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Determining the Optimal Donation Acceptance Policy for Nonprofit Stores

Robert Shearer, Kelly Carpentier

Pepperdine University

Many nonprofits derive a considerable amount of their financial support through the resale of donated items. Given the razor thin margins at which many of these organizations operate, it is critical that they maximize the proceeds that come from the sale of these items. In order to do so, nonprofits require policies that guide their donation acceptance decisions so as to optimize revenue generation. This paper presents research into determining the optimal donation acceptance policy for Habitat for Humanity. Habitat affiliates sell donated material at their ReStores, or discount home improvement centers, and the revenue from the ReStores directly supports the building of new homes. Several constraints limit the revenue that the ReStores derive from the donated items, to include the supply rate of items from donors, the demand rate of items from customers, and the space limitations of the ReStores. We develop a two-step method to determine the optimal acceptance policy - the daily amount of donations to accept in order to maximize revenue. This approach increases revenue by up to 20% and additionally provides insights into pricing options, marketing strategy, and optimal store size.

Keywords: inventory management, donations, optimization, simulation

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Nonprofit organizations obtain the revenue needed to fund their operations from a range of sources. These sources include government grants, private contributions, and commercial activities (Kerlin and Pollak, 2011). Sales of inventory, a subset of commercial activities, are an important source of funding as many nonprofits derive much of their revenue through the resale of donated items. The Salvation Army collected $625 million in sales at their Home Stores in 2012, accounting for 15% of their revenue that year (Salvation Army). Goodwill generated $3.5 billion in 2012 from sales in their stores, 82% of which went directly into mission services (Goodwill, p. 3). Habitat for Humanity affiliates generated a profit of $76 million in 2012 from more than 750 ReStores in the United States (Habitat for Humanity International, p. 4). These organizations and others require donation acceptance policies to determine which items to accept as donations for resale, if they are to efficiently manage their resources in support of their missions. Habitat for Humanity builds and repairs homes for low income families. Essential to these efforts are their ReStores, discount home improvement centers, which can generate more than half of an affiliate's revenue. The ReStores accept donations of new or gently used, surplus or salvaged materials. The donated items are resold at prices far below retail and donors receive a tax deduction in return. The supply rate of donations typically exceeds the demand rate for material, so the manager of a ReStore has to decide which items to accept as donations and which to reject. The problem faced by the manager is not trivial; both the supply and demand for material are random with considerable variability from day to day, and yet the importance of this source of revenue should not be overlooked.

This paper presents recent efforts by the authors to develop a donation acceptance policy that maximizes revenue for a ReStore. We develop a two-step method to determine and evaluate this policy. First, we formulate a mathematical model to determine the optimal policy under fixed conditions. This model identifies the number of items by type that should be accepted each day to maximize revenue, subject to the demand, supply, and space constraints faced by a ReStore. We assume the fixed conditions to make the problem tractable, despite knowing that conditions are variable and also understanding this assumption will overestimate future revenues. Second, we develop a simulation to model the suggested policy under actual, varied conditions. The simulation yields the range of revenue that we should expect from day to day, allows us to compare alternative policies, and also provides insight into the optimal size for a ReStore.

Literature Review

The inventory problem faced by a ReStore is to determine which donations to accept. These decisions will determine how much inventory is available for the ReStore to sell to their customers and how much revenue can be generated to build more homes. Inventory control is no new problem to the business world. The most common method used is the economic order quantity (EOQ) model that determines how much inventory to order and when to order the inventory. Harris (1913) first derived the EOQ in his seminal article, “How many parts to make at once.” EOQ determines the optimal order quantity by minimizing the relevant costs of inventory. Researchers for decades have built upon Harris’ work, expanding the method to include quantity discounts, backorders, stock-outs, perishable products, variable demand, and other issues. The inventory problem for a ReStore is slightly different. Whereas a for-profit firm either orders or produces their inventory, Habitat receives their inventory exclusively as donations. Rather than deciding when to order the inventory and in what amount, a ReStore has to decide which offered items to accept. We have adopted the term economic acceptance quantity, or EAQ, to designate the amount of donations by type and number that a ReStore should accept in order to maximize revenue.

