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Life-Cycle Planning in Closed-Loop Supply Chains: A Study of Refurbished Laptops

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Abstract

Waste electrical and electronic equipment (WEEE) is one of the fastest growing waste streams. Therefore, the reduction of discarded electronic equipment is of immense importance in order to reduce virgin material consumption and hence the environmental impact associated with the production and consumption of consumer electronics. Using the market for new and refurbished laptops as a reference industry, a typical life-cycle of a laptop including refurbishment and resale of the returned product is modeled and analyzed in order to explore the related profitability. Therefore, we first investigate actual market prices of new and refurbished laptops using data gathered from bestbuy.com. Subsequently, we introduce a newsvendor model where we use the insights into pricing of these products obtained from the

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empirical study. The model integrates different reverse channels like recycling or disposal which have a crucial impact on the original equipment manufacturer’s optimal decision making. Our studies highlight how the return rate and fractions of returned cores that are refurbished by the OEM as well as new and refurbished product prices are interrelated and influence the OEMs production decision problem.

1 Introduction

Product recovery operations like remanufacturing, refurbishing or recycling gain increasing importance in real world businesses as well as in research. By using end-of-life product returns for reprocessing purposes, significant amounts of virgin raw materials as well as energy needed for the production of new products can potentially be saved. Furthermore, marketing of reprocessed products may lead to an increase in total sales and profits, as offering recovered items often allows a company to address an additional customer segment. Such an increase in the market share could mainly be caused by price-sensitive and ecologically concerned customers, who typically are attracted by lower prices of recovered products and their green image (Atasu et al, 2008; Thierry et al, 1995). From a practical perspective, companies realize the potential benefits from product recovery operations in order to increase sales and hence profits. However, this positive effect of recovery operations is often overshadowed by fears of negative cannibalization effects, where consumers may substitute high-priced new products by lower-priced reprocessed products (Guide and Li, 2010; Atasu et al, 2010). Furthermore, the cost-efficient handling of product returns as well as their integration into the traditional production processes is a significant challenge for businesses. Beside these economical and ecological drivers, legislative regulations like the European WEEE Directive 2012/96/EU extend producers’ responsibility for their products by requiring them to finance the collection, treatment or disposal of their products by participation in a compliance scheme. Additionally, the WEEE directive requires the member countries to provide an adequate collection infrastructure, where consumers can return their obsolete products free of charge.

In our research work we cope with many of the points indicated above. In detail, this study investigates life-cycle planning of a product, i.e., laptops, facing a usage phase as a new and a subsequent second usage phase as a
refurbished item. An empirical analysis of actual market prices for new and refurbished laptops gives information on pricing of both kind of laptops. Based on these prices, an analytic model representing a typical life-cycle of a laptop is introduced which is used to analyze the impact of varying model parameters on profitability.

The laptop industry is chosen as a reference industry in this study, since there is a vivid market refurbished laptops on platforms like bestbuy.com, ebay.com, walmart.com or on OEM-run platforms. This provides us with large enough sample sizes, necessary for the empirical investigation. Based on evidence for the market of new and refurbished laptops, we seek to answer the following research questions:

- What are the drivers for market prices for new and refurbished products?
- How do consumers react on new and refurbished products’ prices and which implications does this have on an OEM’s profits?
- How should OEM’s react on changes in the return rate, as imposed by legislative initiatives?

In detail, our analysis concerning the pricing strategies of an OEM engaged in refurbishing operations is separated in two parts: first, we analyze market prices using an empirical study of the prices of a large US-based retailer of IT equipment. The empirical part analyzes the impact of several performance indicators of new and refurbished laptops on the prices of both new and refurbished laptops. In a second step, we formulate an optimization problem to maximize a product’s expected life-cycle profits, where a product is sold as new in a first period and may be sold as a refurbished product in a second period. By means of our model, we are able to obtain interesting insights on the interrelations between customer perceptions of new and refurbished products, targeted return rates as well as the structure of reverse channel. Using our model that is based on a real-world parameter setting, we conduct extensive numerical investigations.

The study is structured as follows: Section 2 provides insights into the market prices of new and refurbished laptops by considering several performance characteristics of laptops in an empirical study. Section 3 outlines the assumptions needed for the formulation of the model, provides a comparison of the approach with current scientific literature, and presents the
model framework. This section also includes an analytic solution to our production-refurbishment newsvendor model with market effects. Based on empirical data from the sample of new and refurbished laptops and by using real-world parameter estimates, the numerical analysis of our model in Section 4 gives managerial insights. Numerical studies provide insights into factors influencing the production decision and hence the profitability of an OEM, particularly with respect to strategic pricing decisions. Section 5 summarizes our main findings and concludes the paper.

2 An analysis of market prices of new and refurbished laptops

For a company engaged in reverse logistics operations, as for instance remanufacturing or refurbishing of its products, the pricing of these recovered products is of crucial importance (see for instance Liang et al, 2009; Wu, 2012). Since recovered products typically are offered at a lower price than new products, there is the danger that recovered product sales cannibalize new product sales. Therefore, as Guide and Li (2010) note, marketing of recovered products is a bottleneck that may discourage companies from selling remanufactured products.

