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Spackling: Smoothing Make-to-order Production of Custom Products with Make-to-stock Production of Standard Items

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Abstract

Motivated by issues at a manufacturer of customized- and standard messenger bags, we develop an iterative two-stage framework (involving marketing and operations models) to determine the conditions under which a firm benefits from production *spackling*. With spackling, the firm uses flexible capacity to produce custom products as demanded each period, and then fills in, or spackles, the production schedule with make-to-stock output of standard products to restock inventory. Spackling broadly addresses market preferences, while mitigating the effects of "bumpy" demand for custom products by smoothing production, thereby improving capacity utilization as compared to a focused approach, where standard items are made with efficient capacity and custom products with flexible capacity.

The marketing model employs logit-based choice and, given product costs and customer preferences, identifies optimal pricing, expected demand, and demand variability. Interestingly, we find that, under certain assumptions, the firm should price all products to achieve a constant absolute dollar markup. The resultant demand parameters are fed into an operations model, which specifies optimal efficient and flexible capacities (and decides between spackling and focus), thereby determining product costs, which are fed back into the marketing model to solve iteratively. That is, we link operations decisions regarding capacity to marketing decisions regarding price, and vice-versa. We examine conditions under which convergence of the two models is achieved, and illustrate our framework with data from the messenger bag manufacturer.

Spackling: Smoothing Make-to-order Production of Custom Products with Make-to-stock Output of Standard Items

1. Introduction

Timbuk2, a San Francisco manufacturer of messenger bags, recently introduced an Internet site where customers configure and order a customized laptop bag direct from the manufacturer. This direct channel takes advantage of Timbuk2's flexible manufacturing capabilities and complements the firm's traditional retail channel where pre-configured bags are sold. In particular, Timbuk2's San Francisco factory can rapidly produce a bag of any configuration and deliver it within days. This combination of a flexible manufacturing system with a web-based custom configurator makes direct selling not only feasible, but quite attractive to the firm and its customers.

Timbuk2's management has considered moving at least some manufacturing offshore in order to reduce production costs, but although more efficient, the off-shore capacity would have longer lead times and would be unable to fill demand for customized make-to-order (MTO) bags in a timely manner. Management wonders what effect a shift to off-shore production of standard make-to-stock (MTS) bags would have on manufacturing cost and demand for all bags, including the custom bags produced in San Francisco. Ultimately, of course, Timbuk2 is concerned with profitability.

This paper developed as we sought to analyze Timbuk2's situation. Should Timbuk2 utilize efficient (off-shore) capacity? Or, should it continue to produce standard off-the-shelf configurations for retail demand with MTS production using the flexible production capacity in San Francisco, thereby establishing a mix of MTO and MTS manufacturing in the same factory?[1] (The term MTS refers to production in anticipation of demand, with output being added to inventory, while MTO production fills specific end-customer orders after they are received, as is the case for custom bags.) What are the optimal prices in the two channels? How many

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[1] At Timbuk2, standard and customized products are associated with retail outlets and the direct internet channel, respectively. In reality, the distribution channel and product type need not be linked – the firm could also sell standard bags directly to customers and could sell customized bags through retail distribution. The resulting analysis would be similar, although the discussion would use different terminology.

customers are expected to buy standard products through the traditional retail channel, and how many are expected to buy customized bags via the Internet?

In this paper, we address these questions by developing a simple two-stage framework, comprised of a marketing model integrated with an operations model. We assume the firm markets both standard and custom products, and that customers make choices based on a linear random utility model such as the logit framework. Given the firm's production costs, the marketing model determines the optimal prices (markups) for the standard and customized products. Remarkably, the marketing model shows that, under a representative customer framework, the optimal pricing policy is to add the same absolute dollar markup to the costs of standard and custom products (see §3 and Theorem 1). These optimal prices in turn yield expected demand volumes for each, and the level of demand variability, by aggregating the probabilistic choices of individual customers.

Given the demand parameters for standard and custom products, the operations model next determines the type and level of capacity to acquire, and whether to operate in MTS or MTO fashion. Capacity comes in two forms: *efficient capacity* which can only produce standard products in MTS fashion, and *flexible capacity* which can produce either standard or customized products and can operate in either MTS or MTO fashion. That is, efficient capacity is associated with lower costs from a relatively steady production schedule for a limited set of product configurations, where output is added to inventory. Flexible capacity, on the other hand, is associated with resources that can produce multiple product configurations on relatively short order and need not run at stable output, but is subject to a capacity constraint. The efficient and flexible capacities have different fixed and variable, per-unit costs.

We solve the marketing and operations models sequentially, for tractability, recognizing that an optimal solution relies on solving them simultaneously, since the marketing model uses costs which are influenced by the operations model, and the operations model uses demand parameters (means and variances) to determine costs. As we show in §5, under the right conditions an iterative approach converges to the jointly consistent, optimal solution. We show that when operations adds the incremental costs of demand stochasticity (due to overage and underage) as an input to marketing, the optimal prices and demand quantities differ from the prices based only the traditional fixed and variable unit costs. Similarly, we show that when marketing provides feedback to operations regarding demand and its variability, production

3

capacities and costs change. That is, the price and cost of a product are endogenous to our two-stage model since price affects demand variability, and variability affects cost which affects optimal pricing. We contend that joint consideration of marketing and operations decisions improves the firm's expected return.

We illustrate another key result qualitatively in Figure 1. The firm's choice of operating regime depends on the firm's production capabilities, in particular, the cost premium for flexible production when compared to efficient production.

Figure 1 Optimal Strategy is Determined by the Cost Premium for Flexible Production

| High cost premium	*Cost Boundary, V*	Low cost premium
Focused Strategy: Use efficient capacity to make standard products via MTS. Use flexible capacity to make custom products via MTO.		**Spackling Strategy:** Use one flexible capacity resource to make both standard products via MTS and custom products via MTO.

When demand exists in significant quantities for both standard and customized products, a firm might traditionally implement a *focused* strategy whereby one efficient facility (or production line) focuses on standard products, managed in MTS fashion, and a separate flexible capacity focuses on custom products, operated as MTO. We indeed find this to be optimal if efficient capacity is sufficiently less expensive. However, as the cost penalty for the flexible resource diminishes, it becomes more attractive to consider a dual MTS/MTO strategy we call *spackling*.[2] A theoretical contribution of this paper is to define the cost boundary, denoted by V (see §4), between the strategies of focus and spackle.

With spackling, the firm acquires only flexible capacity. Its first priority in any given period is to produce custom products via MTO. However, order patterns for custom products are bumpy (uncertain), yielding an undesirable production profile compared to smooth schedules that would allow for higher capacity utilization. Thus the firm uses the same (flexible) production capacity to produce standard products in MTS fashion, to "fill in the holes" in the

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2 The American Heritage® Dictionary of the English Language: Fourth Edition 2000 defines spackle as "A trademark used for a … paste designed to fill cracks and holes in plaster before painting or papering. This trademark often occurs in lowercase and as a verb…"

production schedule, as shown in Figure 2. The result is that MTO production closely tracks demand for customized products, while MTS output tracks demand for standard products, not over the short-run but rather over the longer-run, with some inventory build-up. In the spackling case, total production output is relatively smooth, or spackled, allowing for higher utilization of the flexible capacity, and improved efficiency.

Figure 2   Spackling Yields Steady Total Output Stream From One Production Facility
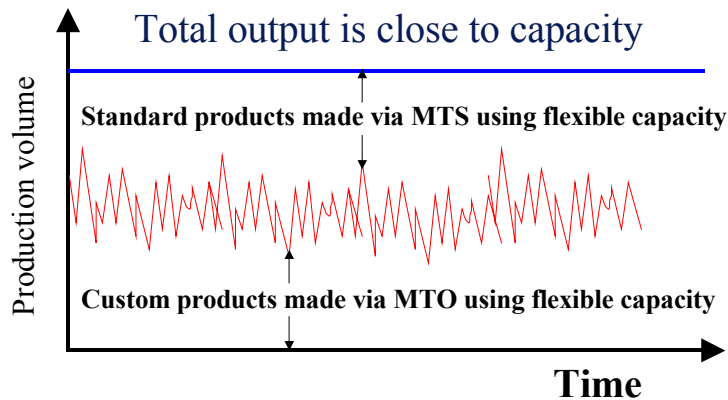
We apply our model to Timbuk2's situation and derive the reservation prices and price sensitivities of individual customers based on information attained in a three-stage study regarding customer preferences. In the first stage, 297 MBA students at MIT completed a conjoint survey, while in stage two they configured and "purchased"[3] a customized Timbuk2 bag, and in stage three they completed a follow-up questionnaire. On the operations side, we use projected cost information from Timbuk2. Solving the marketing and operations models iteratively, we characterize the conditions under which Timbuk2 might prefer a spackling strategy over a focused one. In essence, we determine, for Timbuk2, the boundary between "focus" and "spackling" as illustrated in Figure 1. In doing so, we also inherently address their questions regarding pricing, relative volumes for custom and standard products, and profitability.

In summary, we address issues at the marketing / operations interface, finding:

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[3]   Students were given money a $100 allowance to buy a bag, and received a refund if their selection was priced at less than $100.

(1) *Prices and costs are endogenous*: Marketing's pricing decisions depend on costs, and determine demand. Demand impacts operations decisions, which determine costs, including "hidden" costs such as overage and underage costs resulting from demand variability.

