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A Procedure to Set Prices and Select Inventory in Thinly Traded Markets Using Data from eBay

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Abstract: Prices respond to equate supply and demand. However, price-setting in low-volume or “thin” markets is a challenge as is determining which items to carry. We present an algorithm that takes into account a store’s fixed costs, the cost of goods sold, prices, and listing duration to determine the portfolio of items to maximize profits. Prices can then be assigned as a mark-up over cost. The usefulness of this approach is demonstrated by applying it to a store on eBay in which the seller needs to meet a profit threshold. The findings identify how sellers of unusual items can effectively determine which items to list and how to set price to reach profit goals.

Keywords: pricing; market volume; portfolio profitability; Poisson model

JEL Classification: D4 (Market Structure and Pricing); L1 (Market Structure; Firm Strategy; and Market Performance)



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1. Introduction

A thin market is characterized by few buyers and sellers with few transactions (Armstrong 2006). Artwork, antique collectables, and real estate are often traded in thin markets (Knight 2002). In contrast, a thick market has high trading volume in which prices equate supply and demand (Acemoglu 2007). Understanding how to set prices is especially important when trading in markets with unusual items in which few are sold. (Khezr 2015).

Prices in thin markets tend to be volatile because suppliers often guess when choosing what to charge (Coslor 2016). Lacking the robust pricing rules used in thick markets (Hanson 2003), prices in thin markets use algorithms (Tesauro and Kephart 2002; Yu et al. 2011). Most algorithms focus on fixed costs (Deng and Yano 2006) or macroeconomic variables such as GDP, employment rates, interest rates, or price indices (Cirman et al. 2015). Profits can also be volatile in thin markets with sales of very few items determining gain or loss. Sellers of items in thin markets face the challenge of building portfolios of items and setting prices to reach profit goals (Severini 2017). The choice of inventory to accumulate and sell in thin markets typically fails to account for the duration of shelf time and the timing of cash flows that substantially influences small businesses’ survival (Elmaghraby and Keskinocak 2003). In addition, the advent of e-commerce has increased the need to understand, and potentially improve, how prices are set in low volume long-tail markets (Kendall and Tsui 2011).

The present paper presents an algorithmic approach that sets prices for a portfolio of thinly traded items subject to a cash flow constraint. The algorithm is applied to data from a seller of unique items on eBay to demonstrate how to implement the methodology.

2. Method

The nonsmoothness of sales in thin markets can be modelled as a Poisson distribution. An event is the sale of a single item in the store. This contrasts with typical sales models in

which transactions include multiple items purchased at the same time. The probability of a given number of items selling in a month is given by,

$$\text{Pois}(\lambda) = \frac{\lambda^k e^{-\lambda}}{k!},$$

where k is the number of items sold and λ is the expected frequency of sales. The probability of at least k items being sold (“ProbSold”) is 1 minus the cumulative distribution function (CDF) of the distribution.

Sales frequency is affected by the quantity of goods available to sell, the portfolio of goods that vary in their demand, and prices for each type of good. One can solve for the types of goods to list by modifying [Guadix et al. \(2011\)](#) to include a fixed-cost threshold that must be met every month and segmenting the listed items into one of four categories: (1) high profit, sold fast (HF); (2) high profit, sold slow (HS); (3) low profit, sold fast (LF); (4) low profit, sold slow (LS).

3. Results

We obtained data from a vintage auto parts store on eBay to demonstrate the above method. The store owner obtains parts from junkyards, refurbishes them, and lists them for sale. The customers are individual car owners and repair shops. The uniqueness of listed items means that there are few competitors and therefore uncertainty about market-clearing prices. The data are a sample of 319 items sold over three months of approximately 5000 that the seller has listed. The data include part type, shelf duration, listed price, and item cost. These data were used to calculate gross profit (sale price – item cost). The store owner also shared his estimated monthly fixed costs, but was unable to supply the costs of the time spent sourcing parts, cleaning and refurbishing them, researching prices, and packing and mailing items. The algorithm below is easily modified to reflect these additional costs.