Despite the extensive development of inventory control methods in the for-profit world, there is no corresponding work in the nonprofit literature. Numerous articles have addressed peripheral donation issues, but none have considered actual acceptance policies. We now turn to those papers that considered issues related to the determination and implementation of an optimal acceptance policy.

Several researchers have considered the dynamics between revenue and donations. Gronbjerg (1991) examined the difficulties that nonprofits experience in generating revenue. She found that nonprofits prefer monetary donations over other sources of revenue, as donations tend to come with fewer restrictions. This preference was tempered by the additional risk that nonprofits incurred when relying on donations, due to the uncertainty of their availability. Despite their preferences, many nonprofits do receive numerous non-cash donations. Optimal donation acceptance policies would provide nonprofits with a method in which to derive as much revenue from these donations as possible.

Kingma (1995) considered the interrelationship between donors, donations, profits, sales, and prices. He found that prices crowd-out donations, as increased prices and profits result in decreased donations. Interestingly, increased revenue from other sources crowd-in donations, as increased grant revenue results in increased donations. Kingma suggests that donors may view nonprofits that receive government support as more reliable. Hughes, Luksetich, and Rooney (2014) argue that the crowd-out debate is far more complex. They argue that the size of the nonprofit, the source of the donations, and the type of government funding all impact the crowd-in/out effect. Researchers have also investigated the relationships between nonprofits and their donors. We would not expect an optimal donation policy to have either a significant crowd-in or crowd-out impact. Donors and customers might notice a change in the items that the nonprofit accepts and offers for sale, but sale prices would not change and the accompanying increased revenue would not be directly visible to donors.

Sargeant (2001a) examined the causes behind donors lapsing in their support for a nonprofit. His survey of donors in the United Kingdom found that donors' support lapses for a wide variety of reasons, but that nearly half either shifted their support to another cause or could no longer financially afford to donate. Sergeant (2001b) proposed that nonprofits take a relationship approach toward donors by considering each donor's lifetime value. This is calculated as the net present value of all future contributions (revenue minus cost) from each donor. He suggests that this approach could help nonprofits develop their fundraising strategies by quantifying the value of their donors. We'd recommend that nonprofits build on Sergeant's work, and not just consider the long term potential of a donor, but also determine which donors will offer the most valuable donations. An acceptance policy would help identify these donors. Boenigk and Scherhag (2014), also building on Sergeant's research, considered the impact of donor priority strategies on fundraising. They found that these strategies lead to increases in both donor satisfaction and loyalty. Understanding which donors offer the most valuable donations could help a nonprofit develop the most effective priority strategy.

Finally, Abner and Gazley (2013) conducted an empirical assessment of a national product donation program. They proposed that non-cash donations place additional requirements on the nonprofit, as the recipient organization has to process, transport, and store the donated items. Donated building and home improvement products, the types of items donated to a ReStore, prove even more problematic. Their assessment, the only one found in the nonprofit literature on this topic, surprisingly found that these challenges do not diminish with experience. The challenges faced by nonprofits in handling non-cash donations further argues for squeezing every possible dollar from these donations. Helping store managers identify which items to accept and in what quantity should help allow for a reallocation of capacity to where it is most needed.

These efforts by researchers have all helped nonprofit organizations to better understand the central role that donations play in their operations, but without providing direct guidance as to which donations to accept. This paper attempts to fill this gap in the literature. We do not offer new theoretical advances to the field of inventory management, but rather apply proven quantitative methods to obtain a solution to the unsolved nonprofit inventory problem. The structure for the rest of the paper follows. We present the two quantitative methods used to determine the optimal policy: linear programming and discrete event simulation. A simple example is provided to illustrate the application of the two methods. We then review and interpret the results of the simple example. We also discuss the broader implications of the model, to include numerous implementation issues. We close the paper with a discussion of our current efforts to apply EAQ with two Habitat affiliates.