(2) *Pricing should be based on a constant absolute dollar markup*: If our assumptions hold, it is optimal to price products by adding the same fixed-dollar markup to costs.

(3) *The optimal operations strategy is determined by the cost premium for flexible production*: The firm's choice between focused operations and spackling depends on the relative cost advantage of efficient production; the boundary between the two policies is quantified.

The rest of this paper is organized as follows. We discuss the relationship of our work to the literature in §2. We develop the marketing and operations models in §3 and §4, respectively. In §5 we examine conditions that lead to convergence of the marketing and operations model. In §6 we apply the models to the case of Timbuk2, and we conclude with a discussion in §7.

2.   Literature Review

Determining how best to supply a wider variety of products at low cost in the face of uncertain demand has been a topic of much recent attention. Some of the research deals with the *supply* side of the equation, e.g., the design, manufacture, and distribution of the product. Other work addresses the *demand* side, e.g., determining how demand reacts to broader product offerings or to shorter lead times.

On the supply side, our research question relates to that of finding the optimal mix of less costly, dedicated capacity and more expensive, flexible capacity, as modeled by Van Mieghem (1998). In his model the firm decides between production using only dedicated capacity, only flexible capacity, or a mix of both, as determined by the marginal cost of flexible capacity. All production is MTO, in that capacities are allocated to products after demand is observed. He finds that it may be advantageous to invest in more expensive flexible resources even with perfectly positively correlated product demands. We find additional support for expensive flexible resources. In a different framework, where we assume that production can be MTO or MTS and that both fixed and variable costs are a function of the type of production, we show the positive effect on efficiencies possible with flexible resources through production smoothing.

Other works that consider hybrid approaches to Operations include Eynan and Rosenblatt (1995), Federgruen and Katalan (1999), Rudi (2000), and Muckstadt, et al. (2001).

Eynan and Rosenblatt (1995) study the trade-offs of lower cost assembled in advance production with the higher cost of assemble to order but that doesn't incur excessive and unnecessary assembly costs. Federgruen and Katalan (1999) develop a stochastic Economic Lot Scheduling Problem (ELSP) that evaluates cost and performance measures such as inventory level and waiting-time distributions, as well as average setup, holding, and backlogging costs under a dual MTS/MTO system. Rudi (2000) considers the trade-offs of low-cost, long-lead time production in the Far East (Make to Stock) and local production with short lead times and pre-positioning of components (Assemble to Order).

Muckstadt, et al. (2001) propose a hybrid MTO/MTS production environment (although they use different terminology) for making capacity allocation and inventory stocking decisions in a capacitated system where demand for a large subset of assembled items is highly erratic. The hybrid system uses MTO production for items (called B/C-type) with highly erratic demand while using MTS production for more predictable A-type items. They compare the performance of the hybrid system to an alternative system where all production decisions are made prior to observing demand (MTS). Our spackling model has a similar structure but is motivated by a different setting where MTS production is possible at a lower cost to meet demand for a standard product.

Arreola-Risa and DeCroix (1998) study the optimality of MTO versus MTS policies for a company producing multiple heterogeneous products at a shared manufacturing facility. They model demands as independent Poisson processes with different arrival rates and derive optimality conditions for MTO versus MTS policies considering trade offs in inventory holding costs and backordering costs. Graman and Magazine (2000) study the impact of postponement capacity on the ability to achieve the benefits of delayed product differentiation and conclude that very small postponement capacity is needed to achieve all of the benefits of completely delaying product differentiation for all customer demand. Gupta and Benjaafar (2001) consider delayed product differentiation as a hybrid strategy that strives to reconcile the dual needs of high variety and quick response time. Rajagopalan (2002) considers the portfolio of products at a company and develops a model to determine which products should be made to order and which should be made to stock. Our paper considers the possibility of producing a single product under both MTS and MTO.

The idea of dedicated capacity and reactive capacity, as put forth by Fisher and Raman (1996), is also related to our approach. Early in the production season, capacity is dedicated to products having low demand variability (effectively production is MTS). Capacity used late in the season can react to closer-to-actual demand (effectively production is MTO).

The demand side of the issue involves at least two key issues: variety and lead time. Variety is an issue because as it increases, pooling benefits are lost and demand uncertainty generally increases. (Uncertainty creates an incentive for MTO: if we knew exactly how much product would be ordered, we could simply produce it as MTS without any risk.) Also, an increase in variety reduces the volume for any given product, such that the variable cost of MTS goes up if there are economies of scale. Lancaster (1990) offers a survey of papers addressing the variety issue. The second issue is lead time, as examined by Li (1992), for example. If customers were always willing to wait, again we simply would produce all the items as MTO without any risk. Similar to our results, he finds a boundary between MTS and MTO as reflected by newsvendor–type results, and although he does not consider the possibility of the dual strategy as we do, he examines the effect of competition.

Our research contributes to a small, but growing literature that touches on the integration of marketing and operations management decisions, cf., Chase (1996), Eliashberg and Steinberg (1993), Karmarkar (1996), Lovejoy (1998), and Verma, et al. (2001).

3.   Marketing Model

In this section we present an analytical framework for determining the optimal prices for standard and customized products, given product costs. These prices, in turn, establish expected sales volumes for each type of product and the variance in demand for custom products. After presenting the operations model in §4 and discussing how to solve jointly the operations and marketing models in §5, we apply the approach to actual data from the messenger bag manufacturer in §6.

We take as a given the feature levels the firm incorporates into its standard product and the menu of customizable features it offers to customers.[4] We assume the firm has measured each customer's willingness-to-pay for each possible product attribute, scaled into dollars. This

might be done, for example, through conjoint analysis and user design, as described by Dahan and Hauser (2002). We further assume that this assessment also measures the perceived benefit the customer realizes by taking delivery immediately (as with products already in inventory) as opposed to having to wait for delivery of custom goods. Thus we can find each customer's dollar-scaled utility for any given product, be it a standard product, or any of the customized versions available.

Let c_j denote product j's cost and p_j its price, such that $m_j \equiv p_j - c_j$ denotes the firm's dollar markup on product j. Here, product j can be a standard product (or any one of the standard products, if there are multiples standard offerings) or any one of the custom products. Within each iteration of the marketing model we assume cost is independent of pricing – by accounting for overage and underage costs in the operations model described in §4, and then iterating to find a solution that is consistent between the marketing and operations models as described in §5, we ultimately incorporate these costs into marketing's pricing decision.

Let r^i_j denote customer i's expected dollar-equivalent utility for product j, excluding the attribute of price: we refer to r^i_j as customer i's reservation price for product j. If viewed deterministically, then given the choice of buying product j or buying nothing, customer i buys at a price below r^i_j [cf., Schmidt and Porteus (2000)]. An alternate approach that we use here is to treat the purchase decision as probabilistic, using the logit formulation as described by Ben-Akiva and Lerman (1985) and Guadagni and Little (1998), such that r^i_j can be viewed as the price at which "noise" is equally likely to push the customer's purchase decision one way or the other (r^i_j is the point at which she has a 50% probability of buying product j if her only other choice is to buy nothing).

Define $d^i_j \equiv r^i_j - c_j$ as the discriminating markup; it is the markup the firm could achieve in selling product j to customer i if it could perfectly price discriminate at the individual customer level (to the first degree), under deterministic customer choice. Customer i's net utility from buying product j at price p_j is $(r^i_j - p_j) = (d^i_j - m_j)$, since $d^i_j \equiv r^i_j - c_j$ and $m_j \equiv p_j - c_j$. It is this expression, $(d^i_j - m_j)$, for net utility that we employ in our logit-based choice probabilities.

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[4] The design of the stock product(s) and customization options impact profitability in their own right, but those analyses are outside the scope of the present article. We take these decisions as a constraint on our optimization.

We assume each customer's net utility is scaled by a "price-sensitivity parameter" β^i, such that the net dollar value customer i attaches to product j is $\beta^i (d^i_j - m_j) + \varepsilon^i_j$ where ε^i_j is a random error term assumed to be distributed Gumbel, i.e. double exponential, such that $\varepsilon^i_j - \varepsilon^i_k$ is distributed logistically; hence the standard logit formulation applies. Let P^i_j denote customer i's probability of purchase for product j. Given t choices, a customer's probability of purchase of product j is, following the logit formulation:

$$P^i_j = \exp[\beta^i(d^i_j - m_j)] / \Sigma^t_{k=1}[\exp(\beta^i[d^i_k - m_k])]. \tag{1}$$

In addition to its choice of buying one of the t products, we assume the customer has the option to buy nothing from the firm. For this option, $\exp(\beta^i[d^i_j - m_j]) = \exp(\beta^i[0]) = 1$.

To aid in determining the firm's pricing strategy, we state in Lemma 1 a version of the "constant absolute markup property" that follows from this formulation. This property is noted in Anderson, et al. (1992), p. 251, in a somewhat different context – we include in Appendix I a proof in the setting of our model.

