3D Printing and Product Assortment Strategy

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3D printing, as a production technology, differs from conventional technologies in three characteristics: design freedom, i.e., it can handle certain product designs that conventional technologies cannot; quality distinction, i.e., depending on the focal quality dimension, it can lead to a quality level superior or inferior to that of conventional technologies; and natural flexibility, i.e., it is endowed with capacity flexibility without sacrificing operational efficiency. This paper investigates the joint impact of these characteristics when a firm selects conceptual designs to form its product assortment, taking into account the production technology choices available for each design: 3D printing and two conventional technologies (dedicated and traditional flexible). Some designs can be processed using any technology (generic), whereas others are specific to 3D printing (3D-specific). The firm selects designs to be handled by each technology and then invests accordingly in technology adoption, product development, capacity, and production. We characterize the structure of the optimal assortment based on the popularity of each design. Within the sets of generic designs and 3D-specific designs, respectively, the most popular designs should be included in the assortment; under a mild condition, the optimal assortment comprises the most popular ones among all the designs. Within the optimal assortment, 3D printing should handle the less popular generic designs than conventional technologies. We further demonstrate that the design freedom or improved quality associated with 3D printing may reduce the firm's optimal product variety. In the absence of design freedom and quality distinction, natural flexibility by itself always enhances product variety; by contrast, traditional flexible technology may reduce product variety. Numerical study shows that 3D printing tends to be more valuable when popularities of the generic designs are distributed more evenly and when popularities of the 3D-specific designs are distributed less evenly.

Key words: 3D printing; assortment; product design; flexible technology; multinomial logit model

1. Introduction

Firms are rapidly embracing 3D printing for the mass production of their new product assortments, especially in design-intensive industries. For instance, Nike recently announced its Flyprint series of 3D-printed shoe uppers used in performance footwear (Nike News, 2018). In IKEA's Omedelbar furnishing collection, several 3D-printed objects stand together with traditionally manufactured products (Alexandrea, 2017). IKEA is also developing its ThisAbles line, which includes 13 different 3D-printed add-ons that can help people with disabilities (Fingas, 2019). An Indian jewelry firm, Titan Company Ltd., now uses 3D printing to create new jewelry to satisfy its consumers' constantly shifting tastes (Materialise, retrieved 2019). Another jewelry firm, Nervous System, employs a variety of manufacturing technologies including 3D printing to fabricate its product lines (n-e-r-v-o-u-s.com, retrieved 2020). 3D printing is also prospering in many other industries, such as toys, clothes, medical devices, and aerospace.

When used for mass production, 3D printing features several key characteristics that distinguish it from conventional production technologies:

First, *design freedom*: 3D printing can handle certain designs that conventional technologies cannot. Conventional technologies construct geometric configurations using methods such as injection molding, machining, and casting. These methods use the "subtractive" approach, which has limitations in the geometric shapes it can handle. By contrast, 3D printing constructs items through an "additive" approach: printing an item layer by layer allows almost any geometric shape to be built (Stackpole, 2016); this opens the technology to more designs. Moreover, the additive approach of 3D printing incurs lower product development costs than conventional technologies. Unlike conventional technologies that require a laborious process to transfer a design to a physical prototype, 3D printing requires only a digital file. The aforementioned Titan Company Ltd. and Nervous System benefit substantially from 3D printing's design freedom, which enables them to deliver to the market more versatile and detailed jewelry designs that have proven popular among consumers.

Second, *quality distinction*: Depending on the focal quality dimension, 3D printing can lead to a quality level superior or inferior to that of conventional technologies. On the one hand, the special manufacturing process of 3D printing results in more sophisticated inner microstructures of certain items, leading to a desirable reduction in weight. For example, the special 3D-printed textiles of Nike's Flyprint shoe uppers make the footwear lighter than conventionally made ones, which enhances athletic performance. On the other hand, as a technology in development, 3D printing has yet to overcome the problems of porosity, uneven surfaces, and the limitation of materials (Molitch-Hou, 2017), which have been maturely addressed by conventional technologies. Broadly speaking, if delivery speed is perceived as part of product quality, then the long processing time of 3D printing may negatively affect consumer satisfaction when purchasing 3D-printed products. The good news is that recent technology advancements in high-speed sintering have significantly increased the speed of 3D printing (Jackson 2017) and considerable progress has been made to address the aforementioned quality issues (D'Aveni 2018b).