In order to shed more light on observed market prices, we use regression analysis to explore how performance indicators determine prices for new and refurbished laptops. In contrast to Quariguasi Frota Neto et al (2016), who analyze determinants of market prices for new, remanufactured and used iPods using characteristics of ebay offers, we analyze price determinants of new and refurbished laptops using product-related characteristics only. Our dataset is comprised of laptops from Hewlett-Packard offered on bestbuy.com. First, by concentrating on laptops from one manufacturer, we avoided possible inconsistent pricing effects that may arise from different brand quality perceptions of consumers (Abbey et al, 2015). Second, Hewlett-Packard was chosen for reasons of data availability, in order to gather a sufficiently large dataset needed for the regression analysis.

An analysis of the market prices for both new and refurbished laptops indicates that the variability of prices is significantly higher for laptops in the high-end segment, while the variability is relatively low in the low-end segment. In order to address the problems that arise in regression analysis
with such behavior of the response, we use a gamma regression model for our analysis that assumes a constant coefficient of variation of the response variable. First, by dividing the data into equally large classes (e.g. quartiles or quintiles), we find that the coefficient of variation remains more or less constant. Second, by using Kolmogorov-Smirnov tests, the Null hypothesis, saying that the distribution of our price data coincides with samples of random variables of a fitted gamma distribution can not be rejected with an \( \alpha = 10\% \). Due to a relatively large proportion of equally priced laptops, we used a Bootstrap Kolmogorov-Smirnov Test (implemented in the R-package 'Matching') in order to cover the problems caused by the ties in the dataset. Based on our dataset, gamma distributions described the prices of both new and refurbished laptops sufficiently well. Table 1 summarizes the results of the regression models.

The regression analysis indicates that the estimated coefficients for ‘processor speed’ and ’standard memory’ are both lower for refurbished products than for new laptops. While, for instance, a 1% increase in the processor speed increases the expected price of a new laptop by around 0.86%, the same increase in processor speed would increase the price of a refurbished laptop only by around 0.32%.

The results of table 1 are interesting in several aspects: as Atasu et al (2010) argue, there are two customer segments on the market. ‘Newness - oriented customers’ are supposed to buy new products exclusively, while ’functionality - oriented customers’ value remanufactured products similar as new products. For this customer type, the price-discount is decisive for their decision if they buy a remanufactured product or not. The analysis of our dataset collected from offers on bestbuy.com, shows that this segmentation seems not to be incorporated in the prices. While indicators for the performance of a laptop lead to a higher increase in the prices for new laptops, indicators for a laptop’s newness, like a running version of Windows 8 or the type of the main drive (hard disc drive vs. solid state drive), show a higher influence on the prices for refurbished products. However, this result could be caused, to some extent, by the choice of the OEM. While the laptops in our sample are mainly high-end business laptops, consumer perception could be different when analyzing the prices from other suppliers with different brand-quality perceptions of customers.
Table 1: Results of gamma regressions using an identity link on the prices for new and refurbished products.

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>log(price\textsubscript{new})</th>
<th>log(price\textsubscript{ref})</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(Processor speed) [GHz]</td>
<td>0.85585(***)</td>
<td>0.31846(***)</td>
</tr>
<tr>
<td></td>
<td>(0.12041)</td>
<td>(0.07990)</td>
</tr>
<tr>
<td>log(Standard memory) [GB RAM]</td>
<td>0.71020(***)</td>
<td>0.44316(***)</td>
</tr>
<tr>
<td></td>
<td>(0.10057)</td>
<td>(0.03971)</td>
</tr>
<tr>
<td>Windows 7 [Dummy]</td>
<td>1.07872(***)</td>
<td>0.82871(***)</td>
</tr>
<tr>
<td></td>
<td>(0.14481)</td>
<td>(0.15845)</td>
</tr>
<tr>
<td>Windows 8 [Dummy]</td>
<td>0.69299(***)</td>
<td>0.95478(***)</td>
</tr>
<tr>
<td></td>
<td>(0.11393)</td>
<td>(0.15836)</td>
</tr>
<tr>
<td>Hard disc [Dummy]</td>
<td>-0.56752(***)</td>
<td>-0.69268(***)</td>
</tr>
<tr>
<td></td>
<td>(0.07716)</td>
<td>(0.08967)</td>
</tr>
<tr>
<td>log(Screen size) [inch]</td>
<td>2.28983(***)</td>
<td>2.22101 (***)</td>
</tr>
<tr>
<td></td>
<td>(0.08996)</td>
<td>(0.08047)</td>
</tr>
<tr>
<td>log(weight) [lb]</td>
<td>-0.98351(***)</td>
<td>-0.72453(***)</td>
</tr>
<tr>
<td></td>
<td>(0.17252)</td>
<td>(0.08989)</td>
</tr>
<tr>
<td>Observations</td>
<td>151</td>
<td>200</td>
</tr>
<tr>
<td>(R^2\text{Cox&amp;Snell})</td>
<td>67.95%</td>
<td>74.13%</td>
</tr>
</tbody>
</table>

Note that *** indicates a \(p<0.01\)

3 Model

In this section we focus on modeling an OEM operating in the laptop industry and performing refurbishment operations of her products. In order to reflect the production decision problem of the OEM, we formulate a news-vendor problem, where the demand for products can be influenced by strategic pricing. In our model, the product’s life-cycle consists of two phases: in a first stage, the new product may be sold. Subsequently, it eventually gets returned and refurbished, and may be sold as a refurbished product in a second stage. In order to reflect the two usage phases, we formulate a two-period model, where refurbishing quantities are constrained by (1) the availability of product returns, and (2) customers’ preferences whether to buy a new or
to wait to buy for a refurbished laptop.