Method

The problem of determining the EAQ is known in applied mathematics as an optimization problem. An optimization problem consists of an objective function that one seeks to maximize (or minimize) subject to various constraints. As an illustration, consider a farmer who produces apples and bananas. Every day he fills his bag with apples and bananas and sells them at the market. The problem that the farmer faces each morning is to decide how many apples and bananas to take to the market. If the farmer can sell each apple for \$2 and each banana for \$1, then his revenue will equal $\$2A + \$1B$, where A and B equal the number of apples and bananas placed in the bag. He seeks to maximize his revenue, leading him to this objective function.

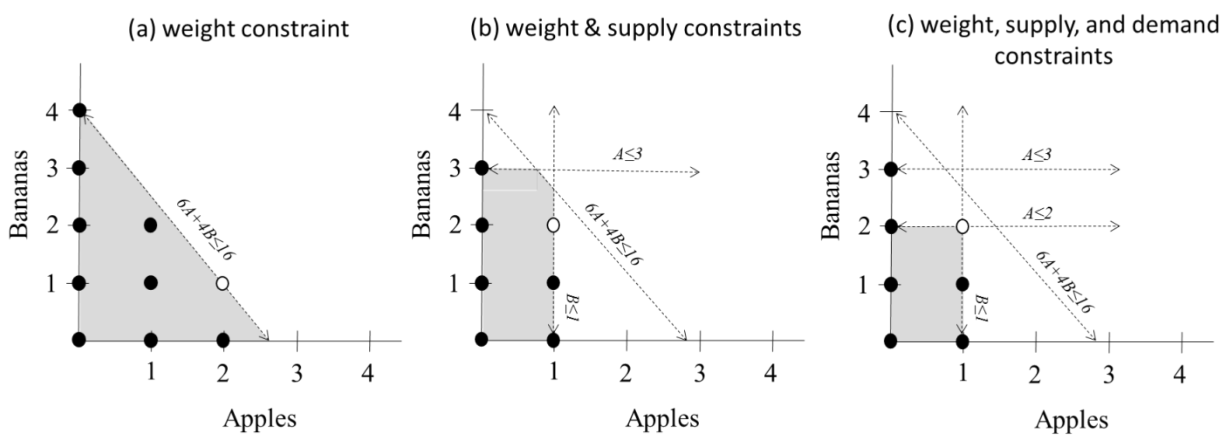
$$max\ \ 2A + 1B$$

But, of course, the bag cannot carry an infinite number of apples and bananas; the farmer must decide what mix of the two to put in the bag. If each apple weighs 6 ounces and each banana weighs 4 ounces, then the total weight of the fruit equals $6A + 4B$. If the bag can carry at most 16 ounces, then the farmer has the following weight constraint.

$$6A + 4B \leq 16$$

Denoting each apple banana combination as (A,B), we see that the farmer has ten feasible options: (0,0), (0,1), (0,2), (0,3), (0,4), (1,0), (1,1), (1,2), (2,0), and (2,1). All other combinations violate the weight constraint. Figure 1 shows graphical representations of the optimization problem faced by the farmer with different constraints. Graph (a) depicts the optimization with the weight constraint.

Figure 1. Farmer's Fruit Optimization Problem



Note: The three figures show the farmer's problem under different constraints. Feasible regions (constraint compliant) are shaded grey. Feasible combinations of apples and bananas are shown as black dots; the optimal combination is shown as a white dot. Notice that the feasible region shrinks as more constraints are added to the problem.

