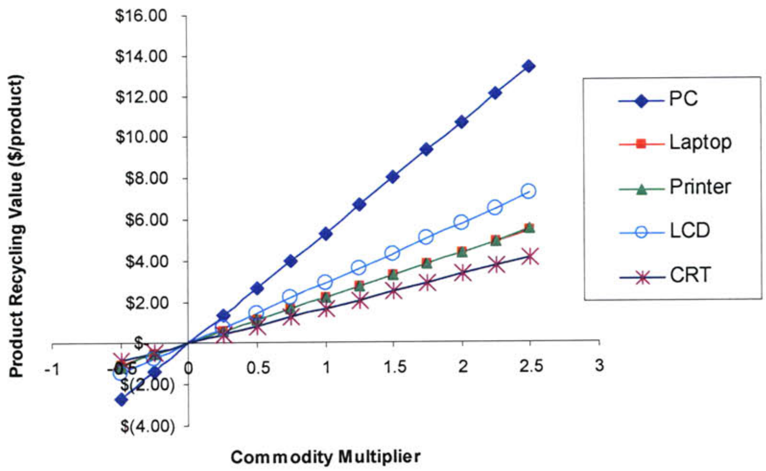

Figure 24: The change in scrap material value as the commodity multiplier changes. A multiplier of one represents the reference point when the commodity market is at average market conditions.

Figure 25 displays the sensitivity of the firm's overall revenue to commodity prices when it operates in the six scenarios mentioned earlier. Upon evaluation of sensitivity, it is not surprising that recovery systems that can rely on the retained use value of B2B returns are unaffected by commodity market fluctuations. Meanwhile, the results about B2C returns confirm the DOE results on older returns. As Figure 25 indicates, a 1% change in commodity price leads to nearly 1% change in gross revenue for both B2C collection scenarios, in which recycling revenue plays a key role. If the state of the secondary commodity market plunged by 50%, similar to the decline in prices seen in 2008, the firm could expect approximately a 40% drop in gross revenue.

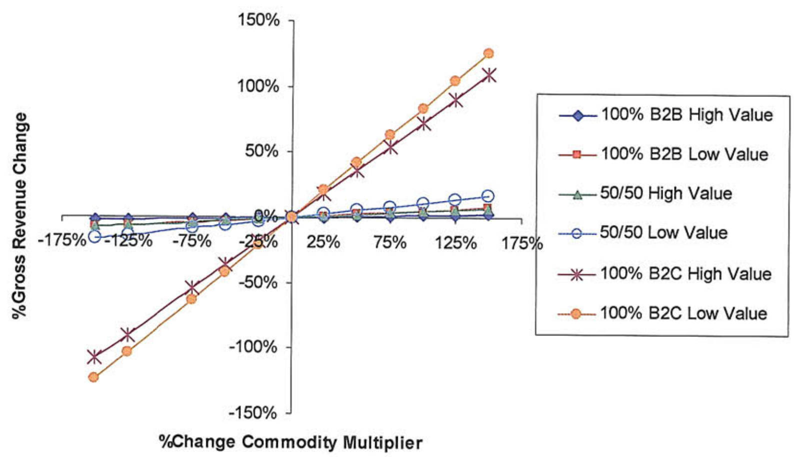

Figure 25: Residential returns are highly influenced by scrap market conditions because of the high rate of recycling that occurs.

3.4.2. Sensitivity to Product Depreciation

In the DOE analysis, depreciation was shown to be important to revenue generation at a firm that receives primarily young and high value returns. To demonstrate revenue sensitivity across a range of possible depreciation rates, a depreciation multiplier was created. The multiplier was applied as a scalar to the right side of Equation 1. The depreciation multiplier simply increases or decreases the rate of depreciation of each product type, with the reference point being the current rate of depreciation of each product type as calculated from the data. A slower rate of depreciation could occur if the used IT market became more viable in the U.S. or if manufacturers increased the use life of products. More likely is the advent of a faster rate of product depreciation because of the decreasing profit margins in the IT industry and the emergence of more competitors (IBISWorld 2009a). Figure 26 illustrates the effect of the depreciation multiplier on the depreciation rate of a desktop PC. A depreciation multiplier of 1 corresponds to a desktop maintaining residual use value until age five. Increasing the multiplier to 4 means use value disappears by age two.

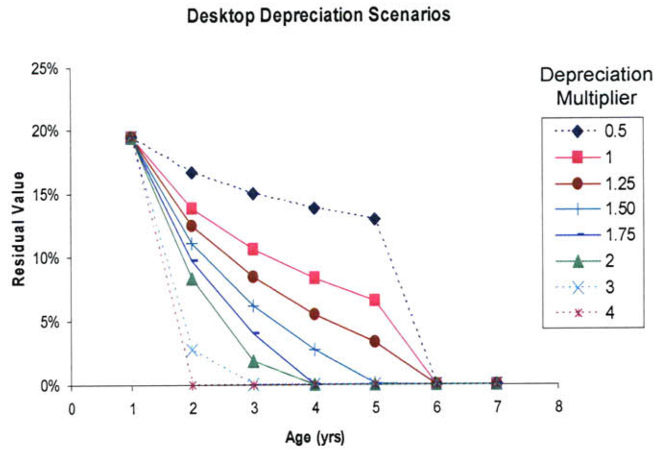

Figure 26: Different possible depreciation rates of desktop PCs. The reference point is at a multiplier of one.

In the analysis of the sensitivity of the operating scenarios to the depreciation multiplier, the commodity market was held constant at average conditions. The sales price distribution of returned products consists of 50% low-end products, 25% mid-range, and 25% high-end products. The analysis shows that there is a nonlinear relationship between revenue and product depreciation (see Figure 27). A moderate change in revenue occurs for all scenarios that involve B2B products. A 100% change in depreciation rate, equivalent to a doubling of the depreciation rate for all products, results in 40% decrease in gross revenue for the 100% B2B and Even 50% scenarios. The effect of even faster product depreciation is less substantial. In fact, it appears that in the case of extreme depreciation (a loss of retained use value by age two for the desktop PC), the effect on revenue bottoms out at -60%. This bottoming-out happens much sooner in the 100% B2C cases and indicates that because of the older age of returns, revenue quickly becomes dominated by recycling activities.

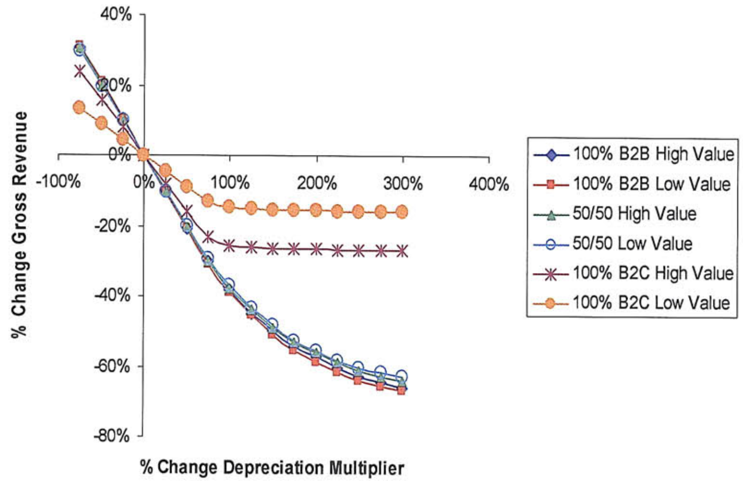

Figure 27: Depreciation rate has the largest impact on 100% B2B collections

3.4.3. Sensitivity to MSRP

DOE analysis also showed the statistically significant impact of sales price on younger return scenarios. A MSRP multiplier was used to move the return stream from one consisting of all low-end products to one consisting of all high-end products. One can imagine a firm that sells and receives back only high-end IT models, such as gamer-oriented laptops. One could also imagine product sales moving to lower price points in the industry and what the impact may be on resale value at product end-of-life.

The reference point of this analysis is the mid-range price point for each product type as calculated from collected data. As Figure 28 depicts, there are a wider range of price points that are covered by laptops as opposed to printers when using the mid-range price point as the reference.

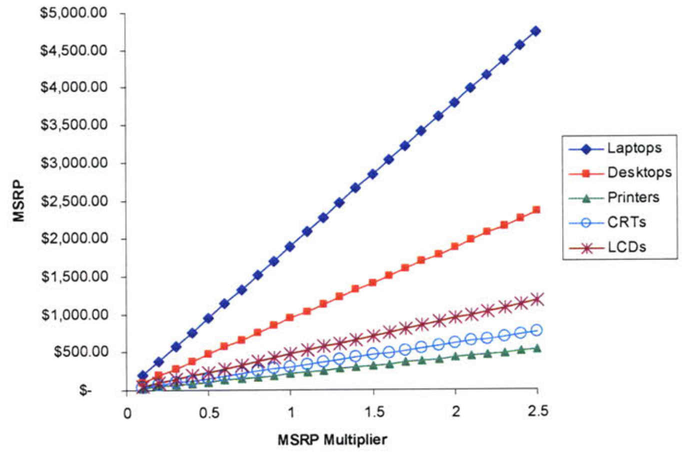

Figure 28: Change in product MSRP with change in multiplier. The reference point is a multiplier of one.

When calculating the sensitivity of the operating scenarios to MSRP, commodity conditions were kept constant at average conditions. Product depreciation was also set at current rates. Revenue is affected in each scenario. The greatest effects occur in scenarios that rely partially or in whole on B2B returns. In those scenarios, a 1% increase or decrease leads to the same change in gross revenue (see Figure 29).

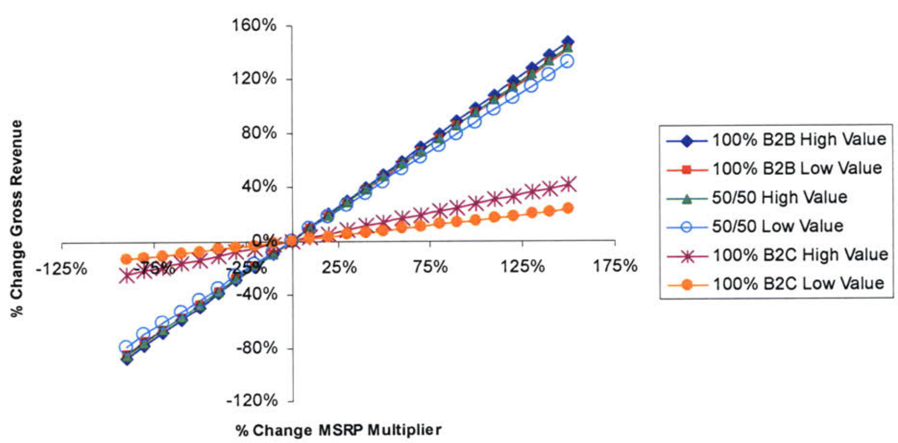

Figure 29: The quality of returns has a strong effect on systems that rely partially or wholly on B2B returns

3.4.4. Summary of Single Variable Sensitivity Analysis Results

The average elasticities of gross revenue to commodity prices, depreciation rates, and MSRPs are listed in Table XIII. Negative elasticities mean an increase in the particular system property results in a decrease in revenue, as is the case with all depreciation elasticities. An elasticity of 0.95 means that 1% change in the system property results in 0.95% change in gross revenue. Large sensitivities are highlighted. As the table shows, when a firm receives only residential returns, its revenue potential is highly dependent on scrap commodity prices. When a firm depends on both B2B and B2C returns, its revenue potential is contingent on the MSRPs of the returns.

Table XIII: Commodity price elasticity of gross revenue

Collection Source	Product Mix	Commodity Elasticity	Depreciation Elasticity	MSRP Elasticity
100% B2B	High Value Mix	0.02	-0.34	0.98
	Low Value Mix	0.05	-0.35	0.94
Even 50%	High Value Mix	0.05	-0.33	0.95
	Low Value Mix	0.11	-0.33	0.88
100% B2C	High Value Mix	0.73	-0.22	0.27
	Low Value Mix	0.84	-0.12	0.15

3.5. Monte Carlo Simulation

Monte Carlo analysis was used to build upon the previous analyses by disaggregating lumped variables to understand their effects on the system when they vary simultaneously. The analysis was completed using @RISK software.

In the following analysis, the same six scenarios from earlier are considered. For B2B returns, the collection volume originating from asset recovery versus end of lease was allowed to vary uniformly. A uniform distribution was also used to describe the percentage of returns originating from municipal pick-up versus retail take-back in the case of B2C returns. Age distributions by product type and collection mode were still characterized using gamma distributions, but uniformly varying the percentage of returns originating from each collection mode allowed the system's overall return age distribution to vary for each simulation iteration. Inverse gauss distributions were fit to the previously collected data on product MSRPs, such that the distribution of incoming products could be set by varying sales price directly, instead of determining the percentage of products at each sales level (i.e. low-end products), which was used previously. The depreciation of product use was allowed to vary for each product type. This was accomplished by associating a distinct depreciation multiplier to each depreciation curve and using a triangle distribution to allow the multiplier to vary between 0.5 and 4. CRT depreciation was not included because, as mentioned earlier, CRTs have no resale value in the U.S. market. The price of individual commodities was allowed to vary using gamma distributions to represent the collected data. The correlation between prices of similar commodities, such as pure aluminum and irony aluminum, was included so that they would vary together. All input distributions are provided in Appendix I.

Finally, two extra variables were added to the sensitivity analysis. Recovery costs were included and were allowed to vary +/- 10% from the average values found in literature. This variation is to partly represent cost differences between manual-heavy and automation-heavy processes. The probability of a product's working status, as related to its age, was also allowed to vary. Originally, the linear relationship was set up such that a product's probability of functioning dropped by 10% with each successive year, meaning that all products are assumed non-working by age nine (see Figure 8). In this exercise, this value was allowed to vary between 7% (no products function after age 14) and 12% (no products function after age 8) using a triangle distribution.

Three simulations of 1000 iterations were run for each scenario. Figure 30 depicts results of the high value mix simulations. As mentioned previously, high value means that 66% of returns are desktops and laptops.

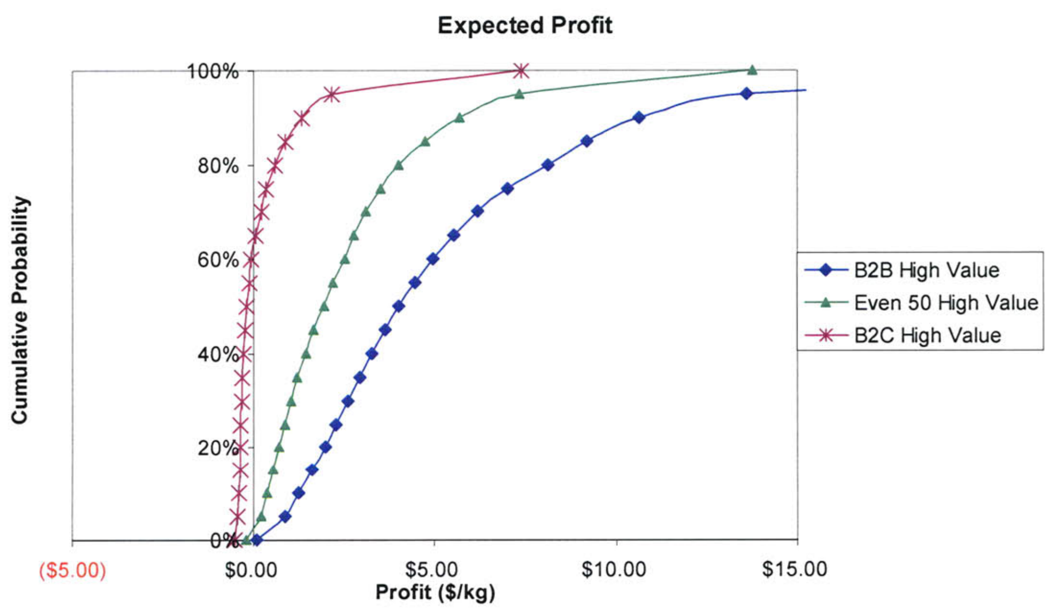

Figure 30: Expected profit in the three operating scenarios where laptops and desktops are 66% of the return volume.

The B2B High Value scenario represents the best case scenario because returns are young and predominantly laptops and desktops, which have the greatest resale value. The system is profitable under these collection conditions. In fact, there is a 40% chance of netting at least \$5/kg. Meanwhile, in the B2C High Value case, there is only a 25% chance of turning a profit. This means that a high value mix is lucrative mainly when the products are young and can be resold.

Figure 31 displays the results of the low value mix simulations. Even though young laptops and desktops make up just 22% of the returns by volume, it is enough to make the B2B Low Value case profitable 70% of the time. When an even number of returns are collected from B2B and B2C sources, there is a 40% chance of being profitable. Meanwhile, the range of possible profits for the worst of the six scenarios, B2C Low Value, is -\$0.62 to -\$1.67/kg. Table XIV summarizes the simulation results for each scenario. In the table, 50% Value at Risk refers to the 50% chance of not achieving above a certain profit.

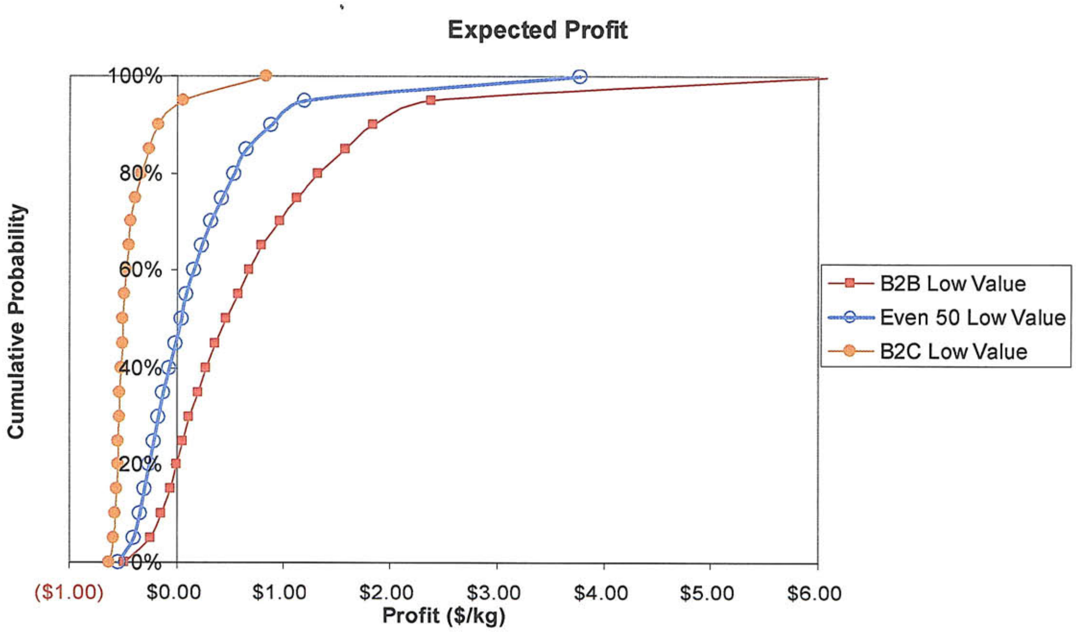

Figure 31: Expected profit in scenarios where monitors comprise 66% of the return volume

Table XIV: A summary of the Monte Carlo results

Scenario	50% Value at Risk (\$/kg)	Maximum Expected Profit (\$/kg)
B2B High Value	\$4.01	\$30.54
B2B Low Value	\$0.47	\$6.25
Even 50 High Value	\$1.95	\$13.78
Even 50 Low Value	\$0.05	\$3.78
B2C High Value	-\$0.19	\$7.38
B2C Low Value	-\$0.49	\$0.84

The effects of product mix and age on fate decisions can be seen clearly in Figure 32. There is an overwhelming chance that two-thirds or more of the returns will be processed for recycling in the B2C Low Value case.

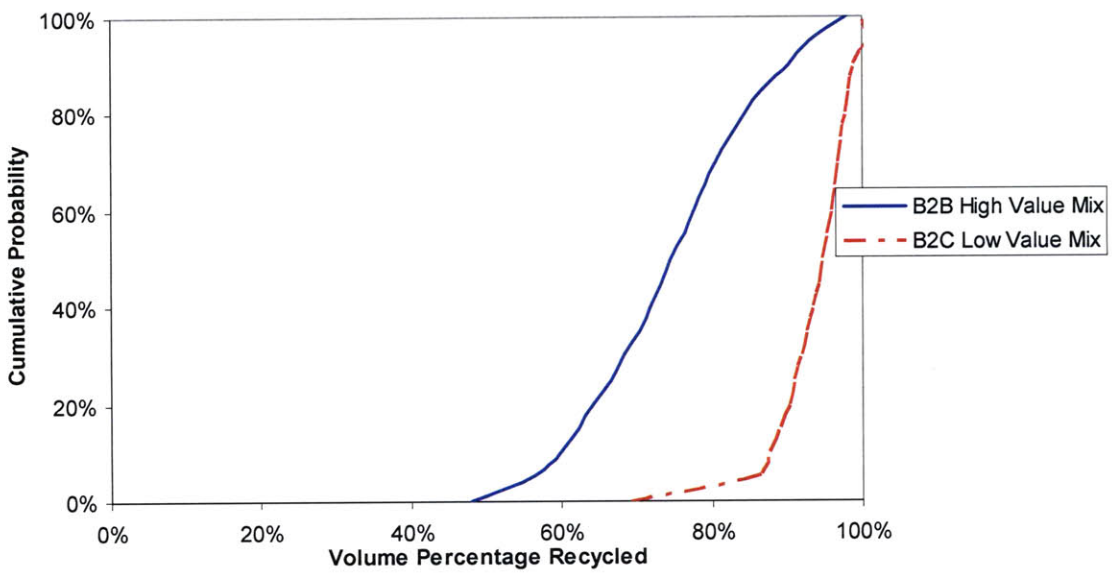

Figure 32: A comparison of fate decisions. Few products are eligible for reuse when returns are older and dominated by monitors.

The algorithm in @RISK uses multivariate stepwise regression to rank input variables according to how important they are to system profit. As listed in Table XV, laptop depreciation was considered the most important factor in profit realization in all six scenarios. The initial quality of laptops and desktop PCs, as represented by MSRP, are influential in every case as well. Age, as represented by collection mode, is also important in every case. Interestingly, commodity prices are not highly influential in the B2C or Even 50 scenarios. In this analysis, the total influence of the scrap market is marginalized because scrap material value was not considered as an aggregate variable as it had been previously. Instead, the variation of each individual commodity was considered. As such, no single commodity could exert a large influence. However, scrap value surely played a part in the expected profit because in every scenario, recycling was the dominant fate.

Table XV: Influential factors as a result of Monte Carlo analysis

Ranking of Factors	B2B High Value	B2B Low Value	Even 50 High Value	Even 50 Low Value	B2C High Value	B2C Low Value
1	Laptop depreciation	Laptop depreciation	Laptop depreciation	Laptop depreciation	Laptop depreciation	Laptop depreciation
2	Laptops MSRP	Laptops MSRP	Laptops MSRP	Laptops MSRP	Municipal pick-up %	Municipal pick-up %
3	Desktops MSRP	Asset Recovery %	Desktops MSRP	Asset Recovery %	Laptops MSRP	Laptops MSRP
4	Asset Recovery %	Desktops MSRP	Desktop depreciation	Desktops MSRP	Desktop depreciation	Desktops MSRP
5	Desktop depreciation	Desktop depreciation	Asset Recovery %	Desktop depreciation	Desktops MSRP	Desktop depreciation

3.6. Strategy Development

The system variables that most affect the economic performance of an e-waste recovery system have been identified. Product age, product quality, product depreciation, and commodity prices have been shown to be important. Broadly speaking, these variables denote a tension between use value and scrap material value, or reuse revenue and recycling revenue. A recovery system manager must develop strategies to mitigate or enhance the effects of these variables on both revenue sources. However, the strategies are chosen based on the manager's constraints. In other words, the manager's actions depend on where s/he is positioned within the recycling system. For example, a firm's interaction with its customer base can influence the quality of the returns it receives. In addition, legislation can influence the mix of product returns.

When an OEM collects all of its returns from B2B consumers, it is almost always guaranteed profit. The interesting cases to investigate are firms who partially or wholly collect from B2C consumers because achieving profitability is uncertain. In the following analysis, two situations were imagined: (1) e-waste collection by an OEM who sources 100% of its returns (by volume) from B2C customers and (2) e-waste collection by an OEM who sources 50% of its returns from B2C customers. For both recovery systems, the current context in which the recovery system operates was examined, as well as two possible future states. In the first future state, no e-waste legislation exists. In the second, there is legislation that requires the responsible disposal of monitors, laptops, and desktop PCs. A comparison of two future states is timely because the U.S. government has refrained from establishing national e-waste legislation unlike the European Union. Instead, the U.S. EPA promotes voluntary e-waste programs run by OEMs and retailers, and individual U.S. states have decided whether or not to enact their own legislation. Many states operate similarly to the first future state imagined; however, 20 states have created IT-specific e-waste legislation in the past five years. Therefore, it is logical to assume that ten years from now, most U.S. states will be operating mature e-waste programs.

3.6.1. 100% Residential Returns

<u>*Current State*</u>

The current state product mix in the 100% B2C scenario is based on the EPA's estimate of the products ready for retirement from 1999 to 2007 (U.S. Environmental Protection Agency 2007). Unlike the previously studied scenarios, the return mix is primarily desktops, CRT monitors, and printers. Therefore, it is a more equal mixture of high and low value products. It is assumed that 50% of the returns are low-end models, 25% are mid-range and 25% are high-end models. This is in line with the estimate of a representative from a leading computer manufacturer (Rockhold 2008). It is also assumed that 80% of returns are collected by community events or municipal pick-up; these are situations in which returned products are generally old and damaged. The assumption is realistic because e-waste take-back from residential consumers is relatively nascent in the United States; today, large collection volumes usually occur because of community events or state-mandated e-waste recovery. The current state product mix (along with the future state product mixes) is shown in Figure 33. The relative sales distributions are shown in Figure 34.

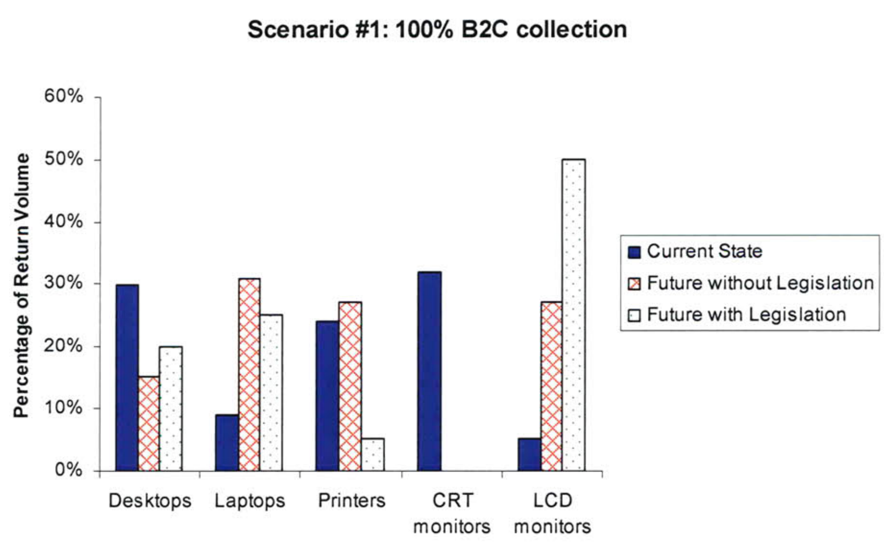

Figure 33: Product mixes for each state of the system

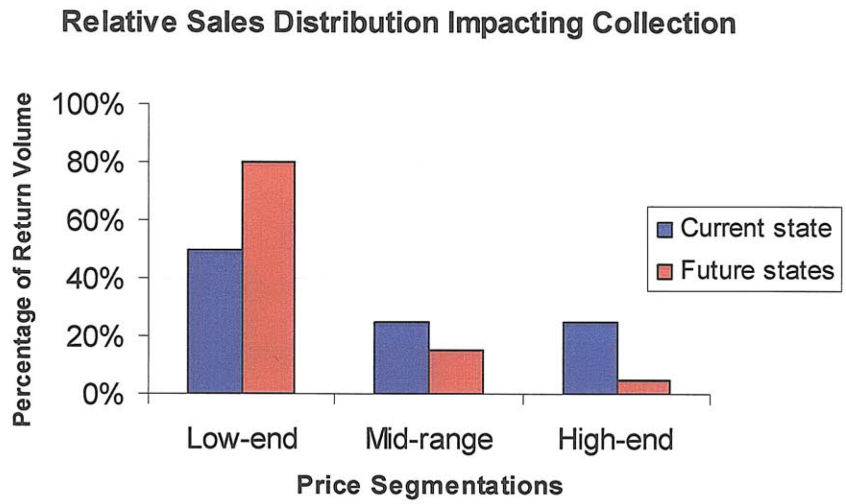

Figure 34: Sales distributions of returns in the current and future states. It is estimated that product prices will continue to decrease in the future and low-end models increase in popularity.

Future State in absence of legislation

The future state scenarios take place at least ten years in the future. In the no-legislation future state, the return mix is based on current and forecast product sales because these sales will be the products available for retirement in the future. Forecasts were created using Holt's exponential smoothing method, which is a forecasting method that incorporates seasonality and weighs more recent observations more than those in the past (National Institutes of Standards and Technology 2003). As Figure 35 shows, laptop, printer, and LCD monitor sales are forecasted to continue to rise (U.S. Environmental Protection Agency 2008). Thus, it is expected that laptop and LCD monitor returns will start to dominate product mixes at the recovery center.

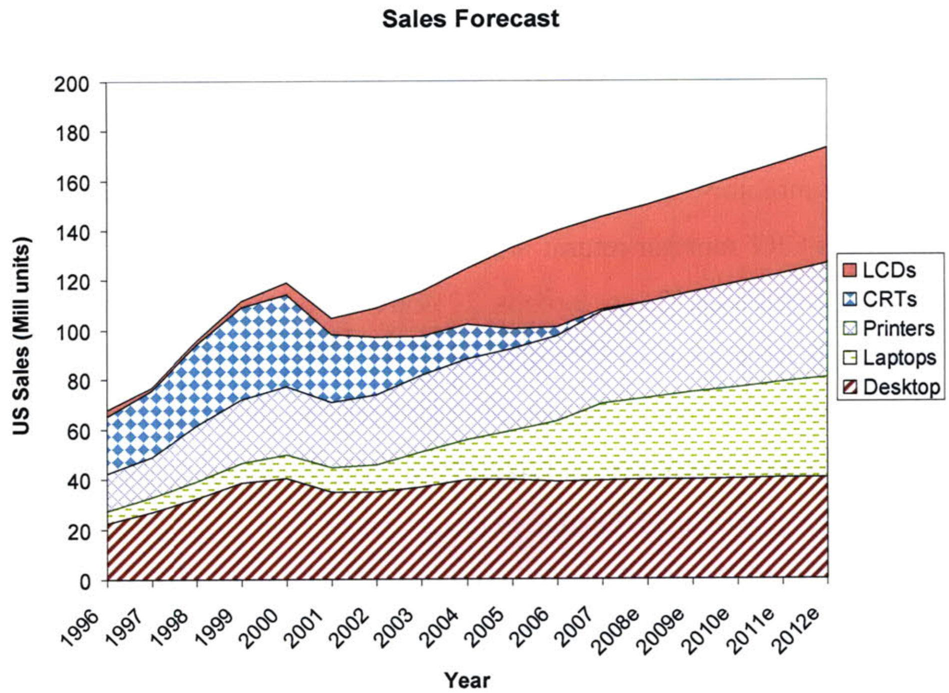

Figure 35: Historical IT sales and forecasts. Historical sales compiled by (U.S. Environmental Protection Agency 2008)

According to market research, IT prices continue to drop as production costs decrease and new low-end models that provide basic computing functions gain popularity (Savitz 2008; IBISWorld 2009a). Thus, it is estimated that returns will increasingly be dominated by low-end models. In this analysis, 80% of returns are characterized as low-end models and 15% as mid-range.

It is hypothesized that as e-waste recovery becomes more prevalent, more people will begin to return their products through retail channels. Here, this is represented as 30% returns occurring through retail take-back and 70% through municipal pick-up.

Currently, the EPA estimates that the mean age of desktop PCs at the end of second life or storage is nineteen (U.S. Environmental Protection Agency 2007). The author believes that as e-waste recovery becomes more commonplace, the mean age should drop. Thus, in this exercise the mean age of municipal returns is twelve years instead of nineteen. The current mean ages of other product categories were also examined but no changes were made because it was deemed that their current retirement ages were reasonable estimates for future retirement ages as well. The future state product mix can be found in Figure 33, presented earlier.

Future State in presence of legislation

All 20 states that have e-waste legislation require responsible disposal of monitors and laptops (Electronics TakeBack Coalition 2010). All but two require the same for desktops. Emphasis in the legislation is placed on minimizing the hazardous effects of display-oriented IT products, such as monitors. Thus, it is assumed that the future return mix will be dominated by LCD monitors (as CRT monitor returns are largely occurring today). In this exercise, 50% of the returns are LCD monitors, 25% are laptops, 20% are desktops, and 5% are printers.

Because of legislation, OEMs and retailers will be forced to take more active roles in ensuring responsible disposals. Thus, retail take-back should become more prominent. In this exercise, 40% of returns occur through retail take-back. For municipal pick-up returns, the mean age of desktop returns was again decreased to 12 years.

Finally, it is still believed that sale prices will continue to fall, so 80% of returns will be low-end models. The future state product mix can be found in Figure 33.

A quick overview of the changes made in all three scenarios is shown in Table XVI.

Table XVI: Parameter settings for each scenario.

	Current State	**Future – No Legislation**	**Future - Legislation**
Return Mix	32% CRTs, 30% PCs, 24% Printers, 9% Laptops, 5% LCDs	0% CRTs, 15% PCs, 27% Printers, 31% Laptops, 27% LCDs	0% CRTs, 20% PCs, 5% Printers, 25% Laptops, 50% LCDs
Age Distributions	See Figure 7	Municipal PCs = 12 yrs	Municipal PCs = 12 yrs
Sales Distributions	50% low-end models	80% low-end models	80% low-end models
Processing Costs	See Table VI	No change	No change
Collection Modes	80% Municipal	70% Municipal	60% Municipal

Analysis

Figure 36 was created while performing a Monte Carlo analysis similar to the analyses in Section 3.5. The system variables that are varied are product depreciation, commodity prices, product functionality, and processing costs. MSRP distributions are taken into account through the fixed ratios mentioned earlier. Similarly, collection mode ratios are also fixed. In the current state, the recovery system can never be profitable. The large volume of returns originating from municipal pick-up and community events means that many of the returns are too old for the resale market and will be sent for recycling. Furthermore, printers and CRT monitors make up over 50% of the volume of returns; their low recycling value is detrimental to the system.

The two future states increase the chance of profitability by only 20%. Interestingly, legislation does not harm the economic welfare of the recovery system; the system behaves as it would in the absence of legislation. This result is likely based on the fact that the system doesn't have to process CRT monitors in either of the future scenarios; CRT monitors were shown to be large cost adders in previous analyses.

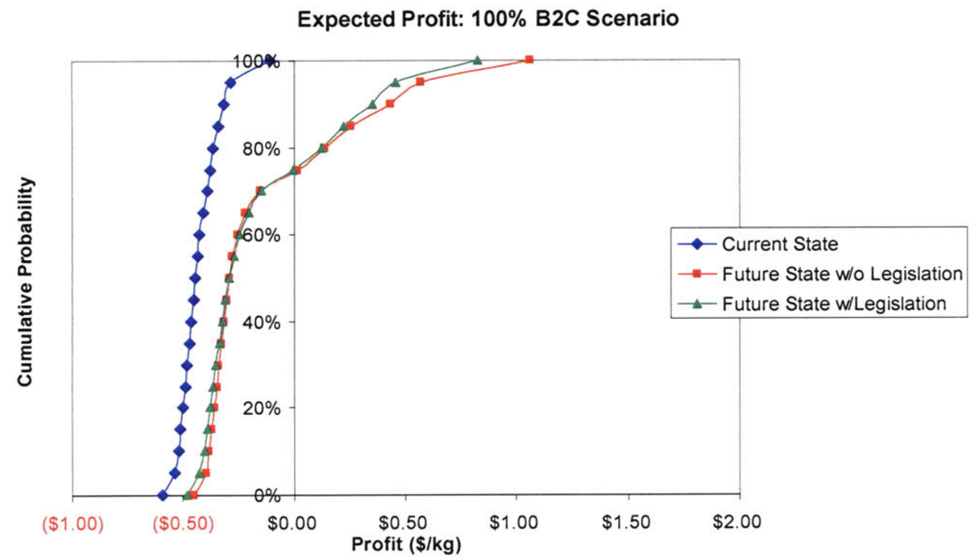

Figure 36: Results of analysis of current and future state scenarios for an IT recovery system

The differences in performance among the three operating contexts can be examined further by analyzing how sensitive profit is to changes in resale value and scrap value. In order for operation in the current state to be profitable, product depreciation must be very slow and the commodity market must be strong (see Figure 37). These are dramatic changes and thus unlikely to occur. Meanwhile, in the two future states, profit can be achieved in some realistic cases. However, if commodity prices drop or if product depreciation rates accelerate, then net cost scenarios will be encountered (see Figure 38 and Figure 39). Thus, profitability in the future scenarios is very sensitive to depreciation and scrap prices.

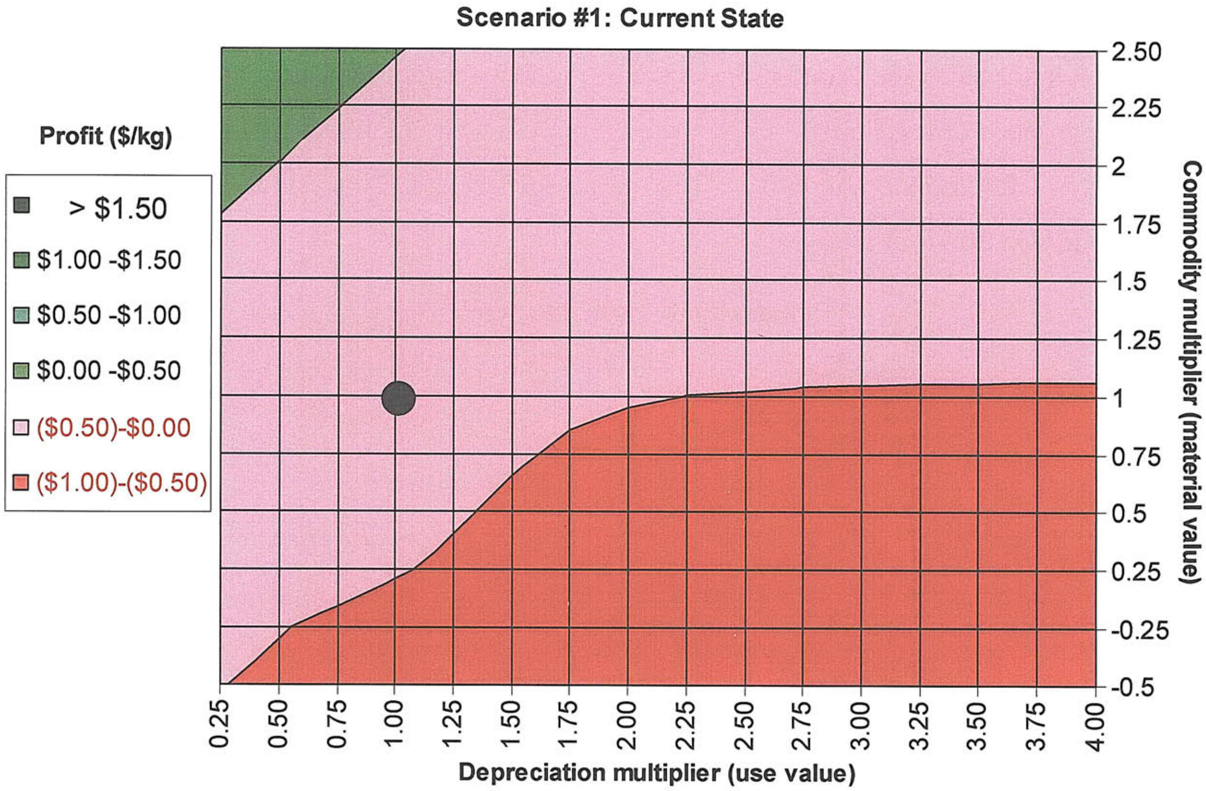

Figure 37: In the current state, profit can be achieved only in unlikely conditions. The circle marks performance under the current depreciation rate and average scrap market conditions.