Our analytic model differs from and extends previous studies in that area by several aspects. First we use the empirical findings of Ovchinnikov (2011) in order to model consumer behavior given a certain pricing strategy of an OEM. To the best of our knowledge no other analytic approach in CLSC-literature directly reflects these findings. Second, by considering discounting between the two time-periods, our model differs from many other studies in the CLSC literature, who study inter-temporal profit maximization problems using a steady state assumption (see for instance Blackburn et al, 2004; Guide et al, 2006; Li et al, 2012a; Reimann and Weihua, 2013; Shulman et al, 2011; Tibben-Lembke, 2004). Since Li et al (2012b) and Shi et al (2011) also analyze newsvendor models with price effects in the context of reverse logistics, these models are closely related to our work. While Li et al (2012b) simultaneously compute pricing and quantity decisions using a newsvendor framework, we derive prices for new and refurbished products from regression analysis and base the parameterization of our model on these empirical findings. Whereas Li et al (2012b) consider a profit maximization problem for a whole supply chain for fashion products, we formulate an OEM’s production decision problem for a specific product over its whole life-cycle. Shi et al (2011) investigate the impact of return and demand uncertainties on (re)manufacturing quantities, acquisition price, and sales price. Different from our model, the authors consider a single period setting without intertemporal effects. Additionally, in contrast to our study, Shi et al (2011) assume perfect substitution between new and remanufactured goods. Also, using similar modeling assumptions, Jena and Sarmah (2014) analyze the effects of stochastic return quantities of used products but focus on different types of acquisition structures.

In the following section, we discuss the guiding assumptions of the modeling process. The model framework and the corresponding formulation of the optimization problem are presented in Section 3.2. We conclude this section by presenting analytical model results in Section 3.3.

3.1 Model assumptions

**Assumption 1.** The objective of the OEM’s optimization problem is to maximize expected life-cycle profits of the product over two periods, where earnings from the second period are discounted by a factor $\beta$. 
Similar to white goods like washing machines (Lechner and Reimann, 2015) or toners (InfoTrends, 2011), laptops usually face two life-cycles, implying that they may get refurbished only once. This assumption is in line with reports on remanufacturing and refurbishing of computers (White et al, 2003), other closed-loop supply chain models (see, for instance, Ferguson and Toktay, 2006) as well as statements from refurbishing companies (Compuritas, 2015). This requires the formulation of a two-period model, where the refurbishing quantity is limited by the availability of returned cores, which in turn is determined by the sales volume in the first period. In this two-period setup, we need to account for the fact that computers quickly lose value over the course of time (Blackburn et al, 2004) and that there is a non-negligible time lag between sale of a new product and sale of the product when it was refurbished. Therefore, we discount earnings from the refurbishing period by a parameter $\beta$ mainly determined by the product’s lifetime duration.

**Assumption 2.** The OEM faces a production decision problem for new and refurbished products in a newsvendor-like environment. In this framework, the demand quantity is affected by the sales price.

In the strategic closed-loop supply chain literature, two kinds of modeling approaches are predominant: quantity-setting newsvendor frameworks which consider return flows of products (see, for instance, Drake et al, 2012; Lechner and Reimann, 2014; Chuang et al, 2014; Raz et al, 2013) and models involving vertical differentiation with a segmented market for new and recovered products. We refer to Souza (2013) and the references therein for an overview of the latter models as well as to Galbreth et al (2013). Chuang et al (2014) and Drake et al (2012) argue that newsvendor models are particularly appropriate for the analysis of joint production-refurbishing operations for products with short life-cycles. Therefore, due to the relatively short life-cycle of laptops, a newsvendor model seems to be especially suitable for our modeling purposes. While traditional newsvendor models assume a price-taking company with no price-setting power, market segmentation models consider a profit maximizing monopolist. Both types of modeling frameworks may not be perfectly appropriate when dealing with questions concerning the market for laptops, as the small number of OEMs in the market provides these companies with limited market power in terms of control of demand by making strategic pricing decisions. Thus, we use an extension of the basic newsvendor framework by considering that demand may be influenced by a company’s pricing decision and a random error. Our approach is inspired by an extension of
the common newsvendor problem which can be found in Petruzzi and Dada (1999). In such a modeling framework, a company first sets the price of a product, which determines the demand quantity. Facing the stochastic demand, the company offers the production quantity to the consumers. In our model, we set the prices according to the values obtained from our dataset consisting of new and refurbished laptops and study an OEM’s optimal production decisions.

**Assumption 3.** The demand for new and refurbished products, respectively, is modeled by functions that reflect the size of market segments of both product types and linearly decrease with the prices. The demand for new products depends to some extent on the price for refurbished products and vice versa.