Last but not least, *natural flexibility*: 3D printing enjoys capacity flexibility without sacrificing operational efficiency. Capacity flexibility refers to the capability of handling different products within one production system. The classic flexible manufacturing system is based largely on soft automation: Production lines are equipped with changeable operations that can be configured to meet the needs of different products. In such systems, a higher variety of products unavoidably requires more complicated tooling and machinery, more frequent changeovers, and higher energy consumption, which decreases operational efficiency. By contrast, 3D printing is not "designed" to be flexible; it is flexible by nature—its production efficiency is not influenced by how many different products are handled, as long as the products meet the 3D printer's material and size standards (Ben-Ner and Siemsen, 2017). Admittedly, 3D printing is not as efficient as conventional technologies in many cases, but its constant efficiency does serve as an appealing advantage over the traditional flexible manufacturing systems, especially in high product variety environments.

Given these distinct characteristics, it is not surprising that design-intensive industries such as apparel, home-furnishings, and jewelry were among the pioneers in adopting 3D printing in large-scale manufacturing. A strategic question accompanies this technology adoption: How and to what extent will the technology adoption affect a firm's product offering strategy? Motivated by the 3D printing adoption in design-intensive industries, we study how the key characteristics of 3D printing would affect a firm's decision when it develops conceptual designs into a product assortment for the market. Since 3D printing is often considered along with conventional technologies as possible technology choices, we also include in our study two representative conventional technologies: dedicated technology and traditional flexible technology. We ask the following questions to understand the role of production technologies, especially 3D printing, in a firm's product assortment strategy: 1) What is the structure of the firm's optimal product assortment? 2) How would the introduction of 3D printing affect product variety offered by the firm? 3) When is 3D printing most valuable for the firm?

We model a firm with two sets of product designs: a generic set, in which the designs can be handled by any technology, and a 3D-specific set, in which the designs can only be handled by 3D printing. The firm selects its product assortment from the two sets of designs, determines the corresponding production technologies, and invests in the required technology adoption, prototyping, capacity, and production. Dedicated technology has no capacity flexibility; traditional flexible technology has capacity flexibility, but handling more designs decreases efficiency; and 3D printing, by its natural flexibility, has capacity flexibility with constant efficiency. Market demand for a product is determined by two factors: First, the product design's intrinsic popularity as perceived by the consumer population, regardless of the production technology, and second, product quality, which depends on the production technology, as 3D printing and conventional technologies can result in varying quality levels.

We start by characterizing the properties of the optimal assortment structure. We find that, for both the generic set and the 3D-specific set, the selected subset must comprise the most popular designs from the corresponding parent set. Although the overall assortment does not necessarily comprise the most popular designs from the union of the two sets, it does if 3D printing is used for handling at least one generic design. Within the assortment, 3D printing should always handle the less popular designs than the two conventional technologies. Between the two conventional technologies, traditional flexible technology can handle the more or the less popular designs than those handled by dedicated technology, as long as designs handled by this technology are in consecutive popularity rankings. Those structural properties are driven jointly by 3D printing's three characteristics, and hold regardless of whether the quality of 3D-printed products is superior or inferior to that of conventional technologies.

We further shed light on how product variety, i.e., the firm's optimal assortment size, is affected by the introduction of 3D printing, especially regarding the three characteristics of this technology. We find that design freedom and quality distinction have the most non-intuitive impact on product variety. Specifically, product variety may decrease despite the design freedom brought by 3D printing. As the quality of 3D printing continues to improve, product variety may increase and then decrease multiple times. We observe these results because, when the firm determines its product variety, it optimizes the overall market share of the assortment; 3D printing's design freedom and quality distinction will introduce market share cannibalization in various ways such that product variety does not necessarily increase. We also find that, in the absence of design freedom and quality distinction, the natural flexibility characteristic by itself always leads to an increased product variety. This is because it allows the firm to use the demand-pooling effect to mitigate the supply-demand mismatch problem for a larger assortment without undermining capacity/production efficiency. By contrast, traditional flexibility, whose greater degree of flexibility compromises capacity/production efficiency, may decrease product variety because the firm may focus on pooling demand for only a few products to simultaneously maintain efficiency and reduce supply-demand mismatch.