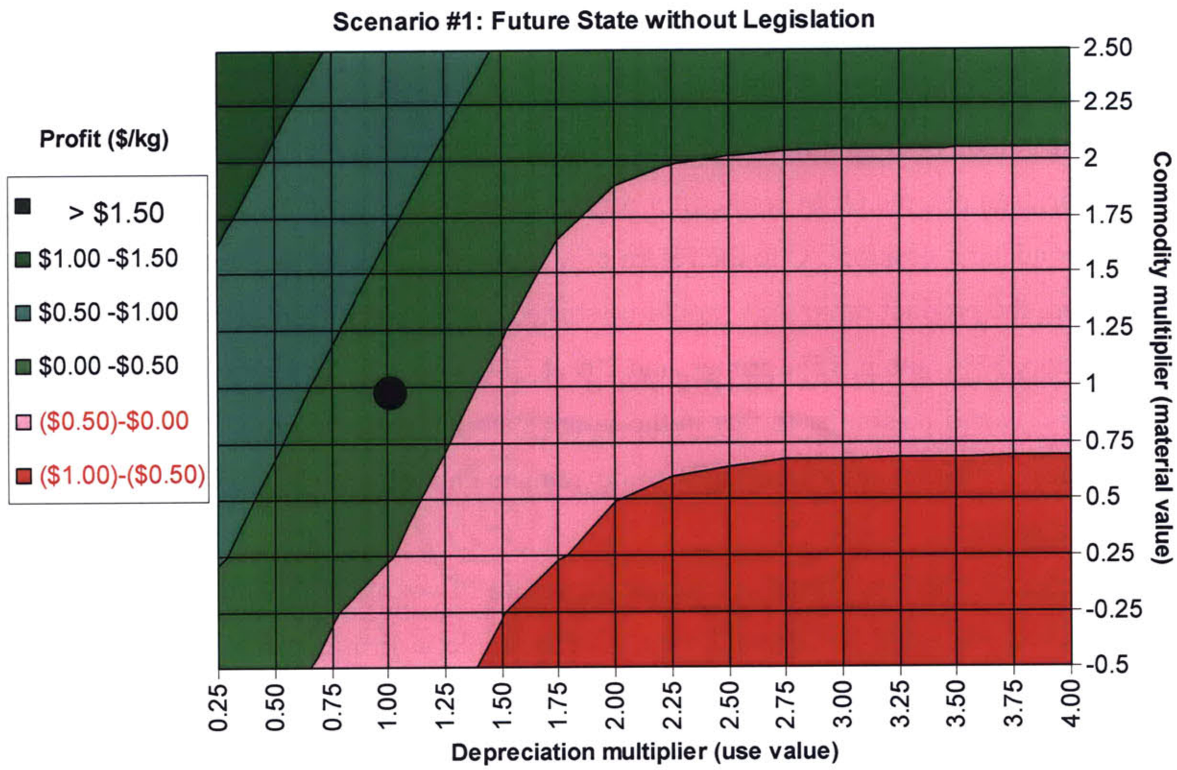

Figure 38: A future without legislation may include some opportunities for net revenue.

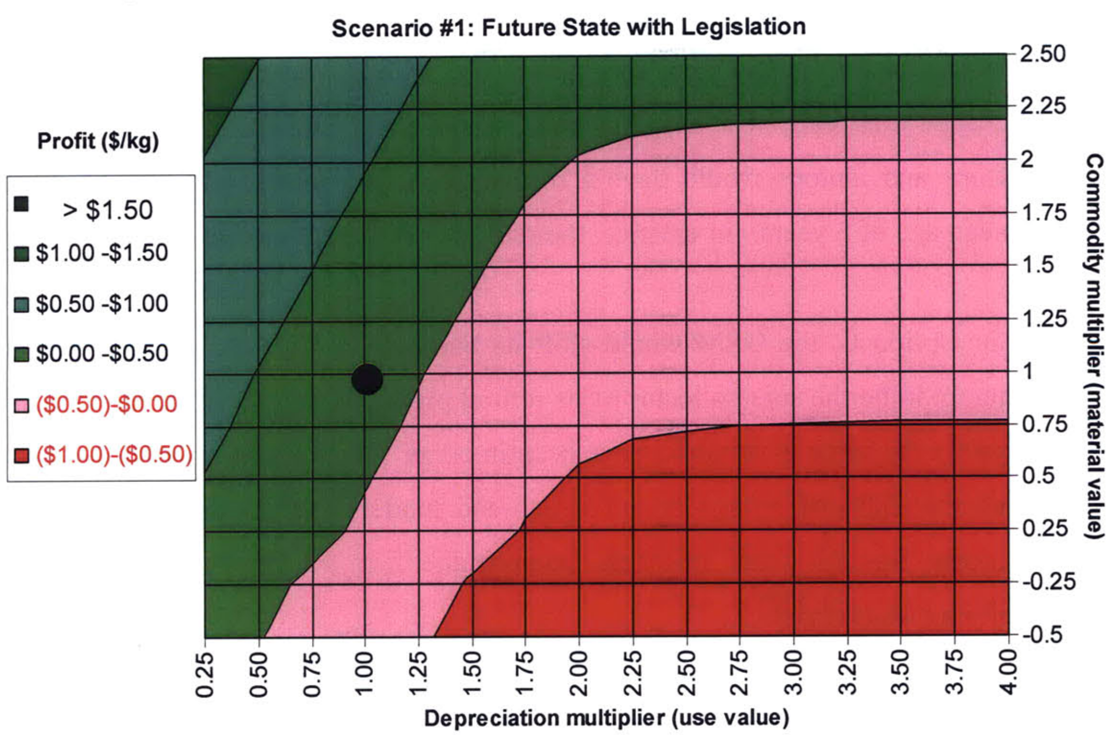

Figure 39: The recovery system should behave the same in the future whether legislation exists or not because CRT processing no longer exists.

Evaluation of Potential Strategies

Based on the analysis conducted in the previous section, four options were chosen as potential strategies that a firm might enact in either future state. Option A is for the firm to encourage the return of high value products. There are several ways in which this could be achieved. For example, the OEM could offer rebates towards new purchases or no-fee collection if a consumer added a desktop PC to the return of a monitor. It is hypothesized that if Option A were executed, the product return mix would be shifted away from either future state return mix to: 30% desktop, 35% laptop, 15% printer, and 20% LCD monitors. Collection flows would also be affected and would be similar to that in the future state with legislation: 40% returns through retail take-back. Product retirement age would remain unchanged. Sales would continue to favor low-end products.

In Option B, the firm would encourage the return of young, high value products. There are several ways this could be accomplished. For example, a firm could offer markdowns on new purchases that are proportional to the age of the laptop or desktop that a person would be returning. A firm could also start a leasing program geared towards residential consumers, akin to B2B leasing programs. In this scenario, the return mix would be impacted exactly as it is in Option A. However, OEMs and retailers would be much more engaged in collection. Thus, it is estimated that 60% of returns would come through retail channels. The age of desktop and laptop returns would change drastically if either plan were implemented. It is estimated that municipal returns of desktops and laptops would have a mean age of five years, whereas retail returns would have a mean age of 3 years. In essence, the returns would begin to have the same cycle as B2B returns.

Finally in Option C, the OEM would shift its business to high-end niche products and aggressively attempt to be the sole collector of its retired products. In this way, even though the return mix is exactly the same as it would have been in either future states, the quality of returns would shift such that 50% of returns become high-end models. It is estimated that 70% of returns would come through retail channels because the firm would attempt to collect its products through its own channels.

Each option was analyzed using Monte Carlo analysis (see Figure 40). Option B is the only one that guarantees profit in all simulations. Option C is slightly favored over the other options; however, implementation would be challenging because there would be a time delay between shifting sales to niche products and collecting those niche products. For a period of time, the firm would have to deal with its legacy low-end products.

Figure 40: Comparison of strategy options

A deeper comparison between the best and worst strategies reveals that Option B is profitable no matter how bad the commodity market becomes or how fast the rate of depreciation becomes (see Figure 41). Meanwhile, in Option A, if product depreciation continues to accelerate, when the commodity market is at its average performance or worse, then net cost scenarios might be encountered (Figure 42).

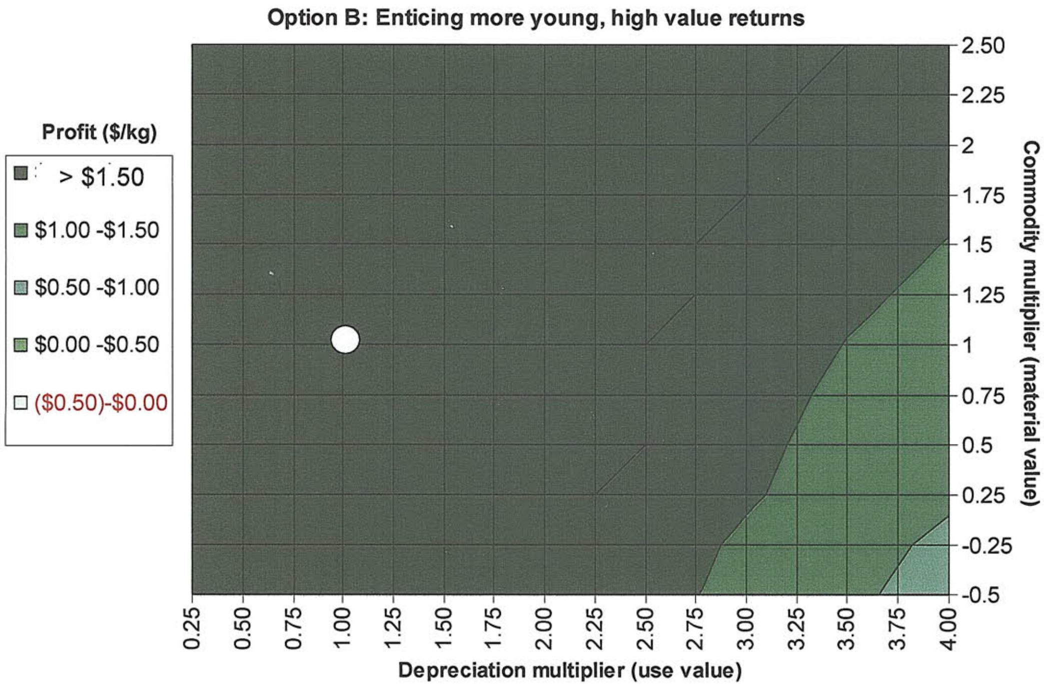

Figure 41: Option B is profitable in all cases

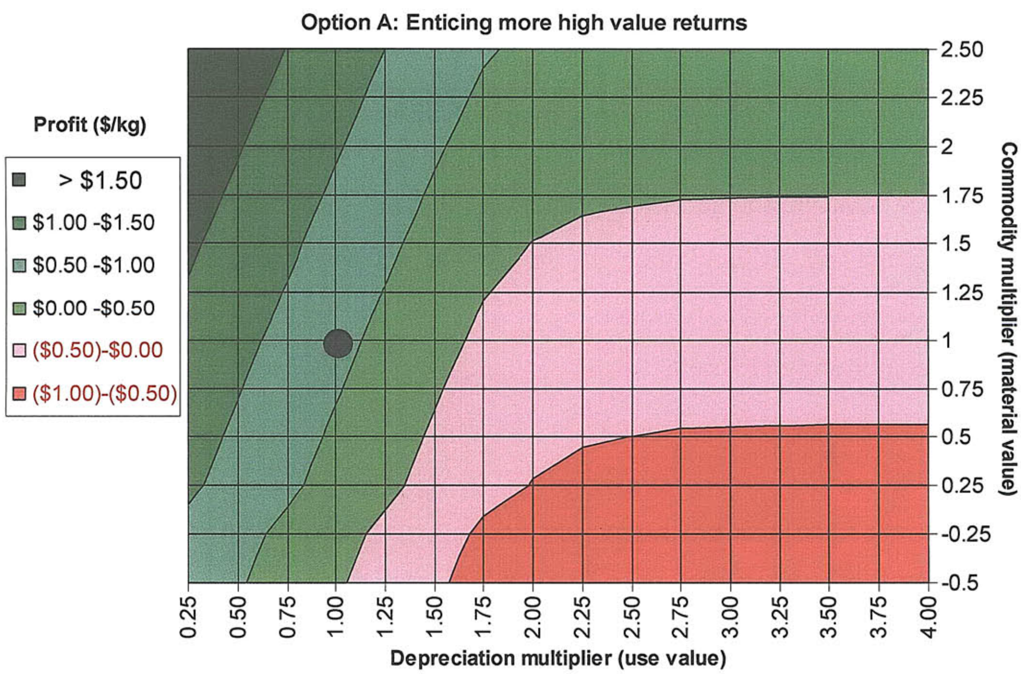

Figure 42: Option A is profitable in some cases.

3.6.2. 50% Residential, 50% Commercial Returns

<u>Current State</u>

In the current state of the Even 50% collection scenario, conditions applying to the B2C returns are exactly as before, in Section 3.6.1. The B2B return mix is based on a recent annual return mix received by an existing recovery facility: 40% desktops, 30% CRT monitors, 15% laptops, 10% LCD monitors, and 5% printers.

For B2B returns in this scenario, it is presumed that 85% of the B2B returns are through end-of-lease, which is also based on a recent annual return mix received by an existing recovery facility. The same B2C collection ratio (80% municipal pick-up) is assumed as before. The quality of returns is assumed to be 50% low-end models with the other 50% evenly split between mid-range and high-end models. The combined return share of products (i.e. all returned desktops, all returned laptops, etc) is shown in Figure 43, along with the return mixes for the two future states. The sales distributions of collected products for the current and future states are shown in Figure 44.

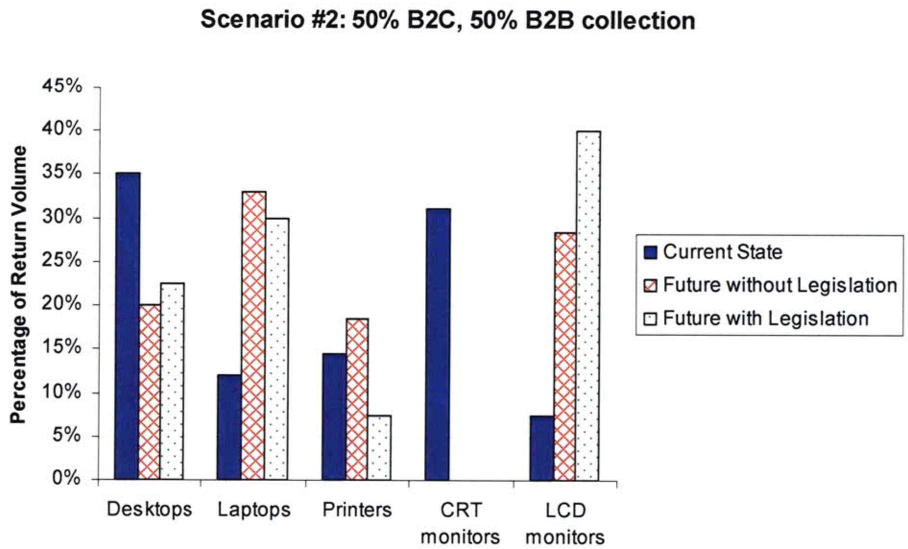

Figure 43: Return mixes of each operating state. Desktops and CRT monitors dominate returns today but shouldn't in the future.

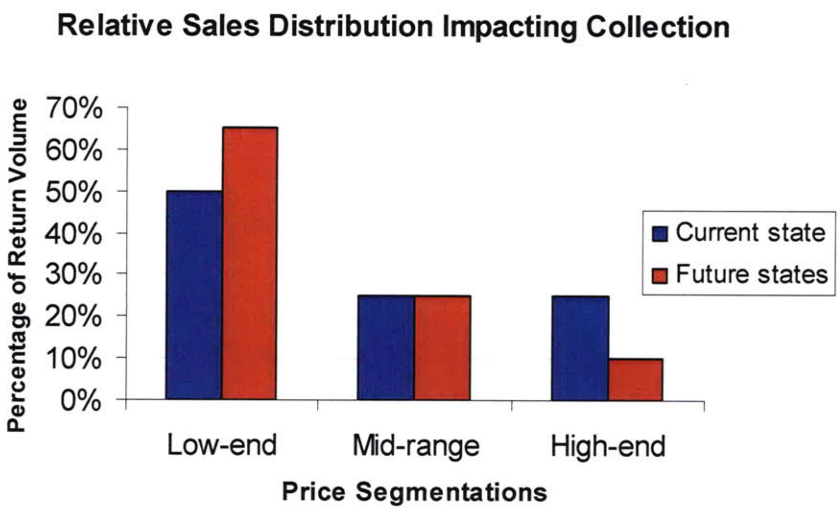

Figure 44: Sales distributions of the current and future states.

Future State in absence of legislation

The B2C collection parameters are characterized the same as they were in the previous analysis of the 100% B2C scenario. Meanwhile, the B2B return mix is assumed to change as more commercial users have switched to using laptops and LCD monitors. The percent of returns from end-of-lease are expected to stay the same at 85%.

Even though it is still expected that sales of low-end models will continue to increase, the effect on return quality in this scenario is less drastic than in the previous 100% B2C scenario. It is believed that B2B customers will continue to buy many mid-range and high-end products that have advanced capabilities. Thus, the expected return quality is only 65% low-end in this case and 25% mid-range.

Future State in presence of legislation

Legislation is expected to impact B2C collection parameters as characterized earlier, but it isn't expected to affect the future state of B2B collection. Thus, the future state of B2B collection is characterized exactly like the future state without legislation. The quality of total returns is expected to be similar to that characterized in the future state without legislation.

Analysis

In the analysis, it was discovered that the system can be profitable in all cases. In fact, in both future states, profit greater than $2/kg can be expected 40% of the time (see Figure 45). A deeper look at system performance with regards to changes in resale value and scrap value reveals that net profit is achievable even in times of accelerated product depreciation or poor scrap market conditions (see Figure 46-Figure 48). Thus, no strategies for improving economic performance are needed in this scenario.

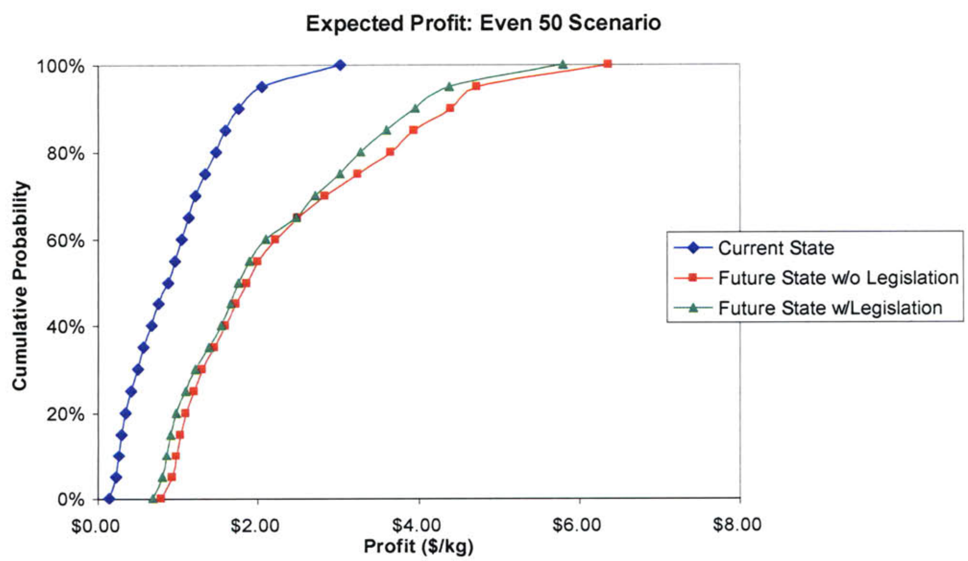

Figure 45: Net revenue is achieved in all three states.

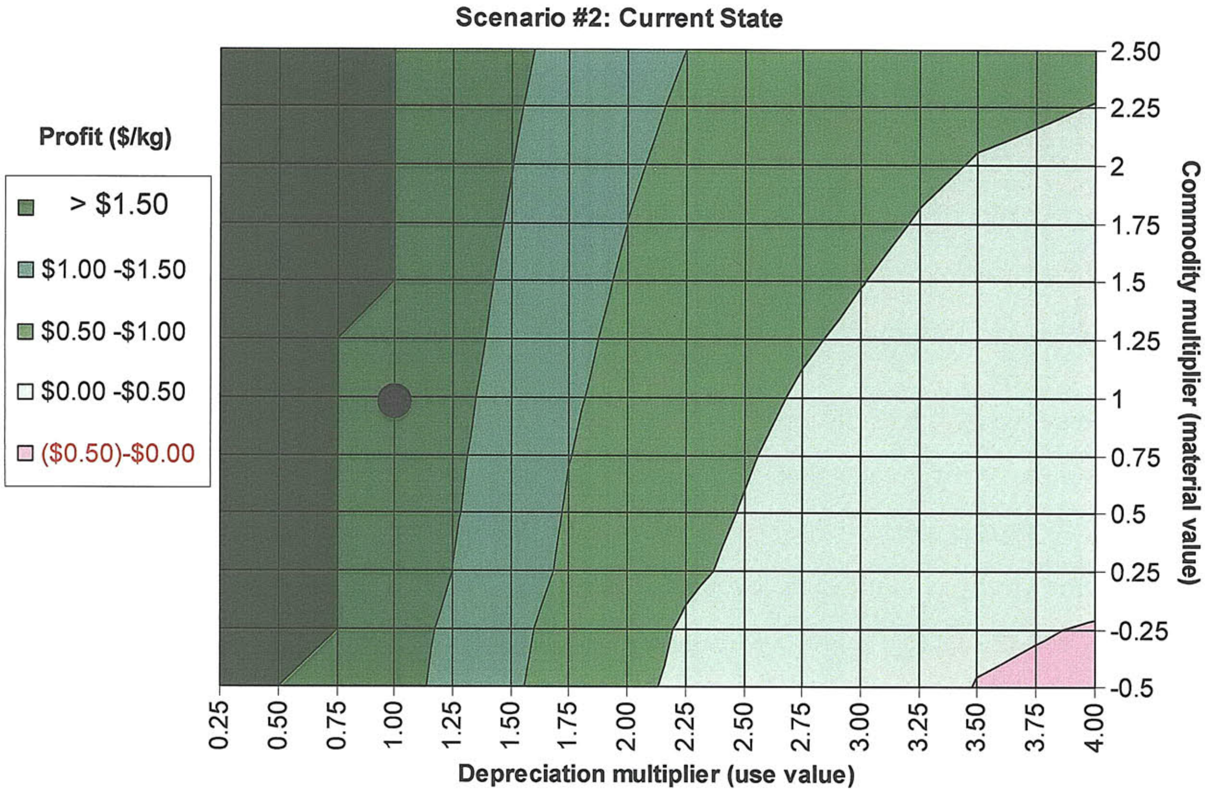

Figure 46: Current state estimation when material value and reuse value alone vary.

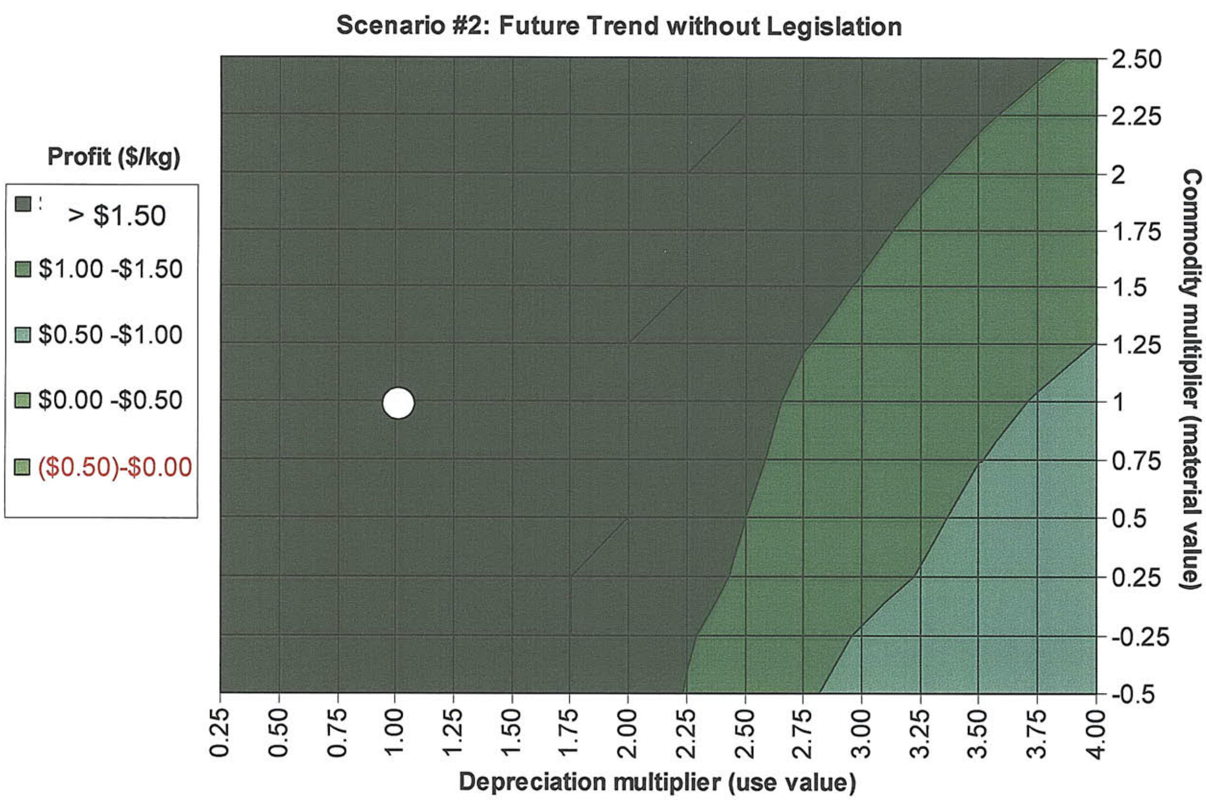

Figure 47: In a future state without legislation, more than \$1.50/kg can be expected in most cases.

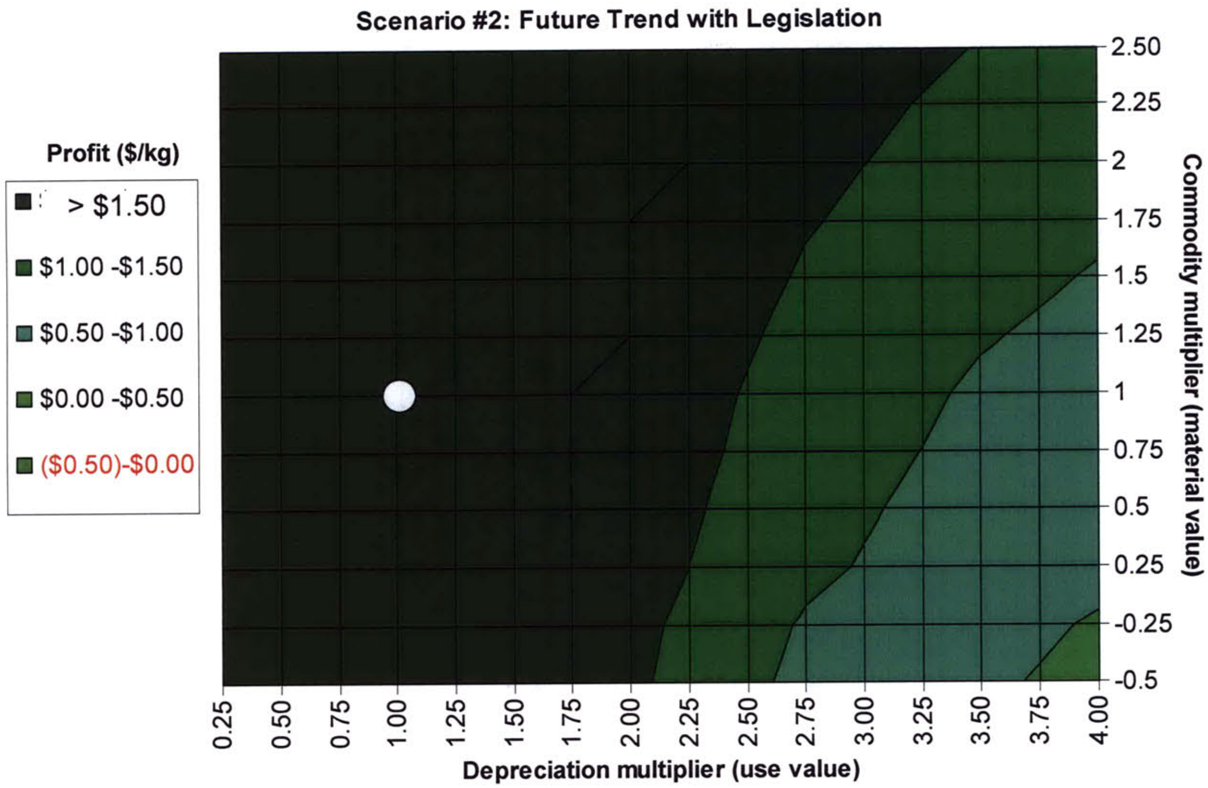

Figure 48: Even with legislation, the recovery system can expect to be profitable in all cases.

3.7. Environmental Analysis

In the previous analyses, the economics of IT e-waste recovery was examined. The analysis illuminated which system parameters cause the greatest difference in economic performance, the level of profitability to expect in specific system contexts, and what strategies might improve profitability.

Strategies to improve system performance cannot be evaluated purely from an economic standpoint; environmental effects must also be included (Huisman 2003). System success involves profit from returns as well as positive impact on total e-waste management. Total e-waste management not only involves the destination of retired products but also the replacement decisions made afterwards. A portrayal of e-waste management was displayed in Figure 5. A consumer can make one of three replacement purchase decisions: (a) purchase a new product, (b) purchase a used product, or (c) do not replace. This decision is influenced by consumer preference but also by decisions made previously by other consumers when disposing their products. The availability of new products made from secondary materials and of refurbished products sold on the used product market are directly linked to how many products are disposed of through e-waste recovery.

In the following analysis, a comparison is made between the environmental impact of Option B of Section 3.6.1, in which younger returns are collected, and Option A, in which the firm increases the relative volume of high value returns but does not influence their return age. The analysis considers the environmental impact of production in terms of energy used, from procuring raw materials to forming them into products. Energy in the use phase of a product is ignored because it is assumed that the same amount of energy will be used whether the product is new or used, even though in reality there would be periodic energy efficiency gains from one iteration of a product to another. Energy used in the EOL phase is also ignored because it is inconsequential when compared to production energy (Swiss Center for Life Cycle Inventories 2010).

The scope of the analysis is laptops. It is assumed that the consumer population is constant at 1000 and that one person owns one laptop at a time. The time period of analysis is 20 years, such that the effects of Options A and B on replacement decisions can be examined. Data were collected on the energy used to procure and refine the major virgin or secondary materials found inside laptops and the energy used in the process of production of new laptops (Keolian et al. 1997; Graedel and Allenby 1998; Atlee 2005; Deng et al. 2010; Swiss Center for Life Cycle Inventories 2010). New energy calculations were also made based on the material compositions of laptops presented in Section 3.1.2, using the Ecoinvent database and Cumulative Energy Demand method in SimaPro life cycle assessment software. It was found that production process energy accounts for 75-80% of the total energy used to create one laptop. A summary of the data is shown in Table XVII. Data from Apple's environmental reports were used to ensure that calculations were within reason (Apple Inc. 2010).

Table XVII: Data collected on production energy of laptops.

Data source	**Primary materials energy (MJ)**	**Secondary materials energy (MJ)**	**Production process energy (MJ)**
SIMAPRO (Ecoinvent database)	580		2431
Atlee (2005)	252	101	
Deng et al. (submitted)	280-665		1036-1981
Averages	444	101	1816

The following equations (based on those presented in Section 2.4) were used to study the system. Variables were defined in Table I. When recycling occurs, the energy used in procuring and refining virgin materials can be avoided. When reuse occurs, the energy associated with the entire production process, i.e. procuring materials and laptop manufacturing, can be avoided.

$$N = n_{buy\_new} + n_{buy\_used}$$

$$n_{buy\_new} = n_{primary\_mfg} + n_{secondary\_mfg}$$

$$n_{buy\_used} = n_{reuse} = N * \Pr(reuse) * \Pr(recovery)$$

$$n_{secondary\_mfg} = n_{recycle} = N * (1 - \Pr(reuse)) * \Pr(recovery)$$

$$\Pr(reuse) = \Pr(functioning) * D_{used\_products}$$

$$E_{life\_cycle} = n_{primary\_mfg} * E_{primary\_mfg} + n_{secondary\_mfg} * E_{secondary\_mfg} + n_{buy\_used} * E_{buy\_used}$$

$$E_{primary\_mfg} = E_{virgin\_materials} + E_{mfg\_process} = 2260MJ$$

$$E_{secondary\_mfg} = E_{secondary\_materials} + E_{mfg\_process} = 1917MJ$$

$$E_{buy\_used} = 0$$

$$E_{20\_yrs} = E_{life\_cycle} * \frac{20yrs}{mean\_retirement\_age}$$

In the first analysis, it is assumed that reuse is not a viable recovery option. Instead, if products are recovered, they are immediately recycled. The production energy consumed was evaluated as a function of the mean retirement age of laptops over the 20 year period. As the mean retirement age decreases, the number of product replacements increases. The reference retirement age is four years old, based on the average of the mean ages of laptop returns by collection source, as discussed earlier (see Section 3.1.2). To compare energy usage across scenarios, the energy saved versus making all 1000 laptops and their replacements over the 20 year period from virgin materials was calculated.

Figure 49 reveals the results of the first analysis. When the mean age of retirement falls below 4 years, there is never an opportunity to save energy through recycling activities. Each scenario aside from the reference scenario reveals that because of the increase in replacement frequency, cumulative production energy over 20 years is always higher than the cumulative production energy when all products are made from virgin materials in the reference case. This is true even when 100% of retired products are recycled. The analysis shows that the new production rate outpaces any environmental benefit realized from recycling when the mean age of retirement drops.

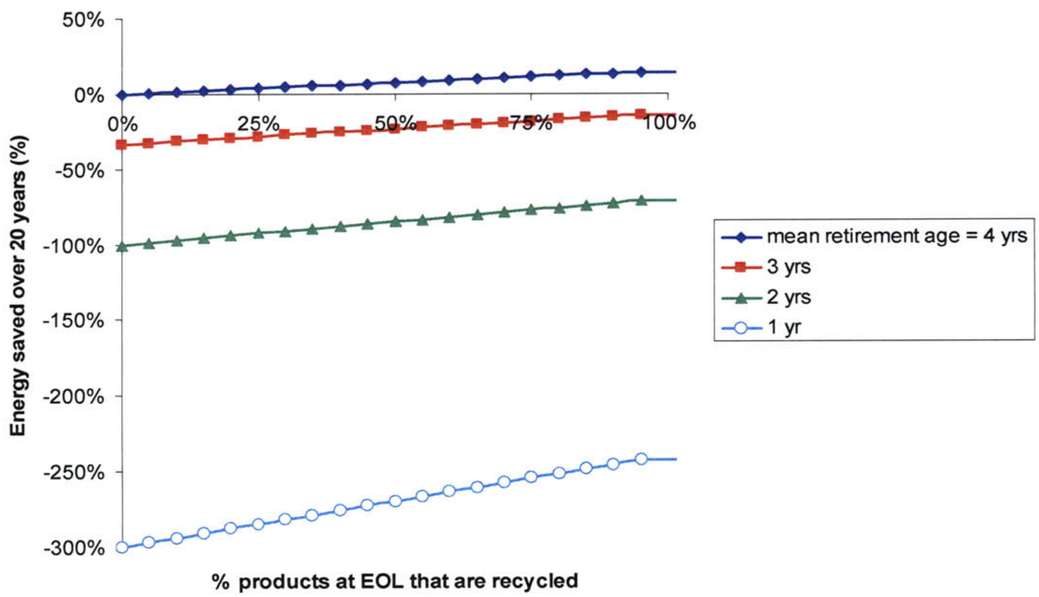

Figure 49: Energy savings in each scenario as compared to the cumulative energy of making 1000 new laptops every five years from virgin materials.

In the second analysis, products that are recovered can be recycled or reused. To estimate how the percentage of recovered products eligible for reuse changes as the mean retirement age decreases, parameters in the MFE model were used. Specifically, the gamma distribution used to describe laptop retirement age was convolved with the function used to describe the probability that a product would still be functioning at a certain age. The mean of the age distribution was shifted to represent different scenarios, i.e. mean age of laptop retirement becomes two years vs. three years vs. four years. The assumption that laptops have no resale value after age five was also incorporated into the calculation of percentage of laptops that are eligible for resale (see Table XVIII). Though in this scenario, an age distribution was used, which implies that products may end up being returned before or after the mean retirement age, the average retirement age is still used in the calculation of total production energy spent over a 20 year period. It is assumed that there is perfect equality between number of refurbished products and demand for refurbished products. The reference for energy savings is still the cumulative production energy when 1000 new products are made from virgin materials every five years for 20 years.

Table XVIII: Percentage of retired products eligible for reuse depends on functioning status and consumer demand on the resale market

Mean retirement age	% products eligible for reuse
7	3%
6	12%
5	28%
4	45%
3	60%
2	72%
1	82%

The results of the second analysis are depicted in Figure 50 and Figure 51. When recovered products can be recycled or reused, savings are realized at some threshold level of recovery in every scenario. Energy savings aren't realized until there is 90% recovery when the mean retirement age is 1 year. Savings can be realized in the 3-yr retirement case when 40% of laptops are recovered. Not surprisingly, savings are always realized when the mean retirement age is above four years.

