Full length article

Probabilistic selling vs. markdown selling: Price discrimination and management of demand uncertainty in retailing ☆

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ABSTRACT

Markdown selling (i.e., price reductions over the course of the selling season) is a strategy to implement price discrimination and to manage market uncertainty that has been widely adopted by retailers. This paper explores the potential advantage of introducing an additional tool to the arsenal of retailers, probabilistic selling (i.e., offering consumers a choice to buy a product that can turn out to be any item from a predetermined set of distinct items). We show that both probabilistic and markdown selling strategies serve as price discrimination tools by offering buyers an option to purchase a "damaged" good (an uncertain product under the former and delayed consumption of a product under the latter). However, the two strategies segment markets based on different types of buyer heterogeneity: buyer preference strength under probabilistic selling and buyer patience under markdown selling. Our analytical model reveals that, compared with markdown selling, probabilistic selling can (1) improve margin management by increasing revenue from full-price sales and reducing the magnitude of discounts; and (2) improve inventory utilization by reducing stockouts and the amount of excess inventory. We identify the conditions required for probabilistic selling to be more profitable than markdown selling.

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1. Introduction

In an effort to obtain the maximum profit across a diverse set of customers, retailers often offer price reductions over the course of the selling season. It is estimated that one-third of all goods are sold at marked-down prices (Friend & Walker, 2001) and discounts due to markdowns by US retailers amount to $200 B a year (Levy, Grewal, Kopalle, & Hess, 2004). Although costly, markdowns can be a valuable tool for improving profit margin management because they allow the retailer to price discriminate across time, i.e., sell the product at a high price early in the season to customers who value the product highly and are unwilling to wait, and at a discounted price later in the season to customers who are willing to delay their purchases (Besbes & Lobel,

2012; Nair, 2007; Su, 2007). The markdown strategy can also enhance inventory management for retailers who are unable to accurately predict consumers' demand for each particular product (Lazear, 1986), e.g., by starting with a high price and reducing the price if units of the item remain unsold. Retailers are continually searching for more efficient ways to improve margin management and enhance inventory utilization.[3] In this paper, we consider one such alternate selling mechanism, namely probabilistic selling (PS), and show that there are situations in which this mechanism can be advantageous relative to traditional markdowns both in enhancing price discrimination and in overcoming the main problems associated with demand uncertainty, namely stockouts and excess inventory.

A probabilistic product is an offer involving the probability of obtaining any one of a set of multiple distinct items (Fay & Xie, 2008). Probabilistic selling (PS) is a selling strategy under which the seller creates probabilistic goods using the seller's distinct products or services and offers such goods to potential buyers as additional purchase choices. Notable examples of sellers of probabilistic products include priceline.

[3] Previous research has focused on developing sophisticated dynamic markdown algorithms (e.g., Bitran & Mondschein, 1997; Chung, Flynn, & Zhu, 2009; Mantrala & Rao, 2001; Sullivan, 2005), implementing inventory management systems (Friend & Walker, 2001; Khouja, 1995; Ross, 1997), and identifying alternate ways to dispose of distressed goods, such as via off-price retailers and outlet stores (Coughlan & Soberman, 2005; Levy & Weitz, 2004, p. 56; Petruzzi & Monahan, 2003) or online auctions (Wang, Gal-Or, & Chatterjee, 2009; Wood, Alford, Jackson, & Gilley, 2005).

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Table 1
Related literature and distinguishing characteristics of current paper.

Research focus	Research paper	Methodology [a]	Endogenous variables		Consumers optimally time purchase	Probabilistic good can cannibalize full-price sales
			Price	Capacity		
Developing theory and applications of probabilistic (opaque) selling strategy	Current paper	AM, LE	Yes	Yes	Yes	Yes
	Fay and Xie (2012)	AM	Yes	Yes	No	No
	Fay (2008)	AM	Yes	No	No	No
	Fay and Xie (2010)	AM	Yes	No	Yes [b]	Yes
	Fay and Xie (2008)	AM	Yes	No	No	No
	Jiang (2007)	AM	Yes	No	No	No
	Shapiro and Zillante (2009)	LE	No	No	No	No
	Jerath et al. (2010)	AM	Yes	No	Yes	No
	Zouaoui and Rao (2009)	E	Yes	No	No	Yes
Developing decision support system to implement probabilistic (opaque) selling strategy	Granados et al. (2008)	AM, E	Yes	No	No	Yes
	Post (2010)	AM	Yes	No	No	Yes
	Anderson (2009)	AM	Yes	No	No	No
	Anderson and Xie (2012)	E	Yes	No	No	Yes
	Gallego and Phillips (2004)	AM	No	No	No	No
	Mang et al. (2012)	E	No	No	Yes	Yes
	Petrick, Steinhardt, Gonsch, and Klein (2012)	AM	No	No	No	No