LEMMA 1. *If customer i is, in isolation, choosing between buying any one of t products offered by a single firm or buying nothing from the firm, the firm should price all t products at the same absolute dollar markup, denoted by m^*. The implicit solution for m^*, which exists and is unique, is given by:*

$$m^* = \frac{1}{\beta^i \cdot \left[1 - \sum_{j=1}^{t} P^i_j\right]}, \text{ where:} \tag{2}$$

$$P^i_j = \frac{e^{\beta^i (d^i_j - m^*)}}{1 + \sum_{j=1}^{t} e^{\beta^i (d^i_j - m^*)}} = \frac{e^{\beta^i \cdot d^i_j}}{\beta^i \cdot m^* \cdot e^{\beta^i \cdot m^*}}. \tag{3}$$

Lemma 1 does not appear to be a well-known result, so a brief interpretation seems appropriate. When considering only one customer in isolation, the firm finds it optimal to price all products at a constant absolute dollar markup. If it deviates from m^* by, say, increasing the markup of product i, there are several competing consequences. It gets higher margin on product i, but reduces i's expected unit sales (i.e., its probability of purchase). In turn it increases the expected unit sales (and profit) derived from each of the other products, but diminishes total expected unit sales. Thus it is not clear which effect will dominate – Lemma 1 suggests there is always a profit loss by deviating from m^* for any product.

At first glance it may appear that the firm fails to take advantage of a customer's preferences by pricing all products at equal markups. Such intuition is misguided: if the customer strongly prefers any one product j (relative to the firm's cost for that product), then d^i_j will be relatively high, yielding, per (3), a relatively high P^i_j. Linking this back to (2), a product that is strongly preferred (leading to a relatively high P^i_j) will dominate in determining the markup m^*. In other words, the firm will set the markup largely based on the product(s) that are most favored by the customer. Products that are not so well liked by the customer will get the same markup, and accordingly will not likely be purchased. Rewriting (2) as:

$$m^* \cdot \beta^i \cdot \left(1 - \sum_{j=1}^{t} P^i_j\right) = 1, \tag{4}$$

we take note of the trade-off between its three terms. The first term is the markup m^*, the second is the customer's price sensitivity β^i, and the third term $(1 - \Sigma_{j=1}^{t} P^i_j)$ is the probability that the customer *doesn't* buy from the firm. Given some β^i, if the customer has a high probability of not buying (i.e., if the firm's products are not strongly preferred), then the firm has to "price low" to compensate. If the customer has a high probability of buying, the firm can "price high" to take advantage of its well-liked product(s). If the customer is more price-sensitive (i.e., if β^i is higher), then the firm must reduce price or face reduced sales.

Next, consider the firm's pricing strategy when it creates its product assortment by adding or deleting individual features (i.e., options) from a "base unit." For example, automobile manufacturers might typically suggest a retail price for a base configuration, along with prices for individual options (the firm may also quote deductions from the base price if certain features are deleted). We assume the cost of any finished unit is equal to cost of the base unit plus the cost of the supplemental features.

COROLLARY 1. *Given the situation described in Lemma 1, it is optimal for the firm to price the base unit at cost plus m*, and price each option to be added or deleted at cost.*

Corollary 1 suggests that the firm needn't optimize the price of each individual option, but only the price of the base unit. Of course, the base-unit price accounts for the desirability of the product, which depends to some extent on the menu of upgrade options that accompany it. The notion of pricing all options at cost seems counterintuitive. While outside the scope of this paper, further investigation is merited, as such pricing does not appear to be widely practiced.

11

For example, it might help address the complex task of optimizing product assortment that many researchers have addressed (cf., Chong, et al. (2001)).

To simplify our model, we adopt the "representative customer" approach to duplicate, or approximate, the aggregate results of the entire population. Ben-Akiva and Lerman (1985) describe the representative customer approach in their discussion of aggregate forecasting techniques, and Anderson, et al. (1992) discuss its validity. One interpretation is that ε^i_j is not a random error term, but rather, it accounts for differences in the way various customers value product j. That is, the representative customer approach is valid if the differences in customer evaluations of a given product are distributed Gumbel. Another possible interpretation is that customers are all part of the same market segment (i.e., all customers are, for practical purposes, "identical"). From here on, we simply use β and d_j (without superscripts) to denote the characteristics of the representative customer.

In our situation, the customer must, at one level, choose between buying a standard product off-the-shelf or ordering a custom product, and must, at another level, make a choice regarding each and every option (if buying custom). Since logit requires that the various alternatives be "equally dissimilar" (to avoid the "red bus/blue bus" paradox), we assume the customer has selected her most-preferred[5] custom product, and likewise her most-preferred standard product and we focus on the customer's choice between, a) her most-preferred standard product, b) her most-preferred custom product, and c) buying nothing. Accordingly, we now restrict our consideration of j to $j \in \{c, s\}$, where c denotes the customer's representative custom product and s denotes the (representative) standard product.[6] Given corollary 1, we assume the firm prices the base custom product to achieve markup m_C^*, and then prices all options at cost. Similarly, the markup for a standard product (or products) is denoted by m_S^*.

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[5] Alternately, we might assume the customer picks a "representative" custom product, where this representative product is assumed to encapsulate the customer's preferences toward all custom products, similar to the way the representative customer is assumed to encapsulate the characteristics of all customers.

[6] This restriction ignores the endogeneity of the firm's pricing decision with the customer's selection of her most preferred product. That is, the customer cannot select her representative custom product until prices are set, and the firm cannot set prices before it knows the customer's representative custom product. We assume either these are solved simultaneously, or that an iterative approach is used. An alternate approach would be to formally apply a nested logit model (see Guadagni and Little (1998)).

Let μ_j denote the expected demand for product j over the population of N customers, then $\mu_j = \Sigma_{i=1}^{N} P^{i}_{j}$ with variance of demand $\sigma_j^2 = \Sigma_{i=1}^{N} P^{i}_{j}(1 - P^{i}_{j})$, since each purchase choice can be thought of as a Bernoulli event.

The operations model in the upcoming section requires the variance of demand only for the custom products, which we denote by σ^2.

THEOREM 1.　*The optimal absolute dollar markups for the standard and custom products are equal, as given by (2). As $N \to \infty$, demand for custom units $\sim N(\mu_c, \sigma^2)$ and expected demand for standard units is μ_S with:*

$$\mu_C = N \cdot P_C, \ \sigma^2 = N \cdot P_C \times (1 - P_C), \ and \ \mu_S = N \cdot P_S. \tag{5}$$

Assuming a relatively large population N, demand for each product at any given set of prices will approach normality, since under the representative customer assumption, the success probabilities are homogeneous, and the well-known normal approximation of the binomial distribution applies. Numerical analysis suggests that the optimal markup of Theorem 1, m^*, is convex decreasing in the cost of each product, asymptotically approaching $1/\beta$ as the purchase probabilities vanish (i.e., as costs become excessive or as willingness-to-pay disappears).

To analyze the Timubuk2 data, in §6 we employ a numerical approach. Given the distributions of β^i and d^i_j, we search numerically for the optimal markups m_S^* and m_C^* yielding the highest profit $\mu_S m_S^* + \mu_C m_C^*$. The demand curve is found by using (5) to find each (potential) customer's purchase probability for each type of product (standard and custom), and summing these to find total expected demand for each type. We do not rely on the representative customer approach in our analysis of the Timbuk2 data, but normality still applies since by Liapounov (see DeGroot (1975), p. 229), the sum of Bernoulli events with heterogeneous success probabilities is normally distributed as the number of events approaches infinity. While in our observations we have found the profit function to be well-behaved, a numerical search ranging from zero markup to the point where demand falls to zero can be performed to insure that the point of maximum profit is located within some arbitrary value ε. Using the logit formulation in this fashion we are able to estimate the mean and variance of the normal demand distribution for each type of product, given a set of customer preferences, products, and prices.

In summary, we use the marketing model, employing either the analytical approach or the numerical approach, to find the point of maximum profit, and feed the associated demand expectations and variances into the operations model which we describe next.

4.   Operations Model

We develop a simple operations model to gain insights regarding the operations issues, given the demand parameters specified by the marketing model for both standard products and custom products.   We consider a single-period model where demand is realized over T subperiods, with T being the lead time to stock retail inventory of standard products. At the beginning of each subperiod, the firm receives its orders for customized products and must deliver them by the end of that subperiod. We do not account for holding costs.

Let μ_c and μ_s denote the mean demands for custom and standard products each subperiod, respectively (as determined by the marketing model). Demands for standard products from retailers are assumed to total exactly $T\mu_s$ units due at the end of the period. Our assumption of deterministic demand for standard products is a modeling simplification but uses the rationale that retail orders are for restocking inventories, where lead times for such orders are T superiods and once an order is accepted, it can't be altered. Demands for custom products are assumed to be independently and identically distributed following a normal distribution $F_c \sim N\left(\mu_c, \sigma^2\right)$ in each subperiod.

We consider two strategies. The first is a focused strategy, under which an efficient production resource focuses on making standard products in MTS mode, and a flexible production resource focuses on making custom products via MTO. Given our assumption that demand for standard units is deterministic, the firm will set efficient capacity at exactly μ_s per subperiod. The firm will hold a flexible capacity exceeding expected demand for custom products if the underage (shortage) cost for customized products is significantly higher than the overage cost, experiencing relatively low utilization of its flexible capacity.

As an alternative to a focused strategy, we consider *spackling*, a dual-strategy of MTO and MTS production that utilizes only flexible capacity but in such a manner that production is greatly smoothed (allowing for increased utilization, and thus increased efficiency of the flexible capacity). With spackling, the firm first meets its demand for custom products and then uses

leftover flexible capacity as needed in making standard products (where a standard product is merely one particular version of a customized product). The firm holds only flexible production capacity, making standard products as a lower-priority filler to smooth out (or spackle) the more unpredictable production that is triggered by demand for customized products.