While the assumption of a linear demand function is a standard assumption in the closed-loop supply chain literature (see for instance Savaskan et al., 2004), we assume in our model that the total market $M$ is divided into two groups: new products with a market size of $\delta M$ are sold at price $p$, while the size of the market for refurbished products is $(1 - \delta)M$ and refurbished products are sold at price $\hat{p}$. As the parameter controlling size of market segments, $\delta$, is influenced to some extent by the price discount of refurbished products, i.e. $(p - \hat{p})/p$, we use the results of Ovchinnikov (2011) in order to model customers switching behavior among the two market segments. Based on an empirical study, Ovchinnikov (2011) find that two effects need to be distinguished here: for small price discounts of the refurbished product, only few customers will be willing to change to refurbished products due to their relatively high price compared to the new product. An increasing price discount, however, will increase the market size of refurbished products. Beginning from a certain threshold level of the price discount, consumers will be deterred from buying refurbished products, since their low price indicated low quality. In order to resemble the results of Ovchinnikov (2011), we model the fraction of customers that would be willing to change from buying a new product to the refurbished product by the following relationship, where $a$ denotes the maximal fraction of customers that would make this change in their consumption decision:

Let $\theta$ denote the share of customer that would never consider to buy a refurbished product, the parameter controlling market sizes $\delta(p, \hat{p})$ for new products is $\delta(p, \hat{p}) = \theta \cdot (1 - a + (1 - 10a)/35 - ((1 - 10a)/7)) \cdot (p - \hat{p})/p$ for $(p - \hat{p})/p < 20\%$ and $\delta(p, \hat{p}) = \theta \cdot (1 - (a/0.2)) \cdot (p - \hat{p})/p$ for $(p - \hat{p})/p \geq 20\%$. With this parameter and a market size $M$, the demand functions for new and
refurbished products are \( d(p) = M\delta(p, \hat{p}) - b_{\text{new}} p \) and \( \hat{d}(\hat{p}) = M(1 - \delta(p, \hat{p})) - b_{\text{ref}} \hat{p} \). In these demand functions, we assume that \( b_{\text{new}} < b_{\text{ref}} \), which implies that customers willing to buy refurbished products are more price sensitive than customers who are only buying new products (Bakal and Akcali, 2006).

**Assumption 4.** Concerning the prices and costs, we assume that (I) \( p > \hat{p} \), (II) \( c_p > c_r \) and (III) \( p > c_p \) as well as \( \hat{p} > c_r \) holds, where \( p \) and \( c_p \) denote the price and unit production cost of new products and \( \hat{p} \) and \( c_r \) denote the price and unit refurbishing cost.

Since new products usually are offered for a higher sales price than refurbished products, the assumption \( p > \hat{p} \) is reasonable (Quariguasi Frota Neto et al, 2016). Unit production costs for new products typically exceed unit refurbishing costs due to technological progress, which causes prices for components needed for the refurbishing process to decrease over time. Furthermore, we assume that the profit per sold new or refurbished product is not negative. This assumption is needed to rule out trivial cases where the OEM would be better off stopping the production process.

**Assumption 5.** Per-unit new production cost \( c_p \) and refurbishing cost \( c_r \) are assumed to be constant. The OEM has to pay constant acquisition cost \( c_a \) in order to trigger returns from the market.

The costs associated with the production of new electronic products are to a large part independent from the production volume, as economies of scale are very limited since material costs are by far the largest cost factor (Reisinger, 2014). The assumption concerning refurbishing costs stems
from the fact that an OEM often can decide which of the returned cores get refurbished and which get disposed of. Thus, only returned items in a proper condition are refurbished, inducing that refurbishing costs can be approximated by a fixed cost factor. Note that this assumption is also in line with Atasu et al (2013), Galbreth and Blackburn (2006), and Savaskan et al (2004).

The constant cost parameter $c_a$ is motivated by the current practice of offering trade-in rebates for customers offered on OEM- or retailer-run platforms, like Hewlett-Packard or BestBuy.com for instance. After providing information concerning the old product’s condition an offer for acquiring the used good is made. Though, offers for the same product type are about the same level for products in different condition and can therefore be assumed to be constant.

Assumption 6. The OEM’s reverse channel structure is described by a parameter $\psi$, where $\psi = 0$ indicates that all returned goods are recycled by a third party recycling company. The case that $\psi = 1$ indicates that all returns are treated by the OEM.

The OEM in our model is faced to heterogeneous quality of products. For each returned products that is given to a recycling company, the OEM pays a fee $c_{rec}$. This assumption is in line with the schematic presented in Atasu et al (2013). A share of $\tau$ returned products can neither be refurbished nor recycled, so the OEM is required to pay disposal costs $c_d$; disposal can be necessary due to, e.g., technological or economical reasons (Fan et al, 2013; Wiens, 2012). Estimates for these cost coefficients can be found in Silicon Valley Toxics Coalition (2004).

3.2 Model framework and formulation of the OEM’s production decision problem

The objective function in our model reflects expected life-cycle profits of a certain product, where refurbishing operations are limited by the availability of returned cores from the previous period. The availability of returned cores is determined by sales of new products in the first period $S(q)$, multiplied by the return rate $\gamma$ and the fraction of returns $\psi$ that is in a sufficient condition to be refurbished by the OEM herself.