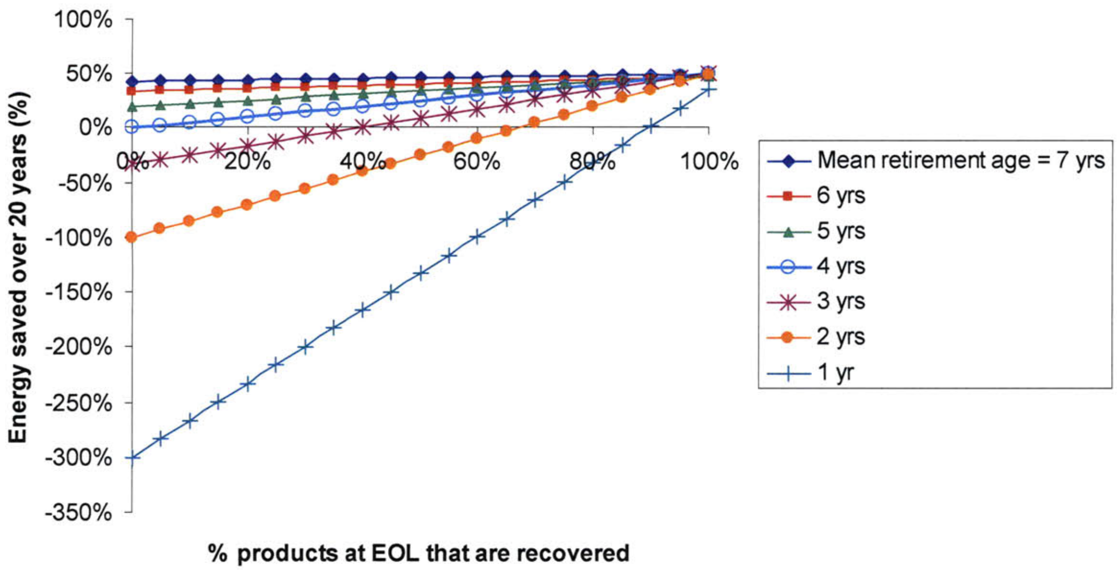

Figure 50: Energy saved over 20 years when laptops are periodically replaced at different intervals.

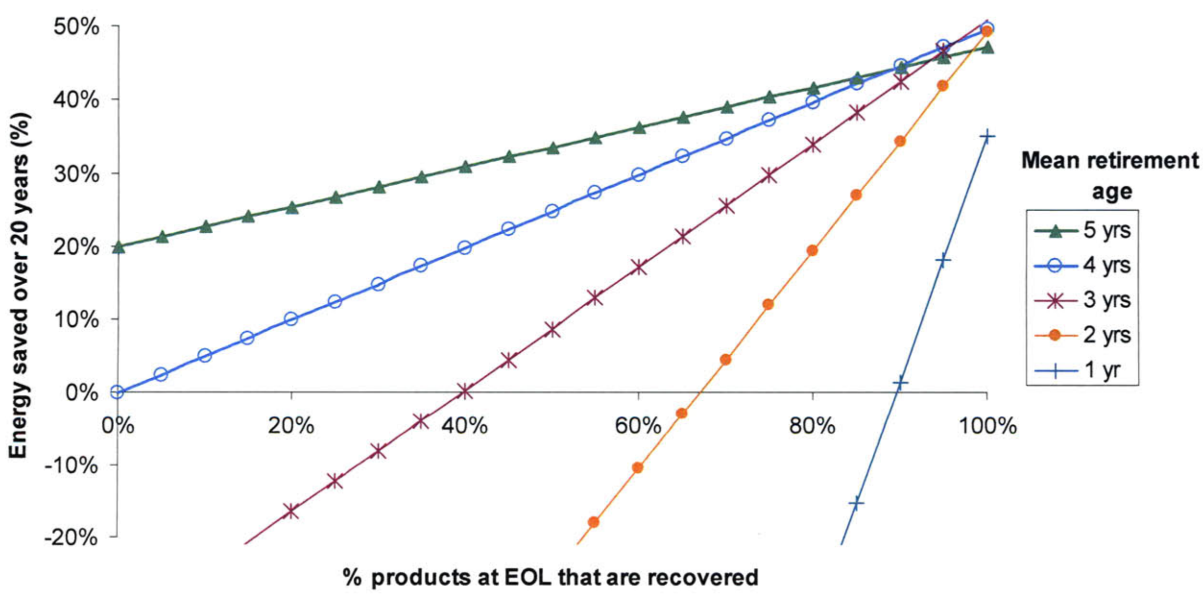

Figure 51: A close-up of the previous graph.

Figure 52 depicts a comparison between the energy savings of two of the retirement age scenarios when (a) recycling is the only recovery option and (b) recycling and reuse are both viable options. If the mean retirement age drops to three or two years, energy savings can only be realized if reuse is a viable option for a subset of the recovered products. The recovery rate must also be high; in the case of a mean retirement age of three, it must be above 40%.

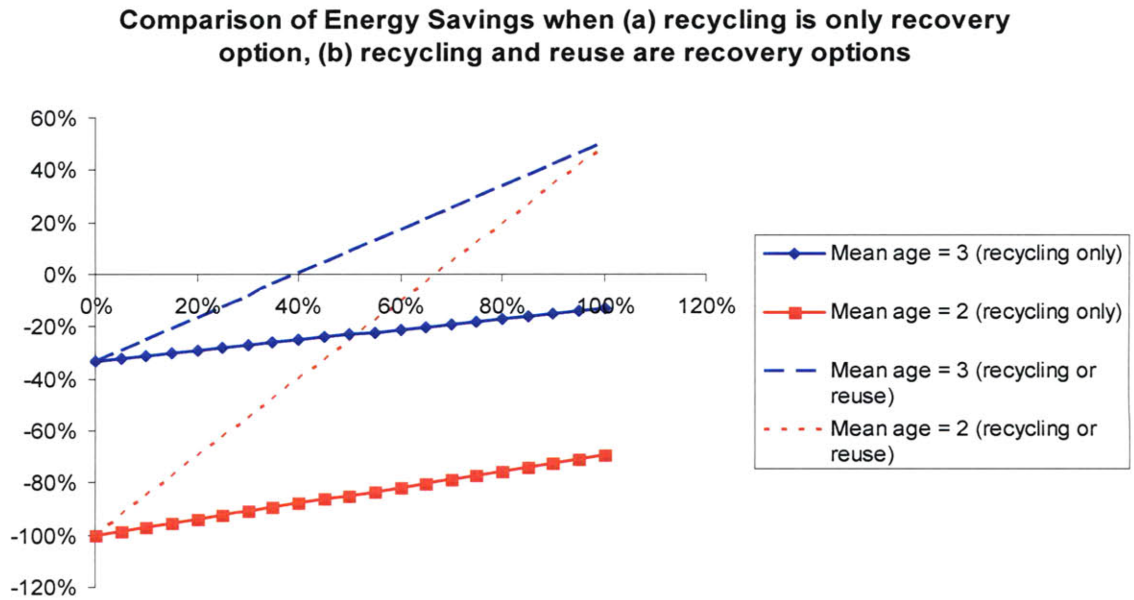

Figure 52: Energy benefits from recovery activities can only outpace the energy tied to the production rate if reuse is a viable recovery option.

Currently, the U.S. EPA estimates that only 23% of IT products at end-of-life are recovered for recycling or reuse (U.S. Environmental Protection Agency 2007). According to the analysis presented here, this is equivalent to 12% energy savings in the four-year retirement scenario. If the mean retirement age decreased but the current 12% energy savings had to be maintained, product recovery would have to greatly increase (see Table XIX). For example, if the retirement age was two years, recovery would have to increase to 73%.

Table XIX:Percentage of products that need to be recovered to achieve 12% energy savings over the reference scenario

Mean retirement age (yrs)	Product recovery needed (%)
3	52%
2	73%
1	92%

In the previous analysis, it is assumed that consumer demand for used products will match the supply of used products. In reality, this may not be the case. Some people like to always purchase next generation products; innovation cycles in IT are quick, making new products attractive. Figure 53 illustrates what may happen to energy savings if consumer demand for used products does not meet the supply. When the mean retirement age of products is greater than four years, consumer demand has little effect on energy savings of recovery because so few products are eligible for reuse anyway. For retirement ages of 4 years or less, the gap in energy savings grows as more products are recovered. This is because the market becomes saturated with reuse-viable products but the demand for used products does not grow at the same rate.

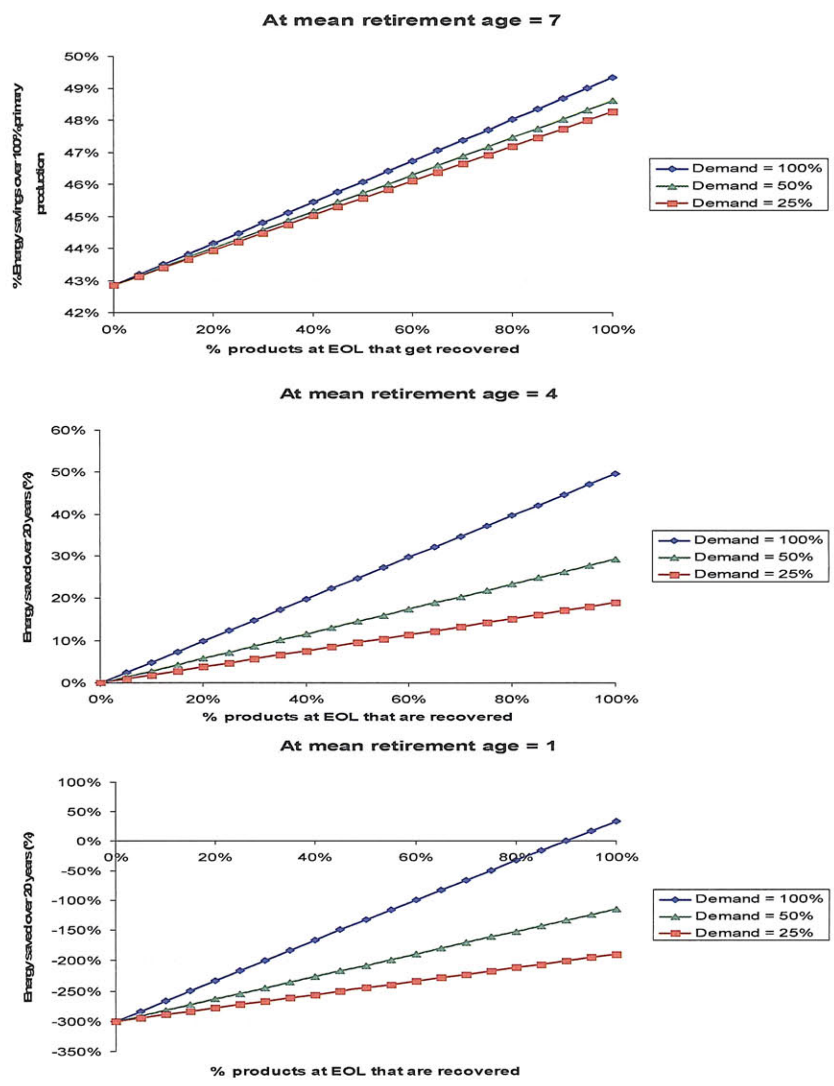

Figure 53: Energy savings in the reuse-and-recycling recovery scenario drop when consumer demand for used products is low.

3.8. Chapter Summary

It has been shown through a mass flow and economic model that product characteristics, secondary market characteristics, and collection characteristics are critical factors in the profitability of IT e-waste recovery. Whether a firm is able to collect high value products, such as laptops and desktops, over monitors and printers is important to profitability and can cause a factor of 10 difference in profit. Reuse revenue exceeds recycling revenue, but the fast depreciation of high value IT products and the inability to control the timing of retirement decisions increases the uncertainty of achieving reuse revenue. In the scenario-based sensitivity analysis, it was specifically shown that laptop depreciation and sales price are the most important determinants of profitability. As laptop prices trend downward, the dominance of revenue generated from laptop reuse will decrease, which will greatly impact profitability.

However, recovery systems will no longer have to incur the cost of CRT monitor disposal in the future because sales of CRTs have almost disappeared. As the analysis in Section 3.6 revealed, the absence of CRTs from the collection mix greatly improves the profitability of IT e-waste recovery. It was also shown that promoting the return of younger products can eliminate any net cost situations when evaluating the realm of possible commodity market conditions and product depreciations. In fact, in the analysis, a profit of $3/kg could be expected 40% of the time. Though such a scenario may be advantageous to an OEM, it may decrease the environmental benefit of e-waste recovery. If consumers return their products earlier but choose to replace those products with new models instead of used ones, the used product supply will become saturated and only energy savings from recycling can be realized. This is detrimental because it was shown that energy savings from reuse are much greater than energy savings from recycling because of the large energy expended during the manufacturing process. Furthermore, to maintain the energy savings achieved today while allowing the mean retirement age to decrease, product recovery would have to increase from 23% to over 50%.

4. Analysis: The Economics of Appliance E-waste Recovery

In this chapter, the economics of appliance e-waste recovery is examined. In Section 4.1, inputs in the appliance mass flow and economic model are described. This is followed by a baseline analysis of the current state of appliance e-waste recovery in Section 4.2. Uncertainty analysis is presented in Sections 4.3 through 4.5, with each section of analysis building upon the previous one. These sections are followed by an evaluation of strategies that a recovery system manager might implement given the results of the system analyses in Section 4.6. The environmental impacts of the most viable strategies are evaluated in Section 4.7. Finally, concluding statements are made in Section 4.8.

4.1. Data collection for the MFE Model

As mentioned in Chapter 2.3, the critical variables in the performance of an e-waste recovery system can be categorized as *collection*, *product*, *secondary market*, and *EOL processing* characteristics.

4.1.1. Collection Characteristics

Product mix refers to the types of appliances that are available for return. As this is largely a function of the products that are available on the sales market, the following analysis includes washing machines, dryers, refrigerators, dishwashers, and ranges or ovens.

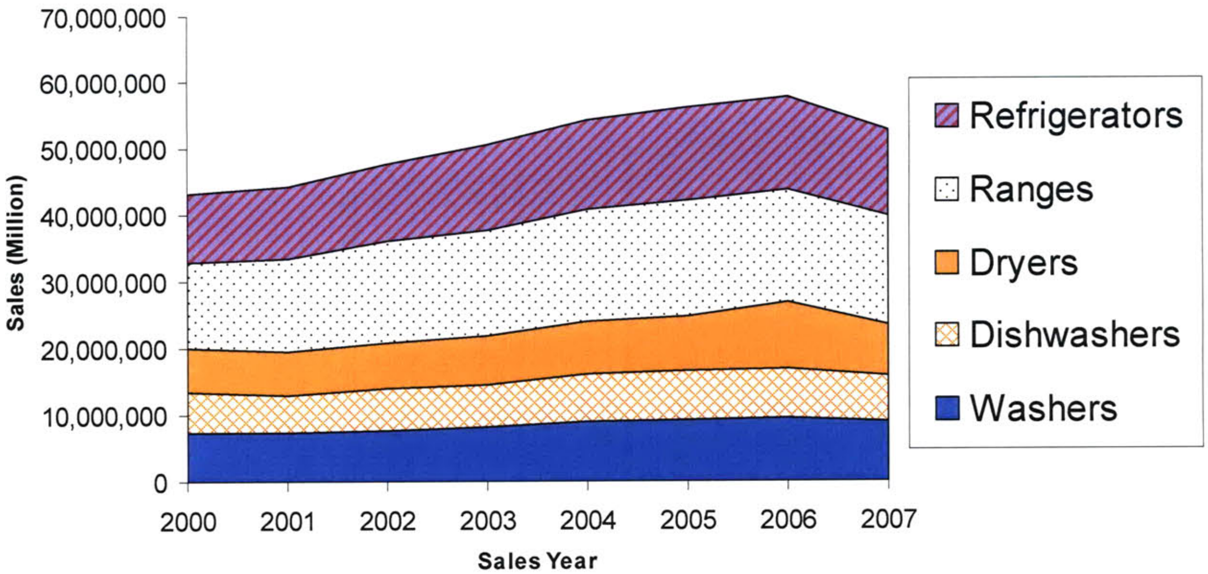

Figure 54: U.S. appliance sales (2000-2007) as listed in (Appliance 55th Annual Report 2008). Ranges (including ovens) account for 30% of sales.

The residential appliance market accounts for over 80% of appliance sales (IBISWorld 2009b). As such, the *collection source* of interest is the residential market, and the commercial appliance business is not covered. According to a review of appliance recycling in the United States sponsored by the Association of Home Appliance Manufacturers (AHAM), 31% of residential consumers dispose of appliances through waste management facilities, 26% send them directly to scrap dealers, while 25% and 18% rely on retailers and local municipalities, respectively (R.W.Beck 2005).

4.1.2. Product Characteristics

As mentioned earlier, sales price, or MSRP, is a useful indicator of initial product quality. Sales data from 2000 to 2009 at different price ranges were collected from Traqline (The Stevenson Company 2010). The typical price points for each appliance are listed in Table XX. Some products, such as refrigerators, have seen a large increase in sales of high-end models in recent years. As such, the overall average appliance sales distribution, as calculated from the data, is approximately 35% low-end, 40% mid-range, and 25% high-end.

Table XX: Price segmentation of different appliances

Price Point	Washers	Dryers	Refrigerators	Dishwashers	Ranges
Low-end	$400	$350	$500	$350	$400
Mid-range	$700	$700	$900	$700	$800
High-end	$1100	$1100	$2000	$1000	$1500

Material composition is a useful indication of a product's material quality. In general, appliances have consistently contained a high percentage of ferrous and non-ferrous metal over the last 25 years (R.W.Beck 2005). In some product categories, sales of stainless steel appliances have increased since 2001 (R.W.Beck 2005). For example, stainless steel dishwashers and ranges have become more popular. However, for appliances, such as washers and refrigerators, the plastic content has been increasing. In addition, over the last 15 years, electronic components have become an increasingly important addition to appliances. Finally, the sales market for each product category has seen an expansion in product offerings, which has an effect on average material compositions. For example, glass-top ranges, bottom-mount refrigerators, and horizontal axis washing machines have impacted the average material compositions of appliances in their respective categories.

Material compositions of products retired in 2005, sold in 1997 and sold in 2005 were averaged together to create representative product compositions (R.W.Beck 2005). The refrigerator bill of materials omits compressors.

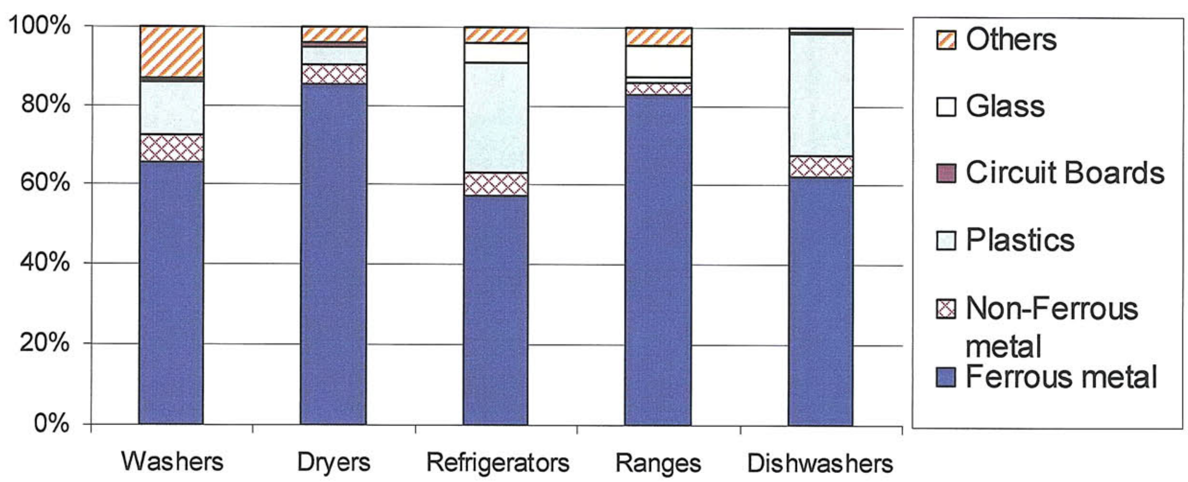

Figure 55: Average appliance material compositions.

Product weights have also been impacted by appliance design decisions (R.W.Beck

2005). The same technique as above was used to create representative product weights.

Table XXI: Average weight of new products from 1997 and new and retired ones from 2005.

Product	Weight (kg)
Washers	72.5
Dryers	50.0
Refrigerators	110.0
Dishwashers	36.0
Ranges	70.4

A product's retirement age is a useful indicator of its value at end-of-life. Data were collected about the retirement ages of the aforementioned appliances (R.W.Beck 2005). As in the analysis of the IT industry, gamma distributions were used to model the age distribution of the product streams. The distributional form in Equation (4) is reproduced here:

$$f(x;\alpha,\beta)=\frac{1}{\beta\Gamma(\alpha)}\left(\frac{x}{\beta}\right)^{\alpha-1}e^{-\frac{x}{\beta}} \text{ for } x>0;\ \alpha,\ \beta>0$$

where x = random variable (here, age), α = shape parameter, β = scale parameter, and Γ = the gamma distribution. Unlike IT products, appliances have long life cycles, averaging 10-15 years. Discussions with industry experts revealed no significant difference in retirement age among the various disposal options, even between retail take-back and municipal pick-up (Hoyt 2010). Because of this, one set of age distributions is used to characterize the return of appliances. Figure 56 depicts the product retirement distributions. Refrigerators and dishwashers have the longest use lives.

No quantitative data exist on the relationship between continued functionality of a product and its age, but industry experts anecdotally correlate the two (Luckman 2010). The designed use life of an appliance is approximately between 10 and 15 years, but industry experts point out that many products continue to function until age 20 (Luckman 2010). Therefore, it was assumed that the functionality drops linearly with age, at a rate of 5% a year, until reaching zero functionality at age 20 (see Figure 57).

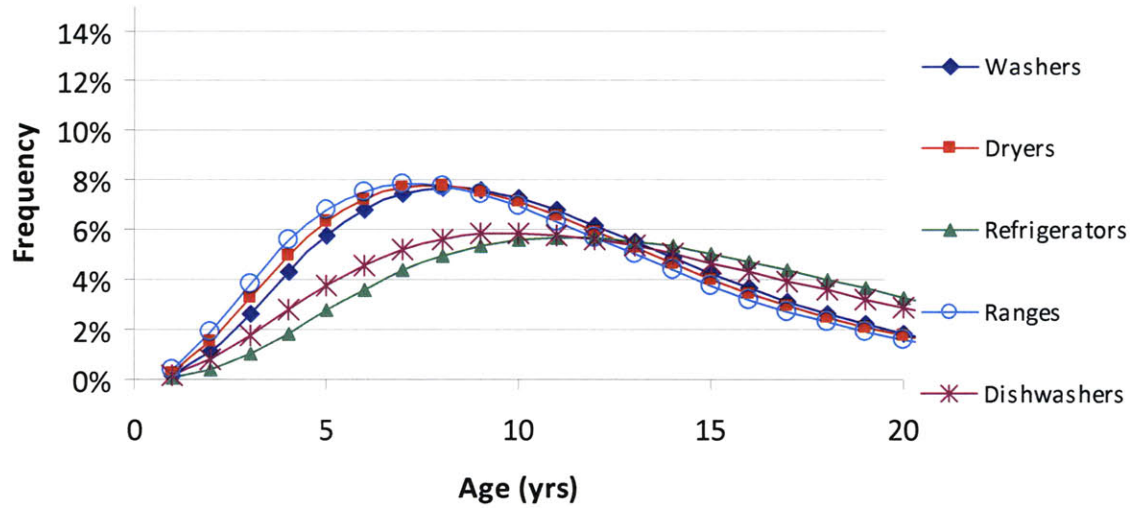

Figure 56: Appliance retirement age distributions.

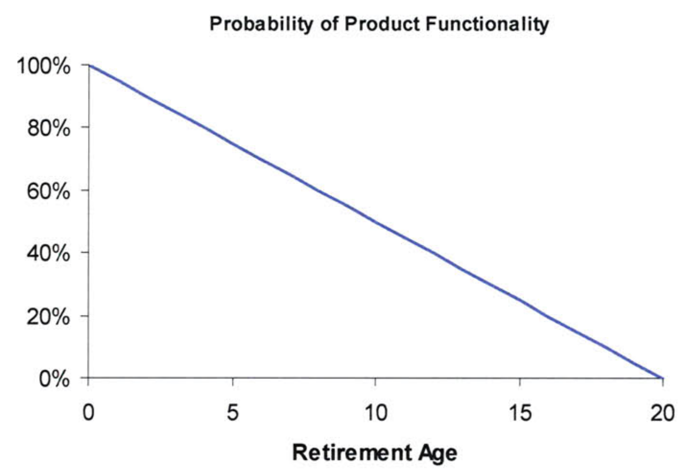

Figure 57: The probability of functionality as compared to product age.

Similar to functionality is a product's depreciation in value over time. As defined by the Bureau of Economic Analysis, depreciation represents the change in value of an asset because of aging, wear and tear, and obsolescence (Fraumeni 1997). No empirical data could be found on the depreciation rates of specific appliances. Thus, the BEA's estimate of a generic appliance's depreciation rate was used as a base equation. The BEA uses a geometric depreciation of the form:

$$d = \delta(1-\delta)^{i-1} \qquad (6)$$

where d = depreciation, δ = rate of depreciation (specific to product type, i.e. appliances), and i = age (in years). For appliances, δ = 0.15. The above equation was altered for specific classes of appliances, namely energy innovators and non-energy innovators. Energy innovators are appliances whose use of energy and/or water improves in every design cycle. Many of these products are Energy Star qualified, which means that they meet the U.S. federal government's standards for energy and/or water efficiency and can feature Energy Star labeling (U.S. Department of Energy and U.S. Environmental Protection Agency 2010). These appliances' dramatic energy and water innovations often coincide with new Energy Star regulations (Hoyt 2010). Washers, refrigerators, and dishwashers fall into this category. Because of their regular energy and water improvements, they depreciate faster than dryers and ranges. Therefore, in the following analyses, their depreciation is estimated to be 1.5 times faster than other appliances. Appliance depreciations are shown in Figure 58.

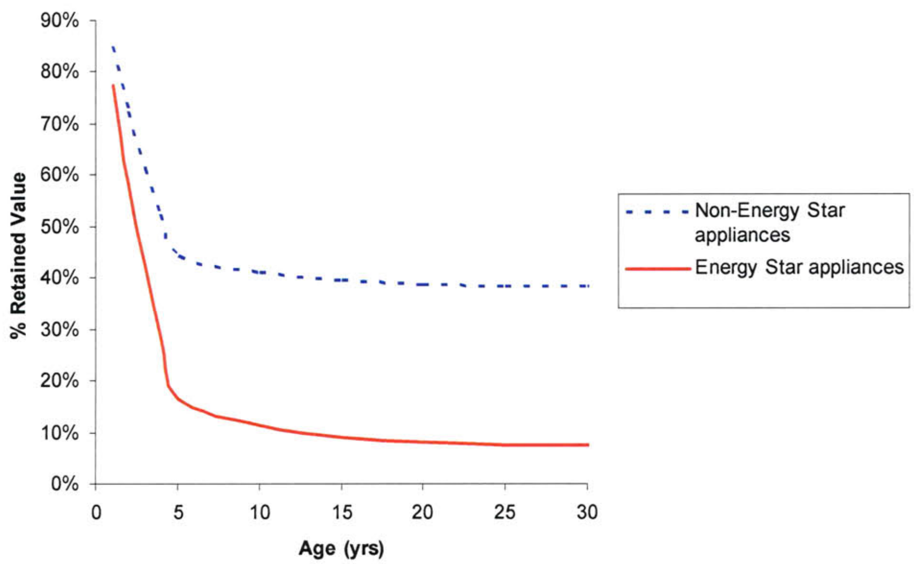

Figure 58: Appliance depreciation

4.1.3. Secondary Market Characteristics

The current analysis compares whole product residual value, or simply resale value, to scrap material value. Industry experts believe that though appliances can have long life cycles, upwards of 15 years, appliance resale is not lucrative beyond eight years (Hoyt 2010). The resale potential of Energy Star appliances ends earlier, around five years. Using this information along with the previously defined depreciation rates and MSRPs, resale value equations were created according to the form of Equation (5), reproduced below:

$$V_{resale} = S * (R \ln x + D) \text{ for } 1 \leq x \leq x_L$$

$$V_{resale} = 0 \text{ for } x > x_L$$

Figure 59 reveals the estimated depreciation rates of products from one to ten years old in the United States. As Figure 60 shows, it is estimated that a high-end washer can command \$900 after one year on the used appliances market, whereas a low-end model is worth \$300.

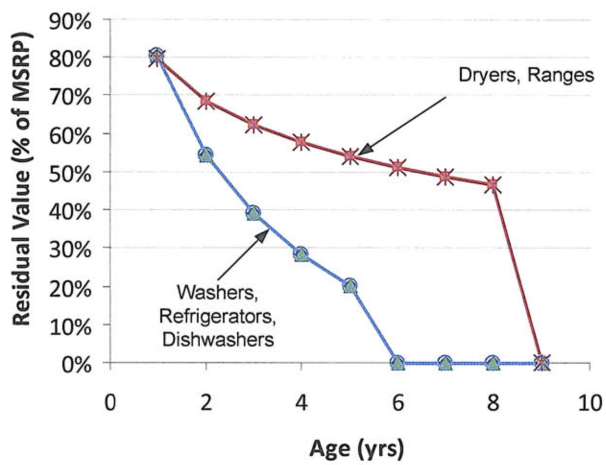

Figure 59: Resale depreciation rates where depreciation is shown as a percentage of MSRP.

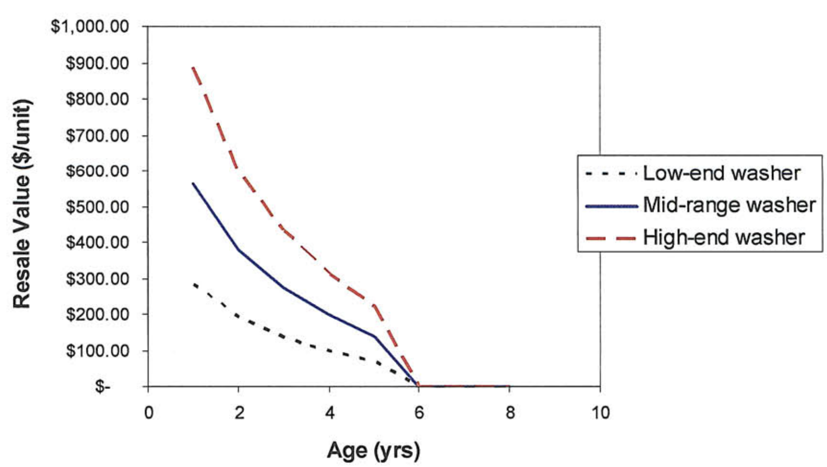

Figure 60: Though adhering to the same decay rate, the resale values of washers differ because of their original MSRPs, which are indicators of their contained features and initial quality.

Figure 61 illustrates the differences in resale value of mid-range appliances at five years of age.

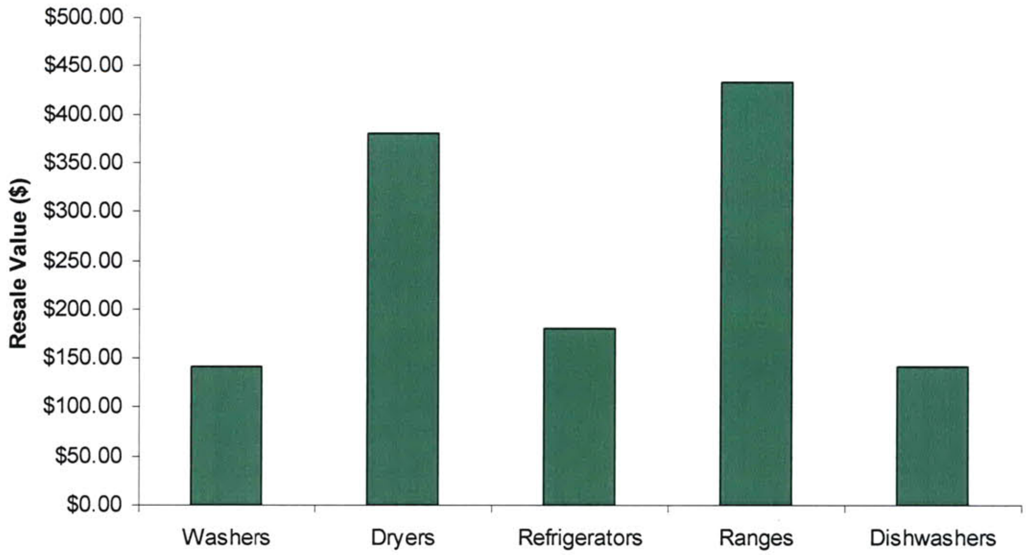

Figure 61: Resale values when appliances are five years old.

As with IT products, appliance scrap value is dependent on material compositions and weights, and secondary commodity prices. Compositions were shown in Figure 55. The method of collecting secondary commodity prices was described in Chapter 3.1.3. The market fluctuation in commodity prices was also explored in the previous chapter (see Figure 14). However, commodity value can also be affected by processing method. There are two methods of appliance recycling (R.W.Beck 2005). In the first method, typically used for automobile recycling as well, appliances are shredded and only ferrous and non-ferrous metals are recovered and sent to smelters (R.W.Beck 2005). Magnetic separators are used to segregate ferrous metals, while eddy current separators or other equipment are used to segregate the remaining metals (Ferrão and Amaral 2006). The rest of the materials, termed fluff or residue, is considered waste and has no value; it is usually sent to landfill. This mode of recycling will be called automobile-based recycling in the rest of the document. In the second method of recycling, electronics-based recycling, plastics, glass, small fractions of precious metals, and even metallic dust are segregated, by a variety of different equipment such as centrifuges, air separators, and imagers (Grant 2009; Rosner 2009). Because electronics-based recycling separates these commodities into purer streams, they have scrap value. In the U.S., automobile-based recycling is the primary method of recycling appliances (R.W.Beck 2005). The prices of commodities that pertain to appliances are reproduced in Table XXII. The highlighted commodities are those whose values become nil after automobile-based recycling. Unlike with IT products, if pure glass is segregated, it has net positive scrap value because glass recovered from appliances is clear or cook-top glass, not hazardous leaded glass. Waste in the appliance case refers to refrigerant and other hazardous materials.

Table XXII: Secondary commodity prices. The highlighted prices are not applicable to automobile-based recycling.

	Value after Electronic Recycling ($/kg)		
Outgoing Commodity	Poor	Avg	Good
100% Al	$ 0.39	$ 0.75	$ 1.11
Mixed plastic	$ 0.22	$ 0.26	$ 0.31
ABS plastic	$ 0.18	$ 0.37	$ 0.55
Low grade CBs	$ 0.07	$ 0.13	$ 0.19
Copper	$ 1.71	$ 4.63	$ 7.56
Steel	$ 0.08	$ 0.25	$ 0.41
Stainless steel	$ 0.67	$ 2.20	$ 3.73
Waste	$ (0.12)	$ (0.12)	$ (0.12)
Glass	$ 0.01	$ 0.01	$ 0.01
Others or process loss	$ -	$ -	$ -

Product scrap value is calculated using Equation (3), reproduced below:

$$V_{recyc} = m\sum_{1}^{N} p_i x_i$$

where V_{recyc} = product scrap value, m = product mass, i = commodity, x = weight fraction of commodity, and p = price of commodity. Figure 62 depicts the difference in product scrap values when automobile-based recycling is used instead of electronics-based recycling. Under any market conditions, the scrap value of a range decreases by only $0.40, but the value of a refrigerator changes by almost $10.

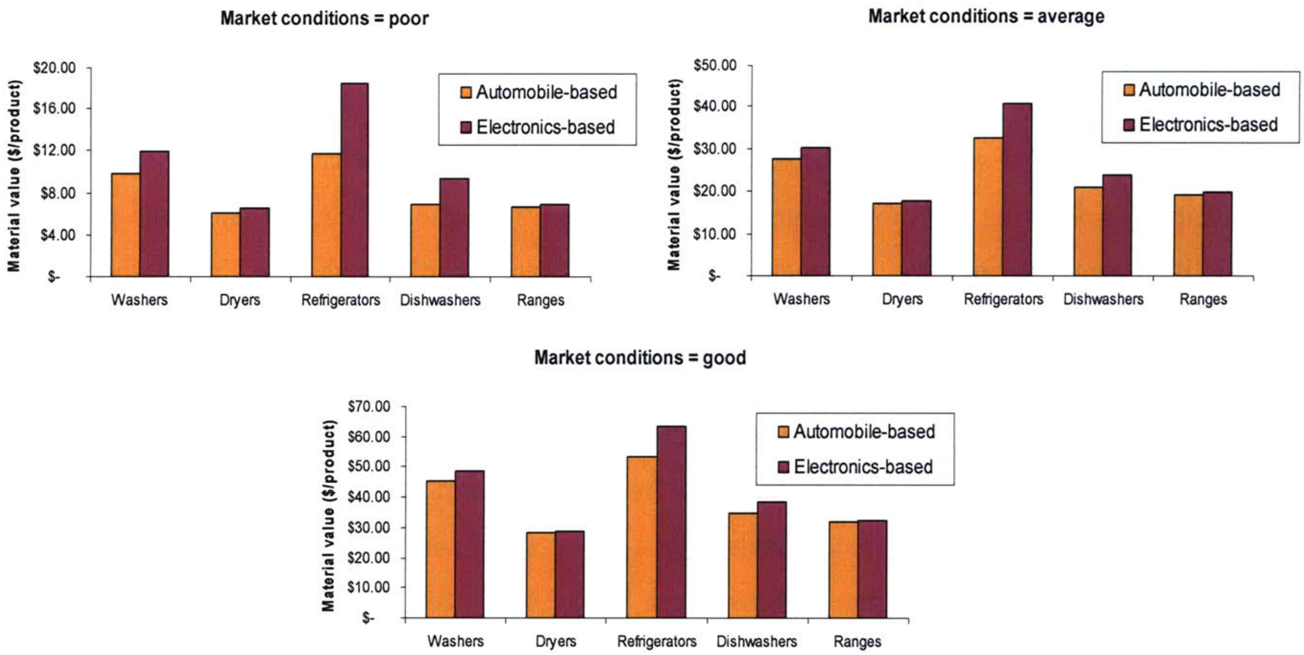

Figure 62: Processing technique has varying effect on the scrap value of different products.

4.1.4. Processing Characteristics

Results of the United Nations University review of the WEEE Directive in the European Union were used to build a range of costs for both reuse and recycling activities (Huisman et al. 2007). In the review, the recycling costs for refrigerators were much higher than for other major appliances because of the cost of responsible disposal of refrigerants and insulation materials. Reuse costs were not delineated in the report, so it was assumed that they were comparable to the listed transportation and collection costs, which usually account for a large percentage of total reuse costs (Walther et al. 2009).