3.1. Listed Items and Duration

The average revenue per sale was USD 19.62 (SD = USD 73.73) and average cost of goods sold was USD 8.56 (SD = USD 7.28). This produced average gross profit of USD 111.06 (SD = USD 68.37). The average listing time prior to sale was 14.1 months (SD = 11.89). The sample of 319 items was used to reflect the population of 5000 items used in the analysis.

We parameterized the Poisson distribution using a month as the event period and the event as the number of items sold per month. The parameter λ is the expected frequency of monthly sales. The dataset shows this to be 68.65. The probability of at least k items being sold in a month is $1 - e^{-68.65} \sum_{i=0}^{[k]} \frac{68.65^i}{i!}$ as shown in Figure 1.

The value $\lambda = 68.85$ for items sold per month maximizes expected gross profit (the product of expected items sold at an average gross profit per item of USD 111.06), earning the owner USD 5798. The value of lambda is scalable with listing quantity, showing that listing more items generates more revenue and profit (Table 1).

Table 1. The maximum expected gross profit increases with increased listings.

Listed Quantity	319	600	900	1200	1500	1800	2100
Lambda (λ)	68.65	129.14	193.70	258.27	322.84	387.41	451.97
Maximum expected gross profit	USD 5798	USD 11,633	USD 18,045	USD 24,559	USD 31,142	USD 37,775	USD 44,444

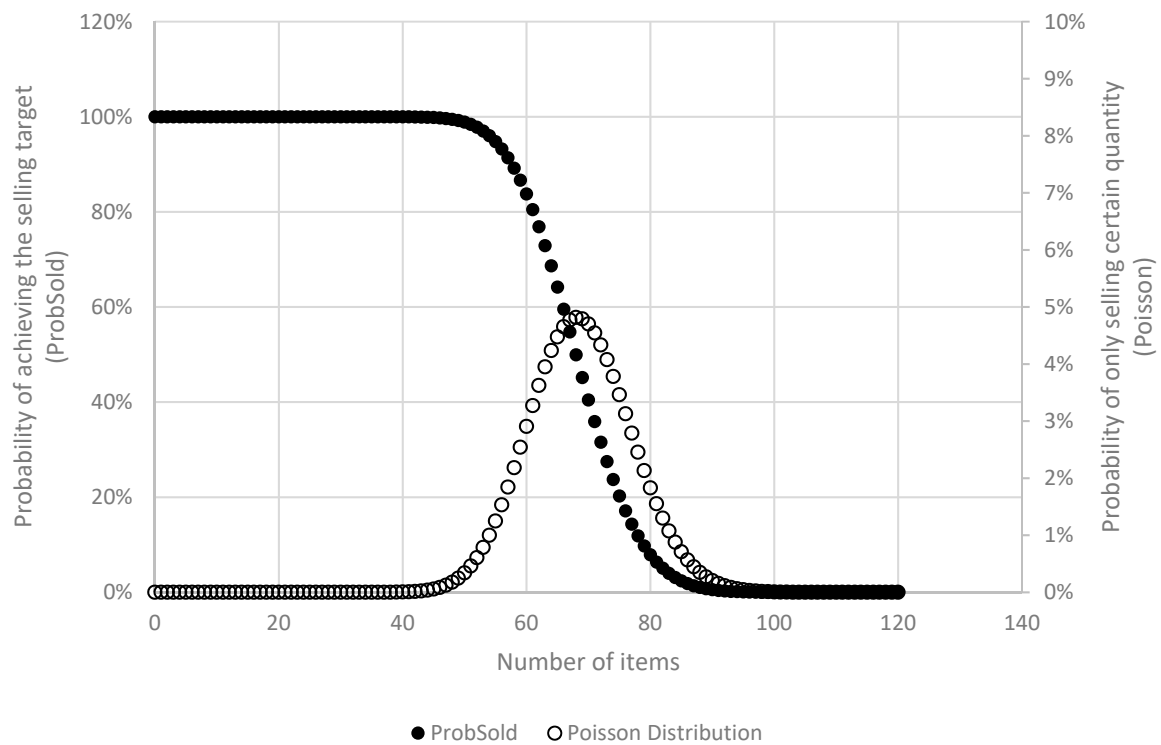


Figure 1. The Poisson distribution for $\lambda = 68.65$ showing the probability of selling at least k items in a month.