Finally, we investigate how the value of 3D printing depends on the characteristics of the product design set. To do so, we simulate design popularities that exhibit a "long tail" pattern by drawing random values from exponential distributions. We use the Gini index, an index that is commonly used for measuring income inequality, to measure the degree of unevenness of design popularities for the generic set and for the 3D-specific set, respectively. We find that 3D printing tends to be more valuable when popularities of generic designs have a lower Gini index (i.e., are more evenly distributed), and when popularities of 3D-specific designs have a higher Gini index (i.e., are less evenly distributed). We also find that 3D printing is more valuable when the generic set is smaller, the 3D-specific set is larger, or designs have lower popularities on average. As an interesting contrast, we observe that dedicated technology is more valuable when the generic designs have a higher popularity Gini index and the 3D-specific designs have a lower popularity Gini index. Traditional flexible technology generally has little value in the presence of the other two technologies.

2. Related Literature

This paper contributes to the growing literature on the operational implications of 3D printing. D'Aveni (2018a) provides a comprehensive summary of the business contexts of 3D printing. Academic research investigates this novel technology from several angles. On the manufacturing side, Westerweel et al. (2018) compare the traditional method and 3D printing for component production through a life cycle cost analysis. Hu and Sun (2021) focus on the self-replicating characteristic of 3D printers, i.e., 3D printers can be used to produce new 3D printers, and characterize the optimal make-or-sell policy in this setting. On the logistics side, Song and Zhang (2020) study the choice between make-to-stock with traditional methods and print-on-demand with 3D printing in spare parts production. Westerweel et al. (2020) study the implementation of 3D printing in the Royal Netherlands Army's logistic system, with a focus on dual sourcing. Zhang et al. (2020) consider a new logistic business model where OEMs can sell intellectual property licenses for 3D-printed spare parts. On the retailing side, Sethuraman et al. (2018) consider the phenomenon that 3D printing digital files may be fabricated by consumers and study whether it should be used as a firm's operational strategy. Arbabian and Wagner (2020) compare manufacturer adoption and retailer adoption of 3D printing in a supply chain. Chen et al. (2021) focus on 3D printing's mass customization capability and examine its impact on dual-channel retailing. Different from the above papers, our paper considers the interaction of technology choices and product assortment decisions with a consideration of several key characteristics of 3D printing. The design freedom characteristic is not considered in the above papers. Although quality distinction and natural flexibility are also considered in some of the above papers, we study these characteristics in a completely different setting that leads to insights specific to assortment decisions and product variety.

This paper also lies within the vast literature on assortment planning. Many papers in this literature seek to understand how to select product assortment based on the order of a certain product feature. The order of revenue markup is considered in Talluri and van Ryzin (2004), Hopp and Xu (2005), Alptekinoğlu and Semple (2016), Wang and Wang (2017), and Wang (2018). The order of product popularity among the consumer population is considered in van Ryzin and Mahajan (1999), Cachon et al. (2005), Gaur and Honhon (2006), Cachon and Kök (2007), and Kök and Xu (2011). The order of product quality is considered in Pan and Honhon (2012) and Wang et al. (2021). Our model is built upon the seminal framework of van Ryzin and Mahajan (1999) with a focus on product popularities, but we also consider different product revenue markups and qualities implied by the different production technologies. The 3D-printing context also triggers factors that are not yet considered in the assortment planning literature, such as flexible capacity and multiple sets of potential designs to be selected by multiple technologies.