Table XXIII: Average appliance recovery costs

	Costs ($/kg)	
Product	Processing for Reuse	Processing for Recycling
Washers	$0.25	$0.31
Dryers	$0.25	$0.31
Refrigerators	$0.38	$1.14
Dishwashers	$0.25	$0.31
Ranges	$0.25	$0.31

4.2. Baseline Analysis

The MFE model is useful for understanding the economics of appliance recycling and how profit changes according to different values of system parameters. For example, in the following scenario, it was imagined that a recovery system receives 1,000,000 appliances from residential consumers annually. The product mix is defined according to the recent trend in appliance sales and product retirement profiles, as described in Sections 4.1.1 and 4.1.2. Therefore, it is assumed that 36% of the retired product volume is ranges, 19% washers, 18% dryers, 15% refrigerators, and 12% dishwashers. In Section 4.1.2, MSRP distributions were calculated. It is assumed that the return mix would also exhibit the same distribution in product quality. Following the model algorithm as outlined in Section 2.3.2 and using the previously defined age distributions, depreciation curves, scrap value calculations, and other system parameters, the profit of the system is calculated. It is assumed that automobile-based recycling is employed and that commodity prices are in average conditions.

In the model, a recovery system achieves an average of \$0.63/kg or \$43.33/product net profit. In total, profit is \$43.3M. Figure 63 reveals that most of the products are recycled rather than reused. Though dryers constitute only 13% of the incoming mass, they represent 40% of the total profit, primarily through reuse. (see Figure 65). Ranges account for half of the profit made from resold products. Meanwhile, refrigerators have the most impact on the recycling stream, but only because their treatment requires the greatest expenditure. In reuse, the firm earns \$325/refrigerator; in recycling, it spends -\$100/refrigerator. Other illustrative graphs can be found in Appendix H.

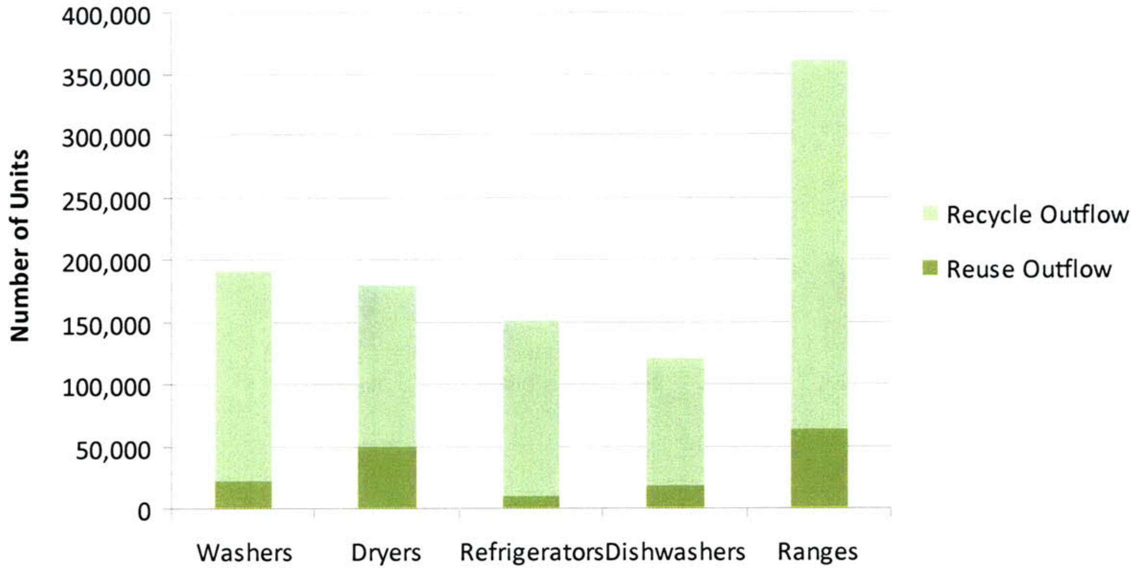

Figure 63: Most of the returned appliances are recycled.

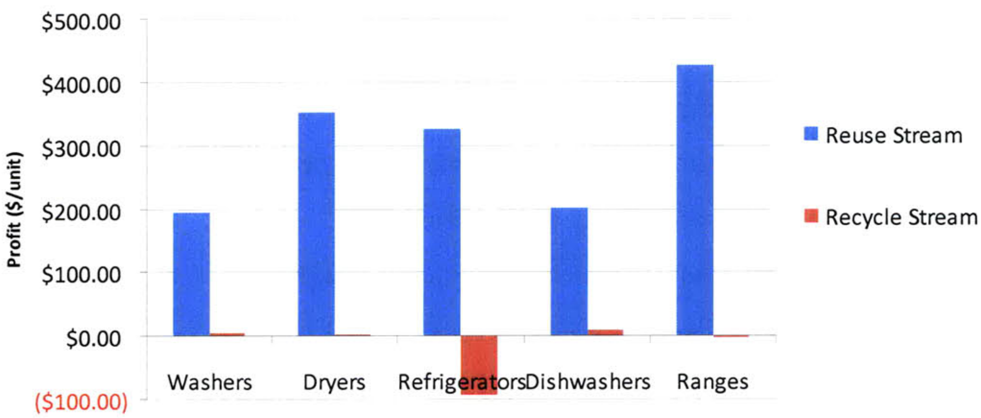

Figure 64: Profit on a per-product basis.

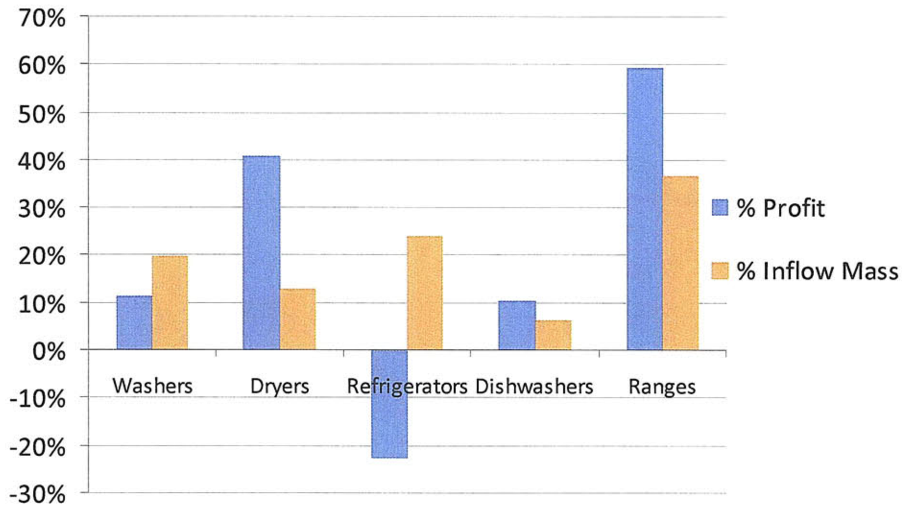

Figure 65: Refrigerators are substantial in mass and in processing costs.

4.3. DOE Analysis

The Design of Experiments (DOE) method of statistical analysis was used to identify which system variables produce the largest variation in revenue potential. The analysis was conducted using JMP® software. Since the intent was to detect variable influence on revenue, the analysis was conducted in a zero cost environment.

A 2^{5-1}_{IV} screening design was used; the experimental matrix is shown in Table XXIV.

Table XXIV: Experimental design for DOE analysis

Factor	Units	- Level	+ Level
Retirement Age	Years	Mean age = 15, σ = 5	Mean age = 7, σ = 5
Product Mix	% by return volume	66% High plastic content	66% Low plastic content
Product Price Points	U.S. Dollars	100% low-end products	100% high-end products
Depreciation Rate	% depreciation	Double current rate	Current rate
Commodity Prices	U.S. Dollars	Poor market	Favorable market

To understand the effect of retirement age, the negative level was set such that within each product type, the mean age of returns was 15 years old, with a standard deviation of 5 years. Meanwhile, the positive level was set at a mean age of 7 years old, with a standard deviation of 5 years. The gamma distribution was used to represent each age distribution. Since product resale value is dependent on age, this variable should have a large impact on system profit.

As for product mix, 66% high plastic content refers to a return mix that is dominated in volume by refrigerators and dishwashers, which both contain over 25% plastic. The remaining 34% of products is evenly split among washers, dryers, and ranges. Plastic is not recovered in the customary form of appliance recycling, which decreases the value of recycling products that have high plastic concentrations. 66% low plastic content refers to a return amount that is 33% dryers and 33% ranges. The remainder is evenly split among the other appliance categories.

To investigate product sales price, the experimental levels were set to describe the quality of returns in each product category. For instance, the negative level setting means that 100% of refrigerator returns are low-end models. This ratio exists for every product category. The positive level means that 100% of returns are high-end appliances.

For depreciation rate, two situations are considered. At the negative level setting, products depreciate at the individual rates that are seen currently on the used market. At the positive level setting, these rates have been doubled. This is believed to be a wide enough range because the decay function changes dramatically. Energy Star appliances will experience the greatest impact. For example, instead of washers maintaining resale value through five years of age, they would only maintain it through one year (see Figure 66).

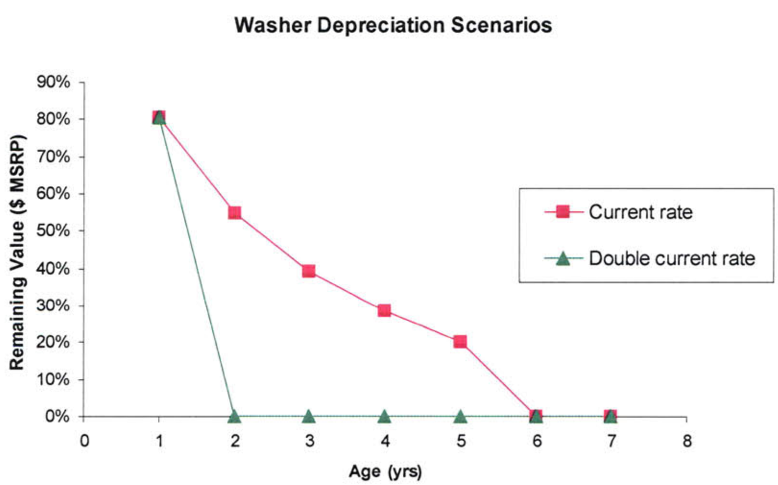

Figure 66: Just by doubling the rate of depreciation, a washer would lose all resale value within one year.

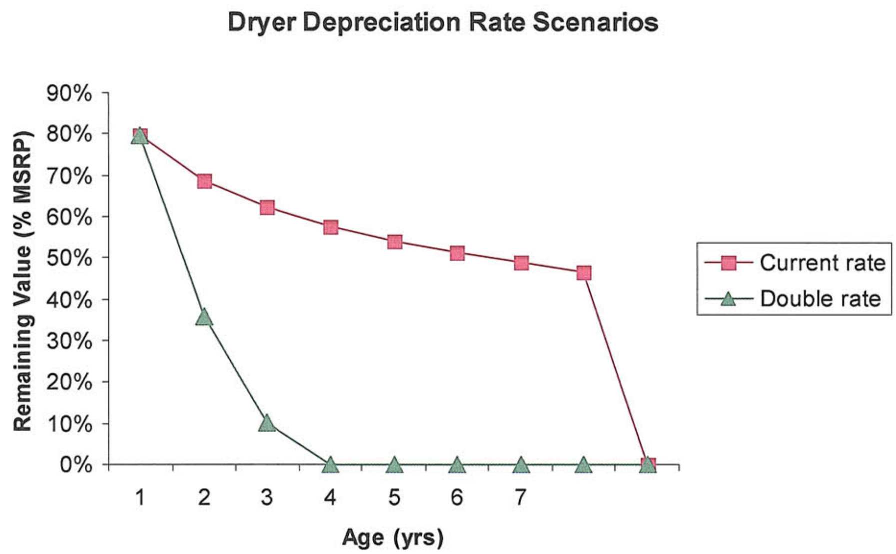

Figure 67: Doubling the rate of depreciation causes a dryer to lose resale value by age 4 instead of age 8.

Finally, to investigate the effect of commodity prices on revenue potential, levels were set such that all prices were either two standard deviations below their average price or two standard deviations above the average price.

Similar to the case of IT products, the analysis revealed that product age is the most influential factor on revenue per unit mass ($/kg). Unlike the IT case, the impact of age does not dwarf the impact of other variables; MSRP is a close second in influence. The influence of product age is extended by the impact of its interaction with both MSRP and depreciation. This is not surprising as all three are crucial to appliance resale value. In the best performing scenario, where resale is the dominant activity, the revenue is $5.11/kg. In the worst performing scenario, where recycling was dominant, the revenue is $0.18/kg. As shown previously, resale value can be substantially greater than scrap material value if a product is retired at a time when it still retains most of its usefulness. Interestingly, the effect of product mix, as defined in this analysis, is not statistically significant on its own, but its interaction with commodity prices is. This result is primarily due to the lack of revenue from plastic content in the high plastic mix.

Table XXV: Results of the first DOE analysis. The parameters found statistically significant ($p < 0.05$) are listed.

Summary of Fit		Analysis of Variance		
R^2	0.999757	Source	DF	F Ratio
R^2 adj	0.99635	Model	14	293.4337
RMSE	0.0925	Error	1	Prob > F
Mean of Response	1.338125	C. Total	15	0.0457
Observations	16			

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	1.338125	0.023125	57.86	0.011
Age	0.930625	0.023125	40.24	0.0158
Sales Price	0.691875	0.023125	29.92	0.0213
Age*Sales Price	0.676875	0.023125	29.27	0.0217
Depreciation	0.353125	0.023125	15.27	0.0416
Age*Depreciation	0.335625	0.023125	14.51	0.0438
Sales Price*Depreciation	0.249375	0.023125	10.78	0.0589
Mix*Commodity Prices	0.224375	0.023125	9.7	0.0654
Commodity Prices	0.198125	0.023125	8.57	0.074

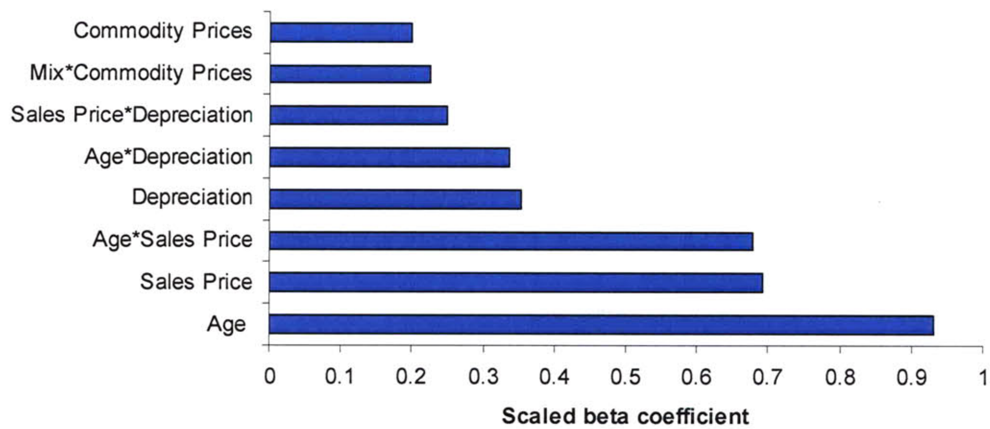

Figure 68: A Pareto chart of the factors that were found to be statistically significant, using DOE analysis. A scaled beta coefficient is the normalized estimate of the half-effect of a parameter on the dependent variable (e.g. revenue).

A second analysis was completed to determine which factors become important when a recovery system finds itself dealing primarily with younger returns versus older returns. Revenue through the resale market would be more attainable in the former case.

Two separate 2^4 full factorial designs were executed, one on young returns and the other on old returns. In the young return scenario, sales price was the most important factor; its impact was double that of the second most important factor (see Table XXVI and Figure 69). In moving from low-end appliances to high-end appliances, the average revenue moves from \$2.27/kg to \$5.00/kg (all other variables held constant).

Table XXVI: Results of the DOE on younger returns. The parameters found statistically significant ($p < 0.05$) are listed.

Summary of Fit		Analysis of Variance		
R^2	0.999833	Source	DF	F Ratio
R^2 adj	0.999499	Model	10	2994.147
RMSE	0.037283	Error	5	Prob > F
Mean of Response	2.27	C. Total	15	<.0001
Observations	16			

Sorted Parameter Estimates				
Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	2.27	0.009321	243.54	<.0001
Sales Price	1.36625	0.009321	146.58	<.0001
Depreciation	0.6875	0.009321	73.76	<.0001
Sales Price*Depreciation	0.48125	0.009321	51.63	<.0001
Commodity Prices	0.14625	0.009321	15.69	<.0001
Mix	0.06625	0.009321	7.11	0.0009
Mix*Sales Price	0.0575	0.009321	6.17	0.0016
Mix*Depreciation	0.03125	0.009321	3.35	0.0203

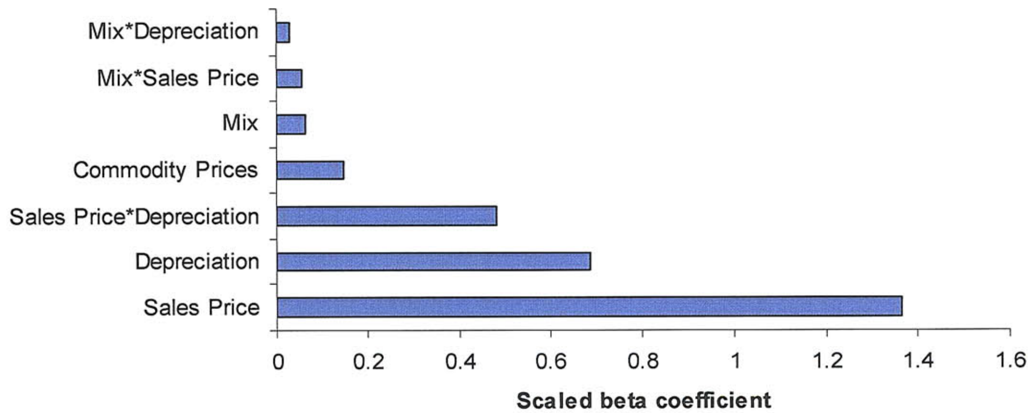

Figure 69: Results of DOE analysis of the most influential factors on revenue potential for a firm that receives younger returns.

Meanwhile, in the DOE analysis on older returns, commodity price is by far the most important factor on revenue. Moving from a poor scrap market to a strong scrap market increases the value of returns by \$0.46/kg as compared to < \$0.05/kg impact from the other variables.

Table XXVII: Results of the DOE on older returns. The parameters found statistically significant ($p < 0.05$) are listed.

Summary of Fit		Analysis of Variance		
R^2	0.999943	Source	DF	F Ratio
R^2 adj	0.99983	Model	10	8820.5
RMSE	0.003162	Error	5	Prob > F
Mean of Response	0.4075	C. Total	15	<.0001
Observations	16			

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	0.4075	0.000791	515.45	<.0001
Commodity Prices	0.23125	0.000791	292.51	<.0001
Depreciation	0.01875	0.000791	23.72	<.0001
Sales Price	0.015	0.000791	18.97	<.0001
Sales Price*Depreciation	0.01375	0.000791	17.39	<.0001
Mix*Commodity Prices	-0.01125	0.000791	-14.23	<.0001
Mix	-0.0275	0.000791	-34.79	<.0001

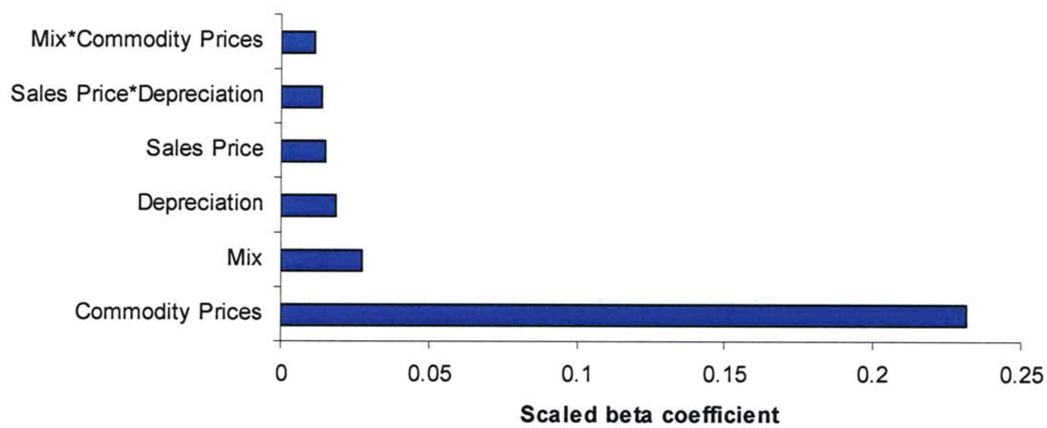

Figure 70: Results of DOE analysis of the most influential factors on revenue potential for a firm that receives older returns

4.4. Scenario-based Sensitivity Analysis

DOE analysis is useful in quickly identifying the most influential variables in a system. However it is limited because it forces the variables into binary states. Other tools are necessary for quantifying sensitivity of revenue to a range of variable states.

It was discussed in Section 4.1.3 that energy-innovating appliances, now referred to as Energy Star appliances, and non-Energy Star appliances have different rates of depreciation; non-Energy Star appliances have longer lives on the resale market. It was also discussed in Section 4.1.3 that electronics-based recycling allows for greater recovery of product materials and thus increases the scrap value of appliances. Four scenarios were considered in the investigation of revenue sensitivity to changes in commodity prices, depreciation rates, and quality of returns, or MSRPs (see Table XXVIII). An Energy Star-heavy mix means a return volume that primarily consists of washers, refrigerators, and dishwashers. Their return volume is evenly split to make up 75% of returns. In the alternate scenario, ranges and dryers together comprise 75% of returns. These two collection mix scenarios are interesting because currently ranges dominate sales and should dominate returns (Appliance 55th Annual Report 2008). However, recent legislation in the U.S. that encourages the purchase of energy-efficient products through cash rebates should result in a greater influx of appliances that have more energy-efficient models on the market (U.S. Department of Energy 2010a).

The following analyses are executed under zero cost conditions. This was considered reasonable because, although processing costs are not constant, they are similar across products and are therefore insignificant. A constant return volume is also assumed; only the relative return of appliance types changes.

Table XXVIII: Four system scenarios considered for analysis

Energy Star-heavy mix Automobile-based recycling	Non-Energy Star-heavy mix Automobile-based recycling
Energy Star-heavy mix Electronics-based recycling	Non-Energy Star-heavy mix Electronics-based recycling

Before testing sensitivities, it is useful to understand how the economic performance of the four scenarios differs under average conditions. In the following table, it is assumed that all returns are mid-range models and that the scrap commodity market is behaving at average conditions. As the table depicts, product mix has a more substantial impact on the overall profit.

Table XXIX: A recovery system's profit when it uses different processing techniques and recieves different product mixes.

	Energy Star-heavy mix	Non-Energy Star-heavy mix
Automobile-based recycling	$0.28/kg	$1.01/kg
Electronics-based recycling	$0.34/kg	$1.05/kg

4.4.1. Sensitivity to Commodity Prices

In the analysis, it is assumed that the market of available returns consists of 35% low-end products, 40% mid-range, and 25% high-end products, as it does today (The Stevenson Company 2010). It is also assumed that each product type is depreciating at the current rate compiled from data. The reference point for the following analysis is a period when product scrap values are at their mean values (i.e. commodity prices are at their mean values). A multiplier is used to move prices below or above this condition. If the multiplier is increased by 25%, then all commodity prices increase by 25% and the scrap value of each product type increases by 25%. Through the sensitivity analysis, it is attempted to show how substantial such movement is on the total revenue of a recovery system when it operates under the previously described scenarios. The reference point is the revenue of the system in each scenario when the multiplier is one.

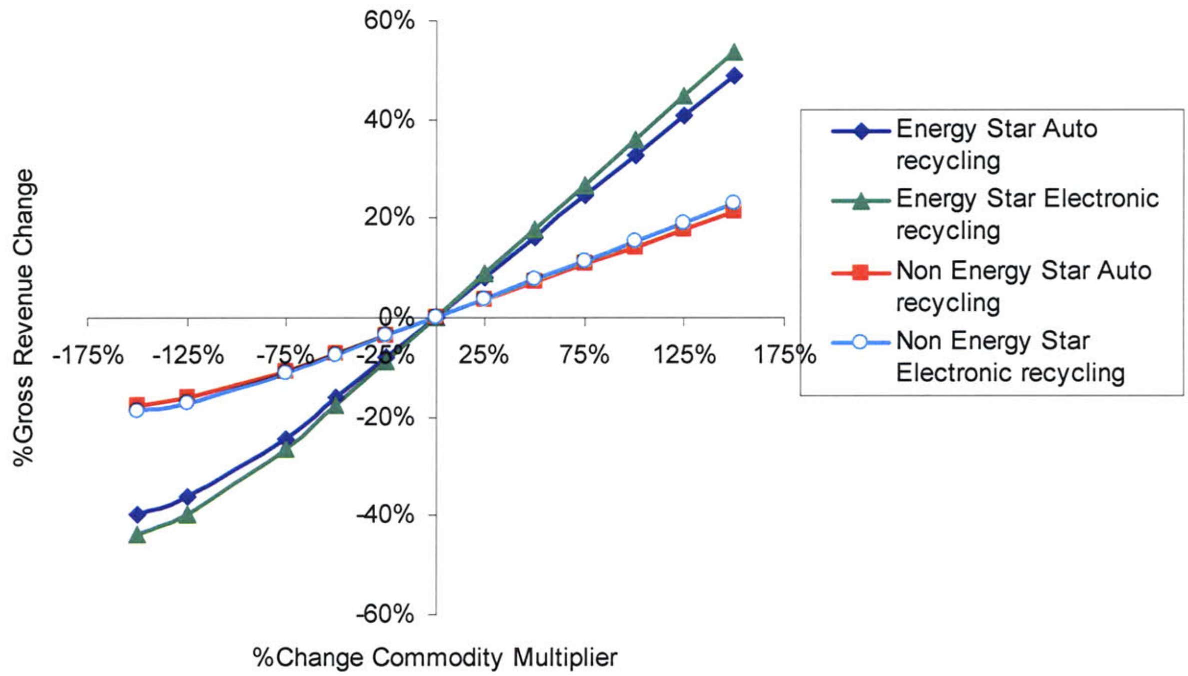

Figure 71: Returns that contain more Energy Star appliances are more sensitive to changes in commodity prices.

Figure 71 displays the results of the sensitivity analysis. Scenarios in which the recovery system receives more Energy Star appliances are more sensitive to changes in commodity prices. However, a 1% change in scrap commodity market conditions results in less than 1% effect on revenue.

4.4.2. Sensitivity to Product Depreciation

Depreciation was shown to be important to revenue generation at a firm that receives primarily young and high value returns. To demonstrate the sensitivity, a depreciation multiplier was created. The multiplier is applied as a scalar to the right side of Equation (1). The depreciation multiplier simply increases or decreases the rate of depreciation of each product type, with the reference point being the current rate of depreciation of each appliance type as calculated from the data. As previously described, Energy Star appliances have faster rates of depreciation because newer, efficient models enter the market every four or five years. This rate could increase if the design cycle accelerates. Depreciation of both Energy Star and non-Energy Star appliances could also accelerate when new break-through technologies emerge (Doyle 2010). Ice-in-the-door refrigerators and heat pump dryers are examples. Figure 72 illustrates the effect of a moving depreciation multiplier on the depreciation rate of a washer. A depreciation multiplier of 1 corresponds to a washer maintaining resale value until age five. Increasing the multiplier to 2 means resale value is only maintained until age one.

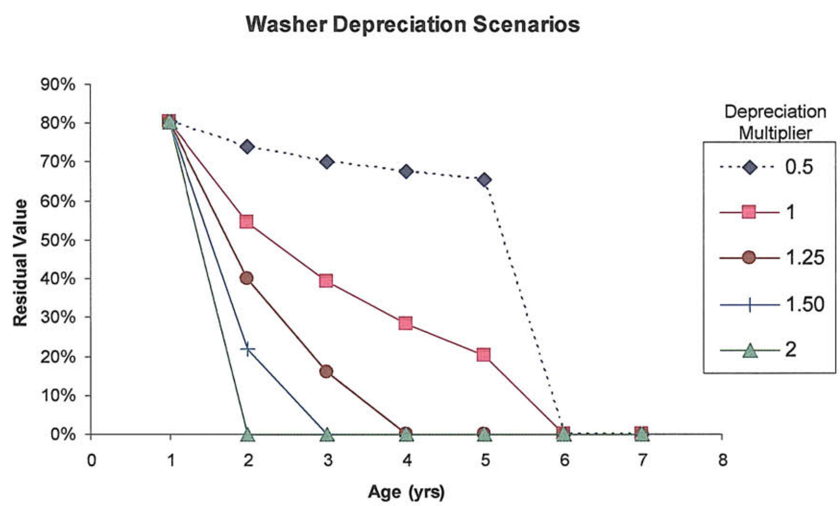

Figure 72: Different possible depreciation rates of washing machines. The reference point is a multiplier = 1.

In the following analysis, the commodity market is held constant at average conditions. The sales price distribution of returned products consists of 35% low-end products, 40% mid-range, and 25% high-end products. Analysis showed that there is a nonlinear relationship between the system's total revenue and product depreciation in every scenario (see Figure 73). This time, non-Energy Star appliances are more sensitive. As their depreciation rates accelerate, they approach the current depreciation rates of Energy-Star appliances, which means their shelf-life on the resale market declines. In the case of extreme depreciation (a loss of retained use value by age two for a washer), the effect on revenue bottoms out, because revenue quickly becomes dominated by recycling activities.

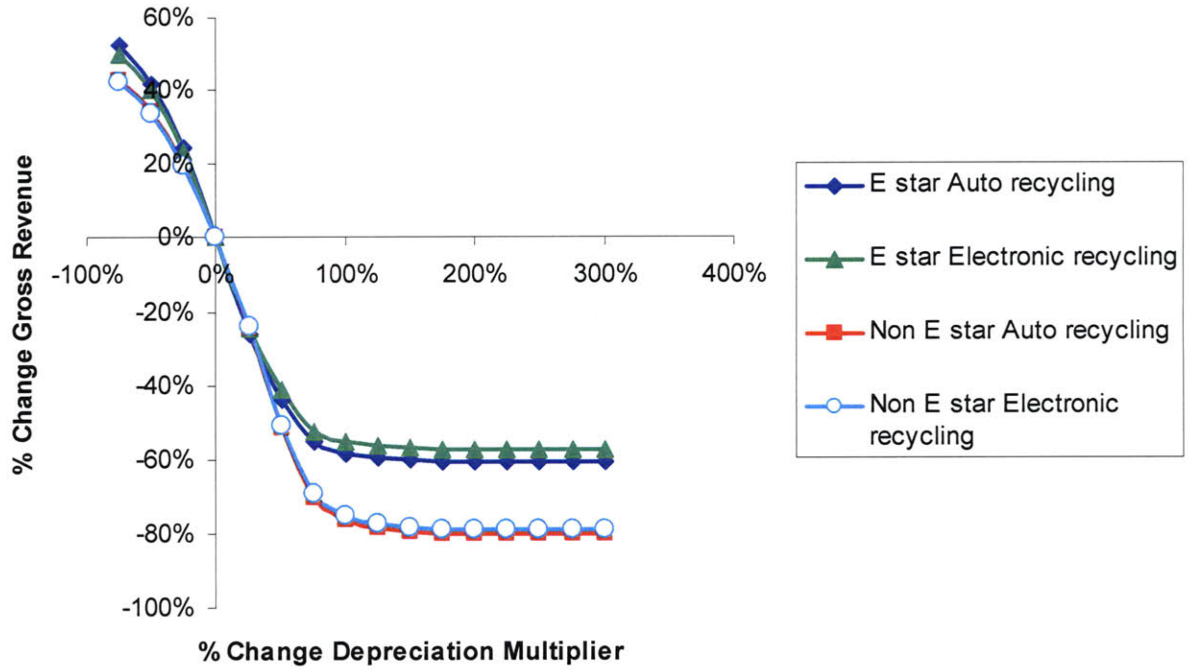

Figure 73: Increasing depreciation affects non-Energy Star appliances more.

4.4.3. Sensitivity to MSRP

DOE analysis revealed sales price to be statistically significant. An MSRP multiplier was used to move the return stream from one consisting of all low-end products to one consisting of all high-end products. One could imagine product sales moving to lower price points in the industry and what the impact may be on resale value at product end-of-life. One could also imagine the opposite future and its effect on resale value.

The reference point of analysis is the mid-range price point for each product type as calculated from collected data. As Figure 74 depicts, refrigerators and ranges cover a wider range of prices because there is a large distinction between their low-end and high-end models.

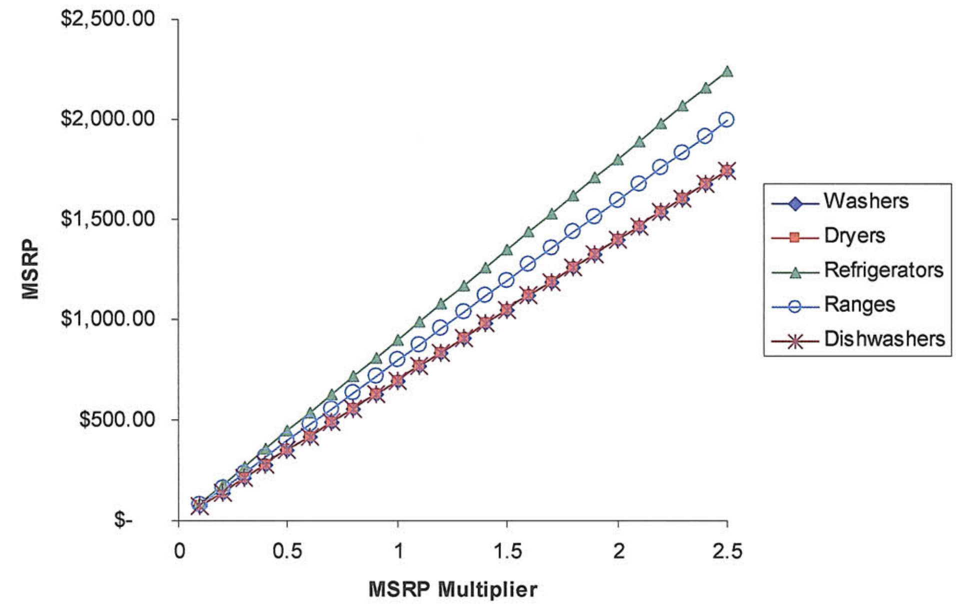

Figure 74: Change in product MSRP with change in multiplier. The reference point is a multiplier = 1.

In testing sensitivity of the scenarios to changes in the MSRPs of returned appliances, commodity conditions were kept constant at average conditions. Product depreciation was also set at current rates.

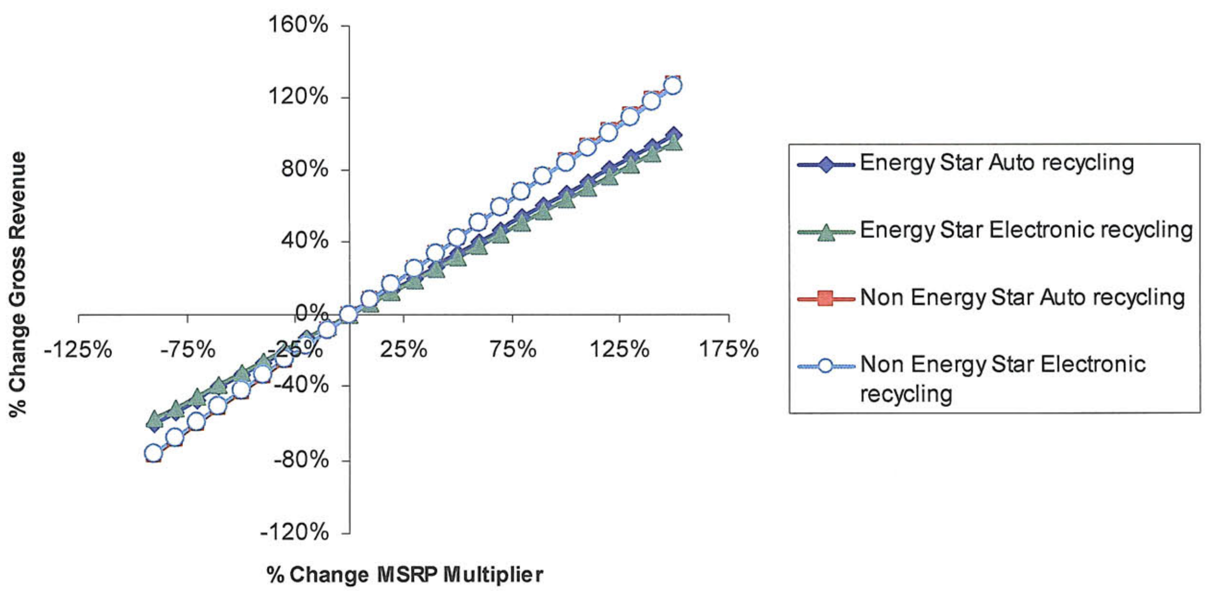

Figure 75: The quality of returns has almost a 1:1 effect on revenue in every scenario.

The effect of MSRP is similar in both the Energy Star and non-Energy Star appliance cases. There is a slightly greater impact in the latter case because more non-Energy Star appliances, mainly dryers, are eligible for resale.

4.4.4. Summary of Single Variable Sensitivity Analysis Results

The average elasticities of gross revenue to commodity prices, depreciation rates, and MSRPs are listed in Table XXX. An elasticity of 0.67 means that a 1% change in the system property results in 0.67% change in gross revenue. Negative elasticities mean an increase in a system property results in a decrease in revenue, as is the case with all depreciation elasticities. Large sensitivities (> 0.7) are highlighted.

Table XXX: Commodity price elasticity of gross revenue

Product Mix	Processing Method	MSRP Elasticity	Commodity Elasticity	Depreciation Elasticity
Energy Star-heavy	Auto recycling	0.67	0.32	-0.55
	Electronic recycling	0.64	0.35	-0.52
Non-Energy Star-heavy	Auto recycling	0.86	0.14	-0.60
	Electronic recycling	0.85	0.15	-0.59

4.5. Monte Carlo Simulation

Monte Carlo analysis was used to build upon the previous analysis by disaggregating lumped variables to understand their effects on the system when they vary simultaneously. The analysis was completed using @RISK software. In the following analysis, the same four scenarios shown in Table XXVIII were considered. Age distributions by product type were still characterized using gamma distributions. Because discrete MSRPs are known for product prices instead of a sample of various prices, histograms were used to describe each appliance's possible sales price. The depreciation of product value was varied for each product type by associating a distinct depreciation multiplier to each depreciation curve and using a triangle distribution to allow the multiplier to vary between 0.5 and 4. The price of individual commodities was varied using gamma distributions to represent the collected data. For the automobile-based recycling scenarios, where plastics and glass are not recovered, the prices of these particular commodities were characterized using triangle distributions centered at $0.00/kg because gamma distributions cannot assume negative values. The correlation between prices of similar commodities, such as mixed and ABS plastics, was included so that they would vary together.

Finally, two extra variables were added to the sensitivity analysis. Recovery costs were included and were allowed to vary +/- 10% from the average values found in literature. This variation is to partly represent cost differences between manual-heavy and automation-heavy processes. The probability of a product's working status, as related to its age, was also allowed to vary. Originally, the linear relationship was constructed such that a product's probability of functioning dropped by 5% with each successive year, resulting in all products being assumed non-working by age 20 (see Figure 57). In this exercise, this property was characterized using a triangle distribution, which varied between 2.5% and 10%. Details about all input distributions can be found in Appendix I.