3.2. Determining the Distribution of Listed Items

The store owner faces a binding revenue constraint that, prior to this analysis, he sought to reach by guessing the types of items to list each month. This experience-based assessment can be complemented by a data-driven algorithm. We used the store's monthly fixed costs, listing price, historical listing time, and cost of each item to develop an algorithm to select items to meet a profit goal. We wrote code that iterates the number of items in each class, extending a previous approach (Guadix et al. 2011). The procedure, written in SAS v 9.4 software, first calculates the cost per item and assigns a portion of the store's fixed costs (USD 2000) to each item in the store. The assigned fixed cost per item is multiplied by the number of months each item remains in the store unsold. Then, the assigned fixed cost per item is compared to the item's gross profit. The item is kept in the portfolio if the gross profit is greater than its cost. This process continues until the portfolio contains only items that generate positive profits. The code converged after 10 iterations, producing a portfolio of 81 items. The flow chart in Figure 2 depicts how the algorithm builds the portfolio. Appendix A shows the iterative process in detail and includes the SAS code.

The optimized portfolio of items varies considerably from the seller's current inventory. High profit items H ($=HF + HS$) make up 71.60% of the optimized mix compared to 50.47% in the seller's current store. Low profit items L ($=LF + LS$) are 28.40% of the new mix, compared to 49.53% previously. Nearly all of the high profit items sell fast in the optimized portfolio and there are no low profit slow selling (LS) items. The proportion of each product class in the optimal mix is shown in Table 2.