Finally, this paper is related to the literatures on product quality design and on flexible capacity. Under the topic of designing differentiated product quality, Netessine and Taylor (2007) study the impact of general technological costs, whereas Chen et al. (2013, 2017) specifically study the impact of the coproduct technology. We consider different product quality delivered by conventional technologies and 3D printing. Within the extensive literature on flexible capacity, Van Mieghem (1998), Van Mieghem and Rudi (2003), Chod and Rudi (2005), Chod et al. (2010), Boyabatlı and Toktay (2011), Chod and Zhou (2013), and Boyabatlı et al. (2015) focus on the investment strategy of dedicated and flexible capacities. We adopt the modeling assumptions of this literature to capture capacity and production decisions. Jordan and Graves (1995), Chou et al. (2010, 2011), Simchi-Levi and Wei (2015), and Wang and Zhang (2015) focus on how to design the flexibility network. The assortment portfolio decision in our paper is also relevant to designing the network that connects products and dedicated/flexible resources. Bassamboo et al. (2010) combine these two streams of research by assuming an increasing unit capacity cost in the degree of flexibility, which inspires us to make a similar assumption for traditional flexible technology. In sum, 3D printing's distinct characteristics indicate that adopting the technology will have multifaceted implications, and thus entail issues (such as assortment and flexibility) that were usually studied in different streams of literature, while introducing new research questions such as the impact of design freedom and the comparison of natural flexibility and traditional flexibility.

3. Model

We consider a monopoly firm planning to launch a new set of product offerings for a specific selling season (e.g., one product life cycle). Product development and capacity building are time-consuming activities and need to be completed before the selling season starts. Hence, before the selling season, the firm selects from a variety of product designs and determines the corresponding production technology from three choices: 3D printing, dedicated technology, and traditional

Table 1 Notations

$\mathbb{G}$	Generic Set	Y_i	Demand
$\mathbb{S}$	3D-Specific Set	x_{Di}, x_T, x_P	Capacity
$\mathbb{D}$	Dedicated Technology Set	p_D, p_T, p_P	Price
$\mathbb{T}$	Traditional Flexible Technology Set	q_D, q_T, q_P	Quality
$\mathbb{P}$	3D Printing Set	a_D, a_T, a_P	Technology Adoption Cost
v_i	Popularity	d_D, d_T, d_P	Product Development Cost
s_i	Market Share	c_D, $c_T(\cdot)$, c_P	Unit Capacity Cost
λ	Market Size	r_D, $r_T(\cdot)$, r_P	Unit Production Cost
σ	Market Uncertainty		

Note: i is the subscript for a product design, and D, T, and P are subscripts for technologies.

flexible technology. During the selling season, the firm fulfills market demand with its production activity.

The firm's product assortment decision and technology selection decision will shape market demand for its products, while investments in the corresponding technology adoption, product development, capacity, and production will determine its supply capability. In the following, we describe the demand side and the supply side in turn. Table 1 summarizes the notations used in the model.

3.1. Assortment Selection and Demand Shaping

The firm is endowed with two sets of potential designs that can be converted into physical products: $\mathbb{G}$ is the generic set, which contains designs that could be produced by both conventional technologies and 3D printing; $\mathbb{S}$ is the 3D-specific set, which contains designs that could be produced only by 3D printing.[1] The existence of $\mathbb{S}$ manifests 3D printing's design freedom. For example, for a jewelry producer such as Nervous Systems, $\mathbb{G}$ includes conventional designs while $\mathbb{S}$ includes novel, eccentric designs that can only be 3D printed. The firm's assortment decision involves selecting designs from the two sets and assigning them to appropriate technologies. Let $\mathbb{D}$ denote all the designs selected for dedicated technology, $\mathbb{T}$ denote all the designs selected for traditional flexible technology, and $\mathbb{P}$ denote all the designs selected for 3D printing (e.g., the 3D-printed designs in IKEA's Omedelbar collection or Nike's designs in the Flyprint collection). By definition, we have $\mathbb{D} \subseteq \mathbb{G}$, $\mathbb{T} \subseteq \mathbb{G}$, and $\mathbb{P} \subseteq \mathbb{G} \cup \mathbb{S}$. Define $(\mathbb{D}, \mathbb{T}, \mathbb{P})$ as the firm's *assortment portfolio* and $\mathbb{A} \equiv \mathbb{D} \cup \mathbb{T} \cup \mathbb{P}$