Three simulations of 1000 iterations were run for each scenario (see Figure 76). As in the previous single variable analyses, there is little difference between automobile-based and electronics-based recycling. However, collection mix has a large influence on expected profit. There is a 90% chance of achieving a net revenue in the non-Energy Star scenarios; there is a 60% chance in the Energy-Star scenarios. Figure 77 reveals that more products can be resold in the Non-Energy Star scenarios. Since items that are sent for reuse versus recycling generate more revenue, the Non-Energy Star scenarios outperform the Energy-Star scenarios.

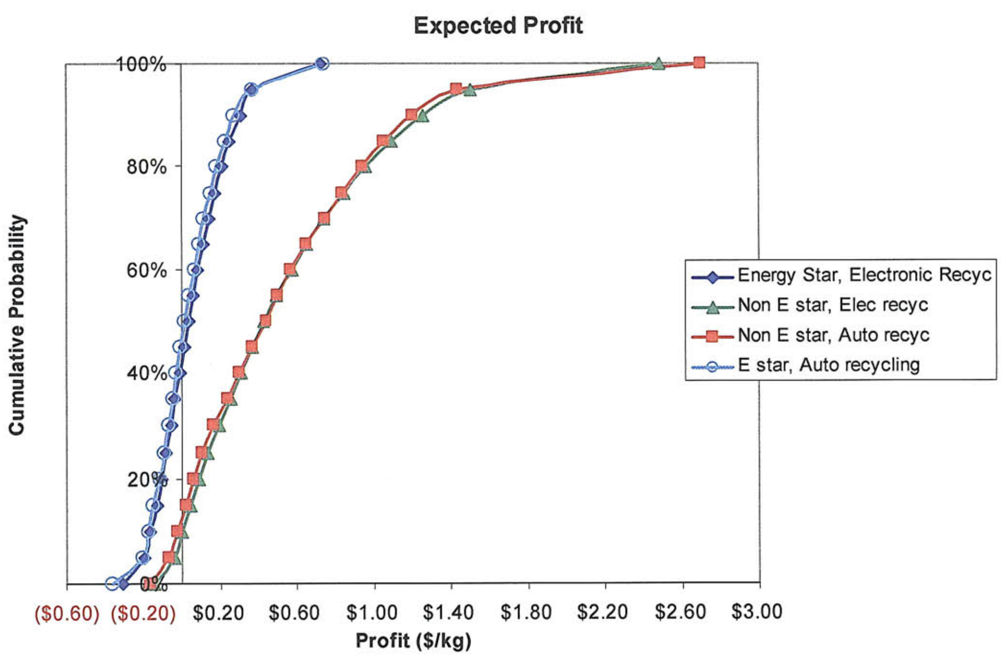

Figure 76: Expected profit in four appliance scenarios that differ by collection mix and processing method.

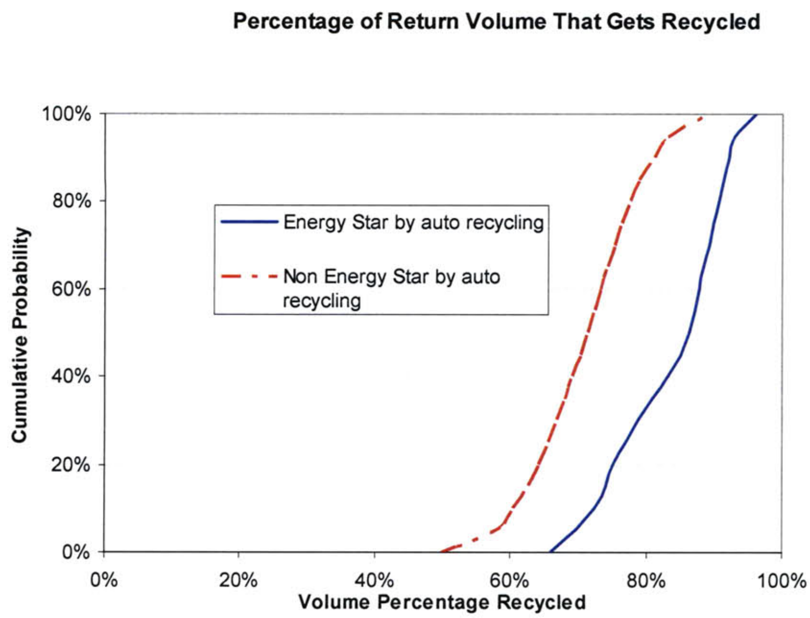

Figure 77: More products are resold in the Non-Energy Star scenario, causing it to outperform the Energy Star scenario.

Table XXXI lists the 50% Value at Risk profits and the maximum expected profits. 50% Value at Risk refers to the 50% chance of not achieving above a certain profit. Values for electronic recycling and automobile recycling scenarios are almost identical in each collection mix case, so the average values are reported.

Table XXXI: A summary of the Monte Carlo results

Scenario	50% Value at Risk ($/kg)	Maximum Expected Profit ($/kg)
Energy Star	$0.03	$0.74
Non-Energy Star	$0.44	$2.60

The algorithm in @RISK uses multivariate stepwise regression to rank input variables according to how important they are to system profit. In all four scenarios, the depreciations of ranges and dryers were the most influential parameters. The top five influential variables are listed in Table XXXII.

Table XXXII: Influential factors as a result of Monte Carlo analysis

Ranking of Factors	Energy Star mix, Auto-based recycling	Energy Star mix, Elec-based recycling	Non-Energy Star mix, Auto-based recycling	Non-Energy Star mix, Elec-based recycling
1	Range depreciation	Range depreciation	Range depreciation	Range depreciation
2	Dryer depreciation	Dryer depreciation	Dryer depreciation	Dryer depreciation
3	Refrigerator depreciation	Refrigerator depreciation	MSRP of ranges	MSRP of ranges
4	Product functionality	MSRP of ranges	MSRP of dryers	Product functionality
5	MSRP of ranges	Stainless steel price	Product functionality	MSRP of dryers

4.6. Strategy Development

The system variables that most affect the economic performance of an appliance e-waste recovery system have been identified. Product quality, product depreciation, and commodity prices have been shown to be important. Broadly speaking, these variables denote a tension between use value and material value, or reuse revenue and recycling revenue. A recovery system manager must develop strategies to mitigate or enhance the effects of these variables on both revenue sources. However, the strategies are chosen based on the manager's constraints. In other words, the manager's actions depend on where s/he is positioned within the e-waste recovery system. For example, an OEM's interaction with its consumer base can influence the quality of the returns it receives. In addition, legislation can influence mix of returns.

The following analysis imagines appliance EOL recovery in the U.S. residential sector for an OEM. The current context in which the recovery system operates is examined, as well as two possible future states. In the first future state, no appliance disposal legislation exists. There are also no government-provided incentives for consumers to replace their appliances with new energy- and water-efficient models. However, appliance designs continue to evolve and the sales market continues to develop. In the alternate future state, legislation prohibits landfilling of retired appliances. In addition, government-provided incentives exist for appliance replacement. Simultaneously, appliance design and the sales market continue to evolve.

A comparison of two future contexts is timely because today 20 states have landfill bans for appliances (R.W.Beck 2005; Castanea Labs 2010). In Europe, major appliances are listed in

Category 1 of the WEEE Directive (European Parliament and Council 2003). In the following analysis, the impact of different system contexts on system profit will be examined.

4.6.1. Current State

The current state scenario is identical to the characterization used in Section 4.2. Product mix is based on sales data from 2000 to 2007 and current product retirement age distributions (R.W.Beck 2005; Appliance 55th Annual Report 2008). MSRP distributions are characterized according to sampled sales data from 2000 to 2009 (The Stevenson Company 2010). It is also assumed that retirement ages are the same whether products are disposed of through retailers or municipalities. The current state product mix and sales distributions can be found in Figure 78.

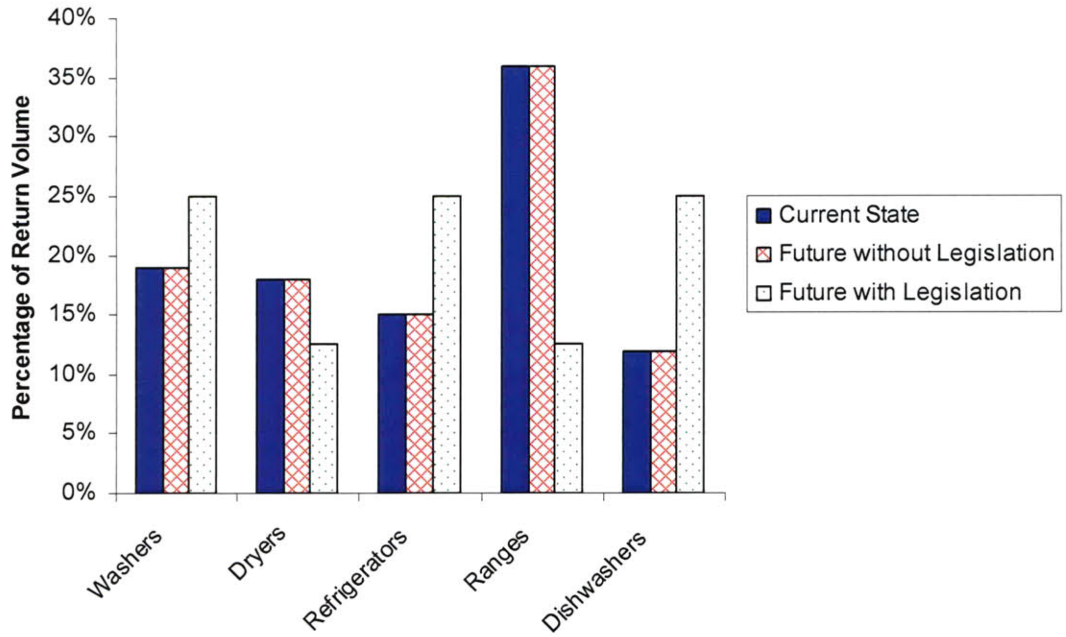

Figure 78: Return volumes for the different scenarios. The largest difference is in the relative return volume of ranges.

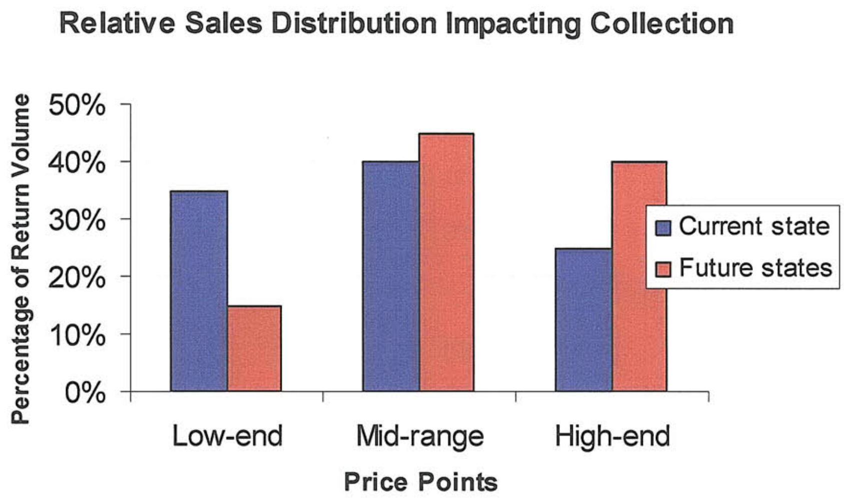

Figure 79: The forecasted trend in appliance sales sees a continued popularity of mid-range and high-end models.

4.6.2. Future State in absence of legislation

The future state scenarios take place at least ten years in the future. In the no-legislation future state, the return mix is based on current and forecast product sales because these sales will be the products available for retirement in the future (Appliance 55th Annual Report 2008). Because full 2008-2009 data was not available, the effects of the current economic recession are not included in the forecast; historically, the performance of the appliance market is a time lag of the housing market (IBISWorld 2009b). The forecast is thus optimistic. Forecasts were created using Holt's exponential smoothing method, which is a forecasting method that incorporates seasonality and weighs more recent observations more than those in the past (National Institutes of Standards and Technology 2003). As Figure 80 shows, ranges represent the dominant relative sales volume. Using the current retirement age distributions, the relative volume of each appliance type in the return mix was estimated. The estimate is similar to today's return mix, so in the analysis the return mix is unchanged from current conditions.

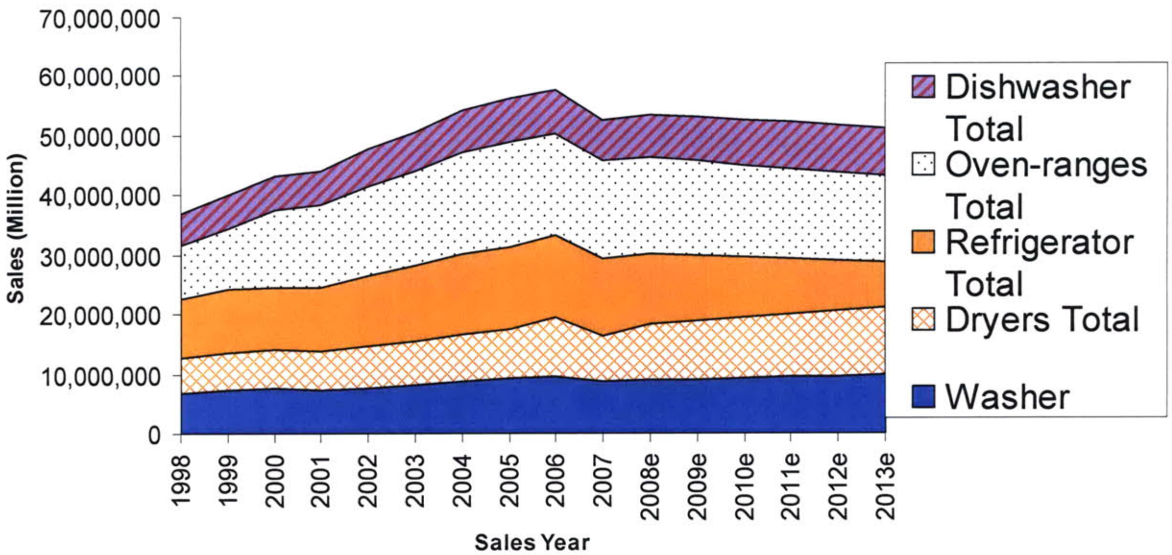

Figure 80: Recent U.S. appliance sales and forecasts

Trend lines were used to estimate the future of relative sales at the different price points. Market research shows that mid-range and high-end appliances have become increasingly popular in recent years (R.W.Beck 2005; IBISWorld 2009b; The Stevenson Company 2010). The dawn of stainless steel appliances, advances in cook-tops, and new washing machine designs have attracted customers to higher-end models. In addition, more advanced electronic controls are being featured in appliances. In both future scenarios, it is estimated that future return volumes will be 15% low-end models, 45% mid-range, and 40% high-end models (see Figure 79).

Current data reveals that there is a general movement in some appliance categories towards increased plastic content and decreased steel content (R.W.Beck 2005). The impetuses are weight savings and functional innovations (Luckman 2010). In this scenario, it was imagined that there was an approximately 10% increase in plastic content in washers, ranges, and refrigerators. Because of this, all three appliance types see an average 20% decrease in steel content and an associated decrease in overall product weight (see Figure 81).

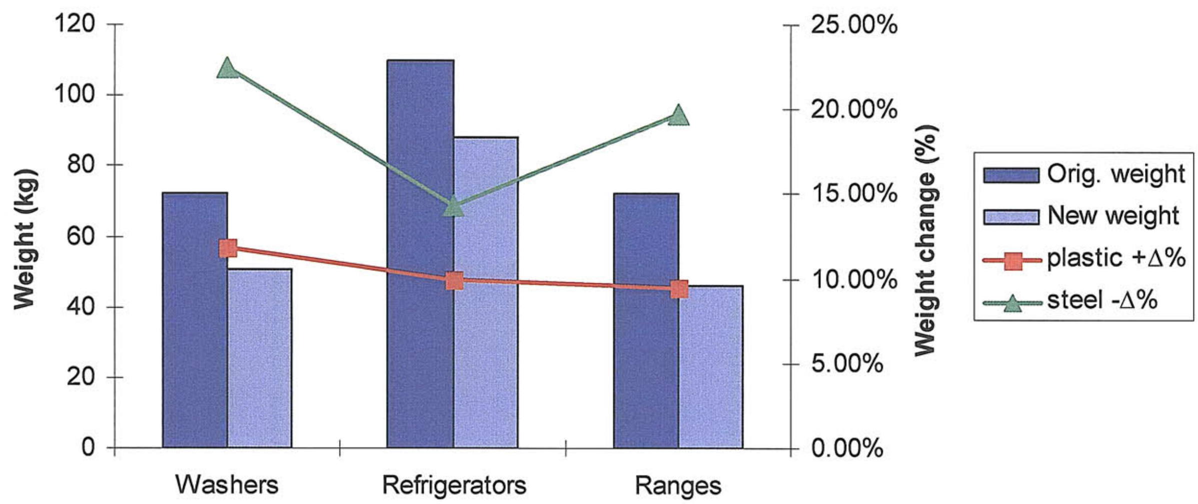

Figure 81: Potential weight and material changes in certain appliances.

Currently, it is estimated that the mean age of refrigerators is 21 years (R.W.Beck 2005). The author believes that the timing of refrigerator returns will begin to trend towards the current timing of other appliance returns. Thus, in the analysis, the mean age of refrigerator returns is 15 years instead of 21. The current mean ages of other product categories were also examined but no changes were made because it was believed that their current retirement ages were reasonable estimates for future retirement ages as well.

4.6.3. Future State in presence of legislation

The U.S. Department of Energy began a "cash for appliances" rebate program funded through the American Recovery and Reinvestment Act in 2010 (U.S. Department of Energy 2010a). The state-operated program is a tool to encourage residential consumers to purchase Energy Star qualified appliances to replace older, less efficient models. Each state chooses the scope of products eligible for purchase rebates. Washers, dishwashers, and refrigerators are a few of the products eligible for rebates in many states. Though the current rebate program is planned to be short-lived, it is expected to have long-term effects on consumer awareness about the value of energy-efficient appliances (Luckman 2010). The legislation scenario considered here assumes that a sustained legislative mandate exists to encourage the purchase Energy Star appliances. It is also assumed that landfill bans are in place. The hypothesized impact on return mix is identical to the Energy Star-heavy return mixes analyzed in Section 4.4 (see Figure 78).

Though legislation should influence return mix, it is not expected to greatly impact retirement ages of products. The emphasis of currently designed legislation is on responsible disposal of appliances and return of old, very inefficient models, i.e. those greater than 10 years old. Thus, it is assumed that retirement age distributions are identical to those featured in the alternative future state scenario. The distribution of sales and the trend in appliance material compositions are also identical to those defined in the alternate future state without legislation.

A quick overview of the changes made in all three scenarios is shown in Table XXXIII.

Table XXXIII: A summary of scenario parameters.

	Current State	**Future – No Legislation**	**Future - Legislation**
Return Mix	36% ranges, 19% washers, 18% dryers, 15% refrigerators, 12% dishwashers	No change	12.5% ranges, 25% washers, 12.5% dryers, 25% refrigerators, 25% dishwashers
Age Distributions	See Figure 56	No change	No change
Sales Distributions	65% mid-range and high-end	85% mid-range and high-end	85% mid-range and high-end
Processing Costs	See Table XXIII	No change	No change
Material Compositions	See Figure 55	10% increase in plastic content of washers, refrigerators, and ranges	10% increase in plastic content of washers, refrigerators, and ranges
Product Weights	See Table XXI	Decreased weights of washers, refrigerators, ranges	Decreased weights of washers, refrigerators, ranges

4.6.4. Analysis

Each scenario was analyzed assuming automobile-based recycling. The following graph was created using a Monte Carlo analysis similar to the previous exercises (see Figure 82). The system parameters that are varied are product depreciation, commodity prices, product functionality, and processing costs. MSRP percentages are taken into account through the fixed ratios mentioned earlier.

The future scenario without legislation outperforms both the current state and the alternative future state. The maximum expected profit is $2.20; there is more than 80% chance of achieving net revenue. Even though washers, refrigerators, and ranges contain less steel and have decreased weights, the large return percentage of ranges helps the system improve economically. Meanwhile, the lower steel content in washers, refrigerators, and ranges as well as the products' increased relative return volumes, decreases the recovery system's expected profitability in the future state scenario when appliance legislation is present.

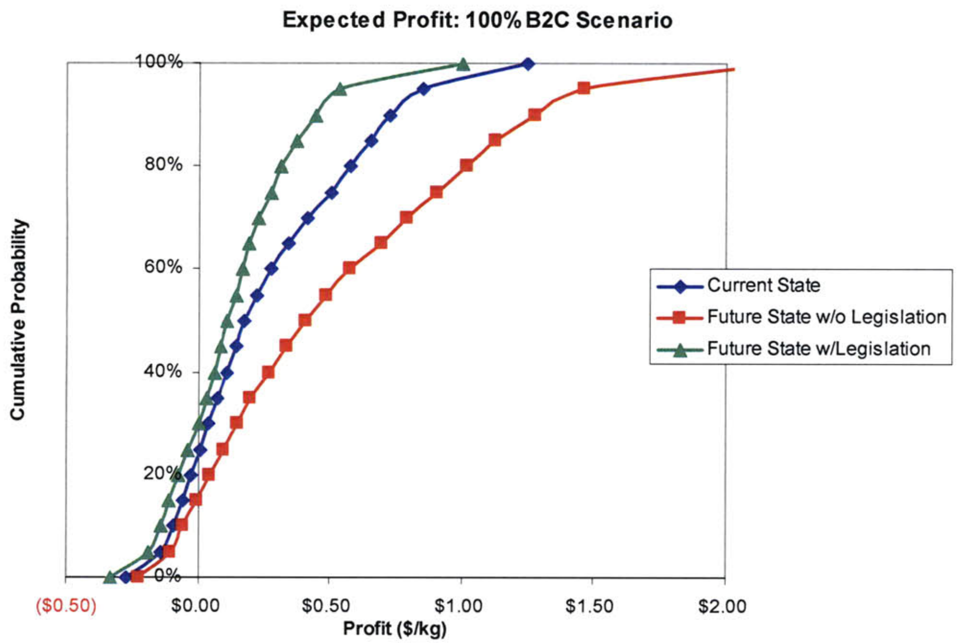

Figure 82: Results of analysis of current and future scenarios for an appliance recovery system

The differences in performance can be examined further by analyzing how sensitive profit is to changes in resale value and scrap material value. In the following graphs, the depreciation of all product types and the scrap value of all product types are changed simultaneously, similarly to the exercises in Section 4.4.

Figure 83 illustrates the profit landscape for the current state scenario. Scrap commodity prices have to be average to poor and the rate of product depreciation has to increase before the system becomes unprofitable. The black dot represents where the firm operates at the current rate of product depreciation and under average commodity prices. Under these conditions, the firm can achieve a profit between $0.50/kg and $1.00/kg.

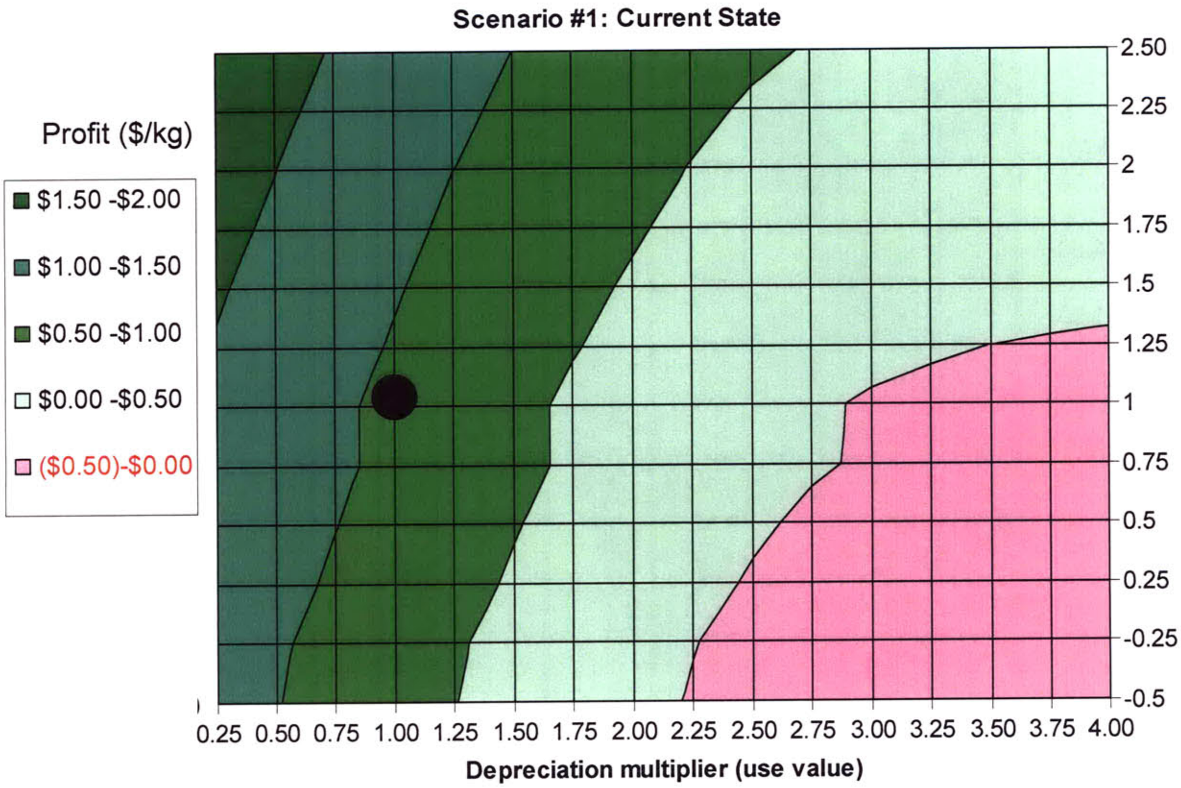

Figure 83: In the current state, net revenue can be achieved in all cases except for when depreciation rates increase by two-fold or more and commodity prices are poor.

Figure 84 reveals that net cost situations in the future state scenario without legislation exist only when commodity prices are poor and depreciation rates have tripled or more. This is an unlikely occurrence. Meanwhile, Figure 85 shows that the future state with legislation has increased the likeliness of zero or less profitability.

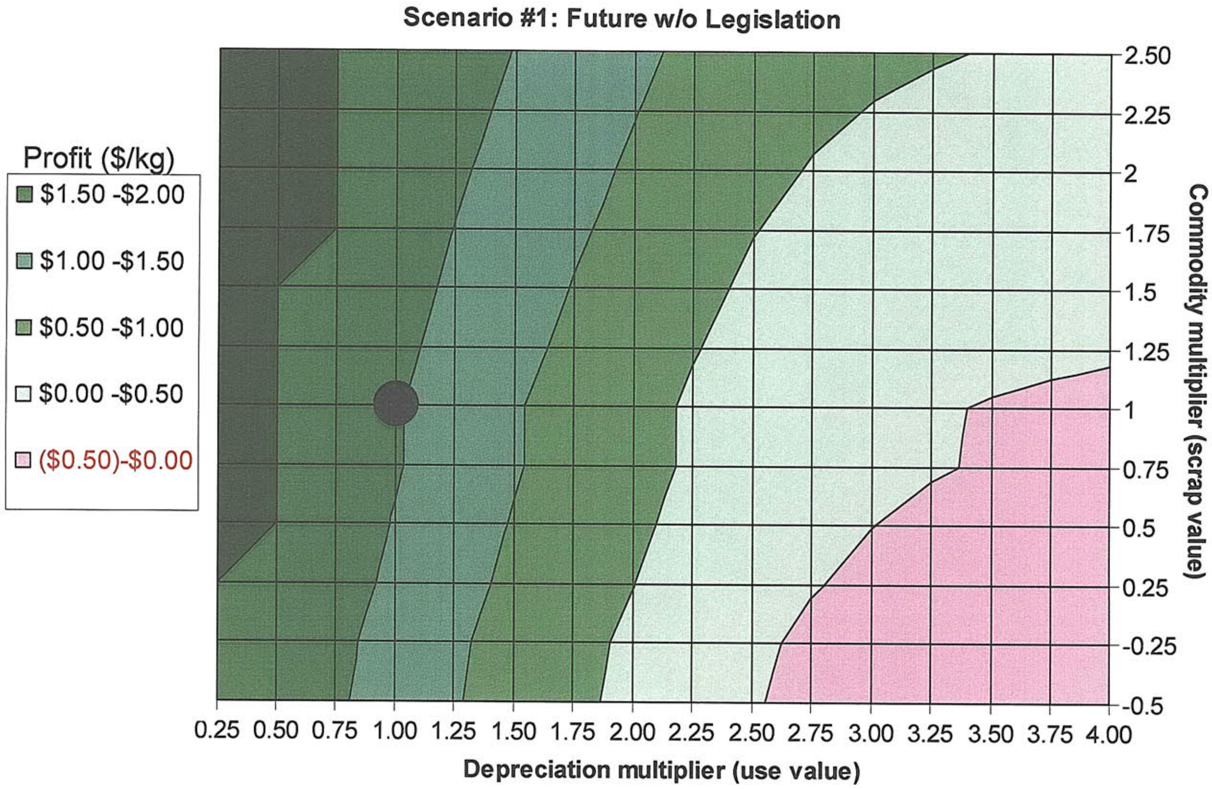

Figure 84: In the future state without legislation, ranges, with their initially slow depreciations, account for 36% of the return volume.

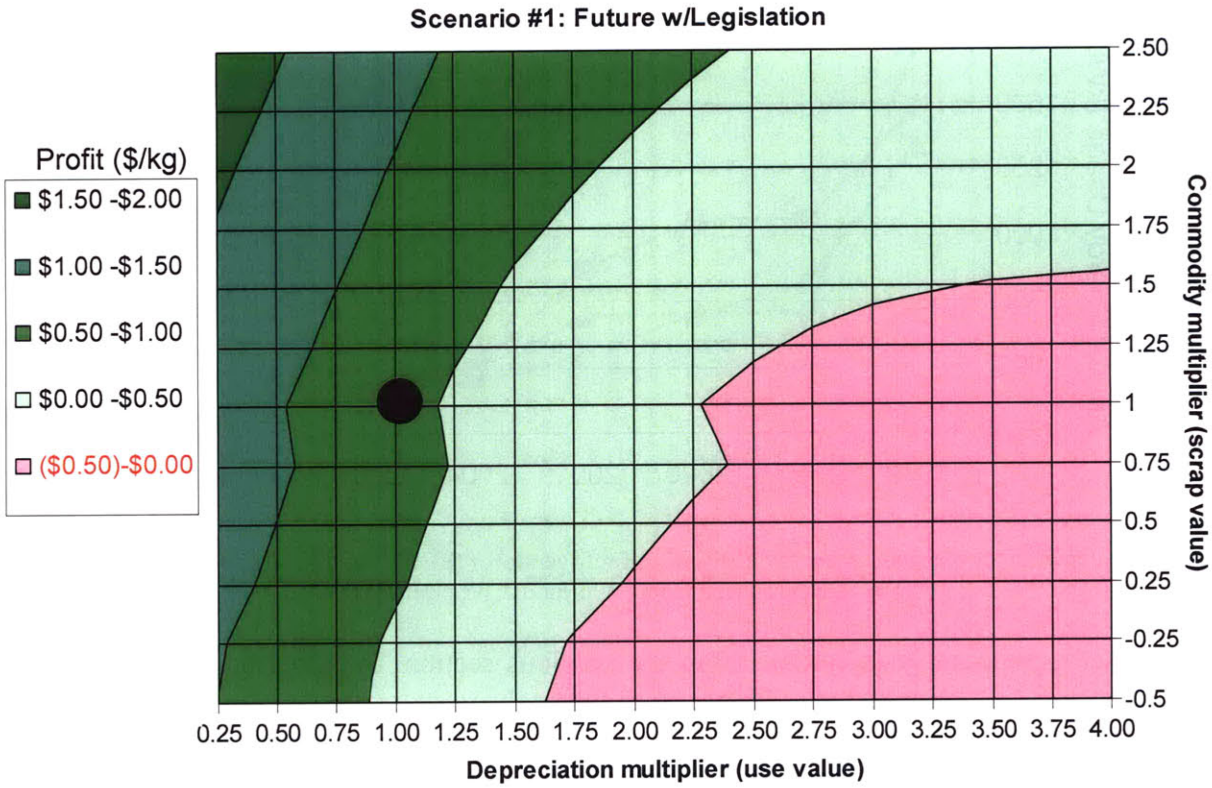

Figure 85: In the future state with legislation, washers, refrigerators, and dishwashers account for 75% of the returns. Their high rate of depreciation and high plastic content negatively impact system profitability.

4.6.5. Evaluation of Potential Strategies

Periodic energy and water efficiency gains in refrigerators, dishwashers, and washers have been the norm for over 20 years as illustrated in Figure 86 (Whirlpool Corporation 2008). Energy Star qualification is a main area of competition among appliances, especially as energy and water usage continue to grow in importance in consumers' minds and in the federal government agenda (U.S. Department of Energy 2010b). Since the key to reaping energy and water benefits from appliances lies in better adoption of energy-efficient products by the public, it can be assumed that more programs like the current "cash for appliances" will be established in the future. Thus, an interesting space of further analysis is the set of possible options to improve the profitability of the future state in which appliance legislation exists.

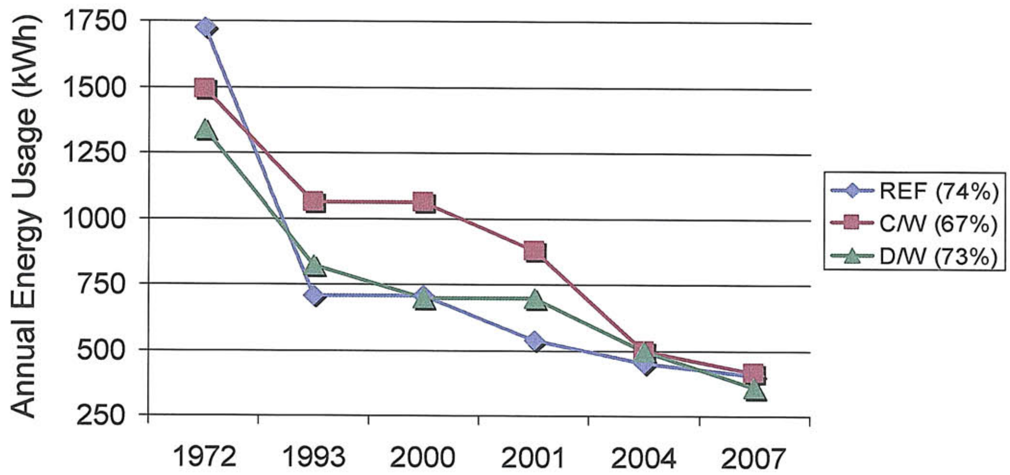

Figure 86: A depiction of the gains in energy efficiency of refrigerators ("REF"), washers ("C/W"), and dishwashers ("D/W"). Reproduced from (Whirlpool Corporation 2008)

Based on the analysis conducted in the previous section, three options were chosen as potential strategies that a firm might enact. In Option A, the firm would encourage the return of younger appliances to take better advantage of new Energy Star regulations being promulgated every three or four years (U.S. Department of Energy and U.S. Environmental Protection Agency 2010). The program could be implemented in many ways, including adopting a purchase incentive scheme that correlates incentives to product age. Any implementation of a program would attract a percentage of consumers who would rather improve their energy and water usage earlier rather than later. To investigate this scenario, it is assumed that 50% of Energy Star appliance returns follow their current retirement age distributions (see Figure 56), while 50% are returned at earlier ages: mean age of 7, standard deviation of 4 years. In this option, the firm may take more advantage of revenue from appliance resale.

In Option B, the firm would adopt electronics-based recycling to increase the revenue generated from recycling washers and refrigerators, whose plastic content had been increased by 10%.

Option C is to simply not design appliances that have greater plastic content than today's levels. This would potentially make recycling of Energy Star appliances, such as washers and refrigerators, more profitable. To investigate this option, the material compositions of washers, refrigerators, and ranges are returned to their current levels of steel and plastic.

Figure 87 depicts the Monte Carlo results. Option C is the worst performing strategy and performs very similarly to the Energy Star-heavy scenario of Section 4.4. Option A performs the best, primarily because more product returns can be resold.

Figure 87: Comparison of strategy options

Another comparison between the best and worst strategies reveals that Option A is profitable when commodity scrap prices are above average and products depreciate at current or slower rates (see Figure 88). Option C is also profitable under those conditions but when commodity prices fall and if overall product depreciation accelerates, the firm may incur a net cost (see Figure 89). Thus, the less risky strategy is Option A.

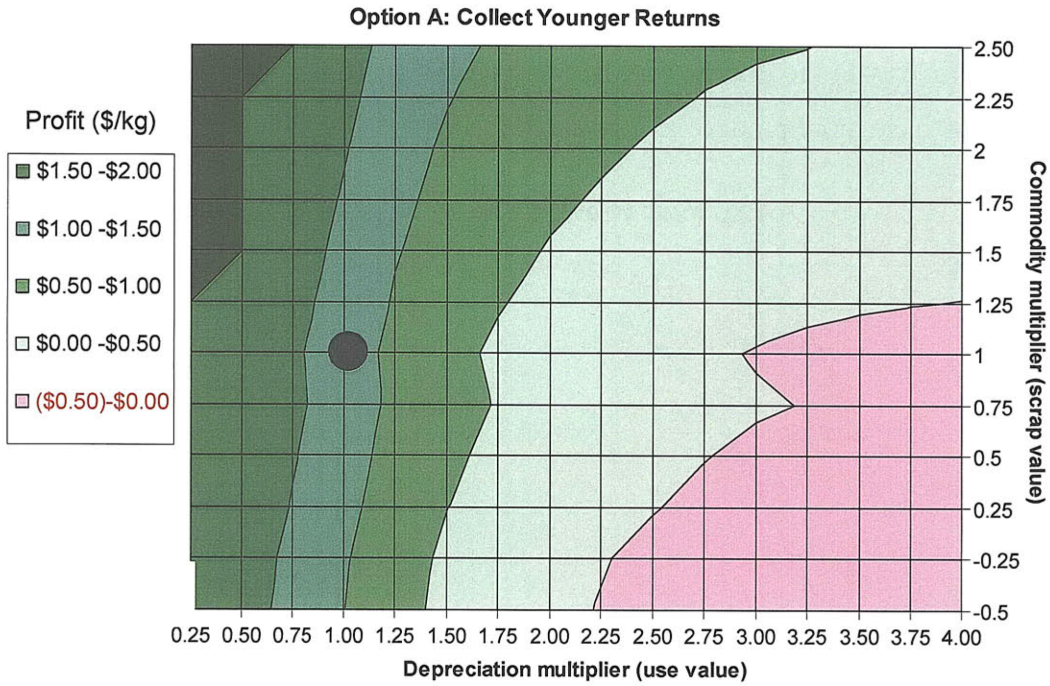

Figure 88: Option A is profitable in most cases.