We can equivalently describe the firm's choice between focused and spackling strategies as being one of setting production capacities for efficient and flexible resources. A focused strategy acquires strictly positive amounts of both types, while a spackling strategy acquires only flexible capacity. Let K_E and K_F denote the capacities of the efficient and flexible resources, respectively, where one unit of capacity can make exactly one unit of one product per sub-period. Let θ_E denote the fixed cost per subperiod for a unit of efficient capacity (used only in the focused strategy to make standard units) and θ_F be the fixed cost of flexible capacity (used in the focused strategy to make custom units, and in the spackling strategy to make both standard units and custom units), and let c_E and c_F denote their respective variable production costs per unit. Since efficient capacity can only make standard products, θ_E and c_E can be used in a straightforward manner to determine the average cost of standard units. However, interpretations of θ_F and c_F merit some clarification. Recall from the marketing model that we can view a custom product as some base product plus or minus a set of options. Without loss of generality, we define such base product to be the standard product. Also, recall that we assume we achieve the same markup on all custom products, such that we effectively sell all options at cost and simply set the markup on the base product. Similarly, here we assume θ_F and c_F apply to the base (standard) product and we ignore all costs of features added (or subtracted) from the base.

The firm's decision is as follows. At the beginning of the period (i.e., the first subperiod) the manufacturer sets efficient and flexible capacities K_E and K_F (if the firm chooses $K_E = 0$, i.e., to spackle, then we simply denote flexible capacity by K). Let $X_T = \sum_{i=1}^{T} X_c$ denote the (random) demand for custom products over T subperiods where $X_c \sim F_c$ and $X_T \sim F_T$. If capacity is insufficient to meet demand, expensive production (or outsourcing) is used at a variable cost of c_P per unit. (We will show in the next section how c_C and c_S, as used in the marketing model, are related to c_E, c_F, and c_P.) For the spackled production case we assume $\mu_c << K$; the firm always

15

has sufficient capacity each subperiod to meet customized orders, i.e., $X_i < K \; \forall i$. (See Figure 2.) (Significant demand for standard units will justify this assumption, since the capacity is used first to meet demand for customized products, but must also meet demand for standard products.)

In the case where there are separate flexible and efficient capacities focusing on customized and standard products, respectively, the optimal flexible capacity is as determined from the traditional newsvendor problem with $K_F^* = F_c^{-1}\left[(c_P - c_F - \theta_F)/(c_P - c_F)\right]$. The optimal capacity for efficient production is simply $K_E^* = \mu_s$, per our earlier assumption of deterministic demand for standard products.

In the spackled-production case, K units are produced in total in each subperiod until $T\mu_s$ units of standardized products have accumulated: X_i units of customized products and $K - X_i$ units of standard products. If demand over the T subperiods for customized products is less than $T(K - \mu_s)$, the firm makes $T\mu_s$ standard units and then stops producing standard products for the remaining subperiods. If period demand for customized products is greater than $T(K - \mu_s)$, then there is a shortfall of standard products which is filled with expensive (outsourced or overtime) production at an incremental cost of $c_P - c_F$ per unit. We balance the fixed costs of capacity with the shortfall cost to determine the optimal capacity K.

We make the following assumptions:

(A 1) $c_P, c_F, c_E, \theta_F, \theta_E > 0$. All production costs are greater than zero.

(A 2) $c_F + \theta_F < c_P$: We avoid the uninteresting case where the firm would never invest in flexible capacity.

Theorem 2 below suggests that the firm's optimal capacities, $K_E *$ and $K_F *$, depend on the premium for flexible production, $(c_F + \theta_F) - (c_E + \theta_E)$. In preparation for Theorem 2, define V as follows (interpretation follows the theorem):

$$V \equiv \frac{\sigma\left(T - \sqrt{T}\right)\left(z^*\theta_F + (c_P - c_F)L(z^*)\right)}{\mu_s T} \tag{6}$$

where $z^* = \Phi^{-1}\left((c_P - c_F - \theta_F)/(c_P - c_F)\right)$, the standardized variate for the given fractile and $L(z)$ is the standard normal loss function.

THEOREM 2. *The optimal capacities $K_E{}^*$ and $K_F{}^*$ are:*

Case A:

If $(c_F + \theta_F) - (c_E + \theta_E) \geq V$, then $K_E{}^* = \mu_s$ and

$$K_F{}^* = F_c^{-1}\left[(c_P - c_F - \theta_F)/(c_P - c_F)\right]$$

$$= \mu_c + z^*\sigma$$

Case B:

If $(c_F + \theta_F) - (c_E + \theta_E) < V$, then $K_E{}^* = 0$ and

$$K^* = K_F{}^* = \frac{1}{T} F_T^{-1}\left[(c_P - c_F - \theta_F)/(c_P - c_F)\right] + \mu_s$$

$$= \mu_c + \mu_s + \frac{1}{\sqrt{T}} z^*\sigma$$

Case A corresponds to the case of individual capacities focused on standard and custom products while Case B corresponds to production spackling, where there is only flexible capacity but it is used in a dual sense: part of it is used in response to orders while the remainder is used to produce to inventory, capitalizing on the schedule flexibility of MTS orders. Safety capacities for the two cases are $z^*\sigma$ and $\left(1/\sqrt{T}\right)z^*\sigma$, respectively.

In Theorem 2, V determines the boundary between Case A and Case B, and this effectively defines the boundary between the columns in Figure 1. That is, Figure 1 suggested spackling is preferred if the cost premium for flexible production is "low," and Theorem 2 defines "low" – anything below V. The definition of V implies that spackling is most compelling when demand for custom products is more variable (σ is large), the lead-time for production of standard units is long (T is large), demand for standard products is low (μ_S is small), the penalty for insufficient capacity is high ($c_P - c_F$ is large), and, of course, when the premium for flexible production is small ($(c_F + \theta_F) - (c_E + \theta_E)$ is small). This implies spackling is relevant for manufacturers of customized products who struggle to achieve high utilization due to high shortage costs along with highly variable demand, but who also have at least some demand for

17

standard units. While we have not accounted for holding costs in our model, we note also that spackling is less attractive when holding costs are high for standard products since significant MTS inventory may accumulate over the T subperiods.

By setting optimal capacities we implicitly establish average costs, c_C and c_S (as delineated in §5), to be fed back to the marketing model in an iterative process described in the next section.

5.   Joint Solution to the Marketing and Operations Models

Separately, the marketing model and the operations model each determine optimal profits given their inputs, but without iteration the two solutions generally do not coincide because the average cost used by the marketing model may not be the same as the average cost that is subsequently derived by the operations model. Likewise, the demand parameters used by the operations model may not the same as those subsequently derived by the marketing model. Jointly, a closed-form solution for the combined marketing and operations models is not achievable given that we do not have a closed-form solution for the demand curve with the logit model. However, for a given set of inputs into the marketing model we can solve it numerically, feeding the results into the operations model, whose results we feed back into the marketing model, and so on. If such iteration results in convergence, then the optimal decisions of the operations and marketing models will be jointly consistent. That is, at the point of convergence the two models will consistently account for average costs and demands, and yield the same expected profit.

We describe an iterative method used successfully with the empirical data and numerical examples described in §6. With this method we iterate to find the jointly consistent optimal solution assuming spackling is used, and separately iterate to find the consistent solution for the case of focused facilities, assuming each solution converges. Then we compare the two solutions and pick the one offering the higher profit, thus determining whether spackling or focused production is preferred. This process has been shown in our examples to be consistent with Theorem 2 (for example, if the solution is to spackle, then Theorem 2 says spackling is optimal when V is calculated using the demand parameters suggested by the convergent spackling result).

First consider the case of spackling: the total expected cost, as derived from the operations model, is comprised of the fixed cost, $T \theta_F [\mu_C + \mu_S + z^* \sigma / \sqrt{T}]$, plus the expected variable cost $T c_F (\mu_C + \mu_S)$, plus the expected shortage cost, incurred when leftover demand for standard units is filled with expensive emergency production, $(c_P - c_F) \sqrt{T} \sigma L(z^*)$. Let $v_{Spackling}$ $\equiv \sigma / (\mu_C + \mu_S)$ denote the coefficient of variation in total demand. From Theorem 1 we find:

$$v_{Spackling} = \sqrt{(\exp(\beta d_C) [\beta m^* \exp(\beta m^*) - \exp(\beta d_C)] / \sqrt{N})} / [\exp(\beta d_C) + \exp(\beta d_S)]. \quad (7)$$

We determine an average unit cost for both standard and custom units, which are built in the same facility, by dividing total expected cost by total mean demand, $T (\mu_C + \mu_S)$, to attain:

$$c_S = c_C = \theta_F + c_F + v_{spackling} [(\sqrt{T})^{-1} [z^* \theta_F + (c_P - c_F) L(z^*)]]. \quad (8)$$

We call this the fully-absorbed cost, and use $c_S = c_C$ as calculated by (8) in the subsequent iteration of the marketing model. Note that this cost is a function of $v_{spackling}$, which is an output of the marketing model; all other parameters that go into calculating $c_S = c_C$ are unaffected by the marketing model.