[1] In Section 8.3, we additionally consider a set in which designs can be produced only by conventional technologies.

as the firm's *overall assortment*. We assume that $\mathbb{D}$, $\mathbb{T}$, and $\mathbb{P}$ are pairwise disjoint; that is, different technologies handle different designs.[2]

A selected design will be turned into a product manufactured by the assigned technology. For expositional convenience, we do not differentiate between the index of a design and the index of its corresponding product, i.e., product i means a product originated from design i. We now describe how the assortment portfolio $(\mathbb{D}, \mathbb{T}, \mathbb{P})$ shapes the firm's demand. We assume that any consumer t's utility of purchasing product i is determined by

$$u_{it}(\mathbb{D}, \mathbb{T}, \mathbb{P}) = v_i + \epsilon_{it} + q_D \cdot \mathbf{1}_{\{i \in \mathbb{D}\}} + q_T \cdot \mathbf{1}_{\{i \in \mathbb{T}\}} + q_P \cdot \mathbf{1}_{\{i \in \mathbb{P}\}} - p_D \cdot \mathbf{1}_{\{i \in \mathbb{D}\}} - p_T \cdot \mathbf{1}_{\{i \in \mathbb{T}\}} - p_P \cdot \mathbf{1}_{\{i \in \mathbb{P}\}}. \quad (1)$$

In addition, there is an outside choice that gives the consumer zero utility.

In this formulation, $v_i + \epsilon_{it}$ represents the extent to which design i is liked by consumer t. It is the value delivered by design i itself and independent of the production technology. v_i captures design i's average valuation by the consumer population, whereas ϵ_{it} captures consumer t's special taste for design i. ϵ_{it} follows a Gumbel distribution with mean 0 and variance $\pi^2/6$ across the consumer population. q_Ω $(\Omega \in \{D, T, P\})$ represents the quality level, which depends on the technology Ω used to produce product i. In practice, dedicated technology and traditional flexible technology typically share similar manufacturing mechanisms (e.g., the subtractive approach); therefore, consumers cannot distinguish between products produced by the two conventional technologies. Thus, $q_D = q_T$ usually holds. Nevertheless, our model allows q_D and q_T to differ for generality. Consumers are indeed informed if a product is 3D printed (e.g., IKEA, Nike, and Nervous System explicitly do so) and aware of the quality distinction between 3D printing and conventional technologies, so q_P usually differs from q_D and q_T. Depending on the scenario, q_P can be higher (e.g., more sophisticated inner microstructure) or lower (e.g., material issue and porosity) than q_D and q_T. Besides physical product quality, q_Ω can also include the service quality delivered by technology Ω; for example, in the case that 3D printing has a long production lead time, q_P can account for the consumer disutility from waiting (a similar assumption is made in Chen et al., 2021). We also allow products handled by different technologies to charge different prices, which are p_D, p_T, and p_P. The prices are exogenously determined by the firm's market environment, which is a widely-adopted assumption in the assortment planning (e.g., van Ryzin and Mahajan, 1999; Cachon et al., 2005; Gaur and

[2] A 3D-printed product and a conventionally produced product can have different qualities. For quality consistency across units, firms often do not produce the same design using two different technologies. Moreover, allowing one design to be handled by multiple technologies significantly complicates product-technology management and the assortment portfolio decision. The analysis of the case with overlapping $\mathbb{D}$, $\mathbb{T}$, and $\mathbb{P}$ is outside the scope of the current paper.

Honhon, 2006) and capacity flexibility (e.g., Van Mieghem, 1998; Van Mieghem and Rudi, 2003) literatures. Section 8.1 extends our model to the endogenous pricing setting.