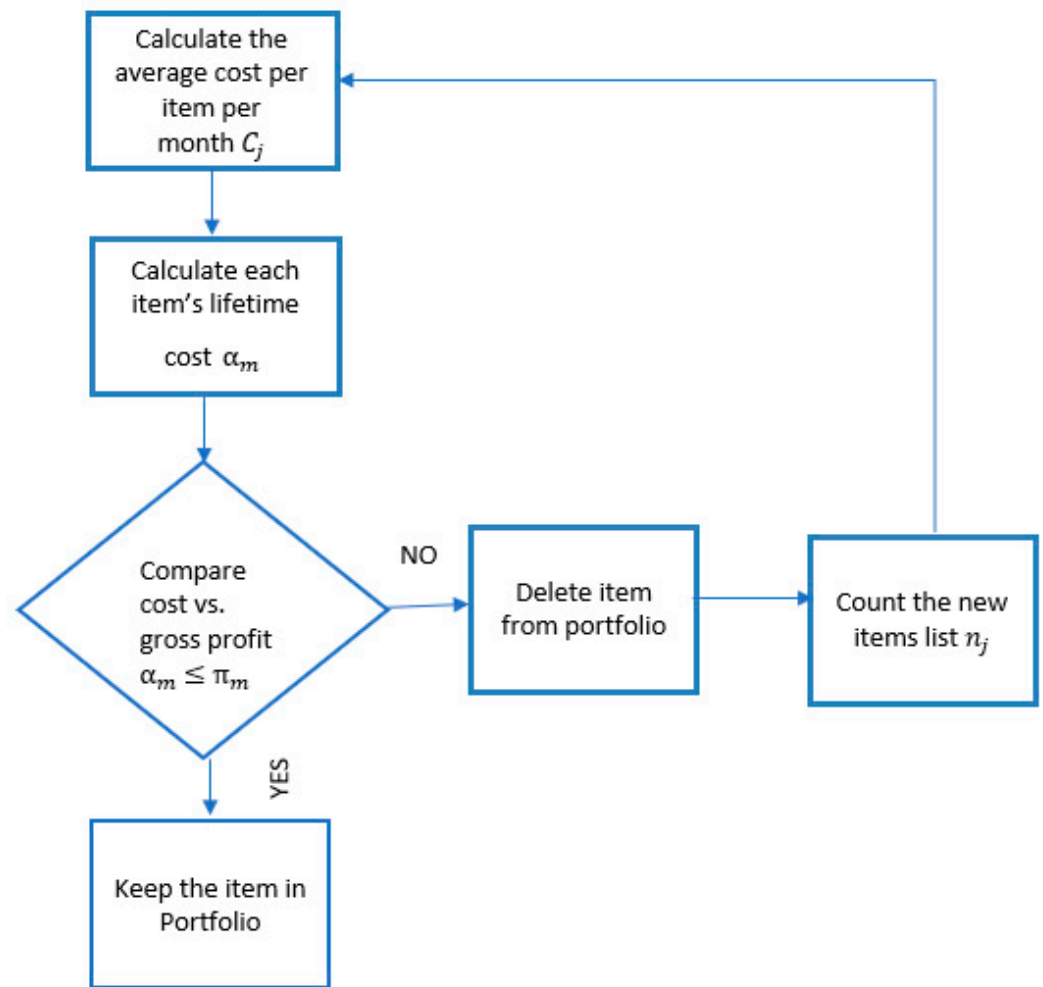


Figure 2. Flow chart of portfolio screening process.

Table 2. The distribution of the optimal portfolio of items. Gross profit and cost are the contribution to overall profit and the cost of goods sold. Weighted profit is the percent of gross profit multiplied by average gross profit (USD 140.57).

Median Split Category	Gross Profit	Item Cost	Weighted Profit (per Item)
High profit, sold fast (HF)	70.37%	50.62%	USD 104.85
High profit, sold slow (HS)	1.23%	1.23%	USD 22.43
Low profit, sold fast (LF)	28.40%	48.15%	USD 5.93
Low profit, sold slow (LS)	0.00%	0.00%	USD 0.00

The optimized portfolio has an average cost of items sold of USD 9.11 (SD = USD 7.41) and an average gross profit per item of USD 140.57 (SD = USD 67.18). The average profit in the optimal portfolio is 26.6% higher than in the seller's present portfolio (*t*-test, $p = 0.0003$). The new portfolio has an average listing duration of 2.81 months (SD = 1.99) compared to 14.1 months for current listings (Figure 3); this is an 80% reduction in turnover duration ($p = 0.0000$). The total expected monthly profit for the optimized portfolio is USD 4052.02 (USD 140.57*81/2.81) that is 61% higher than original monthly profit of USD 2512.63 (USD 111.06*319/14.1). Further, the algorithm we developed reduced the standard deviation of duration by 83.3%. Every month, approximately 81 new items would be added to the store's inventory (Table 2).

In the optimized portfolio, compared to the original set of items, the duration of parts for cars from the 1990s was significantly lower ($p = 0.048$) as was the duration of items for cars from Japan ($p = 0.0172$).