[a] "AM" = Analytical MODELING; "E" = Empirical; "LE" = Lab experiments.
[b] In Fay and Xie (2010), the two selling periods are the advanced period (prior to consumers learning their true valuations) and the spot period. In the current paper, consumers know their valuations in both periods. Thus, the major difference between the two periods is the time delay rather than differences in the information available to consumers.

com, lastminutetravel.com, and hotwire.com, websites where consumers can purchase travel services for which specific attributes of the service (e.g., the itinerary of the flight, the location of the hotel, or the identity of the car rental company) are not revealed until after payment. Recently, the idea of offering probabilistic goods has also been adopted by several online retailers (e.g., swimoutlet.com, agonswim.com, speedo.com, and kidsurplus.com) who offer discounted "grab bag" apparel and shoes, where patterns and styles are chosen randomly by the website.[4] As technological advances make it much more practical to implement PS both in online and brick-and-mortar shopping environments, more retailers can potentially benefit from adopting this novel selling strategy (Fay & Xie, 2008). While the existing research on PS has significantly advanced our understanding of the fundamental drivers of PS and illustrates its general applicability, it is important to extend the research to understand how this novel strategy may address some unique problems in the retailing industry and to explore whether PS can be a valuable alternative to offering late-season markdowns.

Most retailers strategically invest in inventory prior to the selling season, control the prices of their products over the entire selling season, and must account for how consumers time their purchases in response to these chosen prices. We introduce a model that incorporates each of these key characteristics. As shown in Table 1, among the current research on PS,[5] ours is the only model that incorporates all of the following three key characteristics: (1) The seller optimally chooses its prices for the probabilistic goods and the specified goods; (2) the seller optimally adjusts its inventory orders when introducing probabilistic goods; and (3) consumers strategically choose when to purchase in order to maximize their expected surplus. By incorporating these three critical factors, we are able to develop the theory and implications of PS for the retailing industry. In particular, our model enables us to compare discounting on the basis of time (high initial price and a discounted price if the consumer delays her purchase) versus discounting on the basis of product opacity (i.e., setting a high price for each specified good and a discounted price if the consumer will purchase the probabilistic good). Thus, the paper's primary contribution

is that it is the first to examine the profit advantage of the PS strategy relative to the more commonly utilized strategy of marking down merchandise over time, i.e., the markdown (MD) selling strategy. We identify factors under which PS can be a more useful tool for retailers as they attempt to price discriminate across consumers. We find that PS and MD can be complementary strategies since, in some market settings, PS is a profitable form of price discrimination whereas MD is not, while, in other market settings, price discrimination is profitable via MD but not profitable via PS.

A second contribution of the paper is that, by introducing a model that allows a probabilistic good to cannibalize full-price sales, we can examine the factors that affect the extent of cannibalization by the probabilistic good and determine whether PS can remain advantageous in its presence. Most extant analytical research on PS utilizes a Hotelling model to account for consumer heterogeneity (Fay, 2008; Fay & Xie, 2008, 2012; Jerath, Netessine, & Veeraraghavan, 2010; Jiang, 2007). A feature of the Hotelling model is that all consumers have the same expected value for the probabilistic good. As a result, price can be set at this common expected value, thus eliminating consumer surplus for all buyers of the probabilistic good. Since the probabilistic good does not generate positive surplus, the seller does not have to worry about any consumers switching from a higher-priced specified good to the lower-priced probabilistic good. However, cannibalization is a crucial concern under MD in the retailing industry because retailers are apprehensive that a discounted price at the end of the season may entice both low- and high-valuation buyers to delay their purchases (especially if the magnitude of the discount is very large). Thus, to provide an adequate comparison of PS with MD, the model must be capable of capturing the cannibalization effect under both strategies. Note that several empirical studies incorporate the cannibalization effect into their model estimations (Anderson & Xie, 2012; Granados, Gupta, & Kauffman, 2008; Mang, Post, & Spann, 2012; Zouaoui and Rao (2009)). However, since demand is modeled in reduced form in these papers, i.e., cross-price effects exist between the probabilistic good and the specified goods, these studies do not analyze the factors which affect the magnitude of this cannibalization effect or how cannibalization impacts the profitability of PS, as we do here.

The rest of this paper is organized as follows. In the next section, we use a lab experiment to illustrate the potential advantages of the PS and MD strategies relative to a No Discounting strategy. In Section 3, we illustrate how both PS and MD can enable a retailer to price discriminate and then compare the profitability of these two strategies. In Section 4,

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[4] See an example at http://www.swimoutlet.com/product_p/1623.htm
[5] Several papers (Gallego & Phillips, 2004; Mang et al., 2012, and Petrick et al., 2012) consider a seller who does not assign products to buyers of the probabilistic good until a time that is substantially later than the day of purchase. They refer to this business model as flexible selling rather than PS. However, consistent with Fay and Xie (2012), we consider these papers as part of the PS literature since delaying product assignment can be viewed as an alternative way of implementing the PS strategy.