Following the above consumer utility formulation, the market share of product i, s_i can be formulated as a multinomial-logit model:

$$\mathsf{s}_i(\mathbb{D},\mathbb{T},\mathbb{P}) = \frac{\left(\mathsf{e}^{q_D-p_D}\cdot \mathbf{1}_{\{i\in\mathbb{D}\}} + \mathsf{e}^{q_T-p_T}\cdot \mathbf{1}_{\{i\in\mathbb{T}\}} + \mathsf{e}^{q_P-p_P}\cdot \mathbf{1}_{\{i\in\mathbb{P}\}}\right)\cdot \mathsf{v}_i}{1+\mathsf{e}^{q_D-p_D}\cdot \sum_{j\in\mathbb{D}}\mathsf{v}_j + \mathsf{e}^{q_T-p_T}\cdot \sum_{j\in\mathbb{T}}\mathsf{v}_j + \mathsf{e}^{q_P-p_P}\cdot \sum_{j\in\mathbb{P}}\mathsf{v}_j}, \tag{2}$$

where e is Euler's number and $\mathsf{v}_i = \mathsf{e}^{v_i}$. The multinomial-logit model has been commonly used in the literature to formulate consumer choices; see, e.g., Hopp and Xu (2005) and Wang (2018). We define v_i as the *popularity* of design i—everything else being equal, a higher v_i means that the product is more popular among consumers.

Let λ represent market size and σ represent market uncertainty. The aggregate demand for product i, Y_i, follows a normal distribution with mean $\lambda\mathsf{s}_i$ and standard deviation $\sigma\sqrt{\mathsf{s}_i}$. The demands for different products are independent. Note that a product with a higher market share s_i enjoys lower demand variability, which is measured by the coefficient of variation $\frac{\sigma}{\lambda\sqrt{\mathsf{s}_i}}$. This is a classic demand model in the assortment planning literature (see, e.g., van Ryzin and Mahajan, 1999; Cachon et al., 2005; Gaur and Honhon, 2006) that can be shown to be an outcome of aggregating demand from random consumer arrivals. For example, when consumer arrivals follow a Poisson process, the aggregate demands approximately exhibit this distribution.

3.2. Technology Investment

To produce a product with a given technology, the firm needs to incur fixed costs for technology adoption and product development, and variable costs for capacity and production. We now describe the cost components for each of the three technologies.

An adoption cost is incurred when the firm decides to use a technology to handle some designs, i.e., the corresponding set is non-empty. The adoption costs of dedicated technology, traditional flexible technology, and 3D printing are, respectively, a_D, a_T, and a_P. Thus, the total adoption cost for the firm is $a_D\cdot\mathbf{1}_{\{\mathbb{D}\neq\varnothing\}} + a_T\cdot\mathbf{1}_{\{\mathbb{T}\neq\varnothing\}} + a_P\cdot\mathbf{1}_{\{\mathbb{P}\neq\varnothing\}}$. Setting adoption cost $a_\Omega = \infty$ means that technology Ω is prohibitively expensive, i.e., unavailable to the firm, whereas setting $a_\Omega = 0$ means that the technology can be freely adopted or is already available to the firm. These two special cases of adoption cost will be used later for comparative studies.

The development cost is d_D for each product in $\mathbb{D}$, d_T for each product in $\mathbb{T}$, and d_P for each prodcut in $\mathbb{P}$. Product development includes all the effort involved in converting the conceptual design into a real prototype; e.g., the process of converting jewelery paints to a piece of physical jewelery. This process is laborious with conventional technologies because it usually requires frequent interactions between intellectual resources (e.g., designers) and physical resources (e.g., prototyping equipment). Product development would be simpler for 3D printing because it requires mainly working with the digital files. Thus, we assume $d_P \leq \min\{d_D, d_T\}$. The total development cost for the firm is $d_D \cdot |\mathbb{D}| + d_T \cdot |\mathbb{T}| + d_P \cdot |\mathbb{P}|$.[3]

The firm needs to build capacity (machinery, tooling, workforce) for each technology to prepare for production. For dedicated technology, the firm decides a capacity x_{Di} for each product $i \in \mathbb{D}$, with a unit capacity cost of c_D. We assume a homogeneous cost structure for products produced using the same technology because these products are horizontally differentiated and require similar resource inputs.