The farmer is limited to non-negative combinations of (A,B) that do not violate the weight constraint. This feasible region is shaded grey. Possible whole numbered (A,B) combinations appear as black dots. The combination (2,1) is the optimal solution, yielding the farmer $5 in revenue, and appears as a white dot. No other feasible (A,B) combination yields greater revenue for the farmer. If he only has one apple and three bananas, then the farmer must also consider two supply constraints.

$$A \leq 3 \quad and \quad B \leq 1$$

Graph (b) depicts the optimization with the weight and supply constraints. Notice the additional constraints reduce the feasible combinations from ten to seven. The new optimal combination is at (1,2), with revenue of $4. If the farmer expects to sell no more than two apples, then he must also consider one demand constraint.

$$A \leq 2$$

Graph (c) depicts the optimization with the weight, supply, and demand constraints. The optimal combination remains at (1, 2) with revenue of $4. Additional constraints will always either worsen or have no effect on the objective function. A ReStore, while seeking to maximize revenue subject to space, supply, and demand constraints in a manner similar to the farmer, faces a far more complex problem in two ways. First, they have many item types to consider, not just apples and bananas. This is not a serious problem, as it only prevents us from graphically portraying the problem. The algorithms used to obtain the optimal solution are unaffected by the number of item types. Second, and more significantly, the ReStores have to deal with the fact that both the supply and demand constraints are random, changing from day to day. This difference is not trivial, as the constraints are both unknown and variable, expanding and contracting the feasible region daily. No solution to the problem exists that is optimal every day.

Simplified ReStore

We created a simplified version of a ReStore in order to illustrate the determination and evaluation of the optimal acceptance policy. Two local ReStores classify their merchandise into fourteen categories. The top three revenue producers for 2011 were furniture, hardware, and appliances. These three produced nearly one half of the revenue that the stores received, so we limited ourselves to a ReStore that accepts only these three types of items. Historical data from 2011 was obtained and referenced so that the simplified ReStore had comparable supply and demand rates, prices, and size ratios. Our simplified ReStore has only 150 cubic feet of available space and carries three types of items: F (furniture), H (hardware), and A (appliances). Each item F sells for \$50 and takes up 20 ft^3. Each item H sells for \$10 and takes up 1 ft^3. Each item A sells for \$25 and takes up 2 ft^3.

Table 1. Simplified ReStore Characteristics

Item	Type	Price (\$)	Size (ft^3)	Demand	Supply
F	Furniture	50	20	7	9
H	Hardware	10	1	9	35
A	Appliance	25	2	20	12

We assume that the number of donors and customers per day for each item type follow Poisson distributions. The Poisson distribution is commonly used to model the number of arrivals (donors and customers) that occur within a fixed time period when the arrivals are independent and arrive at a constant average rate. Average supply and demand rates for all three item types were estimated from the historical data. Modeling the number of donations and purchases as random variables allows us to capture the variability that the ReStores experience from day to day. This simplified store has several key aspects in common with the actual ReStores. First, average supply of items exceeds average demand for some items, necessitating a method to determine which items to accept. Second, none of the items are donated in sufficient number to fill the ReStore, so the optimal solution will include a mix of item types.

Optimization

We formulated an optimization problem to determine the optimal policy for the simplified ReStore. We sought to identify this policy by determining the EAQ that maximizes revenue over a day subject to supply, demand, and space constraints. The randomness inherent in the rates of supply and demand for items makes such a formulation difficult. We therefore assumed that the supply and demand rates were constant, or deterministic, and equaled their 2011 averages. We also assumed that the price for each item type was constant and equal to their 2011 averages. The simulation will later allow us to remove these assumptions and reintroduce the daily uncertainty into the problem. The optimization then takes the following formulation.

$$
\begin{array}{llll}
\max & 50F + 10H + 25A & & \text{objective function} \\
 & F & \leq 7 & \text{demand constraints} \\
 & H & \leq 30 & \\
 & A & \leq 10 & \\
 & F & \leq 9 & \text{supply constraints} \\
 & H & \leq 35 & \\
 & A & \leq 12 & \\
 & 20F + H + 2A & \leq 150 & \text{space constraint} \\
 & F, H, A & \geq 0 & \text{non-negativity constraint}
\end{array}
$$