The error term $\epsilon$ reflects the stochastic deviations in demand. Therefore, demand is obtained from multiplying the demand function with the error
term, i.e. \(d(p) \cdot \epsilon\) and \(\hat{d}(\hat{p}) \cdot \epsilon\). Such a multiplicative error structure was chosen since, based on our empirical study on prices of new and refurbished laptops (see Section 2), the price variability turned out not to be independent from the price. In such a setting, an additive error structure would be inappropriate (Jammernegg and Kischka, 2013; Aydin and Porteus, 2008).

As assumed in the common newsvendor setting, an OEM is able to sell the production quantity of new (\(q\)) and refurbished (\(\hat{q}\)) products if production is lower than demand, i.e. \(q < d(p)\) or \(\hat{q} < \hat{d}(\hat{p})\). In the case of overproduction, i.e. \(d(p) < q\) or \(\hat{d}(\hat{p}) < \hat{q}\), the OEM will only be able to sell the demanded quantity. According to our modeling guidelines and similar to Petruzzi and Dada (1999), expected sales for new and refurbished products can be expressed in the following way:

\[
S(q) = \mathbb{E}\left\{ \begin{array}{ll}
q & q \leq [d(p, \hat{p}) \cdot \epsilon] \\
[d(p, \hat{p}) \cdot \epsilon] & q > [d(p, \hat{p}) \cdot \epsilon]
\end{array} \right.
\]

\[
S(\hat{q}) = \mathbb{E}\left\{ \begin{array}{ll}
\hat{q} & \hat{q} \leq [\hat{d}(\hat{p}, \hat{\hat{p}}) \cdot \epsilon] \\
[\hat{d}(\hat{p}, \hat{\hat{p}}) \cdot \epsilon] & \hat{q} > [\hat{d}(\hat{p}, \hat{\hat{p}}) \cdot \epsilon]
\end{array} \right.
\]

The expression of expected sales of new products (and analogously, the case very similar for refurbished products which is omitted) can be represented in the following way:

\[
S(q) = \int_0^{d(p)} \epsilon \cdot f(\epsilon) d\epsilon + q \int_{d(p)}^{\infty} f(\epsilon) d\epsilon = q - d \int_0^{d(p)} F(\epsilon) d\epsilon
\]

where \(F(\cdot)\) is the cdf of the distribution of the error term. We assume the error term \(\epsilon\) to be subject to a Weibull distribution; parameters were chosen in a way so that the distribution is symmetric and has \(\mathbb{E}[\epsilon] = 1\). Setting the skewness to zero, the shape parameter \(k \approx 3.602\) and fixing the mean at 1 leads to a scale parameter of \(\mu \approx 0.901\). Using the Weibull distribution, the term for expected sales has a closed form expression that can directly be obtained from the integral. This leads to \(S(q) = \frac{d(p)}{k \mu} \Gamma(\frac{1}{k}) - \Gamma(\frac{1}{k}, (\frac{\mu q}{d(p)})^k)\), with \(\Gamma(\frac{1}{k}, (\frac{\mu q}{d(p)})^k)\) denoting the upper incomplete gamma function. The derivative of \(S(q)\) is needed for the formulation of the first order conditions of the optimization problem. It can be obtained by applying the Leibniz theorem for differentiation of integrals and is given by \(S'(q) = 1 - F(q/d(p)) = \exp(- (\frac{\mu q}{d(p)})^k)\).

Using the terms for expected sales of new and refurbished products, the optimization problem can be expressed as follows:
The first part of the objective function describes earnings that arise from sales of the new product. $p$ denotes the sales price of new products, $c_p$ are unit production costs for new products. The term in curly brackets reflects prospective earnings from sales of the product in its second usage-phase in case that it is reprocessed. These earnings are discounted by a parameter $\beta$ that is determined by the time until initial sale and return of the product. $c_{rec}$ and $c_d$ denote the fees an OEM has to pay when giving products to a recycler or when disposing products, respectively. $c_a$ are product acquisition costs that the OEM has to pay in order to acquire the cores from the customers. Parameter $\gamma$ denotes the return rate and parameter $\psi$ is the fraction of returned products refurbished or disposed by the OEM. Figure 2 summarizes and illustrates the situation reflected by the model.

Concerning the solution method of the presented optimization problem we provide a planning heuristic without the possibility to make decisions.
after realization of first period’s demand. Therefore, we solve the problem by simultaneous optimization of the decision variables without decomposition of the periods. Please note that it can also be solved by assuming a stochastic dynamic program.

3.3 Analytical results

It can be shown easily that the system of Karush-Kuhn-Tucker conditions is necessary and sufficient for a global maximum of the optimization problem given in equation (3). For details we refer to Appendix A. The optimal values of the decision variables can then be derived directly from the system of Karush-Kuhn-Tucker conditions,

\[
q^* = \frac{d(p)}{\mu} \left[ \log \left( \frac{p - \beta \gamma (c_{rec}(1 - \psi) + c_d \psi + c_a) + \lambda \gamma \psi \tau}{c} \right) \right]^{\frac{1}{k}}
\]

\[
\hat{q}^* = \min \left( \frac{d(\hat{p})}{\mu} \left[ \log \left( \frac{\hat{p}}{c_r - c_d} \right) \right]^{\frac{1}{k}}, \gamma \psi \tau S(q^*) \right),
\]

where \( \lambda = \beta \left[ \hat{p} \exp \left( -\left( \frac{\mu q^*}{d(\hat{p})} \right)^k \right) - c_r + c_d \right] \).