For traditional flexible technology, the firm decides a capacity x_T that is shared among all the products in $\mathbb{T}$. We refer to a capacity capable of handling n products as n-flexible, which is consistent with the "mixed flexibility" defined in Suarez et al. (1995). Traditional flexible technology's capacity is thus $|\mathbb{T}|$-flexible. The unit capacity cost $c_T(|\mathbb{T}|)$ weakly increases in $|\mathbb{T}|$ due to more complicated tooling and more frequent changeovers (see Bassamboo et al., 2010 for a similar assumption).

For 3D printing, the firm decides a capacity of x_P that is shared among all the products in $\mathbb{P}$. Different from traditional flexible technology, 3D printing possesses natural flexibility, which means that the unit capacity cost is independent of the variety of products the technology handles.[4] Capacity cost can be used to account for slow speed of 3D printing (if that is the case): A longer processing time calls for a larger number of machines/3D printers to meet the production target on time, which increases the equipment cost for each unit of product. In sum, the unit capacity cost is a constant c_P.

Technology adoption, product development, and capacity investment are strategic decisions with long-term impacts over the entire selling season. Hence, those decisions are made and executed before the selling season. We assume that the firm carries out production activities throughout the selling season to meet consumer demand. We focus on the key interdependence between the firm's ability to meet the season's demand and its capacity level: the season's total sales are $\sum_{i\in\mathbb{D}} \min\{\mathsf{x}_{Di}, \mathsf{Y}_i\}$, $\min\{\mathsf{x}_T, \sum_{i\in\mathbb{T}} \mathsf{Y}_i\}$, and $\min\{\mathsf{x}_P, \sum_{i\in\mathbb{P}} \mathsf{Y}_i\}$ for dedicated technology, traditional flexible technology, and 3D printing, respectively. To deliver clean insights, we abstract away from modeling the firm's in-season inventory replenishment and assume the firm's demand-fulfillment

[3] We use a linear function to model the total development cost for expositional convenience. The main results may still hold under the assumption of a general increasing function.

[4] Capacity cost may depend on the variety of materials it can handle; e.g., handling both plastic and metal will be more expensive than handling just plastic. In this paper, we consider products in the same category and they have the same material requirements under the same technology. Hence, 3D printing has a constant unit capacity cost.

cost has a linear structure with unit costs r_D, r_T, and r_P for the three technologies. The linear demand-fulfillment cost is a common assumption in the operations flexibility literature where the focal decision is capacity investment (e.g., Van Mieghem, 1998 and Bassamboo et al., 2010).[5] For the sake of brevity, we refer to r_D, r_T, and r_P as the unit production costs. Following a similar rationale for the unit capacity costs, dedicated technology and 3D printing have constant unit production costs, whereas traditional flexible technology's unit production cost $r_T(|\mathbb{T}|)$ weakly increases in $|\mathbb{T}|$.

4. Initial Analysis

Given assortment portfolio $(\mathbb{D}, \mathbb{T}, \mathbb{P})$, the firm's capacity decision $\{\mathsf{x}_{Di}\}_{i\in\mathbb{D}}$, x_T, and x_P is akin to a newsvendor problem. Under the normal distribution, solving the optimal capacities gives rise to a closed-form expression of the firm's profit that depends on $(\mathbb{D}, \mathbb{T}, \mathbb{P})$, as follows:

$$\Pi(\mathbb{D}, \mathbb{T}, \mathbb{P}) = \mathcal{G}(\mathbb{D}, \mathbb{T}, \mathbb{P}) - \mathcal{M}(\mathbb{D}, \mathbb{T}, \mathbb{P}) - \mathcal{F}(\mathbb{D}, \mathbb{T}, \mathbb{P}), \tag{3}$$

where

$$\begin{aligned}\mathcal{G}(\mathbb{D}, \mathbb{T}, \mathbb{P}) =& \lambda \Bigg[(p_D - c_D - r_D) \sum_{i\in\mathbb{D}} \mathsf{s}_i(\mathbb{D}, \mathbb{T}, \mathbb{P}) \\ &+ (p_T - c_T(|\mathbb{T}|) - r_T(|\mathbb{T}|)) \sum_{i\in\mathbb{T}} \mathsf{s}_i(\mathbb{D}, \mathbb{T}, \mathbb{P}) + (p_P - c_P - r_P) \sum_{i\in\mathbb{P}} \mathsf{s}_i(\mathbb{D}, \mathbb{T}, \mathbb{P}) \Bigg],\end{aligned} \tag{4}$$