The ReStore seeks to maximize the objective function, or revenue, based upon the number of items accepted and their prices. The demand constraints restrict the items accepted to no more than the number of items the ReStore expects to sell. The supply constraints restrict the items accepted to no more than the number of items the ReStore expects donors to offer. The space constraint prevents the total volume of items accepted from exceeding the space available in the store. The non-negativity constraint restricts the number of items accepted to non-negative values. Note that although supply exceeds demand for all items in the simplified ReStore, the general form of the optimization does allow for demand to exceed supply in some items, providing flexibility to determine the EAQ for other nonprofit stores. *Simulation*

We developed a simulation in Simio© that models the operations in our simplified ReStore to evaluate the EAQ. Based upon the variability observed in historical data, the simulation mimics the real world behaviors of donors and buyers at the ReStores.

Donors randomly arrive and attempt to donate their items for sale at the ReStore. Items are accepted as long as (1) the daily EAQ has not been reached for that particular item and (2) there is space for the item in the store. The ReStore shows three items in inventory. Accepted items are added to the ReStore's inventory for future sale; rejected items depart from the ReStore. Customers randomly arrive at the ReStore and attempt to purchase items from the store. If the inventory is available, a buyer will purchase and then remove the item from the inventory. The simulation tracks the total revenue, the revenue generated by each item type, the total space used by the inventory, and the space used by each item type. The advantage that the simulation provides is that we are able to reproduce a large number of "normal" days for the ReStore. Donors and customers arrive in varied numbers based upon historical data. These varied inputs (demand and supply rates) produce varied outputs (revenue). Through simulation of daily operations, we are able to estimate the distribution of revenue that the ReStore should expect.

The EAQ is near optimal for a specific store size, so we created an experimental design to examine the relationship between the size of the store (space available for inventory) and the revenue generated. The design varied the space available for inventory from 50 ft^3 to 300 ft^3. The design also compared the revenue generated under three scenarios: deterministic EAQ (dEAQ), random EAQ (rEAQ), and random Current Acceptance Policy (rCAP). The first scenario, deterministic EAQ, assumes donors and customers arrive according to the historical demand and supply rate averages. Donation acceptance decisions are made based upon the EAQ. This scenario identifies the maximum amount of revenue that one could expect under EAQ. The second scenario, random EAQ, models donor and customers rates with Poisson random variables, capturing the true variability in the ReStore's daily operations. Donation acceptance decisions are made based upon the EAQ. This scenario determines the range of revenue that one would generate with EAQ. The third scenario, random CAP, also models donor and customers rates with Poisson random variables. Items are accepted if there is space available in the store, which is the current ReStore policy. This scenario determines the range of revenue that one would generate with the current policy. The local ReStores are open for eight hours a day and averaged just over twenty-one days open per month in 2011. We modeled one month of operations in each simulation run. Ten replications were conducted for each space setting in order to capture the range of possible revenue values. The simulation starts with the ReStore empty, so it was necessary to have a 100-hour warm-up period to populate the store before we started tracking revenue.