The solution of the optimization problem given by equation (4) requires numerical solving of the system of nonlinear equations. We compute solutions by using the Levenberg-Marquardt algorithm implemented in Matlab Version R2015b. The solutions are computed by solving the nonlinear systems of equations for the case when the constraint is binding (\( \lambda \geq 0 \)) and the case where the constraint is not binding (\( \lambda = 0 \)). From these two possible solutions, we find the final solution of (4) by checking the feasibility of the constraints of the optimization problem. Using this procedure, we numerically calculate solutions to the OEM’s profit maximization problem.

However, it should be noted that these numerical results largely depend on the chosen parameterization of the model. Therefore, we use well-founded parameters for the numerical calculations, either based on real world examples, the presented empirical study or obtained from an exploration of the related literature. Table 2 summarizes the parameters and their base case values used for the numerical calculations.
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Base Case</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta$</td>
<td>0.6202</td>
<td>Discount factor for profits from refurbishing operations; with an average life of a desktop PC of 4 years (Microsoft Corporation, 2008) and a monthly interest rate of 1%, $\beta = 1/(1+i)^n \approx 0.6202$.</td>
</tr>
<tr>
<td>$\delta(p, \hat{p})$</td>
<td></td>
<td>The market segments for new and refurbished products are modeled according to Ovchinnikov (2011). We set $\delta(p, \hat{p}) = \theta \cdot (1 - a + (1 - 10a)/35 - ((1 - 10a)/7) \cdot (p - \hat{p})/p$ for $(p - \hat{p})/p &lt; 20%$ and $\delta(p, \hat{p}) = \theta \cdot (1 - (a/0.2) \cdot (p - \hat{p})/p$ for $(p - \hat{p})/p \geq 20%$, where $a = 20%$. A search query on ebay.com yielded a share of refurbished Lenovo laptops of 71.12%. Using the base case prices, we obtain $\theta = 95.55%$.</td>
</tr>
<tr>
<td>$p$</td>
<td>810.66</td>
<td>Price for a new laptop, calculated from our sample collected from bestbuy.com.</td>
</tr>
<tr>
<td>$\hat{p}$</td>
<td>375.58</td>
<td>Price for a refurbished laptop, calculated from our sample collected from bestbuy.com.</td>
</tr>
<tr>
<td>$c_a$</td>
<td>57.12</td>
<td>Based on several search queries on OEM or retailer run platforms like Hewlett-Packard, Dell or BestBuy, we set the acquisition cost to be 20% of the sales price of the refurbished laptop $\hat{p}$.</td>
</tr>
<tr>
<td>$c_p$</td>
<td>355.21</td>
<td>Unit production cost for a new product, calculated based on an argument in Reisinger (2014).</td>
</tr>
<tr>
<td>$c_r$</td>
<td>108.99</td>
<td>Unit refurbishing cost, calculated based on an argument in Ahiska and Kurtul (2014), such that $c_r \approx 0.29 \cdot \hat{p}$.</td>
</tr>
<tr>
<td>$k$</td>
<td>3.602</td>
<td>Parameter $k$ of the Weibull distribution is chosen such that the distribution is symmetric and $\mu$ was chosen such that $E[\epsilon] = 1$, i.e. $\mu = \Gamma (1 + \frac{1}{k}) \approx 0.901$.</td>
</tr>
<tr>
<td>$\mu$</td>
<td>0.901</td>
<td>Product return rate; the base case value is taken from the European WEEE directive, Directive 2012/19/EU.</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>45%</td>
<td>Fraction of product returns that can not get refurbished; the base case value was chosen according to an argument in Ferrer and Whybark (2001).</td>
</tr>
<tr>
<td>$\tau$</td>
<td>95%</td>
<td></td>
</tr>
</tbody>
</table>
\[ \psi = 29\% \]

Fraction of returned products refurbished by the OEM; In Kenney (2007) it is reported that around 12.4\% of new product sales are recovered by an OEM. Then, \( \psi = \frac{12.4\%}{(\gamma \tau)} \).

\[ c_d = 37.5 \]

Disposal cost for returned cores that are not refurbished; the estimate taken from Silicon Valley Toxics Coalition (2004).

\[ c_{rec} = 20.36 \]

Fee paid to a third-party recycler; the estimate taken from Silicon Valley Toxics Coalition (2004).

\[ M = 40000 \]

\( M \) denotes the total market size that is split into a segment of customers buying new (\( \delta \)) and \( (1 - \delta) \) products. Since Bakal and Akcali (2006) find that the customer segment willing to buy remanufactured products is more price sensitive than customers typically buying new products, a steeper slope was chosen in the demand function for remanufactured products.

\[ b_{new} = 4 \]

\[ b_{ref} = 5 \]

Using the base parameter setting, the constraint that limits the availability of product returns is binding, which implies a positive shadow price. Hence, in the base case scenario, the optimal refurbishing quantity is determined by \( \hat{q}^* = \gamma \psi \tau S(q^*) \). This parameter setting results in \( q^* \approx 31115 \) and \( \hat{q}^* \approx 3277 \), yielding a profit of 10,238,291.