Applying similar logic to the case of focused production (where an efficient facility produces standard products and a flexible one makes custom products), the fully-absorbed unit cost of a standard product is $c_S = \theta_E + c_E$ (there are no overage or underage costs). Let $v_{focus} \equiv \sigma / \mu_C$ denote the coefficient of variation in demand for custom products. From (5):

$$v_{focus} = \sqrt{([\beta m^* \exp(\beta m^*) - \exp(\beta d_C)] / [N \exp(\beta d_C)])}. \quad (9)$$

And the fully-absorbed unit cost of a custom product is:

$$c_C = \theta_F + c_F + v_{focus} [(z^* \theta_F + (c_P - c_F) L(z^*)]. \quad (10)$$

Using these costs, the iterative process for spackling, or for focus, proceeds as follows. Without loss of generality, assume we start with the marketing model. In the ith iteration we input costs c_C^i and c_S^i into the marketing model, which determines a coefficient of variation in demand v^i (we use v^i to denote v^i_{focus} in the case of focus and $v^i_{spackling}$ in the case of spackling) and the expected demands. Inputting v^i into (8) if iterating to find the spackling solution, or into (10) if iterating to find the solution for focus, determines new costs c_C^{i+1} and c_S^{i+1}, which are returned to the marketing model to find v^{i+1}. In the case of focus, $c_S^{i+1} = c_S^i$ (standard products aren't affected by iteration), and in the case of spackling $c_S^i = c_C^i$, such that in either case we need only concern ourselves with how one cost changes from iteration to iteration: in the case of focus let $c^i \equiv c_C^i$ and in the case of spackling let $c^i \equiv c_C^i = c_S^i$. The profit derived from the combined sales

of standard and custom products, as calculated from the marketing model, is a function of the input cost c^i, such that we denote this profit by $\pi^i(c^i)$.

Recall from the marketing model that the coefficient of variation in the ith iteration, v^i, is a function of the customers' probabilities of purchase, which in turn are functions of differences between discriminating and actual markups, which are determined by the prices set by the firm and its average cost. Thus given the customer preferences, v^i is a function of cost c^i, and can be expressed as $v^i(c^i)$. Plugging $v^i(c^i)$ into (8) or (10), as appropriate depending on whether we are considering spackling or focus, we find c^{i+1} is linearly increasing in $v^i(c^i)$ such that based on this chain of dependencies we use the notation $c^{i+1} = g(c^i)$.

Effectively, the marketing and operations models each find the optimal profit given their inputs; the problem reduces to one of finding the average cost c^i and coefficient of variation $v^i(c^i)$ that do not change from one iteration to the next. Consider the case of spackling – if c^i converges in the iterative process, then $v^i(c^i)$ also converges (given that $v^i(c^i)$ is well-behaved, which we assume), and we say the marketing and operations models are consistent for the case of spackling. Similarly for the case of focus.

For $c^i \geq 0$, we make the following assumptions, which we have found to hold in our limited numerical studies:

ASSUMPTION (A1): $g(c^i)$ is strictly positive, continuous, smooth, differentiable, and strictly convex with $\lim\limits_{c^i \to \infty} \dfrac{g\left(c^i\right)}{c^i} = \infty$.

ASSUMPTION (A2): $\pi^{i'}(c^i) \leq 0$: the profit as derived by the marketing model goes down as the cost input into the marketing model c^i increases.

Given (A1) and (A2), either there is a most-profitable point of convergence, denoted by c^∞, where the optimal solution to the operations model is consistent with the optimal solution to the marketing model, or there exists no solution that is consistent to both the marketing and operations models. To see this, without loss of generality, first consider the case of spackling. As illustrated in Figure 3, clearly, if $g(c^i) > c^i \ \forall \ c^i$, then c^∞ does not exist and there exists no profitable consistent solution for spackling. If c^∞ exists, then it is the most profitable consistent solution for spackling, since any other consistent solution will offer less profit, given $\pi^{i'}(c^i) \leq 0$. Similar logic holds for the case of focus. If c^∞ exists for both spackling and focus, and if the

20

most profitable of these yields a positive profit then it is the optimal profitable consistent solution. If c^∞ exists for only spackling or only focus, and profit is positive under this solution, then it is the most profitable consistent solution. If none of the above holds, or if c^∞ does not exist for either spackling or focus, then there is no profitable consistent solution.

Figure 3 Convergence of Numerical Solution
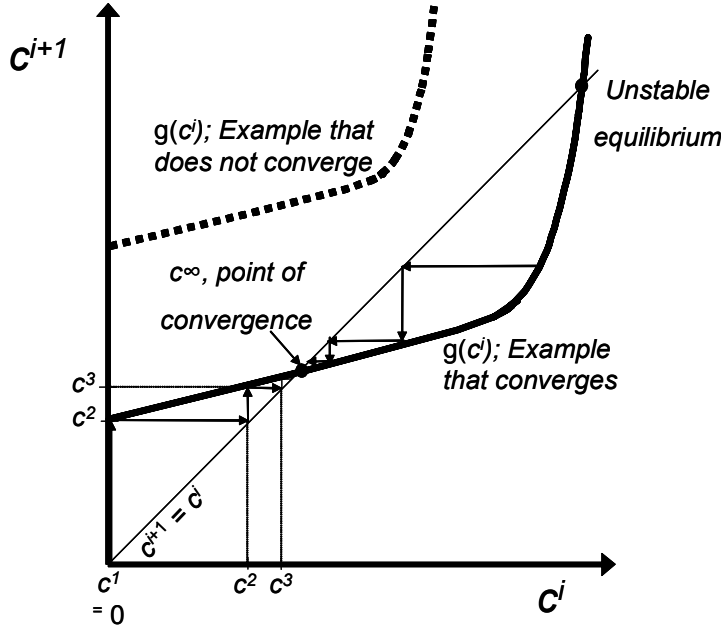
In our numerical studies, we approximate the value of c^∞ or determine that it does not exist by using the following algorithm (we do so individually for the case of spackling and for the case of focus). Without loss of generality, begin iteration with the marketing model. Pick an arbitrarily small number ε (the smaller you pick ε, the closer c^∞ will be approximated, if it exists). Set $i = 1$ and $c^1 = 0$. Use the marketing model to find $v^1(c^1)$, then set $i = 2$ and find $c^2 = g(c^1)$. (Given that $g'(c^i) < 1$ from (A1), we find that, should c^∞ exist, $0 < c^i < c^{i+1} < c^\infty$.) Then:

1)   Use the marketing model to find $v^i(c^i)$ at the point of maximum profit.
2)   Find $c^{i+1} = g(c^i)$.
3)   Check if $c^{i+1} - c^i > c^i - c^{i-1}$. If so, stop: c^∞ does not exist.
4)   Check if $c^{i+1} - c^i < \varepsilon$. If so, stop: c^{i+1} is an approximation of c^∞. If not, set $i = i + 1$ and return to step (1).

Note that if c^∞ exists, c^{i+1} would also converge to c^∞ for any initial value c^1 that is less than what is labeled in Figure 3 as the unstable equilibrium. The unstable equilibrium is a possible second point where the marketing and operations models are consistent, but where the

21

profit is less than at the earlier (stable) equilibrium point c^∞, since $\pi^{i'}(c^i) \leq 0$. Further, the initial choice of c^1 must exactly match this point for it to be an equilibrium (an initial choice of c^1 above the unstable equilibrium results in divergence). Accordingly, in our algorithm we use an initial starting point of $c^1 = 0$.

6.   Empirical Analysis and Examples

6.1.   Marketing Model

Timbuk2's launch of a new laptop bag offered a setting in which to apply some of our model concepts.   We first analyzed data from a three-stage study to determine customer preferences, allowing us to calculate each individual's probability of purchase as a function of price, delivery time, and bag features. From this, along with cost information, we numerically searched to find the firm's optimal pricing and the accompanying expected sales of custom and standard bags, along with an estimate of the variance in sales.

The three-stage analysis consisted of the following steps. First, 297 MBA students at MIT participated in an adaptive conjoint analysis, as described by Dahan, et al. (2002). The conjoint survey involved nine attributes, including size (medium or large), color (red or black), type of closure of the laptop sleeve (a full flap or a small tab), and six "on-off" attributes (by on-off we mean the bag either included the attribute or lacked it). The on-off attributes were a logo, a holder for a cell phone, a holder for a personal digital assistant, a laptop sleeve, a mesh pocket, a bottom boot, and a carrying handle separate from the shoulder strap. From the conjoint we were able to determine part-worths for each attribute (how much each attribute adds to a customer's reservation price, as compared her reservation price for the product without that attribute).   However, from the conjoint data alone we could not determine a customer's reservation price for a bag in its entirety (the conjoint did not give the customer the option to buy nothing). To do so, we incorporated data from the second and third stages.

In the second stage, each student was given \$100 to spend on a self-configured customized bag. If the student configured a bag priced for less than \$100, she received a cash refund of the difference. The third stage consisted of a follow-up survey in which the student indicated the probability that she would have actually purchased her customized bag, and identified her delay penalty for having to wait for the MTO bag.

a) **Finding reservation prices**: Here we lay out the process whereby we used data from all three stages to find r^i_j, customer i's reservation price for bag j, $j \in \{c,s\}$, where the subscript s denotes the standard bag and c denotes the customer's preferred custom bag, all scaled into dollars. Our analysis is based on the assumption that reservation prices for individual attributes are additive – that is, a customer's reservation price for any custom bag is assumed to be equal to her reservation price for a standard bag, denoted by r^i_S, plus her part-worths for those attributes incorporated into the custom bag but not present in the standard bag, minus her part-worths for those attributes present in the standard bag but absent in the custom bag. (The ten attributes are the nine included in the conjoint survey, plus delivery via MTS versus MTO.) Without loss of generality, define a standard bag to be a black, large-sized bag with a small tab and a boot, offered via MTS. (The features of the standard bag(s) could be selected through combinatoric optimization methods, taking into account the possibility of the custom bag option; in the Timbuk2 experiment these four options were selected because they were preferred by the majority of potential buyers.)