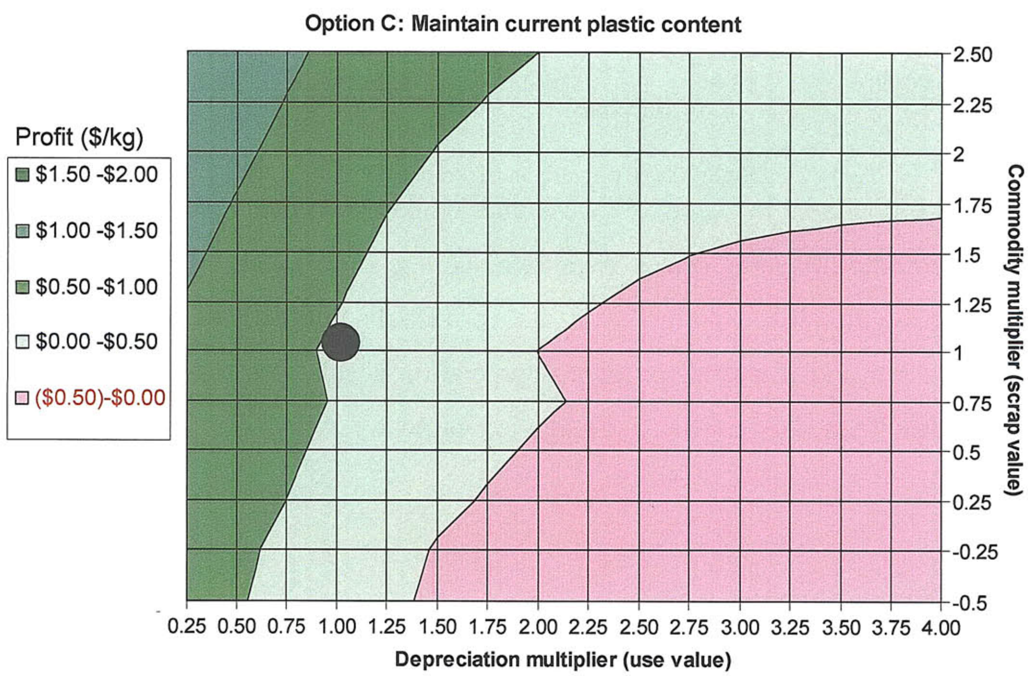

Figure 89: In Option C, there is a greater chance of being unprofitable.

4.7. Environmental Analysis

An environmental analysis similar to that conducted in Section 3.7 was performed in the case of appliance recovery by focusing on the replacement cycle of washing machines. The time scale is now 40 years, as the mean retirement of washers is around 10 years. Therefore, the reference replacement frequency is four. The following calculations were made from the equations shown in Section 2.4, based on materials and production information from (Atlee 2005; Cullen and Allwood 2009):

$$E_{primary\_mfg} = E_{virgin\_materials} + E_{mfg\_process} = 4854MJ$$

$$E_{\sec ondary\_mfg} = E_{\sec ondary\_materials} + E_{mfg\_process} = 1541MJ$$

$$E_{buy\_used} = 0$$

$$E_{20\_yrs} = E_{production\_cycle} * \frac{40yrs}{mean\_retirement\_age}$$

Table XXXIV: Energy values determined from acquired data sources

Data source	Primary materials energy (MJ)	Secondary materials energy (MJ)	Production Process energy (MJ)
Atlee (2005)	3829	1541	
Cullen and Allwood (2009)	5880		784
Averages	4854	1541	784

Energy in the use phase of a product is ignored because it is assumed that the same amount of energy will be used whether the product is new or used, even though in reality there would be periodic energy efficiency gains from one iteration of a product to another. In fact, many environmental impact assessments of appliances, particularly washers, have shown that use phase energy is the biggest contributor to an appliance's environmental impact (Devoldere et al. 2006; Garcilaso et al. 2007; Cullen and Allwood 2009). The point of this exercise is to understand how recovery decisions impact the energy associated with product replacement, i.e. production energy.

In the first analysis, recovery where recycling is the only option is considered. Energy savings were calculated as compared to the energy consumed in producing 1000 washers every 10 years from virgin materials. As Figure 90 shows, energy savings can be achieved even when the mean retirement age decreases, a.k.a. replacement frequency increases. However, recovery of retired washers must be almost 70% when the retirement age is 6 yrs before energy savings can be achieved.

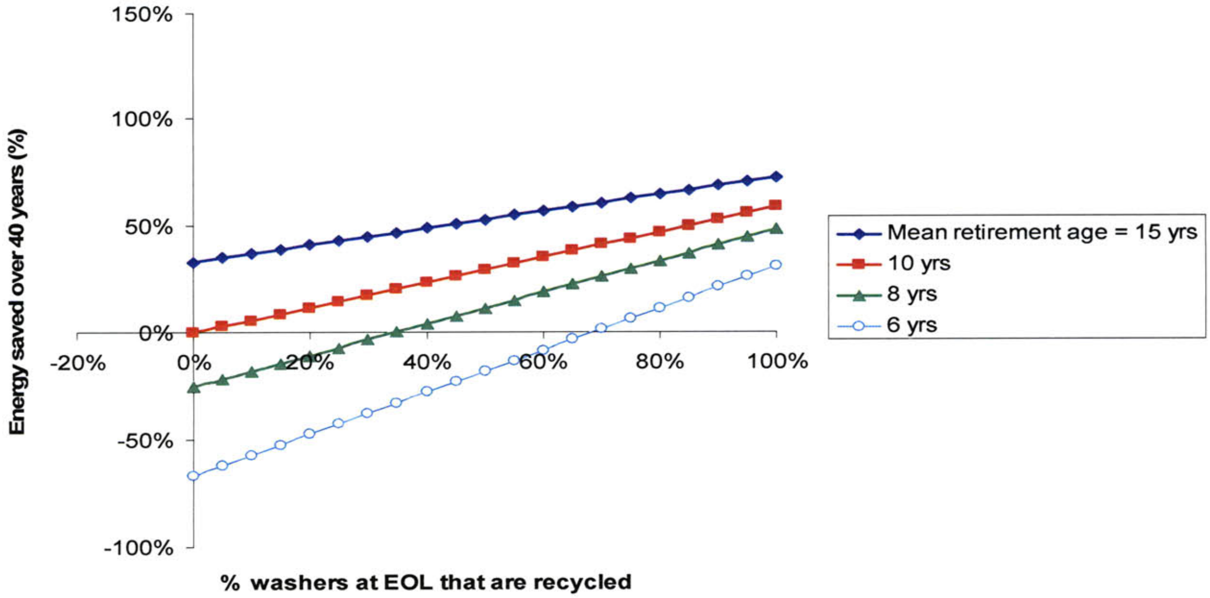

Figure 90: Energy savings are still plausible if the replacement frequency of washing machines increases.

In the second analysis, reuse and recycling are considered as viable recovery options. As displayed in Figure 6, when products are reused, the total energy of new production is avoided. When products are recycled, only the energy of materials procurement is avoided. Results of the analysis are depicted in Figure 91.

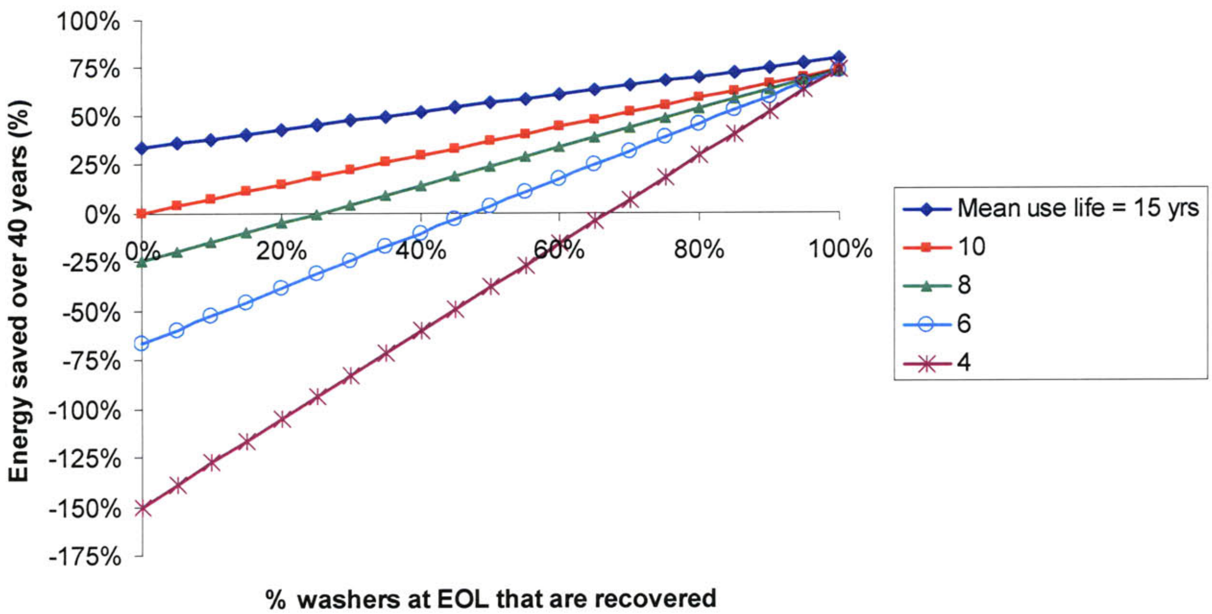

Figure 91: Energy savings versus all products and their replacements being made from virgin materials every 10 years. Adding reuse as a recovery option only slightly improves energy savings.

It can immediately be seen that adding reuse improves energy savings in a less dramatic way than in IT recovery. Regarding the case when the mean retirement age is 6 years (see Figure 92), energy savings are achieved when 50% of retired washers are recovered as opposed to 70% in the recycling-only analysis. This modest improvement can be explained by examining the components of production energy. In IT, the energy used in the production process is much greater than that used in materials procurement, which is a reflection of the complexity of the manufacturing processes involved in creating circuit boards and other hardware. Meanwhile, in appliances, the materials energy usage is much greater than the energy used in production. Because of this, the primary gains in energy in appliance replacement are through recycling activities instead of reuse activities.

Since reuse is not the major contributor to energy savings, consumer demand for used products has less impact in appliance recovery than in IT recovery. Figure 93 displays the effect of lower consumer demand when the mean retirement age is 4 years.

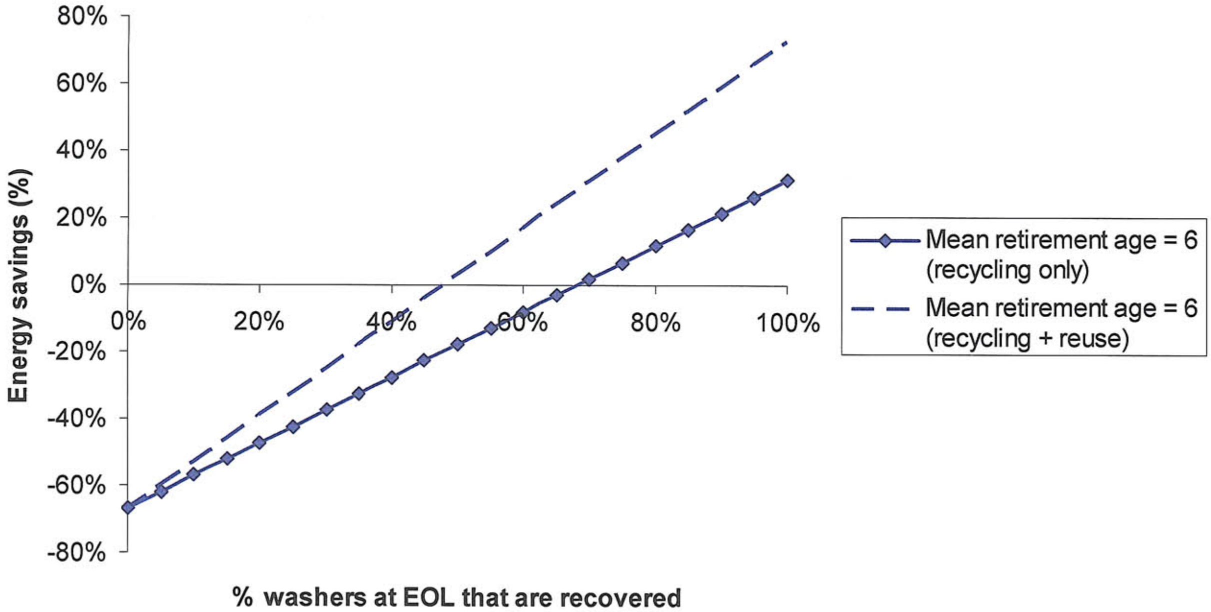

Figure 92: A comparison of energy savings achieved between recycling only and recycling + reuse recovery options.

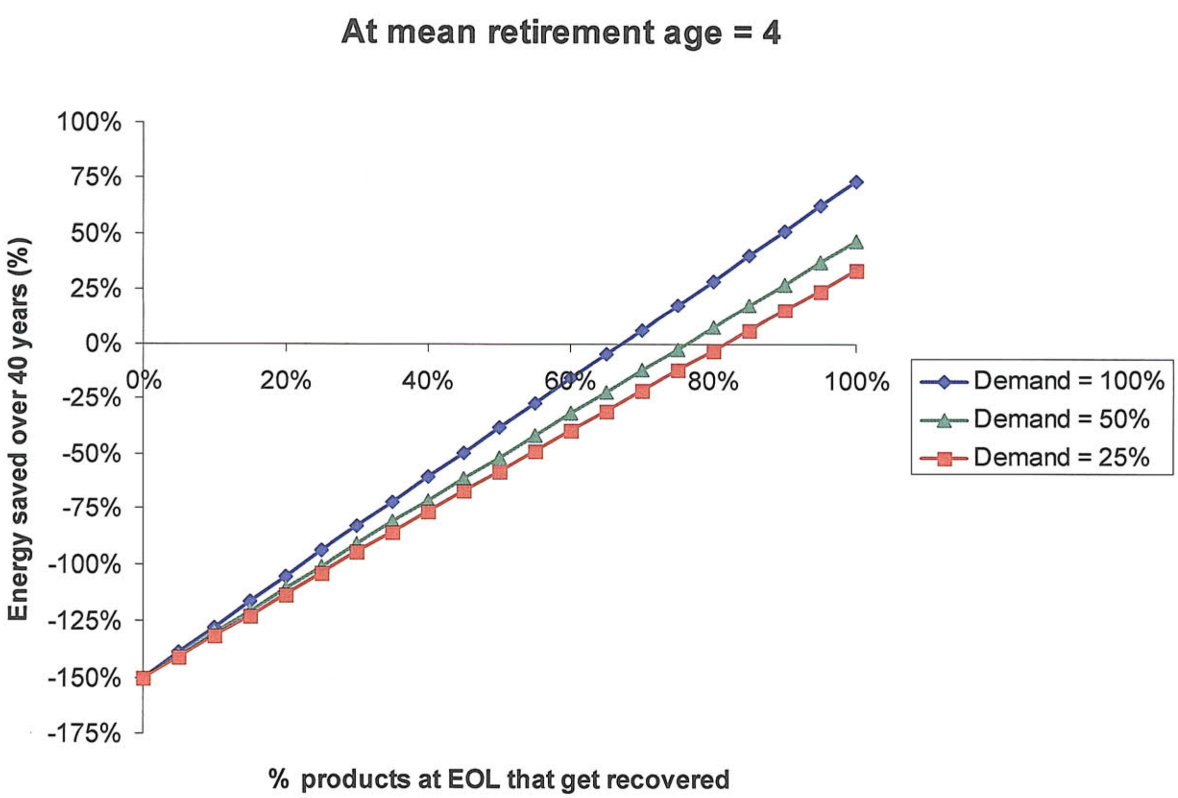

Figure 93: If only 25% of consumers desired used washers, there would still be 20% energy savings over primary production at a mean retirement age of 10 years.

According to (R.W.Beck 2005), it is estimated that 89% of appliances are recovered today. If so, then if the mean retirement age of appliances were to decrease to 4 years, there would still be an energy savings of 50% over primary production at a mean retirement age of 10 years. Furthermore, even in times of low demand for used washers, there would still be energy savings. However, at today's mean retirement age and 89% product recovery, there is a 65% energy savings. To achieve the same energy savings but at lower retirement ages, more recovery would be necessary (see Table XXXV and Figure 94).

Table XXXV: Increase in product recovery needed to achieve 65% energy savings.

Mean retirement age (yrs)	Product recovery needed (%)
8	92%
6	94%
4	96%

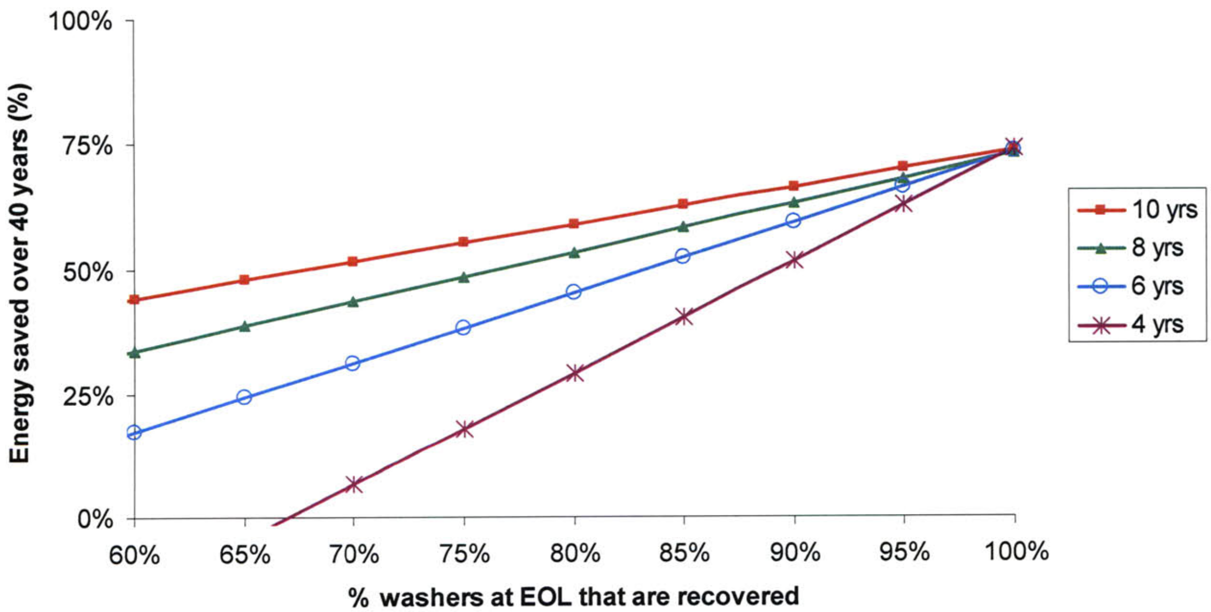

Figure 94: A close-up of the previous graph. Today, 89% of appliances are recovered.

4.8. Chapter Summary

In the analysis of appliance recovery, it was shown that product characteristics, collection characteristics, and secondary market characteristics influence system profitability. Using the

MFE model, it was shown that dryers and ranges are the major sources of revenue in appliance recovery because of their high steel content and slow depreciation rates. When a recovery system collects primarily ranges and dryers, it can expect up to \$2.60/kg. However, if current and future legislation push consumers to retire energy- and/or water-innovating appliances, such as washers and refrigerators, in greater numbers, the profitability of appliance recovery may decrease to less than \$1.00/kg. Furthermore, if appliance innovations lead to greater plastic content and decreased steel content, the benefit of recycling appliances may decrease because the most widely used method of automobile-based recycling is not tailored towards recovery of non-metallic components.

Because of appliances' long life cycles (as compared to IT equipment), there are currently more opportunities for recycling instead of reuse. However, if firms begin to encourage the return of younger appliances, perhaps tied to energy legislation, recovery system managers may be able to expand reuse revenue opportunities. For example, a five-year-old, mid-range dryer can command almost \$400 on the reuse market, but its scrap materials are worth little more than \$15.

From an environmental standpoint, the current state of appliance recovery provides a net energy benefit of 65% over 40 years, when examining only production energy. This is because recycling is able to greatly decrease production energy, since it minimizes the energy of materials procurement, which in appliance production is the greater energy consumption (over production processes). It is perhaps just as well that reuse is not a major contributor to energy savings from a production energy standpoint, because reuse may lead to prolonged use of appliances that are inefficient during the use phase (Devoldere et al. 2006).

5. Conclusions and Policy Recommendations

5.1. Summary of Conclusions

Three research questions were posed at the beginning of this thesis. Below is a summary of how each question was answered.

- **What characteristics of collection and the end-of-life markets affect the economic performance of an e-waste recovery system? *What are the effects of uncertainty in those characteristics on the expected economic performance?***

A mass flow and economic (MFE) model was developed to examine the economics of e-waste recovery. By incorporating important system characteristics such as collection mix, scrap material prices, and product depreciation rates, the author was able to utilize the MFE model to quantify the effect of system characteristics on product fate decisions.

Specifically, the recovery of EOL products in two industries was examined. Through various methods of sensitivity analysis, it was shown that profitability in IT recovery is highly dependent on the collection mix, product ages, and the depreciation of high value products, e.g. laptops and desktops. Profitability in appliance recovery is also highly dependent on these factors and on product material compositions. Currently, IT recovery system managers must rely on the resale value of young returns from B2B customers to ensure profitability. Appliance recovery system managers rely on the scrap value of steel, which is abundant in appliances, and focus little on the reuse value of appliances, though dryers and ranges maintain good resale values for long periods of time.

- **Are there measures a firm can take to mitigate the effect of system uncertainties on economic performance? *What are the relative merits of these measures?***

For both industries, different strategies were compared for their robustness to future trends and ability to minimize the effect of system uncertainties. For IT e-waste recovery, they were: (1) collect more high-value returns, (2) collect more young high-value returns, and (3) shift to selling high-end niche products. It was shown that a collection strategy that promotes the return of young returns will improve profitability the most and limit the risk of net cost occurrences when scrap commodity prices are low and depreciation rates accelerate. For appliance e-waste recovery, the following strategies were examined: (1) collect more young high-value returns, (2) implement electronics-based recycling, and (3) don't increase plastic content in certain appliances. It was shown again that a collection strategy that promotes the return of young returns will improve profitability the most and limit the risk of net cost occurrences.

❖ **What are the environmental impacts of the business strategies intended to promote economic performance?**

An environmental analysis was conducted to quantify the effect of leading strategies on the energy demand of production. Implementing a strategy in IT recovery in which more young returns are collected may be detrimental to the environment if overall product recovery does not increase. In fact, product recovery would have to more than double to compensate for energy used in product replacement. It may also be detrimental if the demand for used products does not match the supply of used products. Meanwhile, appliances are already recovered at a high percentage, such that energy savings will continue, though somewhat diminished, if mean retirement ages move below 10 years old.

5.2. Policy Recommendations

The analyses presented in this thesis provide insight into the economic forces at play in e-waste recovery. They also provide a basis for policy recommendations to recovery system managers and legislators.

5.2.1. Policy Recommendations for Recovery System Managers

Consider uncertainty when evaluating system performance

It is easy to base business decisions on the average states of system characteristics; however, the average behavior of a system does not often coincide with the average value of system parameters (de Neufville et al. 2004). In order to adequately determine the expected performance of an e-waste recovery system, system managers must incorporate the range of possible values of system parameters. Scrap commodity prices, the quality and ages of product returns, and mix of products are never constant. By incorporating uncertainty into their analyses, system managers can better quantify how system design affects profit and ultimately create effective strategies for a variety of operating scenarios.

Take advantage of the business opportunities in e-waste management

E-waste management does not have to be a financial burden. It seems clear from the analysis in this thesis that the most viable method for OEMs to improve the economic performance of IT recovery is to encourage the return of products at earlier ages. The resale value of products greatly outweighs their scrap material value at young ages; this can steer a recovery system from making no profit to making over \$5.00/kg. Some companies already pursue this strategy through buyback programs (Hewlett Packard 2009; Sprint 2010). However, reuse revenue is contingent on the demand for used products. If no one wants to buy used, then the value of a used product will fall. In today's marketplace, even if an 8-year old laptop is still functional, it cannot be resold in the U.S. because it is technologically obsolete. Thus, it is also recommended that if OEMs pursue a strategy to encourage younger returns, they should encourage consumers to replace their returns with used items. As shown in Section 3.7, the energy savings of IT recovery can still be net positive at low recovery rates if product reuse is successful.

There are two serious obstacles to encouraging consumers to buy used IT products. First, the current conditions of the IT industry make this difficult. New products are becoming cheaper every day, and there is a large attraction in IT towards products with more speed and more memory. There is a subset of the population that prefers used products because of financial savings or environmental concerns. However, buying used can hinder a person technologically, both in his or her professional and private lives. Second, when an OEM operates a recovery system, IT recovery is a secondary business. The primary business is to sell new products. A vibrant used product market will inevitably transfer some market share from the new sales market. Thus, consumers do not have adequate incentives to buy used, and OEMs do not have adequate incentives to sell used products.

Likewise, it was shown that a strategy to promote the return of younger products would also benefit an OEM running an appliance recovery system because it would be able to take greater advantage of the resale market where profit margins are much higher than in recycling. For example, previous analysis showed that a resold dryer could command \$350/unit (or \$7.02/kg) versus \$1.61/unit (or \$0.03/kg) for its recoverable commodities. Such a strategy could be beneficial to new sales too because it may encourage consumers to increase their appliance replacement frequency. In addition, it may generate more sales of energy efficient products. However, issues similar to the IT case arise if such a strategy is pursued. First, a vibrant used sales market may develop and transfer market share from the new sales market. A result of this may be the prolongment of the lives of products that are inefficient in energy and water usage.

Some researchers have already begun to develop strategies for OEMs to realize benefits in their new sales business by strengthening their used sales business (Guide Jr. et al. 2003b;

Atasu et al. 2008). They also contend that when an OEM takes special care to develop a strong reverse supply chain, it may improve forward supply chain activities and create additional revenue streams (Guide Jr. et al. 2003a). Embracing the used sales market in the IT industry may also help an OEM strengthen its corporate image with regards to environmentally conscious consumers who may complain about the early replacement of IT purchases. Meanwhile, by becoming more involved in e-waste recovery, appliance manufacturers may realize more benefit in supply chain design than through finding another revenue stream in the used sales market. The use phase energy of used washers, refrigerators, and dishwashers may negate their desirability. However, dryers, which have long depreciations and no major changes in energy efficiencies from one iteration to the other, may be very lucrative on the used product market.

Appliance recyclers and OEMs can also take better advantage of the revenue generated from appliance recycling. Unlike in the IT industry, where recycling almost always produces a net cost, appliance recycling can be profitable in most cases because of steel and nonferrous metal recovery. System managers may be able to incrementally increase recycling revenue by adopting electronics-based recycling techniques, which would liberate plastic streams and increase value-added recovery of small electronic components. This may become more important as future appliance designs incorporate more plastic and electronics. Increased plastic content, and possibly increased electronic content, could be an impetus for managers to realize that automobile-based recycling is no longer tenable. It is recommended that recovery managers understand the impact, either positive or negative, on recycling profit that electronics-based recycling may have. This would also entail developing a strategy for the destinations of recovered plastic and other new materials.

Prevent saturation on the supply side of the resale market

Reuse is viable in both industries because products that are in working condition, feature high quality components (as evidenced through large MSRPs), and are young in age retain a sufficient amount of use value to some consumers. However, if demand for used products declines or does not increase at the same pace as the number of products recovered for reuse, then the resale market will become saturated. Once saturation occurs, resale value will drop for many products, and reuse activities will no longer be profitable. Market saturation could occur in the domestic market as well as in overseas markets.

What is needed to counteract this development is an overhaul of how consumers and OEMs think about products at end-of-life. A greater percentage of the population in developed countries needs to see value in buying used products. OEMs need to either see value in expanding their participation in the sales of used products or recognize that purchases from resellers may become more prevalent.

Be conscious of early replacement strategies on life cycle energy savings

In Sections 3.7 and 4.7, it was shown that promoting earlier returns of products decreases the energy savings of product recovery. If OEMs pursue this strategy, they should be mindful of its impact on the intended goal of environmental recovery. Appliance OEMs can still expect net energy savings even if the mean retirement age decreases to four years. The environmental savings of appliance recovery increase when reuse and recycling are recovery options versus recycling alone. However, in IT, net energy burdens can be encountered. Though OEMs would prefer that consumers replace their EOL products with new products, the life cycle energy impact would be substantial; it was shown that the current energy saved through recycling cannot be achieved if the mean retirement age of products decreased to two or three years, unless recovery is increased above 60% and 40% respectively.

Make design for recycling more institutionalized in product development

Two of the goals of design for recycling, or DfR, are ensuring that the materials in EOL products can be dismantled and separated at low costs and that products are manufactured from recyclable materials, i.e. those that can be used again in new applications once the product is disposed. In Section 4.6, analysis of possible future states of appliance recycling showed that a change in material compositions can decrease the profit potential of recycling activities. If OEMs gain more control over the processing of e-waste from mandated collection systems, they must incorporate DfR thinking into their product design development and material selection. Otherwise, increased commingling of materials or use of non-recyclable materials could increase recycling costs.

Define specific e-waste recovery goals

OEMs need to define their goals in e-waste recovery. If an appliance OEM's goal is to achieve maximum profitability, then promoting younger returns is useful. If, instead it is to maintain the current level of profitability or at least offset the cost of recovering refrigerators, then the best strategy may simply be to increase the revenue generated from recycling, through greater segregation of materials. New sales would not be impacted because the primary fate for recovered products would still be recycling, as the mean retirement age would remain unchanged from today's value.

If an IT firm's goal is to achieve maximum profitability, then it needs to promote early returns of products. However, young returns are only profitable if there is demand for used products. Therefore, the IT firm must also learn how to encourage product reuse without harming new sales. In addition, the firm must realize that the energy savings of recovery activities are tied not only to the fates of EOL products but also to the replacement of them.

5.2.2. Policy Recommendations to Legislators

Anticipate strategies that firms will implement to improve the profitability of mandated e-waste recovery

Most e-waste legislation stipulates what needs to be recycled, how much mass needs to be recycled, and what financial and managerial roles governments and OEMs must play (European Parliament and Council 2003; Electronics TakeBack Coalition 2010). Thus, e-waste legislation is currently a useful tool to promote the environmental recovery of EOL products. However, in writing future legislation or revisions to current laws, legislators need to anticipate the actions OEMs may take to improve the profitability of e-waste recovery. As discussed previously, one response to a mandate of OEM financial responsibility may be to encourage consumers to return products earlier. This could increase the rate of new production and have negative effects on total energy demand. Legislators should explicitly monitor how OEM reactions to legislation affect the environmental benefit of recovery similar to their monitoring of the specific dismantling and shredding processes that recyclers use.

In addition, legislators should incorporate other metrics into how they measure the success of recovery activities. Many authors have discussed the faults of mass-based metrics which are prevalent in e-waste legislation (Huisman 2003; Atlee 2005; Bohr and Gutowski 2007). Along with the ideas presented by these authors, it is proposed that legislators monitor annual energy savings due to e-waste recovery, taking into account energy used in the entire life-cycle. Energy savings cannot be evaluated only by quantifying the impact of recovery activities but must also include energy used during replacement.

5.3. Future Work

An investigation of recovery activities in other industries would be a useful future endeavor. The MFE model is built in such a way that applying it to different industries is relatively straightforward.

Before looking at other industries, however, more analysis of IT and appliance recovery would be useful. Sensitivity of economic performance to system costs was not fully explored. Additional variables that influence cost should be added. These include processing characteristics, such as cycle time parameters for automated and manual disassembly processes, and fees that are charged to or by recovery systems for collecting and/or transferring products and materials.

There are other IT and appliance products that were not included in the previous analyses that would be interesting to incorporate because their sizes, material compositions, and retirement ages may alter the results. These include cell phones and small portable appliances, such as blenders or microwaves.

System behavior under other operating scenarios should also be tested as more information about future trends becomes available. It would be useful to build and compare a wide range of possible scenarios in the MFE model.

As mentioned earlier, energy savings from e-waste recovery can be greatly affected by use phase energy in certain industries. Many authors have investigated which recovery activity, reuse or recycling, would be more environmentally beneficial with respect to a product's entire life cycle (Williams and Sasaki 2003; Sahni et al. 2010). It would be useful to build upon their work by expanding the environmental analysis presented here, that examines the effect of replacement frequency, to include use phase energy that varies with product iterations.

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7. Appendices

Appendix A. Original Retirement Age Distributions

Gamma distribution characteristics:

$$f(x;\alpha,\beta)=\frac{1}{\beta\Gamma(\alpha)}\left(\frac{x}{\beta}\right)^{\alpha-1}e^{-\frac{x}{\beta}}$$

$\mu = \alpha\beta$

$\sigma^2 = \alpha\beta^2$

IT products

Retirement Age Distributions using the gamma distribution									
Product Type	Client	Mode	Data Source	Alpha	Beta	Mean Age	St Dev	RMSE	Fit
Desktop	B2B	End of Lease	Babbitt (2009)	1.947	1.541	3.00	2.15	0.0378	Best
		Asset Rec	Shifting of above	3.448	1.155	3.98	2.15		
	B2C	Municipal Pick-up	EPA (2007), 2nd life	5.408	0.925	19.24	8.39	0.0213	2nd best
		Retail Take-back	Shifting of above	1.947	1.541	8.00	4.00		
Laptop	B2B	End of Lease	Babbitt (2009)	1.947	1.541	3.00	2.15	0.0378	Best
		Asset Rec	Shifting of above	3.448	1.155	3.98	2.15		
	B2C	Municipal Pick-up	EPA (2007), 2nd life	5.408	0.925	7.28	1.37	0.0472	2nd best
		Retail Take-back	Shifting of above	1.947	1.541	5.00	1.40		
Printer	B2B	End of Lease	EPA (2007), 1st life	28.590	0.105	3.00	0.56	0.0182	Best
		Asset Rec	Adjustment on above	28.590	0.160	4.59	0.86		
	B2C	Municipal Pick-up	EPA (2007), 2nd life	6.085	1.999	12.16	4.93	0.0124	Best
		Retail Take-back	Same as above	6.074	2.002	12.16	4.93		
LCD	B2B	End of Lease	EPA (2007), 1st life	20.258	0.279	5.65	1.25	0.0102	2nd best
		Asset Rec	same as above	20.258	0.279	5.65	1.25		
	B2C	Municipal Pick-up	EPA (2007), 2nd life	13.617	0.675	9.19	2.49	0.0226	2nd best
		Retail Take-back	Same as above	13.631	0.674	9.19	2.49		
CRT	B2B	End of Lease	Same as municipal	5.742	2.600	14.93	6.23		
		Asset Rec	Same as municipal	5.743	2.600	14.93	6.23		
	B2C	Municipal Pick-up	EPA (2007), 2nd life	5.742	2.600	14.93	6.23	0.0088	2nd best
		Retail Take-back	Same as municipal	5.742	2.600	14.93	6.23		

Appliances

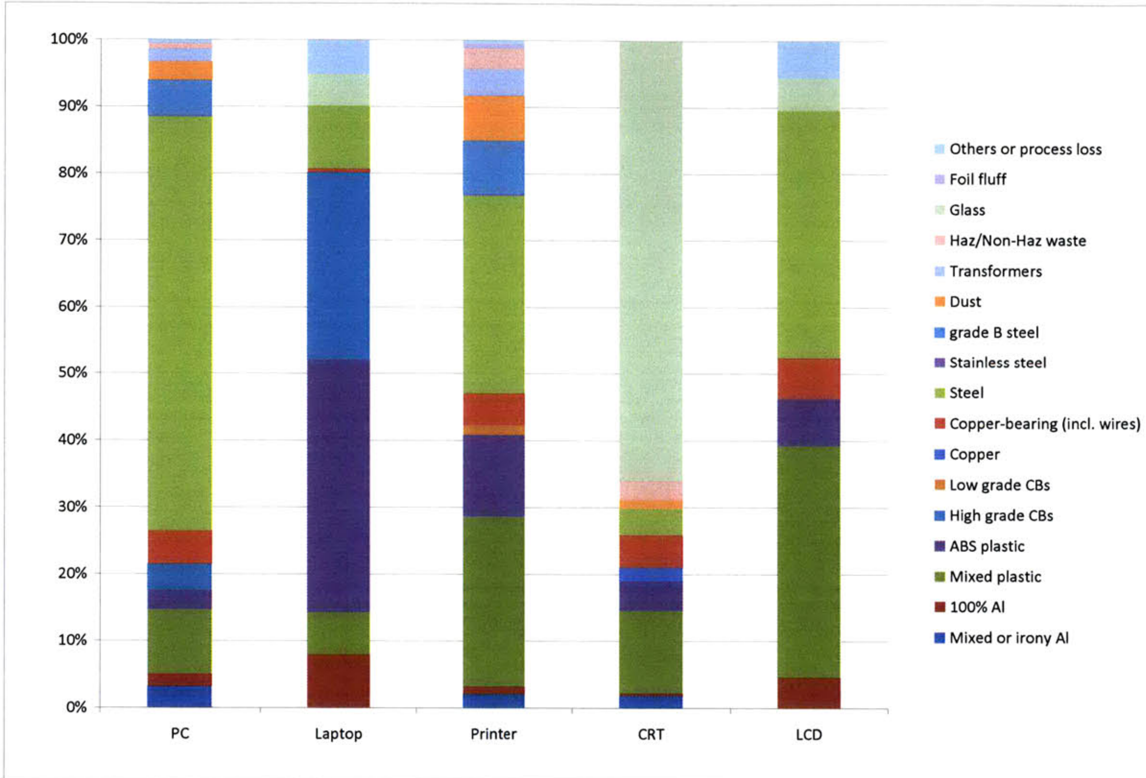
Retirement Age Distributions using the gamma distribution									
Product Type	Client	Mode	Data Source	Alpha	Beta	Mean Age	St Dev	Chi-Sq Stat	Fit
Washers	B2C	Municipal Pick-up	Beck (2005)	3.349	3.279	10.98	6.00	3.90	Best
		Retail Take-back	same as above	3.349	3.279	10.98	6.00		
Dryers	B2C	Municipal Pick-up	Beck (2005)	3.127	3.393	10.61	6.00	10.50	2nd best
		Retail Take-back	same as above	3.127	3.393	10.61	6.00		
Refrigerators	B2C	Municipal Pick-up	Beck (2005)	2.009	10.583	21.26	15.00	12.92	2nd best
		Retail Take-back	same as above	2.009	10.583	21.26	15.00		
Ranges	B2C	Municipal Pick-up	Beck (2005)	2.930	3.505	10.27	6.00	54.27	3rd best
		Retail Take-back	same as above	2.930	3.505	10.27	6.00		
Dishwashers	B2C	Municipal Pick-up	Beck (2005)	3.041	4.588	13.95	8.00	13.06	Best
		Retail Take-back	same as above	3.041	4.588	13.95	8.00		

Appendix B. Material Compositions

IT products:

	PC						Laptop				Printer				CRT						LCD			
Final Commodity List	Recycler1	Recycler2	EPA (2007)	Hikwama (2005)	Miyamoto (1998)	Musson (2006)	Recycler1	Lu (2006)	Miyamoto (1998)	Musson (2006)	Recycler1	Recycler2	EPD (2001)	Musson (2006)	Recycler1	EPA (2007)	Kuehr (2003)	Huisman (2007)	Lee (2008)	Huisman (2003)	Recycler1	Huisman (2007)	EPA (2007)	Musson (2006)
Mixed or irony Al	3.17%	0.00%	0.00%	1.57%	0.00%	0.00%	3.17%	0.00%	0.00%	0.00%	2.04%	0.00%	0.00%	0.00%	1.81%	0.00%	1.60%	0.00%	0.00%	0.00%	1.81%	0.00%	0.00%	0.00%
100% Al	1.90%	10.10%	4.80%	12.53%	2.38%	0.00%	1.90%	8.00%	4.50%	11.00%	1.14%	0.00%	0.40%	5.00%	0.36%	1.60%	0.00%	1.96%	0.00%	0.33%	0.36%	4.64%	2.50%	9.00%
Mixed plastic	9.61%	0.00%	7.00%	1.85%	30.74%	8.00%	9.61%	6.21%	7.40%	38.00%	25.39%	0.00%	34.90%	46.00%	12.36%	16.00%	22.90%	8.36%	19.87%	17.80%	12.36%	34.63%	34.40%	24.00%
ABS plastic	2.88%	15.70%	0.00%	2.88%	0.77%	0.00%	2.88%	37.89%	30.10%	0.00%	12.26%	88.40%	1.50%	0.00%	4.39%	0.00%	0.00%	8.71%	0.00%	0.00%	4.39%	7.08%	0.00%	0.00%
High grade CBs	3.89%	7.80%	0.00%	12.45%	0.00%	16.00%	3.89%	28.02%	0.00%	16.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Low grade CBs	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	1.41%	2.60%	0.00%	7.00%	0.00%	0.00%	0.00%	0.00%	14.34%	0.00%	0.00%	0.00%	0.00%	10.00%
Copper	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2.12%	0.00%	0.00%	0.00%	0.00%	0.00%	2.12%	0.00%	0.00%	0.00%
Copper-bearing (incl. wires)	5.01%	11.80%	7.20%	4.74%	6.88%	3.00%	5.01%	0.56%	12.20%	1.00%	4.78%	0.00%	0.10%	1.00%	4.76%	6.10%	4.50%	4.70%	5.65%	6.09%	4.76%	6.10%	0.00%	4.00%
Steel	61.96%	42.10%	65.30%	62.24%	55.91%	68.00%	61.96%	9.43%	19.90%	7.00%	29.62%	9.00%	40.60%	41.00%	4.13%	24.50%	18.40%	7.74%	10.35%	9.04%	4.13%	37.13%	48.90%	25.00%
Stainless steel	0.21%	0.00%	0.00%	0.00%	0.00%	0.00%	0.21%	0.00%	0.00%	0.00%	0.23%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
grade B steel	5.29%	0.00%	0.00%	0.00%	0.00%	0.00%	5.29%	0.00%	0.00%	0.00%	8.02%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Dust	2.78%	0.00%	0.00%	0.00%	0.00%	0.00%	2.78%	0.00%	0.00%	0.00%	6.74%	0.00%	0.00%	0.00%	1.26%	0.00%	0.00%	0.00%	0.00%	0.00%	1.26%	0.00%	0.00%	0.00%
Transformers	1.92%	0.00%	0.00%	1.21%	0.00%	0.00%	1.92%	0.00%	0.00%	0.00%	3.95%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Haz/Non-Haz waste	0.80%	0.00%	0.00%	0.00%	0.00%	0.00%	0.80%	0.00%	0.00%	0.00%	3.13%	0.00%	22.10%	0.00%	2.80%	0.00%	0.00%	0.10%	0.82%	0.00%	2.80%	0.05%	0.90%	0.00%
Glass	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	4.76%	10.10%	0.00%	0.00%	0.00%	0.00%	0.00%	66.00%	44.30%	44.30%	54.90%	43.52%	64.10%	66.00%	4.88%	11.40%	0.00%
Foil fluff	0.16%	0.00%	0.00%	0.00%	0.00%	0.00%	0.16%	0.00%	0.00%	0.00%	0.64%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Others or process loss	0.42%	12.30%	15.70%	0.53%	3.18%	0.00%	0.42%	5.14%	16.00%	27.00%	0.60%	0.00%	0.00%	0.00%	0.00%	6.30%	8.30%	13.53%	0.41%	2.63%	0.00%	5.49%	1.00%	28.00%

Product	statistical averages of commodities in each product type									
	PC		laptop		printer		CRT		LCD	
	mean	stdev	mean	stdev	mean	stdev	mean	stdev	mean	stdev
Mixed or irony Al	**0.79%**	*1.32%*	**0.00%**	*0.00%*	**0.51%**	*1.02%*	**0.57%**	*0.88%*	**0.00%**	*0.00%*
100% Al	**5.29%**	*4.97%*	**7.83%**	*3.25%*	**1.64%**	*2.29%*	**0.71%**	*0.85%*	**5.38%**	*3.31%*
Mixed plastic	**9.53%**	*11.03%*	**17.20%**	*18.02%*	**26.57%**	*19.62%*	**16.22%**	*5.24%*	**31.01%**	*6.07%*
ABS plastic	**3.71%**	*6.02%*	**22.66%**	*20.01%*	**25.54%**	*42.26%*	**2.18%**	*3.65%*	**2.36%**	*4.09%*
High grade CBs	**6.69%**	*6.61%*	**14.67%**	*14.06%*	**0.00%**	*0.00%*	**0.00%**	*0.00%*	**0.00%**	*0.00%*
Low grade CBs	**0.00%**	*0.00%*	**0.00%**	*0.00%*	**2.75%**	*3.02%*	**2.39%**	*5.85%*	**3.33%**	*5.77%*
Copper	**0.00%**	*0.00%*	**0.00%**	*0.00%*	**0.00%**	*0.00%*	**0.35%**	*0.87%*	**0.00%**	*0.00%*
Copper-bearing (incl. wires)	**6.44%**	*3.04%*	**4.59%**	*6.60%*	**1.47%**	*2.25%*	**5.30%**	*0.73%*	**3.37%**	*3.10%*
Steel	**59.25%**	*9.32%*	**12.11%**	*6.85%*	**30.06%**	*14.99%*	**12.36%**	*7.59%*	**37.01%**	*11.95%*
Stainless steel	**0.04%**	*0.09%*	**0.00%**	*0.00%*	**0.06%**	*0.12%*	**0.00%**	*0.00%*	**0.00%**	*0.00%*
grade B steel	**0.88%**	*2.16%*	**0.00%**	*0.00%*	**2.01%**	*4.01%*	**0.00%**	*0.00%*	**0.00%**	*0.00%*
Dust	**0.46%**	*1.13%*	**0.00%**	*0.00%*	**1.69%**	*3.37%*	**0.21%**	*0.51%*	**0.00%**	*0.00%*
Transformers	**0.52%**	*0.84%*	**0.00%**	*0.00%*	**0.99%**	*1.98%*	**0.00%**	*0.00%*	**0.00%**	*0.00%*
Haz/Non-Haz waste	**0.13%**	*0.33%*	**0.00%**	*0.00%*	**6.31%**	*10.63%*	**0.62%**	*1.12%*	**0.32%**	*0.51%*
Glass	**0.00%**	*0.00%*	**4.95%**	*5.05%*	**0.00%**	*0.00%*	**52.85%**	*10.36%*	**5.43%**	*5.72%*
Foil fluff	**0.03%**	*0.07%*	**0.00%**	*0.00%*	**0.16%**	*0.32%*	**0.00%**	*0.00%*	**0.00%**	*0.00%*
Others or process loss	**5.36%**	*6.87%*	**16.05%**	*10.93%*	**0.15%**	*0.30%*	**5.19%**	*5.23%*	**11.50%**	*14.47%*
Mixed metals	**0.83%**	*2.04%*	**0.00%**	*0.00%*	**0.00%**	*0.00%*	**0.83%**	*2.04%*	**0.00%**	*0.00%*

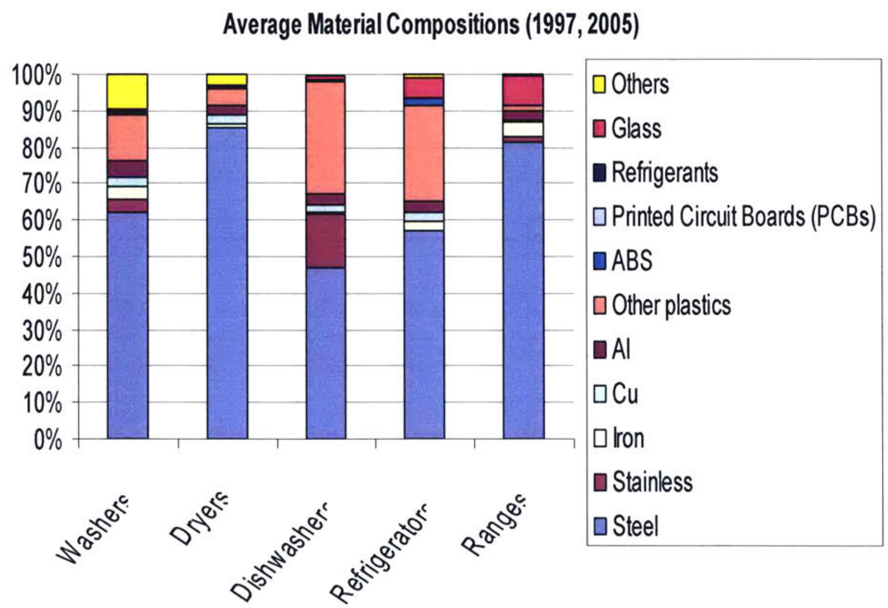


Full material compositions of IT products

Appliances:

Beck (2005): From (a) products retired in 2005 and (b) products sold in 1997 and 2005					
Current material compositions					
	Washers	**Dryers**	**Refrigerators**	**Ranges**	**Dishwashers**
100% Al	4.4%	2.6%	2.9%	2.5%	2.8%
Mixed plastic	12.9%	4.6%	26.0%	2%	31.0%
ABS plastic	0.4%	0.0%	1.9%	0.2%	0.1%
Low grade boards	0.6%	0.7%	0.1%	0.3%	0.7%
Copper	2.7%	2.4%	2.8%	0.4%	2.5%
Steel	62.3%	85.4%	56.9%	81.2%	47.3%
Stainless steel	3.2%	0.1%	0.2%	1.7%	14.9%
Waste (Refrigerant)	0.0%	0.0%	0.2%	0.0%	0.0%
Glass	0.5%	0.2%	5.2%	7.8%	0.8%
Others or process loss	13.1%	4.1%	3.9%	4.5%	0.0%

New wt% when increase plastic wt% by 10%			
	Washers	**Fridge**	**Ranges**
100% Al	6%	4%	4%
Mixed plastic	24.36%	35.84%	10.34%
ABS plastic	0.53%	2.34%	0.24%
Low grade CBs	0.79%	0.13%	0.40%
Copper	3.88%	3.55%	0.64%
Copper-bearing (incl. wires)	0.00%	0.00%	0.00%
Steel	40.01%	42.79%	61.85%
Stainless steel	4.53%	0.19%	2.73%
Refrigerant, other waste	0.00%	0.19%	0.00%
Glass	0.72%	6.55%	12.57%
Others or process loss	18.81%	4.86%	7.17%
Averages taken over range of 1-20% volume increase			
Avg wt loss (kg)	21.8	21.8	26.2
Avg plastic wt % increase	11.80%	10%	9.50%
Avg steel wt % decrease	22.50%	14.30%	19.80%



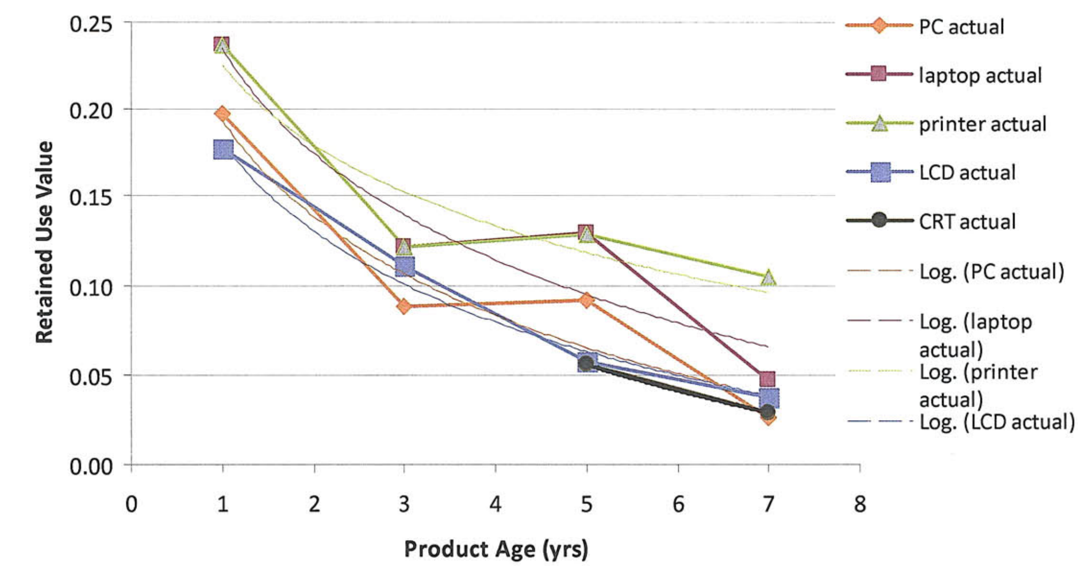
Appendix C. Product Depreciation Calculations

IT products: From (The Orion Blue Book 2009)

Product Tally					
Year	Prod	# units	# Dells	# HPs	# Lexmarks
2002	laptop	12	6	6	
	desktop	14	7	7	
	flat panel	10	5	5	
	CRT	14	6	8	
	printer	12		10	2
2004	laptop	21	11	10	
	desktop	15	8	7	
	flat panel	6	5	1	
	CRT	3	3	0	
	printer	12		10	2
2006	laptop	14	7	7	
	desktop	16	7	9	
	flat panel	10	5	5	
	CRT	0			
	printer	12		10	2
2008	laptop	15	7	8	
	desktop	18	9	9	
	flat panel	9	5	4	
	CRT	0			
	printer	12		10	2

	Sale Yr	depreciation	Std Dev
desktop	2002	0.97	0.003
	2004	0.91	0.02
	2006	0.91	0.02
	2008	0.80	0.01
laptop	2002	0.95	0.01
	2004	0.87	0.04
	2006	0.88	0.03
	2008	0.76	0.03
printer	2002	0.90	0.03
	2004	0.87	0.04
	2006	0.88	0.03
	2008	0.76	0.03
LCD	2002	0.96	0.01
	2004	0.94	0.01
	2006	0.89	0.03
	2008	0.82	0.03
CRT	2002	0.97	0.01
	2004	0.94	0.02

	Logarithmic Decay Equation	R^2
PC	y = -0.0801Ln(x) + 0.1943	0.921
Laptop	y = -0.0872Ln(x) + 0.2354	0.897
Printer	y = -0.0666Ln(x) + 0.2256	0.881
LCD	y = -0.0732Ln(x) + 0.1811	0.986
CRT	y = -0.0732Ln(x) + 0.1811	0.986



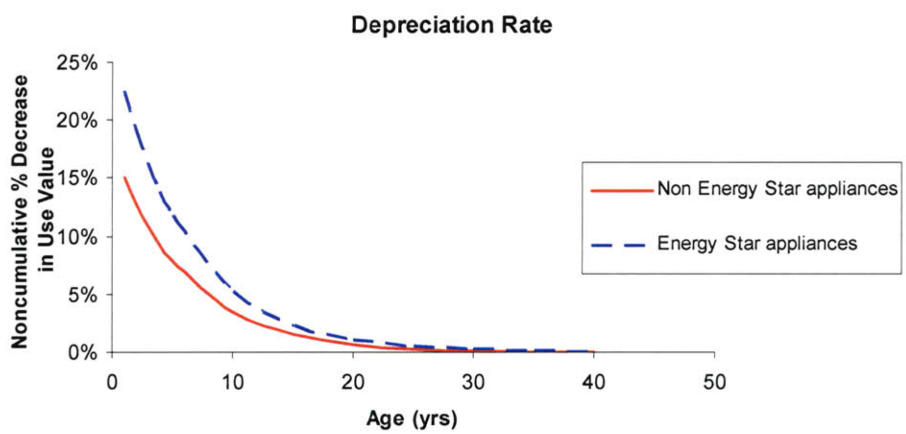
Appliances: From (Fraumeni 1997)
Product depreciation (geometric depreciation) is:

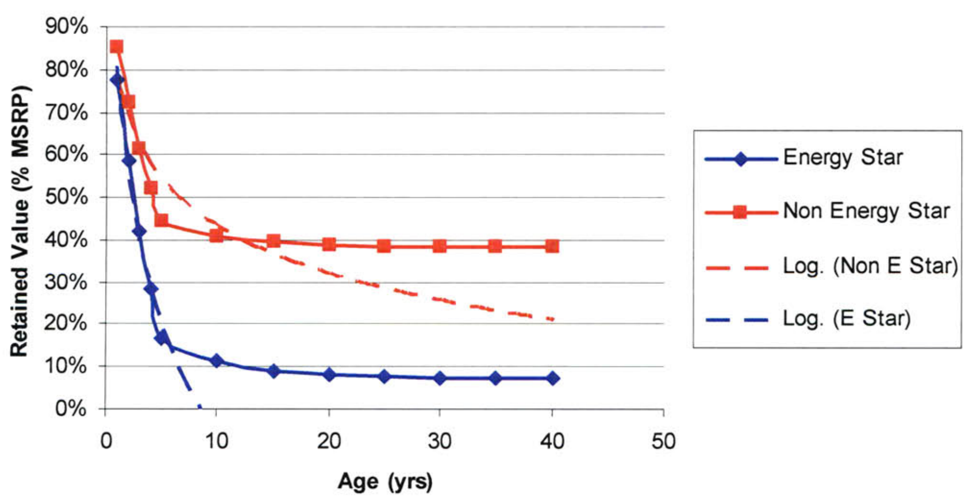
$d = \delta(1-\delta)^{i-1}$

Where, for appliances:

Rate of depreciation [δ]	0.15
Service life (yrs) [T]	11
Declining-balance rate [R]	1.65

Estimated that Energy Star-capable appliances = 1.5*d based on (Hoyt 2010)



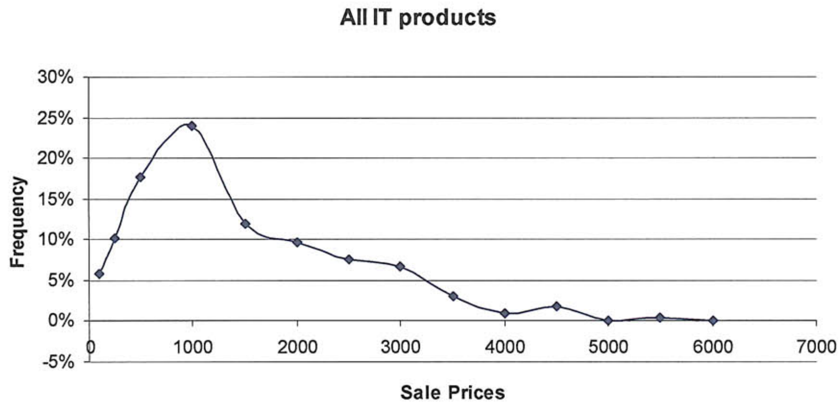


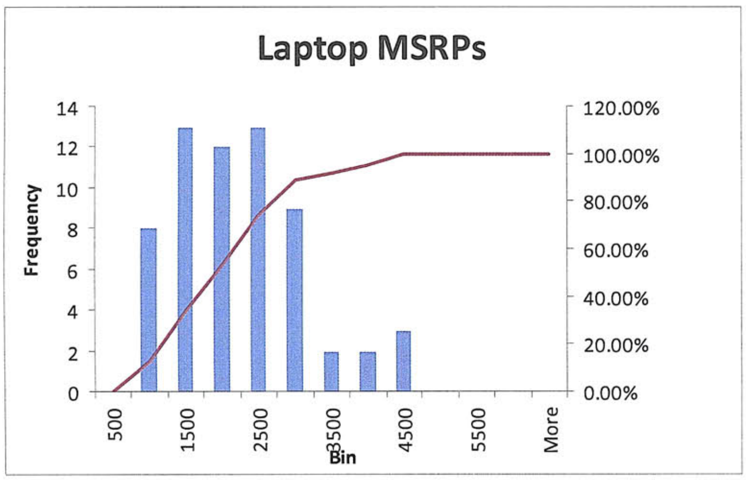
Decay curves were fit to the depreciation profiles when x < 10 years old

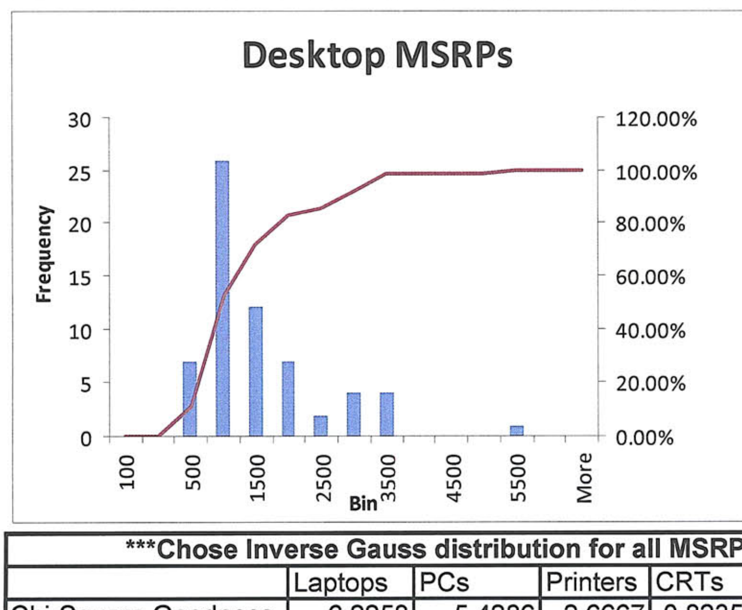
	Logarithmic Decay Equation	R^2
Washer	y = -0.3761Ln(x) + 0.8059	0.9808
Dryer	y = -0.1584Ln(x) + 0.796	0.8926
Refrigerator	same as Washer	
Dishwasher	same as Washer	
Range	same as Dryer	

Appendix D. MSRP Calculations

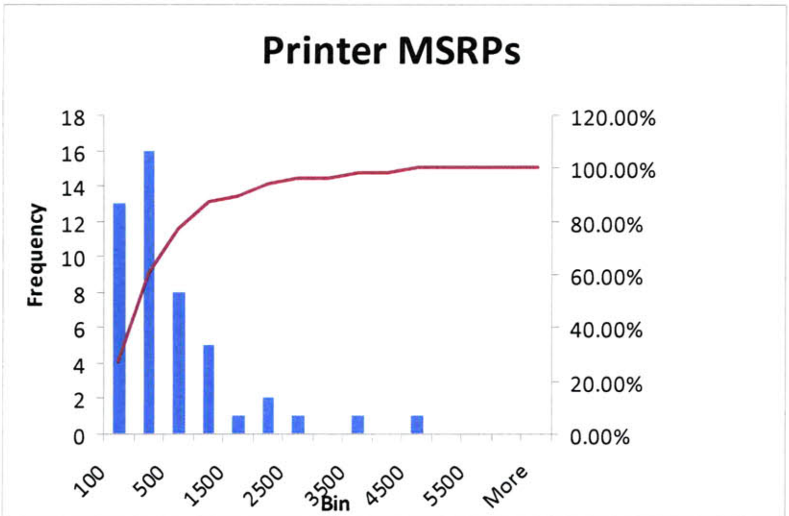
IT products: Data collected from (The Orion Blue Book 2009)

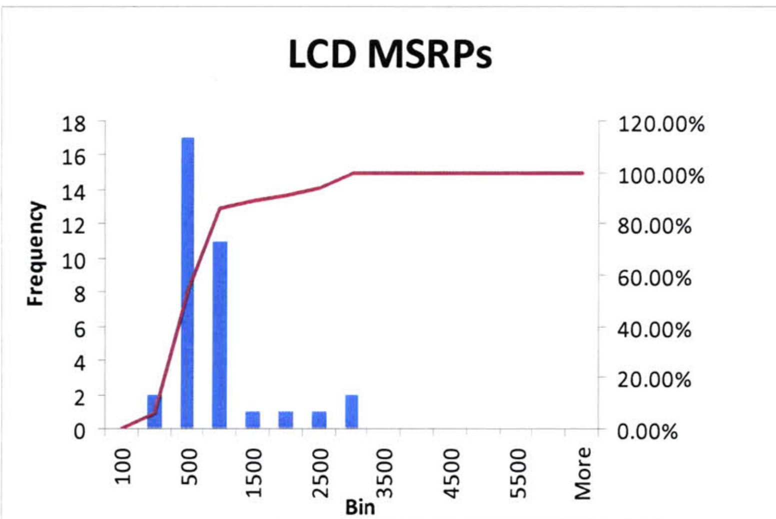


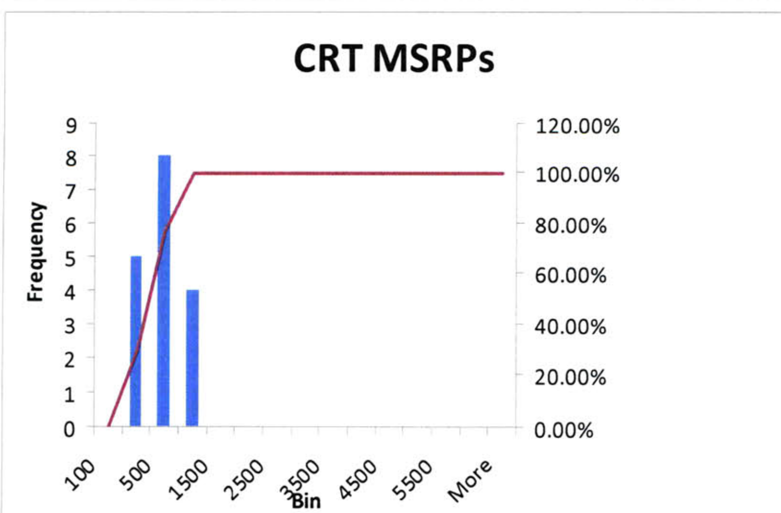




Chose Inverse Gauss distribution for all MSRPs					
	Laptops	PCs	Printers	CRTs	LCDs
Chi-Square Goodness	6.2258	5.4286	2.6667	0.8235	9.2

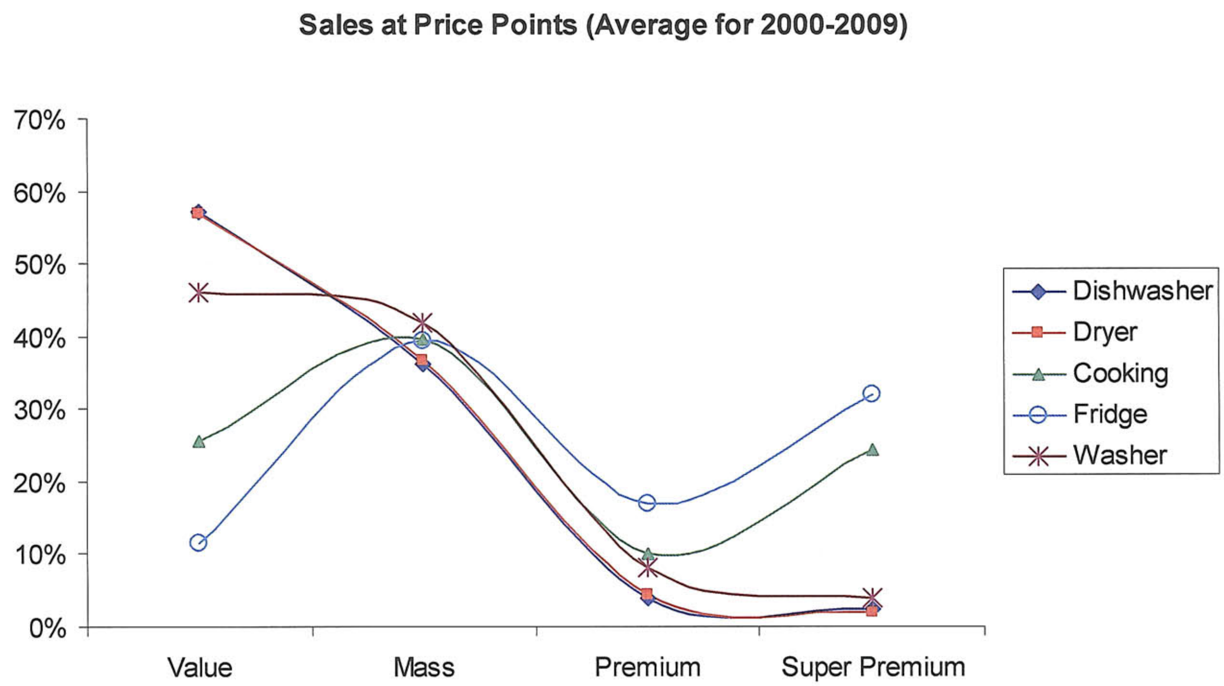

Printer MSRPs
Frequency
18
16
14
12
10
8
6
4
2
0
120.00%
100.00%
80.00%
60.00%
40.00%
20.00%
0.00%
100
500
1500
2500
3500
4500
5500
More
Bin


LCD MSRPs
Frequency
18
16
14
12
10
8
6
4
2
0
120.00%
100.00%
80.00%
60.00%
40.00%
20.00%
0.00%
100
500
1500
2500
3500
4500
5500
More
Bin


CRT MSRPs
Frequency
9
8
7
6
5
4
3
2
1
0
120.00%
100.00%
80.00%
60.00%
40.00%
20.00%
0.00%
100
500
1500
2500
3500
4500
5500
More
Bin

Appliances: Data collected from (The Stevenson Company 2010)

Price Points
Value: \$1-\$500
Mass: \$501-\$1000
Premium: \$1001-\$1300
Super Premium: >\$1301



Trend in Total Appliance Sales (The Stevenson Company 2010)				
Year	Value	Mass	Premium	Super Premium
2000	45%	39%	8%	9%
2001	42%	37%	9%	12%
2002	40%	38%	10%	12%
2003	39%	38%	10%	13%
2004	38%	38%	10%	14%
2005	33%	38%	11%	18%
2006	30%	40%	10%	19%
2007	29%	41%	11%	19%
2008	27%	40%	12%	21%
2009	25%	41%	12%	22%

Appendix E. Scrap Commodity Prices

Outgoing commodity streams			
From Recyclers			Used in MFE Model
Recycler #1	**Recycler #2**	**Recycler #3**	**My Final List**
75/94 aluminum	ABS Plastic	15-30% Cu conc. wires	Mixed or irony Al
Polycarbonate plastic	Aluminum	Steel (0.5% Cu)	100% Al
ABS plastic	Transformers	Mixed plastic	Mixed plastic
Mixed plastic	High Grade Copper Bearing	Al (8-10% Cu conc)	ABS plastic
Hard drives	Mixed Transformer / Motors	Dust	High grade CBs
CD-ROMs, floppy drives	Steel	CRT by itself	Low grade CBs
High-grade circuit boards	Grade B Steel	Copper	Copper
Low-grade boards	Dust	Circuit boards	Copper-bearing (incl. wires)
Copper tube heat exchanger	High Grade Circuit Boards		Steel
Low-grade mixed wire	Irony Aluminum		Stainless steel
Low grade ferrous/steel	Low Grade Copper Bearing		grade B steel
Transformers	Miscellaneous Wire		Dust
#2 copper	Foil Fluff		Transformers
Mixed stainless steel	Non-Hazardous Waste		Haz/Non-Haz waste
100% aluminum	Ink / Toners		Glass
Fans	Stainless Steel Mixed		Foil fluff
Mixed metal	Mixed plastic		Others or process loss
CRTs	Cast Aluminum,Max 2% FE		Mixed metals
	Mixed Metals (Cu heavy)		
	Mixed Metals (Al heavy)		

All price data from September 2004 to August 2009 from (Recycler's World 2009)[2] unless otherwise noted. Sample sizes differ because of differences in availability of past prices.

		$/kg			
Final Commodity List	**Sample size**	**Mean**	**Std Dev**	**Source**	**Name on Source**
Mixed or irony Al	28	$ 0.49	$ 0.12	Recycler's World	Scrap mixed irony Al
100% Al	38	$ 0.75	$ 0.18	Recycler's World	Old mixed scrap Al
Mixed plastic	97	$ 0.26	$ 0.02	Recycler's World	Poly e-scrap baled
ABS plastic	20	$ 0.37	$ 0.09	Recycler's World	ABS scrap
High grade CBs	for variation: 97	$ 3.12	$ 0.66	Recycling facilities	Used "High grade circuit board scrap" on Recycler's World for price variation shape [NOT price values]
Low grade CBs	for variation: 97	$ 0.13	$ 0.03	Recycling facilities	Used "Populated circuit board scrap" on Recycler's World for price variation shape [NOT price values]
Copper	42	$ 4.63	$ 1.46	Recycler's World	#2 scrap copper
Copper-bearing (e.g. wires)	100	$ 1.27	$ 0.30	Recycler's World	Unclipped internal wires + connectors
Steel	38	$ 0.25	$ 0.08	Recycler's World	#2 steel
Stainless steel	41	$ 2.20	$ 0.77	Recycler's World	Mixed nonmagnetic stainless steel
grade B steel	41	$ 0.22	$ 0.07	Recycler's World	Mixed scrap iron + steel
Dust		$(0.15)	$ -	Recycling facilities	
Transformers	100	$ 1.21	$ 0.28	Recycler's World	Transformers + transformer windings
Haz/Non-Haz waste		$(0.12)		Recycling facilities	
CRT Glass	for variation: 68	$(0.20)	$ -	Recycling facilities	Used "1/8 inch CRT glass" on Recycler's World for price variation shape [NOT price values]
Appliance glass	18	$ 0.01	$ -	Recycler's World	Mixed scrap glass
Foil fluff		$(0.15)		Recycling facilities	
Others or process loss		$ -	$ -		
Mixed metals		$ 0.22	$ 0.07	Used grade B steel value	

[2]Some of the prices were collected by Susan A. Fredholm, a former TPP student in the Materials Systems Lab, who graduated in September 2008

Appendix F. Processing Costs

IT products:

IT e-waste Recovery Activities (excl. collection costs)	Avg Cost ($/kg)	St Dev	Sources
Transportation	$ 0.08	$ 0.05	NW Product Stewardship Council (2006), US EPA (2004), Maine's DEP (2009), Product Stewardship Institute (2005), Huisman (2007), Sepanski (2005), Hainault (2001), Walther (2009), Boon (2000)
Processing	$ 0.37	$ 0.21	NW Product Stewardship Council (2006), US EPA (2004), Maine's DEP (2009), Product Stewardship Institute (2005), Huisman (2007), Sepanski (2005), Hainault (2001), Walther (2009), Boon (2000), Caudill (2003), CA Dept of Resources (2009)
Sorting	$ 0.14		Boon (2000)
Testing	$ 0.02		Walther (2009)
Shipping = Transportation	$ 0.08		same as Transportation
Total Recycling Costs	$ 0.69		
Total Reuse Costs	$ 0.33		

The average cost of each recovery activity was then adjusted by 5%, 10%, or 25% depending on the ease of processing by product type. For example, the processing of CRTs is more expensive than for other IT products. Desktops and laptops require more testing upon recovery to determine their status.