4 Managerial Insights

The analysis of the model is divided into three parts: first, we analyze the implication of an OEM’s reverse channel structure. Second, we study the impacts of different sales prices of new and refurbished products. As these results are to a large part driven by consumers reaction on the OEM’s sales prices, we analyze the implications of different shares of consumers that would switch to buy a refurbished item in the third part.
4.1 Impact of return and refurbishing rates on an OEM’s profit

In contrast to the literature on reverse channel choice (see for instance Toyasaki et al, 2011; Atasu et al, 2013; Govindan et al, 2012; Das and Chowdhury, 2012), our study assumes that the reverse channel can not be influenced by the OEM. As the reverse channels are to a great extent influenced by legislative requirements, OEMs often cannot freely design the reverse channel for their products. Thus, the fraction of returned cores that is refurbished by the OEM, recycled or disposed is exogenously given. The EU’s WEEE directive, for instance, requires OEMs to participate in a collection system that finances the collection, reprocessing or proper disposal of returned electronic products. Therefore, we study the profit effects of different fractions of product returns an OEM can refurbish on her own.

Figure 3: Effect of varying return rate $\gamma$ and varying fractions of returned cores refurbished by the OEM $\psi$ on profit.

The analysis of our model highlights the interrelationship of the level of the return rate $\gamma$ and the parameter $\psi$ that determines the reverse channel
structure. With $\psi = 29\%$ as assumed in the base case scenario, an increase in the return rate has two effects: first, due to relatively small refurbishing amounts, the OEM would be able to sell all refurbished products and hence, refurbishing would have a positive impact on profits. However, in our setting, quantities that are recycled are very high in this situation which incurs significant recycling costs. As this effect dominates, an increase in the return rate has a negative impact on profits for low values of $\psi$. However, this effect may change, when the OEM could increase her level of $\psi$ and hence increases refurbishing operations compared with the situation discussed above. In such a situation an increase in the return rate could also have a positive impact on profits. Note that for relatively low value of the return rate the profit maximizing combination of $\gamma$ and $\psi$ can be found in the right lower corner; this is mainly determined by the OEMs marketing capabilities of refurbished products. In the right upper corner of figure 3, where both $\gamma$ and $\psi$ are very high, profit decreases with a further increase of both parameter, since the market shows an increasing degree of saturation.

4.2 Pricing new and refurbished products

Caused by consumers’ reaction on the price discounts of refurbished products compared to new products, i.e. $(p - \hat{p})/p$, very low prices of $\hat{p}$ will deter consumers from buying refurbished products, since consumers will infer low quality (Ovchinnikov, 2011). Driven by this effect, we differentiate in our analysis of the impact of strategic pricing of the OEM between several situations: while profits tend to increase with rising prices of new laptops due to a relatively large market size, figure 4 demonstrates the importance of the interplay between $p$ and $\hat{p}$ on the potential profitability of refurbishing operations. In the lower left corner an increase in the price of the refurbished product $\hat{p}$ would have a positive impact on profits, as consumers would deduce that the refurbished product is of higher quality. When the price of the refurbished product is increased even higher, this effect could be reversed since demand is a decreasing function of the price. Interestingly, this result is influenced by the price level of the new product $p$. Whenever sales prices of the new product are high, revenues are primarily generated by new product sales, and product recovery operations are less important for the OEM. In these situations an increase in the price of the refurbished product would generate a higher demand for refurbished laptops (due to consumers’ increased quality perceptions), resulting in a higher $\hat{q}$ and in a lower $q$. For
laptops with high sales prices, our model therefore provides evidence for the existence of negative cannibalization effects.

Figure 4: Effects of various prices of the refurbished and new product on profits.

4.3 Consumer reaction towards new and refurbished laptop prices

As the results from the previous sections are mainly driven by consumers’ reaction towards prices of new and refurbished laptops, this section sheds more light on the optimal response of the OEM concerning her product recovery operations.

Figure 5 demonstrates how the OEM should adapt her product recovery operations for changes in consumers’ reaction towards prices of new and refurbished laptops. Figure 5 shows that optimal refurbishing quantities will tend to fall when the percentage of customers willing to switch to refurbished product \( a \) increases. As in our calculations the availability of returned cores are a limiting factor for product recovery operations, an increase in \( a \) will directly lead to decreased production quantities of new products and hence to fewer returned cores and a smaller number of refurbished laptops.
Figure 5: Effects of various prices of the refurbished and new product on profits.