We utilize the logit formulation described in §3 and summarized by (1). We assume the β^i's are equal to the individual price part-worths as measured by the conjoint analysis. That is, β^i is the relative importance of price to individual i, calculated as the change in utility due to price as a percentage of the total possible spread in utility for the product, including the effect of changing all of its attributes. (The raw data indicated some customers were irrational in that their price sensitivity was negative – indicating they had higher utility for a higher-priced bag. We followed the sometimes-used approach of adjusting these negative sensitivities to a minute positive number, resulting in the high concentration of customers with price importance just above zero.)   Two alternative approaches that could have been used to estimate the heterogeneous β^i's are to use the Hierarchical Bayes method (c.f. Allenby and Rossi (1999)) or to assume that β is homogeneous across consumers and estimate it using the maximum likelihood fit method.

In stage three, customer i identified P^i_C, her purchase probability for her customized bag when offered at some markup m_C, with not buying as the only alternate choice. Since P^i_C, m_C, and β^i are known, we solve (1) algebraically for d^i_C, the discriminating markup that individual i attributes to her ideal customized bag design, and in turn can find $r^i_C = d^i_C + c_C$.

Let $r^i{}_{C\text{-}features}$ denote the net sum of customer i's part-worths for those attributes of her preferred custom bag that differ from the attributes of the standard bag. Since $r^i{}_{C\text{-}features}$ can be determined from the conjoint analysis along with the survey question regarding MTO delay cost, customer i's reservation price for a standard bag can readily be calculated as $r^i{}_S = r^i{}_C - r^i{}_{C\text{-}features}$, and since we know the firm's costs, from $r^i{}_S$ we can deduce the discriminating markup for a standard bag, denoted by $d^i{}_S$.

b) **Adding the Standard Bag to the Choice Set**: In the three-stage study described above, the customer's only had the opportunity to buy a custom bag – we now add the (hypothetical) option to purchase a standard bag. To do so we assume independence of irrelevant alternatives (IIA). That is, if we originally found a customer would purchase her custom-designed bag at a given price with probability x, and not purchase with probability $(1 - x)$, yielding a ratio of $[x / (1 - x)]$, then adding the choice a standard bag does not change this ratio (since there is some probability of buying the standard bag, adding it to the choice set reduces the probabilities of buying the custom bag, and not buying, by the same fraction).

c) **Expected Demand Function**: Using the data set containing each customer's beta and reservation prices (for standard and custom products), we find the demand curves for the standard and custom products. Figure 4 shows an example as a function of markups m_S and m_C. Since markups are functions of costs, and since the costs change with each iteration of the model (as described in §5), the demand curves also change with each iteration. The curves shown below are those for the jointly-consistent spackling solution, where we find $c = \$16.23$ at the point of convergence. (The "optimal point" in Figure 4 is where maximum profit is achieved, as will be described shortly.) Note that lowering the price of one type of product decreases demand for the other type, and that demand is somewhat less sensitive to price for the standard product relative as compared to that of the custom product. As a result, the shape of the total demand surface is more similar to that of the demand surface for custom products.

d) **Price Optimization**: From the sales volumes and markups in Figure 4 we calculate total profit and find the point at which it is maximized, as shown in Figure 5. The coefficient of variation v is identified as shown in Figure 6, to be fed into the operations model along with the mean demands. Note that v is increasing in markups. This likely contributes to the observed convexity of $g(c^i)$: as cost increases (as c^i increases), the prices (markups) as derived by the marketing model tend to increase, which increases v^i, which increases $c^{i+1} = g(c^i)$.

24

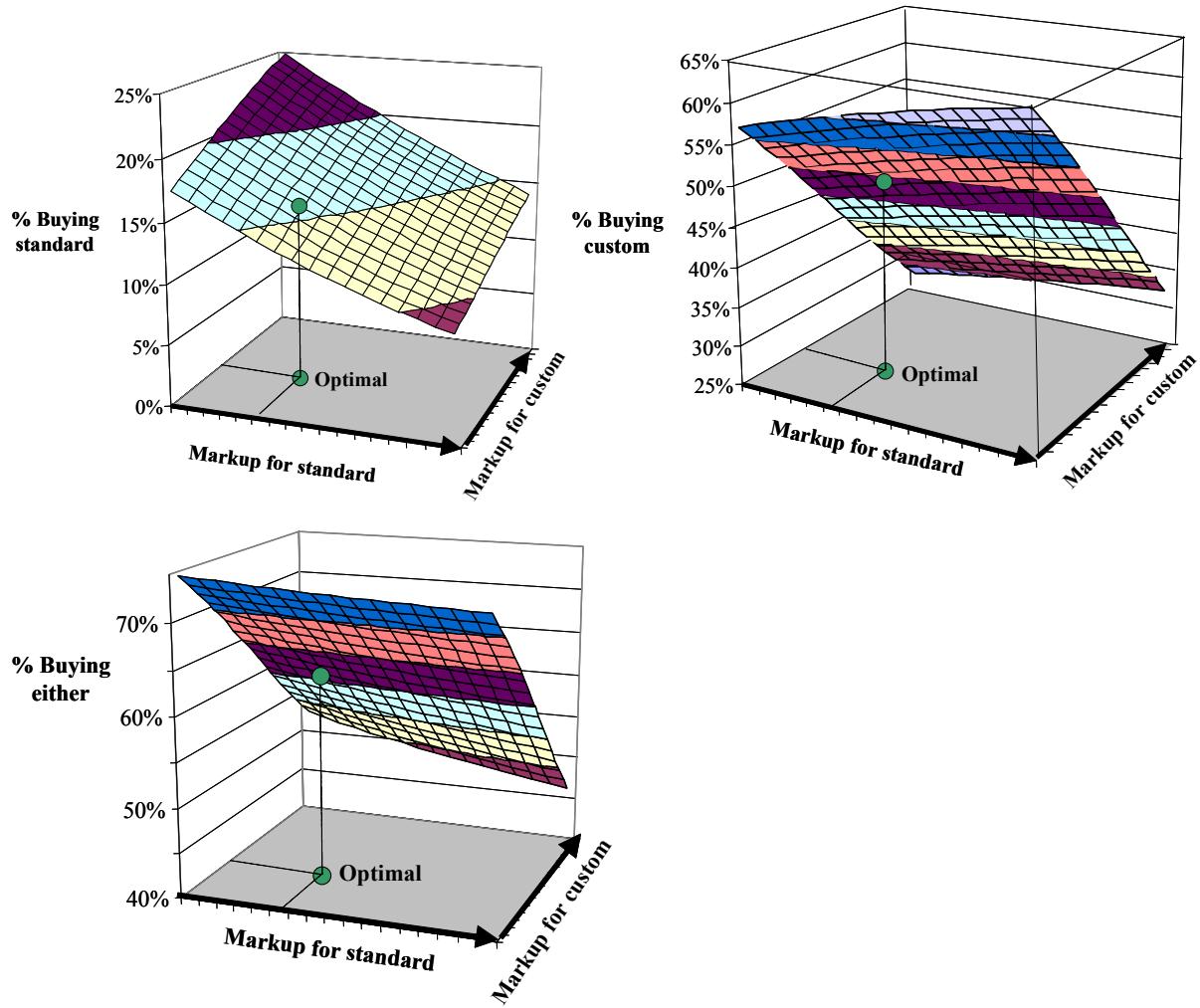**Figure 4   Expected Demand for Standard and Custom Products, and in Total**

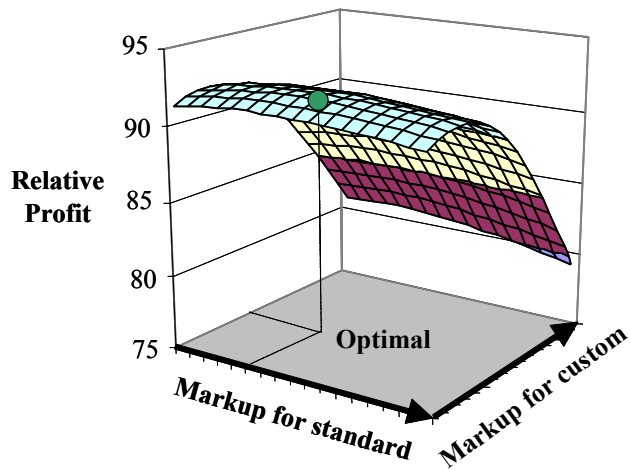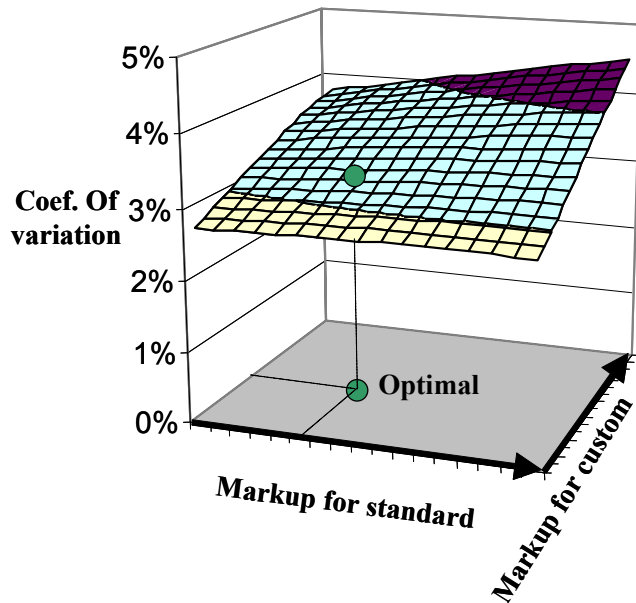**Figure 5 Expected Profit as a Function of Markups**

Figure 6   Coefficient of Variation in Total Demand


6.2.   Operations Model

Following the algorithm of §5, we feed the results of the marketing model into the operations model and solve numerically, in iterative fashion. Timbuk2's options are to spackle, using its existing flexible manufacturing capacity in San Francisco to produce both standard and custom bags, or to focus, taking advantage of less expensive off-shore production for sourcing of standard products (custom units cannot be produced off-shore because of excessive lead-times).