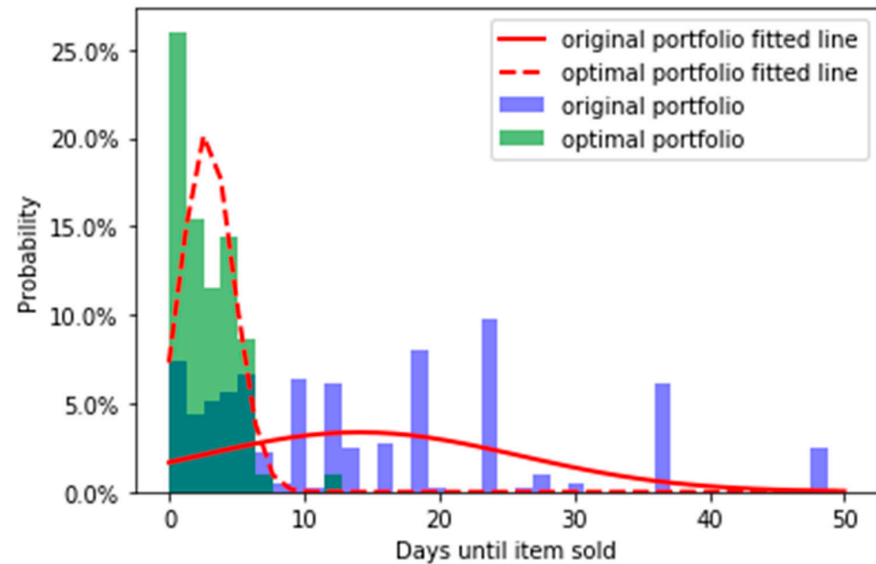


Figure 3. The histogram of duration for original and optimal portfolio.

3.3. Duration and Prices

One way to determine prices is a linear markup over cost. Estimating a linear regression using the original set of listed items (Figure 4), the average markup over cost is 668%. The estimated pricing equation is

$$\text{Item Price} = 53.877 + 7.6822 \times \text{Item Cost}.$$

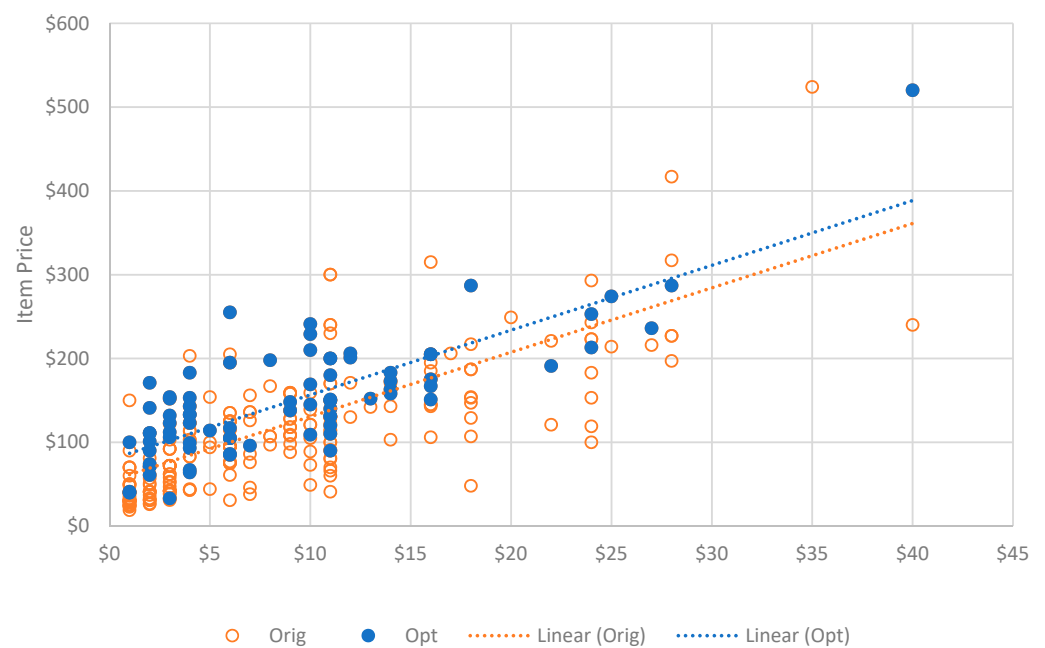


Figure 4. The relationship between cost and price for the original (Orig) and optimal (Opt) portfolio.

In the optimized portfolio, the average markup over cost is 673%. The pricing equation is

$$\text{Item Price} = 79.23 + 7.7322 \times \text{Item Cost}.$$

Using the number of items sold per month (69) and the optimized distribution of item types (Table 2), the optimized listings include 49 HF and 20 LF items. Assuming the markup of each group follows the same ratio, the markups are 821% for HF and 335% for LF goods.