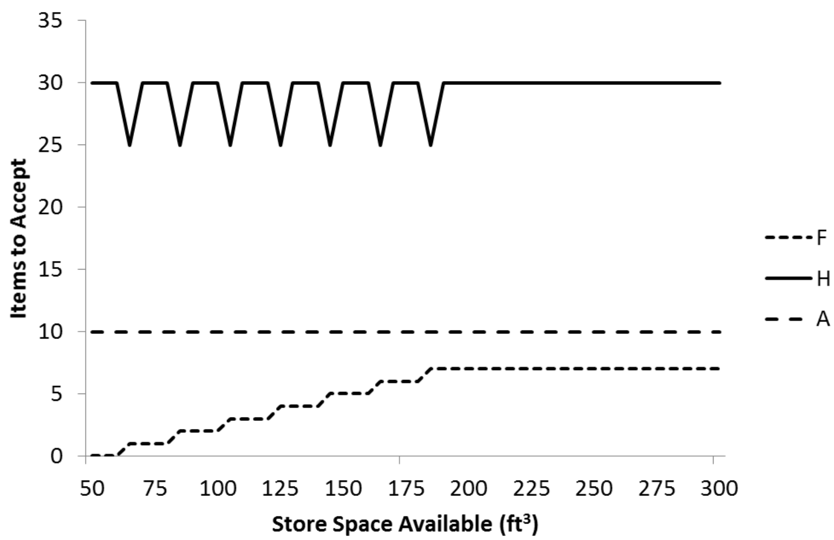
Results

The results from the optimization and simulation follow. Again, we obtained the optimization results from a simplified, deterministic model of inventory and obtained the simulation results from a more realistic model with inherent variability.

Optimization

The optimization yielded the solution, EAQ = (5, 30, 10) for the 150 ft^3 store. The store manager should daily accept up to 5 items of type F, 30 items of type H, and 10 items of type A. This solution yields average revenue of $17,215 per month and uses all 150 ft^3 of available space. Optimization models also offer three additional insights beyond the solution that optimizes the objective function. These insights are gained through conducting sensitivity analysis on the problem parameters. First, we considered what impact changes in the prices would have on the EAQ. The price of each item F could vary from $0 to $200 without changing the EAQ; the price of each item H could vary from $2.50 to any larger amount without changing the EAQ; and the price of each item A could vary from $5 to any larger amount without changing the EAQ. These ranges would provide a ReStore manager with flexibility in pricing and identify when the EAQ would need to be recalculated. Second, we identified which constraints were binding. Binding constraints are constraints that are met at the optimal solution. Changes in binding constraints change the optimal solution. None of the supply constraints were binding, so additional items offered by donors would have no effect on revenue. Two of the demand constraints (H and A) and the space constraint were binding. If the ReStore could increase demand for either item or obtain more floor space, then revenue would increase. Third, we determined the increase in revenue that unit increases in the value of each constraint would cause. These values are referred to as shadow prices. Shadow prices for non-binding constraints are zero, as increases in non-binding constraints have no effect on revenue. The shadow prices for the binding constraints were $7.50 (H), $20 (A), and $2.50 (space). If we could increase the demand for item A from 11 to 12 per day, then the revenue would increase by $20. The information from these last two insights could help inform the affiliate on how to market their inventory, showing where increased demand most increases revenue. We then solved the optimization for the range of store sizes called for in the experimental design. Figure 2 shows the EAQ for these different sized stores.

Figure 2. Impact of Store Size on EAQ



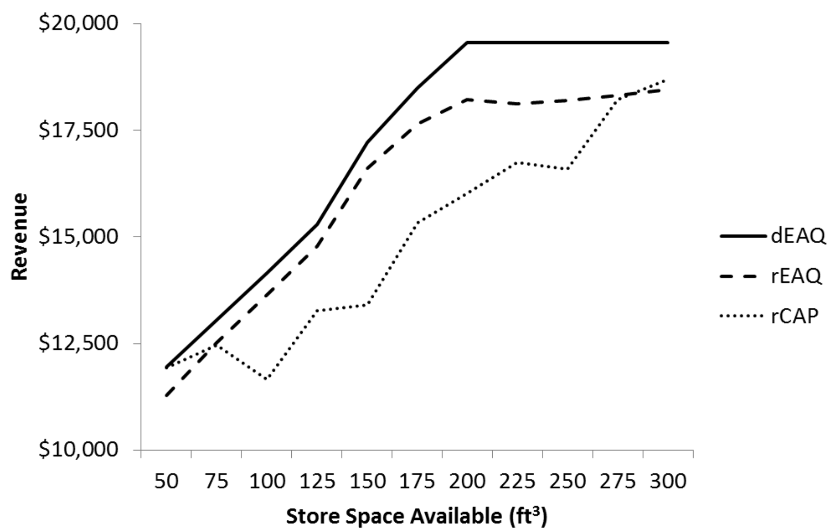
Note: The optimal number of each item type to accept depends on the store space available.