Efficient off-shore production has estimated costs of $\theta_E = \$11.50$ and $c_E = \$2.50$. Given $\theta_E + c_E = \$14$, we examine the how the cost of domestic flexible production impacts the choice of spackling versus focus. In all scenarios evaluated, results converged in 3 or fewer iterations between the marketing and operations models when using $\varepsilon = \$0.01$. We assume a subperiod to be one day and a period to be one month ($T = 31$).

First we examine Timbuk2's preferred strategy (spackling versus focus) as a function of the fixed cost of flexible capacity, θ_F, assuming $c_F = \$5$. Figure 7 shows Timbuk2's expected profits. Spackling is preferred as long as $\theta_F < \$11.13$. In other words, the sum of fixed plus variable costs for flexible capacity can be about 15% higher than that for efficient capacity and Timbuk2 will still be better off souring all products from its domestic flexible facility. At this point of indifference between spackling and focus, cost c is \$16.23 for spackling and cost c_C is
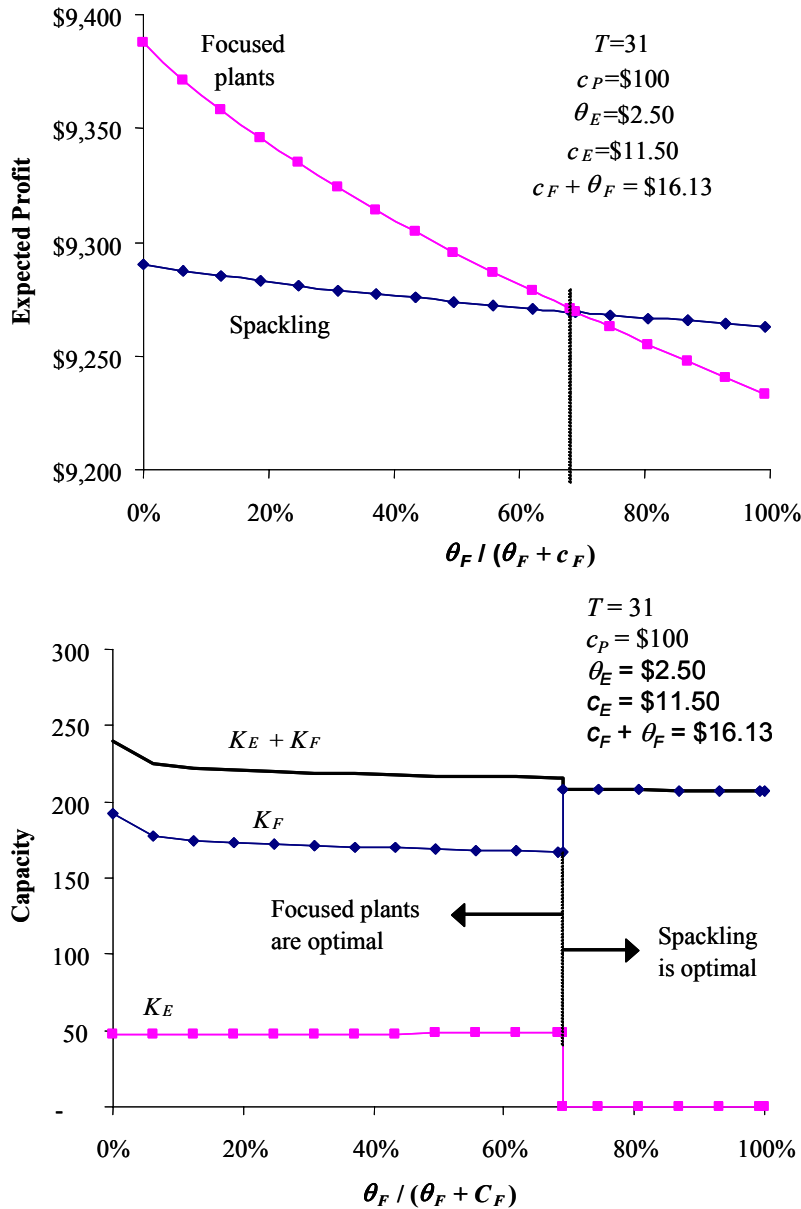
$16.88 for focus. Spackling increases utilization of the flexible capacity, reducing the combined per-unit costs of overage and underage from 75 cents ($16.88 – $16.13) to 10 cents ($16.23 – $16.13).

Figure 7   Effect of Fixed Cost of Flexible Capacity on the Choice of Spackling vs. Focus
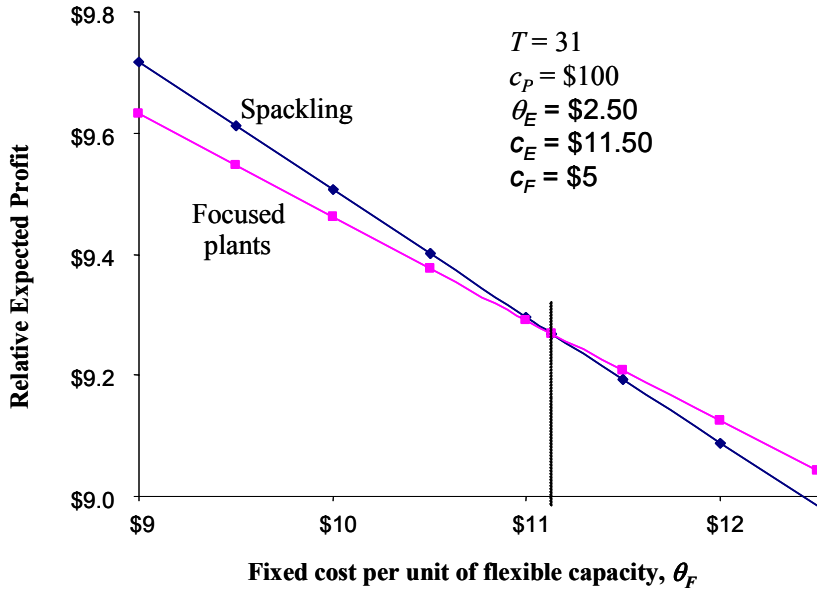
Continuing to assume the efficient resource costs are $\theta_E =$ $11.50 and $c_E =$ $2.50, we next examine the choice of spackling versus focus as a function of how much of the cost of flexible production is fixed, i.e., the ratio $\theta_F/(\theta_F + c_F)$. For example, Figure 8 shows profits and optimal capacities for varying ratios given $\theta_F + c_F =$$16.13. Note in the second frame of Figure 8 that total capacity is lower under spackling, as one might expect, due to the pooling effects. Spackling facilitates greater capacity utilization, but this is of lesser advantage if most of the cost is variable (the cost is not incurred unless demand materializes). If a high percentage of capacity is fixed, spackling becomes more attractive than a set of focused facilities.

Figure 8   Profits and Capacities as Determined by How Much of the Cost is Fixed

We also performed comparative statics associated with the parameters T, c_P, and the magnitude of the β's. In summary, we found that spackling becomes more beneficial as T and c_P increase, but with diminishing effects (this is intuitive due to the "square-root law" of pooling efficiencies). Regarding the magnitude of the β's, over the range of cutting their magnitude in half to doubling them, we found that lower price sensitivity (lower β's) favors spackling but in a relatively minor way.

In comparing our results to Timbuk2's actual practice we must consider several shortcomings of our model. First, our "customer base" may not be reflective of the actual

customer base (MIT students may not be representative of the actual customer population). Additionally, our stylized model provides insights into the various tradeoffs involved, but will not completely capture all nuances of an ongoing, multi-period problem. Also, we do not model the effects of double marginalization, leaving that extension for future research. Further, there are many considerations outside our model that Timbuk2 may want to consider in making its strategic decision of spackling versus focus, including the impact of sourcing overseas on its company culture and brand image.

7.   Conclusion

Motivated by the experiences of Timbuk2, a manufacturer of messenger bags, we have sought to gain insight as to when the practice of spackling, involving the use of a flexible production facility to produce both standard and customized products, is preferred to focus, where an efficient resource makes the standard items and a flexible factory produces the custom units. Our model suggests that spackling is the preferred strategy as long as the cost premium of the flexible resource is "not too high." In the case of Timbuk2, this means the firm should spackle as long as the cost premium is less than about 15%.

We approach the question of spackling versus focus from a joint operations-marketing perspective. The advantage of such an integrated approach is that it offers the firm a way to link its strategic production decisions to customer preferences and actions. For example, many production models have previously examined how to operate given a certain level of demand variability. In other words, production reacts to the level of demand variability inherent in the marketplace. Here we show how the firm's production decisions (along with its marketing decisions) can lead to an increase (or reduction) in demand variability. That is, decisions impacting product cost also impact expected demand and its associated variability when fed back through the marketing model. On the marketing side, models have examined pricing as a function of customer preferences and costs, but here we show that marketing decisions themselves have an impact on cost, by impacting capacity acquisitions. Further, through our iterative process, we show how marketing's pricing decisions will change as a result of consideration of overage and underage implications.