The correlation between price and duration in the optimized portfolio was 0.56, substantially higher than the 0.04 correlation in the original portfolio ($z = 4.67$, $p = 0.0000$). The higher correlation was due to the selection algorithm.

4. Discussion

The growth of eBay and other online stores has been phenomenal. In 2019, USD 22 billion of goods were sold on eBay from 1.3 billion listings and 182 million users (Lin 2020). In the US, 40% of items sold on eBay were used rather than new. Setting a price of items with high volume is easy—one simply searches eBay to establish the average and range of prices. However, sellers in thin markets have a paucity of information on prices and must also choose a selection of items to source and sell. Our contribution provides online and physical retailers in thin markets with an algorithmic approach to stocking their stores.

The algorithm developed in this paper offers sellers of items in thinly traded markets a methodology to improve the distribution of items sold, while at the same time increasing the likelihood that profit thresholds are met. The algorithm can select the type of items to list by calculating the profitability of item categories and is relatively straightforward to implement (Appendix A). The approach we have developed can easily be generalized to include additional costs, including storage, overhead, administrative, utilities, and taxes.

The optimal portfolio did not sacrifice the seller's high per item markup. Indeed, the markup that maximizes profits was shown to be higher than that currently used. Prices in thin markets are typically only weakly correlated with demand (Sudhir 2001). An additional insight from our approach is that the seller should avoid listing LS (low profit, sold slow) items. The algorithm thus provides a screen that reduces the sourcing, cleaning, and listing of LS items, eliminating an entire class of inventory to manage. The cutoff for LS items can be varied from the median split used here by assessing the profit contribution of such items when they sell. An exception to this rule could be rare or antique items that might sell slowly but could drive visitors to a store as a form of advertising (Barney and Hesterly 2014).

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Data Availability Statement: The data contain personally identifiable information and must be kept confidential.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Iterative procedure to build portfolios of HS, LS, HF, HS items.

1. Let n_j be the number of items kept in the portfolio and let j be the number of iterations ($j = 0, 1, 2, \dots$).
 - a. when $j = 0$, $n_0 = 319$.
2. Let C be the total cost of items based on current cycle's portfolio.
 - a. $C_j = \text{cost} / n_j$

3. Let α be the cost of an item, T be the duration of the listing, m be the index of items kept in the j th cycle. The cost to source an item is assumed to increase in proportion to duration based on data from the original portfolio,
 - a. $\alpha_m = C_j * T_m$
4. Compare each items' profit π_m vs. cost α_m such that if $\pi_m > \alpha_m$, keep the item in the portfolio. Otherwise, delete the item from the portfolio.
5. Recalculate n_j
6. Repeat this process until there is no $\pi_m < \alpha_m$ to obtain the final optimal portfolio.

SAS code

```

1. proc import out=my_Ebay
2. datafile='C:\SAS\Ebay'
3. dbms=xlsx replace;
4. sheet="Orig data"my_Ebay
5. run;
6.
7. /*Add column of 1/T=orig d*/
8. data my_Ebay;
9. set my_Ebay;
10. orig_d=1/Dur__Months;
11. run;
12. sheet="Orig data";
13. run;
14.
15. proc contents data=my_Ebay;
16. run;
17.
18. /*Add column of 1/T=orig_d*/
19. data my_Ebay;
20. set my_Ebay;
21. orig_d=1/Dur__Months;
22. k=_N_;
23. fact_k=fact(k);
24. run;
25.
26. /*calculate the total orig d*/
27. proc sql;
28. select sum(orig_d)/count(*) into: final_d
29. from my_Ebay;
30. quit;
31. %put &final_d.;
32.
33. /*test count*/
34. proc sql;
35. select count(*) from my_Ebay;
36. quit;
37.
38. /*calculate p*/
39. data my_Ebay;
40. set my_Ebay;
41. p=exp(-&final_d.)*(&final_d.*k)/fact_k;
42. run;

```

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