The number of items of type F to be accepted increased from zero to seven as the store size increased. The number of items of type H varied from twenty-five to thirty. This is a function of the optimization exchanging item types in order to maximize revenue. The number of items of type A to be accepted was ten, that is, the expected daily demand, for all store sizes. This is not surprising as item A has the greatest price to size ratio, yielding the greatest revenue per cubic foot of store space.

Simulation

Figure 3 shows the average revenue generated by scenario and store size. Three points on the graph are marked for discussion.

Figure 3. Impact of Store Size and Policy on Revenue



Note: The revenue generated under each model depends on the store space available.

As expected, the deterministic EAQ scenario (dEAQ) generated higher average revenue than the other two scenarios. The maximum possible revenue fell just below $20,000 and required a store with at least 200 ft^3 (point 1). The random EAQ scenario (rEAQ) outperformed the random CAP scenario (rCAP) except when the store was too small or too large. When the ReStore has inadequate capacity (supply is insufficient to meet demand), the EAQ policy is more likely to under fill the ReStore (point 2). When the ReStore has excess capacity (supply exceeds demand), the buyers were nearly always able to purchase their desired items, making the two donation acceptance policies equivalent in terms of the revenue that they generate (point 3). The improvement from changing the acceptance policy from the CAP to EAQ yields up to a 20% increase in revenue. But note that this is only for a right-sized store. As discussed earlier, when a store is too small or too large, the EAQ is no longer optimal. The EAQ then not only provides an optimal acceptance policy for the ReStore, but also identifies the correct size for the store. The ideal store size for the given supply and demand rates was 200 ft^3, generating $1600 per month more in revenue than the 150 ft^3 store. Stores larger than 200 ft^3 return no more revenue, but would likely have higher rents.

Discussion

It is important to interpret both the optimization and simulation results together. Th e former identifies the optimal EAQ policy while the latter specifies the range of plausible revenues that policy would yield.

Optimization

The optimization yields an EAQ solution that a store manager could easily implement as donors arrive at the ReStore with items for the store. The manager should accept up to the EAQ and no more, provided space exists in the store. But the optimization provides insights into the ReStore's operations beyond the optimal acceptance policy. The range of allowable prices that would still yield the same EAQ provide a store manager with flexibility in pricing items and also identify when the EAQ would need to be recalculated. The shadow prices could be used to determine which items to market to the local community. Resources should first be applied to advertise those items with the greatest shadow prices, as they would yield the greatest increase in revenue.

Simulation

The simulation provides the ReStore manager with the distribution of revenue that the EAQ is expected to yield. It is important to understand not just how much revenue to expect on average, but also to grasp how much variability the revenue will exhibit. Given that Habitat uses the revenue from the ReStores to finance the building of new homes, knowing how often and by how much a ReStore will under-perform will likely prevent poor financial decisions by the organization. The simulation also yields an unexpected capability: the ability to determine the optimal size of a ReStore. Knowing how large each store should be is a critical piece of information that Habitat executive directors have not had in the past.

Implementation Issues

How then should a nonprofit implement the results of the EAQ model? It would be a mistake to view EAQ as a solution only for Habitat ReStores. The proposed methodology is applicable to all nonprofit donation acceptance policies as long as both the supply and demand for items are variable and outside the control of the nonprofit. The magnitude of the improvement in revenue generation exhibited in the example provided should not be viewed as guaranteed for all situations. Some stores will see a greater increase, others less. Rather, the insight to be taken from the simplified ReStore example is that gains can be made with a more efficient policy.

It would also be a mistake to view the acceptance policy as hard numbers that should be strictly enforced. Store managers should have the flexibility to make adjustments to the policy. Donations from frequent, valued donors should not easily be dismissed only to follow the EAQ.

The model doesn't capture the fact that not all donors are equal. Nonprofits have established relationships with their supporters that should not be quickly thrown aside. High valued items should almost always be accepted, while low valued items should almost always be rejected, regardless of EAQ. It is also important to recognize that many of these stores serve purposes beyond revenue generation. The store manager that we support also views her store as providing a low-cost alternative to Home Depot for the local community. In such a situation, the store manager might want to set minimums for the number of each item type that the store maintains. This will reduce revenue, but help the nonprofit achieve its other purpose for the store.