In our Timbuk2 example, we found greater demand for custom products than for standard products. In the reverse situation, where demand for standard products dominates that for

customized configurations, one might envision a more elaborate "multi-layered" spackling strategy. Here the firm would start with a layer of efficient capacity to produce most of the standard products in a constant stream (for example, sourcing them off-shore). On top of this focused and efficient production volume, the firm would add a layer of spackled (local) production to meet the periodic (say, daily) MTO orders for custom products. As in the case of "traditional" spackling that we described herein, it would also use the local flexible capacity to produce standard products when capacity is available, such that its flexible facility also runs at near-full capacity utilization. We leave the determination of optimal capacity levels under this strategy to future work. We also leave to future work extensions of our model that address the many simplifying assumptions we have made herein.

On the one hand, there seems to be heightened interest in customized products, possibly due to the successes of companies such as Dell, as well as to the spread of the Internet. The Internet facilitates customization because it allows rapid, two-way communication between the firm and its customers, facilitating product configuration and pricing, and media-rich conceptualization of product alternatives by customers (Dahan and Hauser (2002)). This attracts customers who can thus attain a better product fit or who simply prefer to configure their own products, despite having to wait for delivery and/or pay a higher price.

On the other hand, some customers still prefer to buy standard products off-the-shelf, and firms face significant production challenges in simultaneously satisfying demand for both standard and custom products. For example, the automotive industry has been talking about the "10-day car" or "3-day car" for over a decade (where a custom order would be filled in x-days), but in the U.S. firms still generally sell the bulk of their cars off-the-lot.

In practice, determining how to best meet customer needs and preferences for standard and/or custom products involves many issues and trade-offs. Our model hopefully provides some insights into the role that marketing and operations factors play this decision making process, and helps identify those situations where spackling is an attractive strategy.

Appendix: Proofs

Proof of Lemma 1.

We apply the technique of Anderson et. al. to our context. Let n denote the number of products offered to a customer, and N the number of customers. We suppress the superscripts denoting the customer.

The firm maximizes its profit, π, given by:

$$\pi = N \sum_{i=1}^{n} m_i P_i \tag{11}$$

Note that $\dfrac{\partial P_i}{\partial m_i} = \beta P_i (P_i - 1)$ and $\dfrac{\partial P_i}{\partial m_j} = \beta P_i P_j$ for $i \neq j$. The first order conditions (FOC), with respect to m_i, result in:

$$\frac{\partial \pi}{\partial m_i} = N P_i (1 + \beta \sum_{j=1}^{n} m_j P_j - \beta m_i) = 0 \ \forall \ i. \tag{12}$$

Noting $N P_j \neq 0 \ \forall \ i$, manipulation of (12) yields:

$$m_i = \frac{1}{\beta}(1 + \beta \sum_{j=1}^{n} m_j P_j) \ \ \forall \ i. \tag{13}$$

From (13), $m_i = m_j \equiv m^* \ \forall \ i, j$. Replacing m_i and m_i with $m^* \ \forall \ i, j$ in (13), m^* is the solution to:

$$m^* = \frac{1}{\beta(1 - \sum_{j=1}^{n} P_j)} \tag{14}$$

Need yet to prove the existence and uniqueness. (Again, their 7.10.1 is a very slightly different context, I believe.)

To prove the FOC result in a globally optimal solution, we show there exists a lower boundary at which profit is everywhere increasing with each margin, $\dfrac{\partial \pi}{\partial m_i}\Big|_{m_i=0} = N P_i (1 + \beta \sum_{j=1}^{n} m_j P_j) > 0$, and show (in the next paragraph) there exists an upper boundary at which profit is everywhere decreasing with each margin, that is there exists an $\bar{m}$ such that $\dfrac{\partial \pi}{\partial m_i}\Big|_{m_i=\bar{m}} < 0$ for all $m_j \leq \bar{m}$ where $j \neq i$. Given the conditions at these two boundaries, the global maximizing set of prices must lie strictly within the interior they define, i.e., all markups must be strictly greater than zero and strictly less than $\bar{m}$. Since $m_i = m_j \equiv m^* \ \forall \ i, j$ is a solution, and the only solution, to the FOC, it must lie within this interior and must be the global maximizing set of prices.

31

Next we show the existence of $\bar{m}$. Assuming it exists, let $\bar{m} \geq m_j \ \forall \ j$, and let $m_i = \bar{m}$.

Then $\left.\dfrac{\partial \pi}{\partial m_i}\right|_{m_i = \bar{m}} = NP_i(1 + \beta \sum_{j=1}^{n} m_j P_j - \bar{m}\beta) \ \leq \ NP_i(1 + \beta\bar{m}\sum_{j=1}^{n} P_j - \bar{m}\beta) \ = \ NP_i[1 - \beta\bar{m}(1 - \sum_{j=1}^{n} P_j)]$.

Note that $0 < \beta(1 - \sum_{j=1}^{n} P_j) < \beta$ such that we can find $\bar{m} > \dfrac{1}{\beta(1 - \sum_{j=1}^{n} P_j)}$

Proof of Corollary 1.

Define the base unit to be any product j with cost c_j. Consider any other product k with cost c_k. By Lemma 1, $m^* = p_j^* - c_j = p_k^* - c_k$. Thus $p_k^* - p_j^* = c_k - c_j$. That is, the optimal incremental price for the feature set that transforms product j into product k equals the incremental cost of that feature set.

Proof of Theorem 1.

The Theorem follows directly from Lemma 1, along with the normal approximation to the binomial distribution.

Proof of Theorem 2.

Let $n_i(K) = \int_K^\infty (x - K) f_i(x) dx$ be the expected loss function and $L(z)$ be the standard normal loss function.

Total expected costs over the period for the traditional case (A) are:

$$C(K_E) = \begin{cases} K_E T(c_E + \theta_E) + T(\mu_s - K_E), & K_E \leq \mu_s \\ K_E T(c_E + \theta_E), & K_E > \mu_s \end{cases}, \text{ and}$$

$$C(K_F) = T\left[\theta_F K_F + c_F \mu_c + (c_P - c_F)\int_{K_F}^\infty (x_c - K_F) f_c(x_c) dx_c\right]$$
$$= T\left[\theta_F K_F + c_F \mu_c + (c_P - c_F) n_c(K_F)\right]$$

Total expected costs over the period for the spackled-production case are:

$$C(K) = \theta_F TK + c_F(\mu_c + \mu_s)T + (c_P - c_F)\int_{T(K-\mu_s)}^\infty (x_c^T - T(K - \mu_s)) f_c^T(x_c^T) dx_c^T$$

$$= T\theta_F K + Tc_F(\mu_c + \mu_s) + (c_P - c_F) n_T(K).$$

The functional form of $C(K_F)$ and $C(K)$ is the traditional newsvendor equation from which the optimal values for the capacities are readily derived:

$$K_E^* = \mu_s$$

$$K_F^* = F^{-1}\left[\left(c_p - c_F - \theta_F\right)/\left(c_p - c_F\right)\right] = \mu_c + z\sigma$$

$$K^* = \frac{1}{T}F_T^{-1}\left[\left(c_p - c_F - \theta_F\right)/\left(c_p - c_F\right)\right] + \mu_s = \mu_c + \mu_s + \frac{1}{\sqrt{T}}z\sigma$$

where $z^* = \Phi^{-1}\left(\left(c_p - c_F - \theta_F\right)/\left(c_p - c_F\right)\right)$, *the standardized variate for the given fractile.*

To find the lower bound for c_E and spackled production, we note that spackled production will be preferred when $C\left(K_E^*\right) + C\left(K_F^*\right) > C\left(K^*\right)$, or $C\left(K_E^*\right) + C\left(K_F^*\right) - C\left(K^*\right) > 0$.

Since $C\left(K_E^*\right) + C\left(K_F^*\right) - C\left(K^*\right)$

$$= T\mu_s\left(c_E + \theta_E\right) + T\left[\theta_F K_F^* + c_F\mu_c + \left(c_p - c_F\right)n_c\left(K_F^*\right)\right] - T\theta_F K^* - Tc_F\left(\mu_c + \mu_s\right) - \left(c_p - c_F\right)n_T\left(K^*\right)$$

$$= T\left(\theta_E\mu_s + \theta_F K_F^* - \theta_F K^*\right) - T\mu_s\left(c_F - c_E\right) + \left(c_p - c_F\right)\left(Tn_c\left(K_F^*\right) - n_T\left(K^*\right)\right)$$

$$= T\left(\theta_E\mu_s + \theta_F\left(\mu_c + z\sigma\right) - \theta_F\left(\mu_c + \mu_s + \frac{1}{\sqrt{T}}z\sigma\right)\right) - \mu_s T\left(c_F - c_E\right) + \left(c_p - c_F\right)\sigma L(z)\left(T - \sqrt{T}\right),$$

this difference is greater than zero when

$$\left(c_F + \theta_F\right) - \left(\theta_E + c_E\right) > \frac{\sigma}{\mu_s}\left(1 - 1/\sqrt{T}\right)\left(z\theta_F + \left(c_p - c_F\right)L(z)\right) \equiv V.$$

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