5 Conclusions

The work presented in this paper aims to contribute to life-cycle planning literature particularly for products with potential product recovery, i.e. laptops and other electronic equipment. We consider an OEM with limited market power, where the OEM may refurbish returned products which are in appropriate condition. In order to account for inter-temporal effects that arise with a product’s different usage phases, we formulate a two-period newsvendor model with price-sensitive demands. The approach reflects customers’ perception towards new and refurbished products, their reaction towards different price discounts of the refurbished product compared to the new product and the fact that a company’s refurbishing operations are restricted by the returns from first period sales. The results emphasize that the model is an efficient approach to understand the impact of interrelated usage-phases and consumers’ attitude toward refurbished products on profitability of closed-loop supply chains.
In a first step, we use regression analysis to analyze the drivers of market prices of new and refurbished laptops offered on bestbuy.com. The regression models provide partial elasticities of product-related characteristics on prices. Based on the price data from a large US based retailer of consumer electronics, we find that characteristics related to the newness of laptops have a higher impact on prices of refurbished laptops, while performance-related indicators have a higher impact on the prices of new laptops.

In a second step, we study a two-period newsvendor model with price-dependent demand, where demand for new and refurbished products is influenced by both customers’ perception towards new and refurbished products and the price discounts of the refurbished product compared to the new product. In order to gain realistic insights from our model, the underlying parameterization is based on the price data from our empirical study, evidence from the laptop industry as well as research papers. The analysis of our model highlights the interrelations between refurbishing fractions and the return rate as well as the prices for new and refurbished products. Our results show that the impact of changes in the return rate as required by current legislation in the EU, may or may not have a positive impact on an OEMs profit. If this effect is positive or negative is mainly determined by the OEM’s reverse channel structure. According to our model, an increase in the return rate will have a negative impact on the OEM’s profit if the fraction of returns the OEM refurbishes is small. If the level of the return rate is low and refurbishing fractions of the OEM are high, an increase in the return will have a positive effect on the OEMs profits. However, starting from a certain threshold level, a further increase in the return rate would have a negative impact on profits as the market gets more and more saturated.

An analysis of the implications of different prices of new and refurbished products on the OEM’s profits reveals interesting relations between the two price levels. While in our parameterization an increase in the price of the new product leads to higher profits, the impact of the price of refurbished products is mediated by the new product’s price. As expected, the numerical calculations assuming high priced new products and low priced refurbished products show that revenue is mainly generated by new product sales. Interestingly, when the price of the refurbished product is increased in such a situation, consumers would get more confidence in the quality of the refurbished product. Then optimal refurbishing quantities would increase at the expense of new product which leads to a decline in profits.

Of course, our study is subject to several limitations. Concerning the
empirical study, we only analyze the pricing decisions of one retailer for one brand. However, it would be interesting to compare the price drivers for several brands and several retailers, as different brand perceptions of customers will likely play an important role. Additionally, if demand data were available, demand functions could be estimated directly, which, on the one hand, would make the analysis of models as ours much more realistic, and, on the other hand, would allow for an evaluation of the efficiency of prices offered on platform like ebay.com or bestbuy.com. Concerning our analytic model, we assumed that both prices of new and refurbished products as well as the parameter determining the fraction of returned cores that are refurbished by the OEM are deterministic parameters. An interesting aspect for further research could be to relax this assumption by considering them as decision variables. Another extension of the model presented in this paper could analyze the effects of competition among stakeholders in a reverse supply chain. This aspect could effectively be modeled for instance by formulating variational inequality models similar to Qiang (2015), Toyasaki et al (2014), and Wakolbinger et al (2014).
A Necessary and sufficient conditions

Solving the system of Karush-Kuhn-Tucker conditions is necessary for a maximum of the objective function, since the there exist \( q' \) and \( \hat{q}' \) such that the inequality sign of the constraint holds strictly and thus Slater’s constraint qualification holds (Bazaraa et al, 2006). The Karush-Kuhn-Tucker conditions are sufficient for a maximum since the constraints form a convex set (note that \( S(q) \) is concave since the second-order derivative is negative whenever \( d(p), q, k, \mu > 0 \) holds) and the objective function is concave. The concavity of the objective function holds whenever \( p > c + \beta \gamma (c_{rec} (1 - \psi) - c_d \psi + c_a) \) holds, which is automatically true for \( q \) to be non-negative in the optimal solution.

The system of Karush-Kuhn-Tucker conditions is as follows:

\[
\frac{\partial L}{\partial q} = p \cdot e^{-(\frac{a}{\bar{p}})^k} - c_p - \beta \gamma e^{-(\frac{a}{\bar{p}})^k} (c_{rec} (1 - \psi) + c_d \psi - c_a) + \lambda \gamma \psi \tau \leq 0
\]

\[
\frac{\partial L}{\partial q} \cdot q = 0
\]

\[
\frac{\partial L}{\partial \hat{q}} = \beta \hat{p} e^{-(\frac{a}{\bar{p}})^k} - \beta c_r + \beta c_d - \lambda \leq 0
\]

\[
\frac{\partial L}{\partial \hat{q}} \cdot \hat{q} = 0
\]

\[
\frac{\partial L}{\partial \lambda} = \gamma \psi \tau S(q) - \hat{q} \geq 0
\]

\[
\frac{\partial L}{\partial \lambda} \cdot \lambda = 0
\]

\[
\lambda \geq 0
\]

\[
q \geq 0
\]

\[
\hat{q} \geq 0
\]
References