Additional resources are required for a nonprofit to determine their store's EAQ. Historical data are needed to estimate the demand and supply distributions for each item type that they accept. The volume available in the store (minus walk-around space) and the volume required for each item type must also be determined. The optimization step can be solved in Excel with the Solver add-in. Gass (1970) provides the classic introduction to linear programming for those unfamiliar with this optimization technique. The simulation step will most likely require assistance from business / engineering faculty or a consultant. However, only the optimization is needed to determine the EAQ; the simulation is needed only if one seeks to predict the increased revenue or determine the optimal store size. One potential solution to the modeling challenges would be have personnel at the nonprofit's headquarters conduct the analysis for local affiliates.

Should all nonprofit stores invest the time and effort required to determine and implement EAQ? We doubt that many stores are operating near the optimal policy, but there are costs in determining the EAQ that may not be offset by the increased revenue that comes with implementing the EAQ. We suggest that store managers consider two simple metrics to determine whether their store is a candidate for this methodology. First, the ratio of unit price to size provides insight into how much revenue the store is obtaining for the space taken up by the item. If there is a wide range of ratios across the store's item types, then implementing EAQ is recommended. Second, the turnover rate of the store provides insight into the optimal store size. If several weeks pass before a store turns over, then the store is too large and determining the optimal store size with EAQ is recommended.

Current Applications

One of the authors is currently assisting two Habitat for Humanity affiliates, one in southern California and one in southern Virginia, in determining and implementing the appropriate EAQ policies for their ReStores. The California affiliate operates two ReStores, both of which reside in leased buildings. The affiliate is interested primarily in determining the optimal store size as they consider possibly moving their stores at the end of the current leases. They are currently collecting data to provide estimates for the average demand and supply rates for all fourteen item types. The stores maintain hand written receipts for both donations and sales, so while the required data exists, consolidating it into an easy-to-use format requires time and people. ReStores with computerized transaction could easily generate the needed data with little effort. The manager of the two ReStores, who participated in both the data collection and model building efforts, strongly supports the modeling efforts, stating, "This is the type of analysis that we should have conducted two years ago before we opened our second ReStore. We would have saved the money to build at least two more homes."   The Virginia affiliate does not currently operate any ReStores, but is investigating the possibility of opening one in the near future. They are most interested in what size store is optimal for their location and how much revenue they could expect to generate from the store. Their challenge lies in the fact that they have no historical data from which to forecast future supply and demand rates. We expect that this is a common situation for many Habitat affiliates. One possible solution to their problem is to aggregate similar data from the surrounding affiliates. Another is to find a ReStore with similar donor and customer demographics and utilize their data.

Conclusions

We have developed a two-step method to determine and evaluate the optimal acceptance policy for a Habitat for Humanity ReStore. The method has been shown to yield revenue up to 20% greater than revenue generated under the current acceptance policy. The resulting policy is straight forward and simple for ReStore personnel to implement, identifying the number of each type of item to accept as donations per day. This method could easily be modified for use with other nonprofits that also generate revenue through the resale of donated items. Given the dependence that many of these organizations have revenue from donated items, it is essential that they maximize these revenue streams. The approach also provides insight into several other aspects of a store’s operation, to include pricing, marketing, and future store selection. ReStores are not static operations. Periods of excess inventory require sales to free floor space. Sensitivity analysis would provide a range for price reductions and shadow prices could help managers decide which items to advertise. Significant changes in either the demand for or the supply of donations could also lead to the need to relocate to a larger of smaller facility. This approach allows executive directors to identify the optimal store size for their area and predict future revenue for alternative store locations. Many nonprofit organizations depend on revenue from the resale of donated items. The efficient determination of which items to accept will improve not just their financial position but also their ability to provide services to their communities.

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