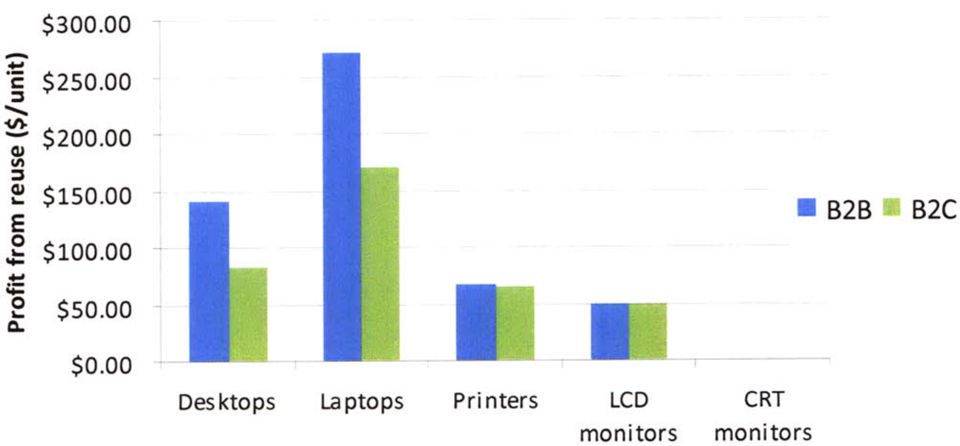
Automatic Processing ($/kg)										
	PC		Laptop		Printer		CRT		LCD	
Stage	Reuse	Recycle	Reuse	Recycle	Reuse	Recycle	Reuse	Recycle	Reuse	Recycle
Transportation	$ 0.09	$ 0.08	$ 0.08	$ 0.08	$ 0.10	$ 0.08	$ 0.10	$ 0.08	$ 0.09	$ 0.08
Sorting and Testing	$ 0.16	$ 0.16	$ 0.16	$ 0.16	$ 0.14	$ 0.14	$ 0.14	$ 0.14	$ 0.14	$ 0.14
Recycling Processing	$ -	$ 0.37	$ -	$ 0.37	$ -	$ 0.39	$ -	$ 0.46	$ -	$ 0.39
Refurbishing	$ 0.01	$ -	$ 0.01	$ -	$ 0.01	$ -	$ 0.01		$ 0.01	$ -
Waste Disposal	$ -	$ 0.04	$ -	$ 0.04	$ -	$ 0.06	$ -	$ 0.06	$ -	$ 0.06
Shipping	$ 0.09	$ 0.09	$ 0.08	$ 0.08	$ 0.10	$ 0.08	$ 0.10	$ 0.08	$ 0.09	$ 0.08
TOTAL	**$ 0.36**	**$ 0.74**	**$ 0.34**	**$ 0.74**	**$ 0.35**	**$ 0.74**	**$ 0.35**	**$ 0.81**	**$ 0.33**	**$ 0.75**

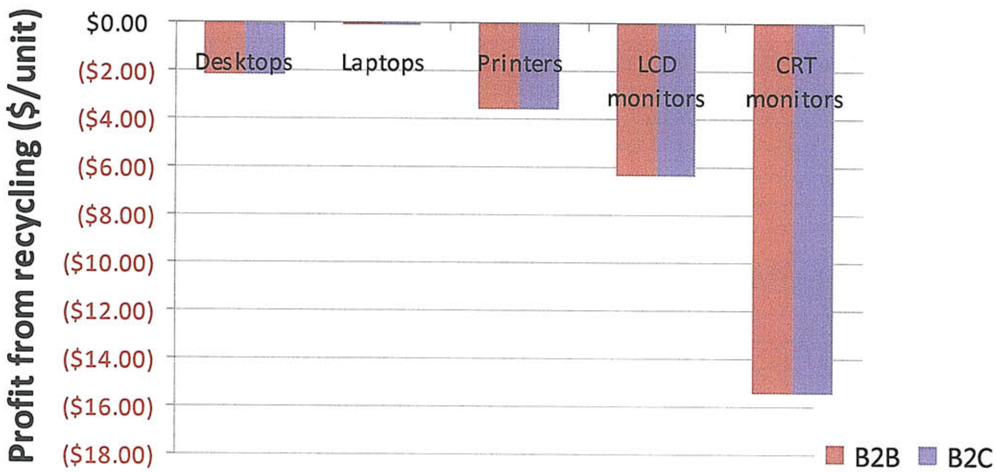
Appliances from (Huisman et al. 2007):

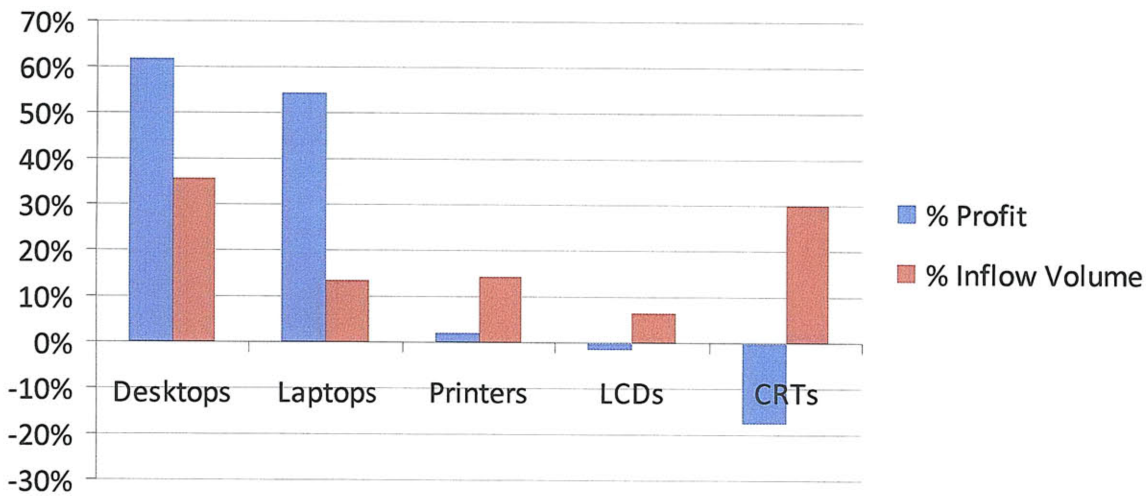
	Costs ($/kg) [negative = revenue]	
Activity	Cooling/Freezing	Major Appliances
Transport/collection	$ 0.28	$ 0.22
Shred/sort/dismantle/pretreat	$ 0.86	$ 0.09
RR processes	$ (0.43)	$ (0.08)
Incineration/landfill	$ 0.02	$ 0.01

Appendix G. IT E-waste Baseline Analysis Supplementary Results

Reuse Volume	B2B (units)	B2C (units)	Total (units)	Total Profit	$/unit	$/kg	Mass (kg)
Desktops (reuse)	121,132	676	121,808	$17,015,207.31	$139.69	$13.83	1,230,263
Laptops (reuse)	53,180	724	53,903	$14,470,432.68	$268.45	$89.48	161,710
Printers (reuse)	14,949	1,076	16,026	$1,062,519.83	$66.30	$8.50	125,001
LCD monitors (reuse)	1,876	66	1,942	$96,264.19	$49.57	$4.43	21,751
CRT monitors (reuse)	0	0	0	$0.00	$0.00	$0.00	0
Total	191,137	2,542	193,679	$32,644,424.01			1,538,725
Recycle Volume	**B2B (units)**	**B2C (units)**	**Total (units)**	**Total Profit**	**$/unit**	**$/kg**	**Mass (kg)**
Desktops (recycle)	83,868	149,324	233,192	($508,898.08)	($2.18)	($0.22)	2,355,237
Laptops (recycle)	36,820	44,276	81,097	($4,168.20)	($0.05)	($0.02)	243,290
Printers (recycle)	10,051	118,924	128,974	($462,743.31)	($3.59)	($0.46)	1,005,999
LCD monitors (recycle)	38,124	24,934	63,058	($397,869.64)	($6.31)	($0.56)	706,249
CRT monitors (recycle)	140,000	160,000	300,000	($4,621,228.52)	($15.40)	($0.67)	6,930,000
Total	308,863	497,458	806,321	($5,994,907.76)			11,240,775
Summary	**Profit**	**% Total**	**% Inflow Volume**	**% Inflow Mass**			
Desktops	$16,506,309.23	62%	36%	28%			
Laptops	$14,466,264.47	54%	14%	3%			
Printers	$599,776.51	2%	15%	9%			
LCDs	($301,605.44)	-1%	7%	6%			
CRTs	($4,621,228.52)	-17%	30%	54%			
TOTAL PROFIT	**$26,649,516.25**						
TOTAL/unit	**$26.65**						
TOTAL/kg	**$2.09**						

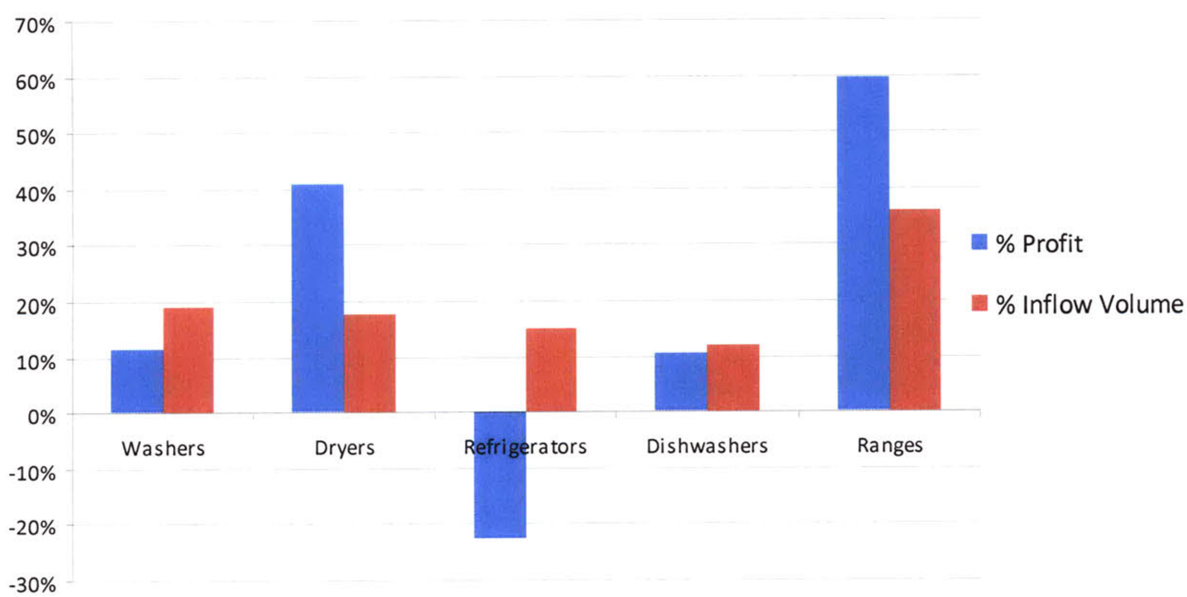


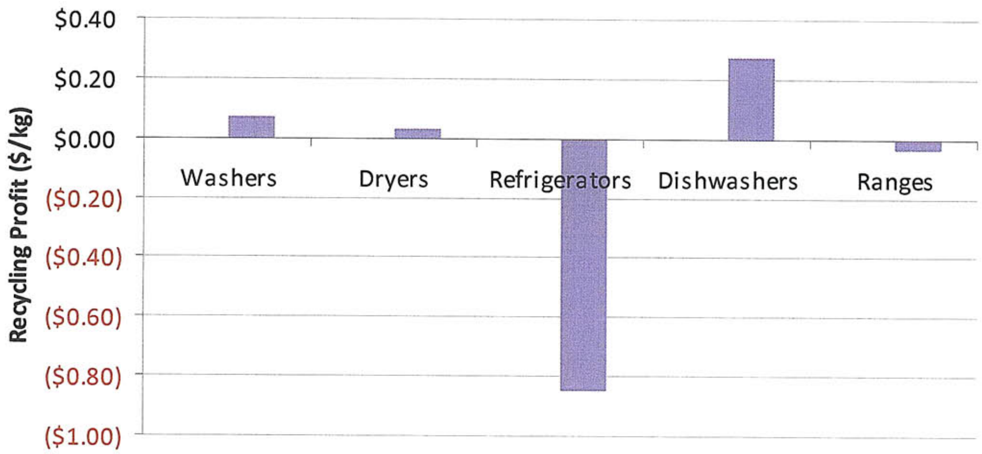

Profit from recycling ($/unit)
$0.00
($2.00)
($4.00)
($6.00)
($8.00)
($10.00)
($12.00)
($14.00)
($16.00)
($18.00)
Desktops
Laptops
Printers
LCD monitors
CRT monitors
B2B
B2C


70%
60%
50%
40%
30%
20%
10%
0%
-10%
-20%
-30%
Desktops
Laptops
Printers
LCDs
CRTs
% Profit
% Inflow Volume

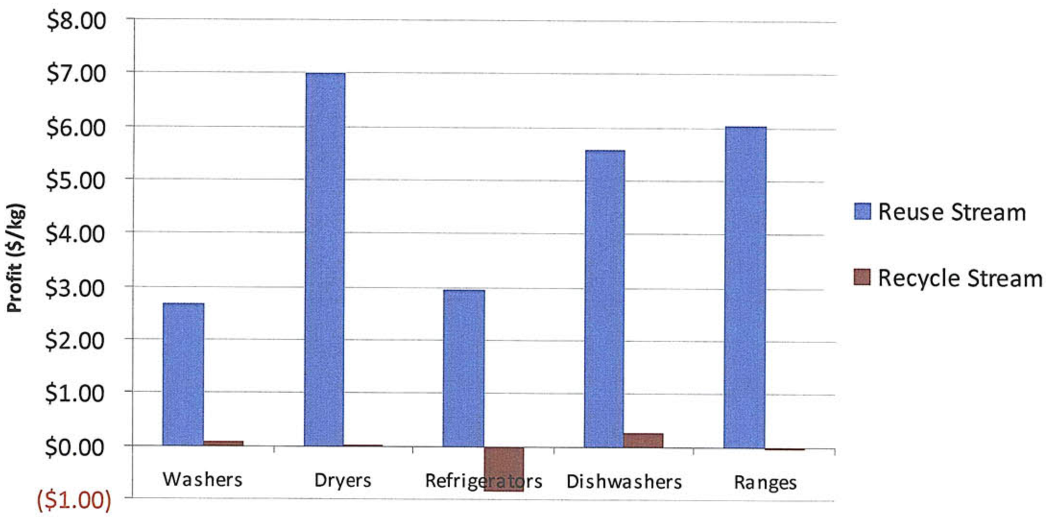
Appendix H. Appliance E-waste Baseline Analysis Supplementary Results

Reuse Volume	B2C (units)	Total (units)	Total Profit	$/unit	$/kg	Mass (kg)
Washers	21,247	21,247	$4,114,057.46	$193.63	$2.67	1,540,372
Dryers	49,868	49,868	$17,514,190.89	$351.21	$7.02	2,493,404
Refrigerators	9,883	9,883	$3,218,719.94	$325.67	$2.96	1,087,184
Dishwashers	17,927	17,927	$3,613,823.42	$201.59	$5.60	645,363
Ranges	62,352	62,352	$26,550,781.11	$425.82	$6.05	4,389,571
Total	161,277	161,277	$55,011,572.82			10,155,893
Recycle Volume	**B2C (units)**	**Total (units)**	**Total Profit**	**$/unit**	**$/kg**	**Mass (kg)**
Washers	168,753	168,753	$873,264.27	$5.17	$0.07	12,234,628
Dryers	130,132	130,132	$209,438.44	$1.61	$0.03	6,506,596
Refrigerators	140,117	140,117	($13,010,864.26)	($92.86)	($0.84)	15,412,816
Dishwashers	102,073	102,073	$990,354.26	$9.70	$0.27	3,674,637
Ranges	297,648	297,648	($742,015.45)	($2.49)	($0.04)	20,954,429
Total	838,723	838,723	($11,679,822.75)			58,783,107
Summary	**Profit**	**% Total**	**% Inflow Volume**	**% Inflow Mass**		
Washers	$4,987,321.73	12%	19%	20%		
Dryers	$17,723,629.33	41%	18%	13%		
Refrigerators	($9,792,144.32)	-23%	15%	24%		
Dishwashers	$4,604,177.68	11%	12%	6%		
Ranges	$25,808,765.66	60%	36%	37%		
TOTAL PROFIT	**$43,331,750.08**					
TOTAL/unit	**$43.33**					
TOTAL/kg	**$0.63**					





Recycling Profit ($/kg)
$0.40
$0.20
$0.00
($0.20)
($0.40)
($0.60)
($0.80)
($1.00)
Washers
Dryers
Refrigerators
Dishwashers
Ranges



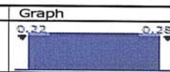
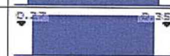
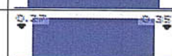
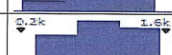
Profit ($/kg)
$8.00
$7.00
$6.00
$5.00
$4.00
$3.00
$2.00
$1.00
$0.00
($1.00)
Washers
Dryers
Refrigerators
Dishwashers
Ranges
Reuse Stream
Recycle Stream

Appendix I. Monte Carlo Analysis Input Distributions

For IT analysis

Name	Graph	Function	Min	Mean	Max
% Asset Recovery returns		RiskUniform(0,1,RiskStatic(0))	0%	50%	100%
% Municipal Pick-up returns		RiskUniform(0,1,RiskStatic(1))	0%	50%	100%
Desktop depreciation		RiskTriang(0.4,1,4,RiskStatic(1),RiskName("Desktop depreciation"))	0.4	1.8	4
Laptop depreciation		RiskTriang(0.4,1,4,RiskStatic(1),RiskName("Laptop depreciation"))	0	2	4
Printer depreciation		RiskTriang(0.4,1,4,RiskStatic(1),RiskName("Printer depreciation"))	0	2	4
LCD depreciation		RiskTriang(0.4,1,4,RiskStatic(1),RiskName("LCD depreciation"))	0	2	4
Laptops MSRP		RiskInvgauss(2015.7,9173.2,RiskShift(0),RiskStatic(1891),RiskName("Laptops MSRP"))	$0.00	$2,015.70	+∞
Desktops MSRP		RiskInvgauss(1321,2834.7,RiskStatic(938),RiskName("Desktops MSRP"))	$0.00	$1,321.00	+∞
Printers MSRP		RiskInvgauss(521.1,198.92,RiskShift(0),RiskStatic(208),RiskName("Printers MSRP"))	$0.00	$521.10	+∞
CRTs MSRP		RiskInvgauss(353,1793.86,RiskShift(0),RiskStatic(299),RiskName("CRTs MSRP"))	$0.00	$353.00	+∞
LCDs MSRP		RiskInvgauss(737.9,1339.1,RiskStatic(469),RiskName("LCDs MSRP"))	$0.00	$737.90	+∞
Aluminum price		RiskGamma(16.845,0.044596,RiskStatic(0.751217250173893),RiskCorrmat(Commodity_Price_Correlations,2))	$ -	$ 0.75	+∞
ABS plastic price		RiskGamma(17.3,0.021199,RiskStatic(0.366740088105727),RiskCorrmat(Commodity_Price_Correlations,4))	$ -	$ 0.37	+∞
Copper price		RiskGamma(9.3942,0.49333,RiskStatic(4.63446612125026),RiskCorrmat(Commodity_Price_Correlations,5))	$ -	$ 4.63	+∞
Copper-bearing price		RiskGamma(15.422,0.082582,RiskStatic(1.27357385361552),RiskCorrmat(Commodity_Price_Correlations,6))	$ -	$ 1.27	+∞
Cost / Reuse PC		RiskUniform(0.32,0.39,RiskStatic(0.36),RiskName("Cost / Reuse PC"))	$ 0.32	$ 0.36	$ 0.39
Cost / Recycle-PC		RiskUniform(0.666,0.814,RiskStatic(0.74),RiskName("Cost / Recycle-PC"))	$ 0.67	$ 0.74	$ 0.81
Cost / Reuse Laptop		RiskUniform(0.306,0.374,RiskStatic(0.34),RiskName("Cost / Reuse Ltop"))	$ 0.31	$ 0.34	$ 0.37
Cost / Recycle-Laptop		RiskUniform(0.666,0.814,RiskStatic(0.74),RiskName("Cost / Recycle-Ltop"))	$ 0.67	$ 0.74	$ 0.81
Cost / Reuse Printer		RiskUniform(0.315,0.385,RiskStatic(0.35),RiskName("Cost / Reuse Ptr"))	$ 0.32	$ 0.35	$ 0.39
Cost / Recycle-Printer		RiskUniform(0.666,0.814,RiskStatic(0.74),RiskName("Cost / Recycle-Ptr"))	$ 0.67	$ 0.74	$ 0.81
Cost / Reuse CRT		RiskUniform(0.315,0.385,RiskStatic(0.35),RiskName("Cost / Reuse CRT"))	$ 0.32	$ 0.35	$ 0.39
Cost / Recycle-CRT		RiskUniform(0.666,0.814,RiskStatic(0.74),RiskName("Cost / Recycle-CRT"))	$ 0.67	$ 0.74	$ 0.81
Cost / Reuse LCD		RiskUniform(0.297,0.363,RiskStatic(0.33),RiskName("Cost / Reuse LCD"))	$ 0.30	$ 0.33	$ 0.36
Cost / Recycle-LCD		RiskUniform(0.666,0.814,RiskStatic(0.74),RiskName("Cost / Recycle-LCD"))	$ 0.67	$ 0.74	$ 0.81
grade B steel price		RiskGamma(12.6,0.017299,RiskStatic(0.217956080354454),RiskCorrmat(Commodity_Price_Correlations,9))	$ -	$ 0.22	+∞
High grade circuit board price		RiskGamma(22.347,0.14,RiskStatic(3.12),RiskCorrmat(Commodity_Price_Correlations,11))	$ -	$ 3.13	+∞
Low grade circuit board price		RiskGamma(18.778,0.007,RiskStatic(0.13),RiskCorrmat(Commodity_Price_Correlations,12))	$ -	$ 0.13	+∞
product functionality slope		RiskTriang(-0.12,-0.1125,-0.067,RiskStatic(-0.1125))	-0.1200	-0.0998	-0.0670
Mixed metals price		RiskGamma(12.6,0.017299,RiskStatic(0.217956080354454),RiskCorrmat(Commodity_Price_Correlations,13))	$ -	$ 0.22	+∞
Mixed or irony Al price		RiskGamma(19.4,0.025507,RiskStatic(0.494808055380743),RiskCorrmat(Commodity_Price_Correlations,1))	$ -	$ 0.49	+∞
Mixed plastic price		RiskGamma(132.57,0.0019855,RiskStatic(0.263186603392789),RiskCorrmat(Commodity_Price_Correlations,3))	$ -	$ 0.26	+∞
Stainless steel price		RiskGamma(6.6713,0.32993,RiskStatic(2.20103148168046),RiskCorrmat(Commodity_Price_Correlations,8))	$ -	$ 2.20	+∞
Steel price		RiskGamma(11.714,0.020961,RiskStatic(0.245516859277824),RiskCorrmat(Commodity_Price_Correlations,7))	$ -	$ 0.25	+∞
Transformers price		RiskGamma(15.585,0.077517,RiskStatic(1.20806558641975),RiskCorrmat(Commodity_Price_Correlations,10))	$ -	$ 1.21	+∞

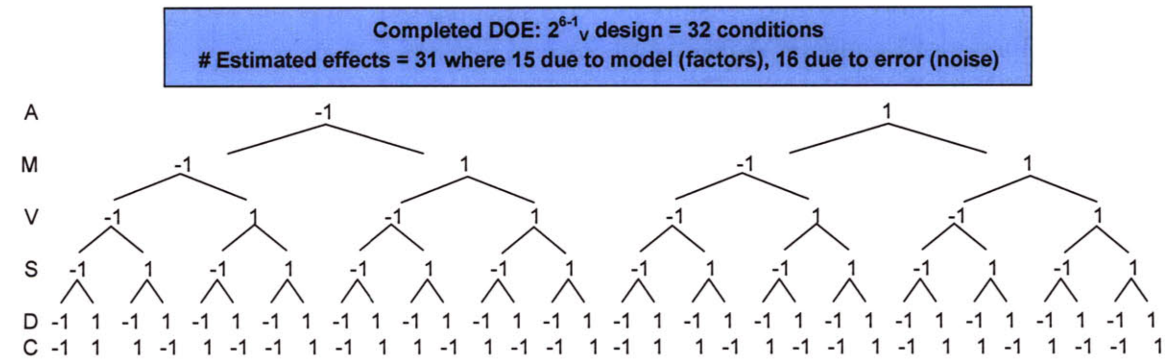
For Appliance analysis

Name	Graph	Function	Min	Mean	Max
Cost - Reuse Washer		RiskUniform(0.225,0.275,RiskStatic(0.25))	$ 0.23	$ 0.25	$ 0.28
Cost - Recycle Washer		RiskUniform(0.279,0.341,RiskStatic(0.31))	$ 0.28	$ 0.31	$ 0.34
Cost - Reuse Dryer		RiskUniform(0.225,0.275,RiskStatic(0.25))	$ 0.23	$ 0.25	$ 0.28
Cost - Recycle Dryer		RiskUniform(0.279,0.341,RiskStatic(0.31))	$ 0.28	$ 0.31	$ 0.34
Cost - Reuse Refrigerator		RiskUniform(0.342,0.418,RiskStatic(0.38))	$ 0.34	$ 0.38	$ 0.42
Cost - Recycle Refrigerator		RiskUniform(1.026,1.254,RiskStatic(1.14))	$ 1.03	$ 1.14	$ 1.25
Cost - Reuse Range		RiskUniform(0.225,0.275,RiskStatic(0.25))	$ 0.23	$ 0.25	$ 0.28
Cost - Recycle Range		RiskUniform(0.279,0.341,RiskStatic(0.31))	$ 0.28	$ 0.31	$ 0.34
Cost - Reuse Dishwasher		RiskUniform(0.225,0.275,RiskStatic(0.25))	$ 0.23	$ 0.25	$ 0.28
Cost - Recycle Dishwasher		RiskUniform(0.279,0.341,RiskStatic(0.31))	$ 0.28	$ 0.31	$ 0.34
Washer depreciation		RiskTriang(0.4,1,4,RiskStatic(1),RiskName("Washer depreciation"))	0.4	1.8	4
Dryer depreciation		RiskTriang(0.4,1,4,RiskStatic(1),RiskName("Dryer depreciation"))	0	2	4
Refrigerator depreciation		RiskTriang(0.4,1,4,RiskStatic(1),RiskName("Refrigerator depreciation"))	0	2	4
Dishwasher depreciation		RiskTriang(0.4,1,4,RiskStatic(1),RiskName("Dishwasher depreciation"))	0	2	4
Range depreciation		RiskTriang(0.4,1,4,RiskStatic(1),RiskName("Range depreciation"))	0	2	4
Dryer MSRP		RiskHistogrm(350,1100,{0.57,0.37,0.06},RiskStatic(700),RiskName("Dryer MSRP"))	$350.00	$597.50	$1,100.00
Washer MSRP		RiskHistogrm(400,1100,{0.46,0.42,0.12},RiskStatic(700),RiskName("Washer MSRP"))	$400.00	$670.67	$1,100.00
Fridge MSRP		RiskHistogrm(500,2000,{0.12,0.39,0.49},RiskStatic(900),RiskName("Fridge MSRP"))	$500.00	$1,435.00	$2,000.00
Ranges MSRP		RiskHistogrm(400,1500,{0.26,0.4,0.34},RiskStatic(800),RiskName("Ranges MSRP"))	$400.00	$979.33	$1,500.00
Dishwasher MSRP		RiskHistogrm(350,1000,{0.57,0.36,0.06},RiskStatic(700),RiskName("Dishwasher MSRP"))	$350.00	$563.38	$1,000.00
100% Al / Price		RiskGamma(16.845,0.044596,RiskStatic(0.751217250173893))	$ -	$ 0.75	+∞
ABS plastic / Price		RiskTriang(-0.02,0,0.02,RiskStatic(0),RiskCorrmat(NewMatrix1,2))	$ (0.02)	$ -	$ 0.02
Copper / Price		RiskGamma(9.3942,0.49333,RiskStatic(4.63446612125026),RiskCorrmat(NewMatrix1,4))	$ -	$ 4.63	+∞
Glass / Price		RiskTriang(-0.02,0,0.02,RiskStatic(0))	$ (0.02)	$ -	$ 0.02
Low grade CBs / Price		RiskGamma(18.778,0.007,RiskStatic(0.13),RiskCorrmat(NewMatrix1,3))	$ -	$ 0.13	+∞
Product Functionality slope		RiskTriang(-0.1,-0.05,-0.025,RiskStatic(-0.05))	-0.1000	-0.0583	-0.0250
Mixed plastic / Price		RiskTriang(-0.02,0,0.02,RiskStatic(0),RiskCorrmat(NewMatrix1,1))	$ (0.02)	$ -	$ 0.02
Stainless steel / Price		RiskGamma(6.6713,0.32993,RiskStatic(2.20103148168046),RiskCorrmat(NewMatrix1,6))	$ -	$ 2.20	+∞
Steel / Price		RiskGamma(11.714,0.020961,RiskStatic(0.245516859277824),RiskCorrmat(NewMatrix1,5))	$ -	$ 0.25	+∞

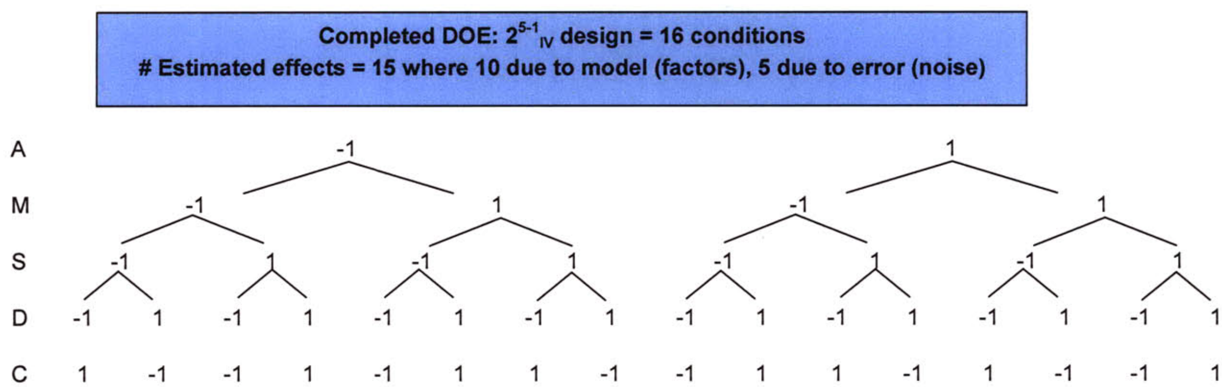
Appendix J. Design of Experiments: Factor Relationship Diagrams

A = Age, M = Product mix, V = Volume, S = MSRP, D = Depreciation rate, C = Commodity prices

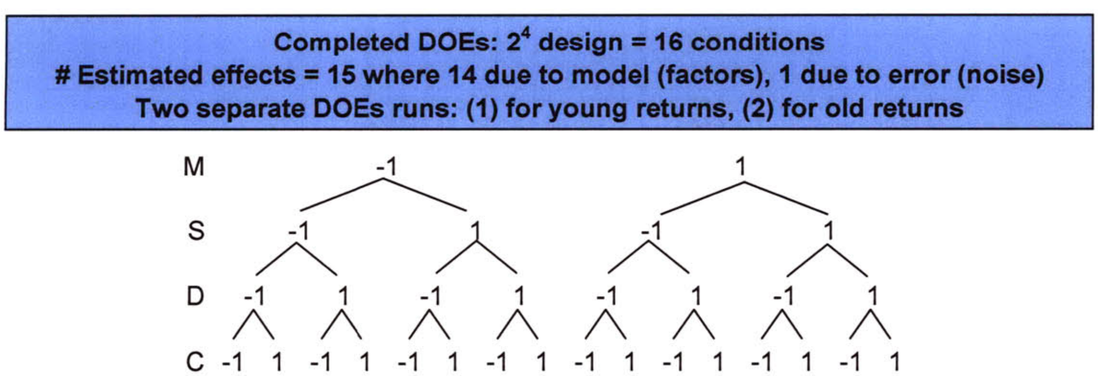
<u>IT analysis: 1st DOE Design</u>



<u>Appliance analysis: 1st DOE Design</u>



<u>IT and Appliance analysis: 2nd DOE Design</u>



Appendix K. Acronyms

Acronym	Phrase or name
AHAM	Association of Home Appliance Manufacturers
B2B	Business-to-Business customer, i.e. commercial customer
B2C	Business-to-Consumer customer, i.e. residential customer
BEA	Bureau of Economic Analysis (U.S.)
CRT	Cathode Ray Tube
DOE	Design of Experiments
EOL	End-of-Life
IT	Information Technology
LCD	Liquid Crystal Display
MFE	Mass Flow and Economic
MSRP	Manufacturer's Suggested Retail Price
OEM	Original Equipment Manufacturer
PC	Personal Computer
U.S. EPA	United States Environmental Protection Agency
WEEE	Waste Electrical and Electronic Equipment

Appendix L. Snapshot of MFE Model Input Structure

Collection Mix Inputs	
Total inflow	1,000,000 units/yr
Client Mix	% of volume
%B2B	0%
%B2C	100%
Total	100%
B2B Product Mix	% of volume
% Desktops	25%
% Laptops	35%
% Printers	10%
% CRT monitors	0%
% LCD monitors	30%
% Servers	0%
Total	100%
B2C Product Mix	% of volume
% Desktops	30%
% Laptops	35%
% Printers	15%
% CRT monitors	0%
% LCD monitors	20%
% Servers	0%
Total	100%
B2B Collection Mix	% of volume
% Asset Recovery	15%
% End of Lease	85%
Total	100%
B2C Collection Mix	% of volume
% Event, Municipal Pick Up	40%
% Retail take-back, Mail-in	60%
Total	100%

Reuse vs. Recycle Revenue Bias Factors	
Desktops	5%
Laptops	5%
Printers	50%
LCDs	75%
CRTs	100%

Quality	Sales Distribution
Low-end	80%
Mid-range	15%
High-end	5%
Total	100%

Commodity Mkt Conditions	True or False?
Poor	0
Average	1
Favorable	0

Calculation product functionality		
m		-0.1125
b		1.0125
Include this? (0/1)		1
Age		P(working)
	1	0.9000
	2	0.7875
	3	0.6750
	4	0.5625
	5	0.4500
	6	0.3375
	7	0.2250
	8	0.1125
	9	0.0000

Costs ($/kg)		
Include costs (0/1)?		1
Desktops - Reuse	$	0.36
Desktops - Recycle	$	0.74
Laptops - Reuse	$	0.34
Laptops - Recycle	$	0.74
Printers - Reuse	$	0.35
Printers - Recycle	$	0.74
CRTs - Reuse	$	0.35
CRTs - Recycle	$	0.81
LCDs - Reuse	$	0.33
LCDs - Recycle	$	0.75

Age Distribution equation parameters

Product Type	Client	Mode	Distrib	Alpha	Beta	Mean Age	St Dev	skew
Desktop	B2B	Asset Rec	Gamma	3.448	1.155	3.98	2.15	1.00
		End of Lease	Gamma	1.947	1.541	3.00	2.15	1.15
	B2C	Municipal Pick-up	Gamma	5.408	0.925	19.24	8.39	0.89
		Retail Take-back	Gamma	1.947	1.541	8.00	4.00	1.15
Laptop	B2B	Asset Rec	Gamma	3.448	1.155	3.98	2.15	1.00
		End of Lease	Gamma	1.947	1.541	3.00	2.15	1.15
	B2C	Municipal Pick-up	Gamma	5.408	0.925	7.28	1.37	0.89
		Retail Take-back	Gamma	1.947	1.541	5.00	1.40	1.15
Printer	B2B	Asset Rec	Gamma	28.590	0.160	4.59	0.86	0.93
		End of Lease	Gamma	28.590	0.105	3.00	0.56	1.15
	B2C	Municipal Pick-up	Gamma	6.085	1.999	12.16	4.93	0.57
		Retail Take-back	Gamma	6.074	2.002	12.16	4.93	0.57
LCD	B2B	Asset Rec	Gamma	20.258	0.279	5.65	1.25	0.84
		End of Lease	Gamma	20.258	0.279	5.65	1.25	0.84
	B2C	Municipal Pick-up	Gamma	13.617	0.675	9.19	2.49	0.66
		Retail Take-back	Gamma	13.631	0.674	9.19	2.49	0.66
CRT	B2B	Asset Rec	Gamma	5.743	2.600	14.93	6.23	0.52
		End of Lease	Gamma	5.742	2.600	14.93	6.23	0.52
	B2C	Municipal Pick-up	Gamma	5.742	2.600	14.93	6.23	0.52
		Retail Take-back	Gamma	5.742	2.600	14.93	6.23	0.52

B2B Product Retirement Age Distributions

Asset Recovery

Age		Desktops	Laptops	Printers	CRT Monitors	LCD Monitors	Servers
	1	3%	3%	0%	0%	0%	
	2	14%	14%	0%	0%	0%	
	3	21%	21%	2%	0%	1%	
	4	20%	20%	24%	1%	8%	
	5	16%	16%	44%	1%	24%	
	6	11%	11%	24%	2%	31%	
	7	7%	7%	5%	3%	22%	
	8	4%	4%	1%	4%	10%	
	9	5%	5%	0%	89%	4%	
Total		100%	100%	100%	100%	100%	

For End of Lease

Age		Desktops	Laptops	Printers	CRT monitors	LCD monitors	Servers
	1	15%	15%	0%	0%	0%	
	2	24%	24%	2%	0%	0%	
	3	21%	21%	50%	0%	1%	
	4	15%	15%	43%	1%	8%	
	5	10%	10%	5%	1%	24%	
	6	6%	6%	0%	2%	31%	
	7	4%	4%	0%	3%	22%	
	8	2%	2%	0%	4%	10%	
	9	3%	3%	0%	89%	4%	
Total		100%	100%	100%	100%	100%	

B2C Product Retirement Age Distributions

Municipal Pick-up, Community Event

Age		Desktops	Laptops	Printers	CRT monitors	LCD monitors	Servers
	1	0%	0%	0%	0%	0%	
	2	4%	4%	0%	0%	0%	
	3	13%	13%	0%	0%	0%	
	4	19%	19%	1%	1%	0%	
	5	20%	20%	2%	1%	2%	
	6	16%	16%	4%	2%	6%	
	7	11%	11%	6%	3%	11%	
	8	7%	7%	7%	4%	15%	
	9	9%	9%	80%	89%	66%	
Total		100%	100%	100%	100%	100%	

Retail take-back

Age		Desktops	Laptops	Printers	CRT monitors	LCD monitors	Servers
	1	15%	15%	0%	0%	0%	
	2	24%	24%	0%	0%	0%	
	3	21%	21%	0%	0%	0%	
	4	15%	15%	1%	1%	0%	
	5	10%	10%	2%	1%	2%	
	6	6%	6%	4%	2%	6%	
	7	4%	4%	6%	3%	11%	
	8	2%	2%	7%	4%	15%	
	9	3%	3%	80%	89%	66%	
Total		100%	100%	100%	100%	100%	

2009 Depreciation Values

Using Logarithmic Function Shape (y = k*[a*lnx+d])

Parameters	Desktop	Laptop	Printer	LCD	CRT
a	-0.08	-0.08	-0.06	-0.07	-0.07
d	0.194	0.235	0.225	0.181	0.181
k multiplier	1				
Age					
1	0.19	0.24	0.23	0.18	0.00
2	0.14	0.18	0.18	0.13	0.00
3	0.11	0.15	0.16	0.10	0.00
4	0.08	0.12	0.14	0.08	0.00
5	0.07	0.11	0.00	0.00	0.00
6	0.00	0.00	0.00	0.00	0.00
7	0.00	0.00	0.00	0.00	0.00
8	0.00	0.00	0.00	0.00	0.00
9	0.00	0.00	0.00	0.00	0.00

-0.08	-0.08	-0.06	-0.07	-0.07

MSRP DATA

Price Pts	Laptops	Desktops	Printers	CRTs	LCDs	Servers	k	
Low-end	$999.00	$500.00	$63.00	$199.00	$298.00	$0.00		1.00
Middle	$1,891.00	$938.00	$208.00	$299.00	$469.00	$0.00		
High-end	$3,010.00	$2,759.00	$1,537.00	$588.00	$1,559.00	$0.00		
	$1,891.00	$938.00	$208.00	$299.00	$469.00			

PRODUCT WEIGHT DATA	
Product Type	Avg Wt (kg)
Desktop	10.1
Laptop	3
Printer	7.8
CRT Monitor	23.1
LCD Monitor	11.2
Server	

		$/kg			wt %				
% variation	**Final Commodity List**	**Poor**	**Avg**	**Good**	**PC**	**Laptop**	**Printer**	**CRT**	**LCD**
23%	Mixed or irony Al	$ 0.26	$ 0.49	$ 0.73	0.79%		0.51%	0.57%	
24%	100% Al	$ 0.39	$ 0.75	$ 1.11	5.29%	7.83%	1.64%	0.71%	5.38%
8%	Mixed plastic	$ 0.22	$ 0.26	$ 0.31	9.53%	17.20%	26.57%	16.22%	31.01%
25%	ABS plastic	$ 0.18	$ 0.37	$ 0.55	3.71%	22.66%	25.54%	2.18%	2.36%
21%	High grade CBs	$ 1.81	$ 3.12	$ 4.43	6.69%	14.67%			
22%	Low grade CBs	$ 0.07	$ 0.13	$ 0.19			2.75%	2.39%	3.33%
32%	Copper	$ 1.71	$ 4.63	$ 7.56				0.35%	
23%	Copper-bearing (incl. wires)	$ 0.68	$ 1.27	$ 1.86	6.44%	4.59%	1.47%	5.30%	3.37%
33%	Steel	$ 0.08	$ 0.25	$ 0.41	59.25%	12.11%	30.06%	12.36%	37.01%
35%	Stainless steel	$ 0.67	$ 2.20	$ 3.73			0.06%		
32%	grade B steel	$ 0.08	$ 0.22	$ 0.36	0.88%		2.01%		
	Dust	$ (0.15)	$ (0.15)	$ (0.15)	0.46%		1.69%	0.21%	
23%	Transformers	$ 0.65	$ 1.21	$ 1.77	0.52%		0.99%		
	Haz/Non-Haz waste	$ (0.12)	$ (0.12)	$ (0.12)	0.13%		6.31%	0.62%	0.32%
	Glass	$ (0.20)	$ (0.20)	$ (0.20)		4.95%		52.85%	5.43%
	Foil fluff	$ (0.15)	$ (0.15)	$ (0.15)			0.16%		
	Others or process loss	$ -	$ -	$ -	5.36%	16.05%	0.15%	5.19%	11.50%
32%	Mixed metals	$ 0.08	$ 0.22	$ 0.36	0.83%			0.83%	
			TOTAL		100%	100%	100%	100%	100%