$$\begin{aligned}\mathcal{M}(\mathbb{D}, \mathbb{T}, \mathbb{P}) =& \sigma \Bigg[(p_D - r_D)\phi(z_D) \sum_{i\in\mathbb{D}} \sqrt{\mathsf{s}_i(\mathbb{D}, \mathbb{T}, \mathbb{P})} \\ &+ (p_T - r_T(|\mathbb{T}|))\phi(z_T(|\mathbb{T}|)) \sqrt{\sum_{i\in\mathbb{T}} \mathsf{s}_i(\mathbb{D}, \mathbb{T}, \mathbb{P})} + (p_P - r_P)\phi(z_P) \sqrt{\sum_{i\in\mathbb{P}} \mathsf{s}_i(\mathbb{D}, \mathbb{T}, \mathbb{P})} \Bigg],\end{aligned} \tag{5}$$

and

$$\mathcal{F}(\mathbb{D}, \mathbb{T}, \mathbb{P}) = \Big[a_D \cdot \mathbf{1}_{\{\mathbb{D}\neq\varnothing\}} + d_D \cdot |\mathbb{D}| \Big] + \Big[a_T \cdot \mathbf{1}_{\{\mathbb{T}\neq\varnothing\}} + d_T \cdot |\mathbb{T}| \Big] + \Big[a_P \cdot \mathbf{1}_{\{\mathbb{P}\neq\varnothing\}} + d_P \cdot |\mathbb{P}| \Big]. \tag{6}$$

In this formulation, product i's market share $\mathsf{s}_i(\mathbb{D}, \mathbb{T}, \mathbb{P})$ follows Equation (2); $\Phi(\cdot)$ and $\phi(\cdot)$ denote the c.d.f. and the p.d.f. of a standard normal distribution; $z_D = \Phi^{-1}(1 - \frac{c_D}{p_D - r_D})$, $z_T(|\mathbb{T}|) = \Phi^{-1}(1 - \frac{c_T(|\mathbb{T}|)}{p_T - r_T(|\mathbb{T}|)})$, and $z_P = \Phi^{-1}(1 - \frac{c_P}{p_P - r_P})$ are the newsvendor safety factors. That is, the optimal capacities are $\mathsf{x}^*_{Di} = \lambda \mathsf{s}_i + \sigma z_D \sqrt{\mathsf{s}_i}$, $\mathsf{x}^*_T = \lambda \sum_{i\in\mathbb{T}} \mathsf{s}_i + \sigma z_T \sqrt{\sum_{i\in\mathbb{T}} \mathsf{s}_i}$, and $\mathsf{x}^*_P = \lambda \sum_{i\in\mathbb{P}} \mathsf{s}_i + \sigma z_P \sqrt{\sum_{i\in\mathbb{P}} \mathsf{s}_i}$. The total profit $\Pi(\mathbb{D}, \mathbb{T}, \mathbb{P})$ equals the gross profit $\mathcal{G}(\mathbb{D}, \mathbb{T}, \mathbb{P})$ minus the supply-demand mismatch cost

[5] The linear demand-fulfillment cost structure also lends itself to formulating make-to-order production and make-to-stock production in a short selling season. We provide a detailed discussion in Section 8.2.

$\mathcal{M}(\mathbb{D},\mathbb{T},\mathbb{P})$ and minus the fixed cost $\mathcal{F}(\mathbb{D},\mathbb{T},\mathbb{P})$. The firm's assortment selection problem is thus formulated as:

$$\begin{aligned} \max_{\mathbb{D},\mathbb{T},\mathbb{P}} \ & \Pi(\mathbb{D},\mathbb{T},\mathbb{P}), \\ \text{s.t. } & \mathbb{D}\subseteq\mathbb{G},\ \mathbb{T}\subseteq\mathbb{G},\ \mathbb{P}\subseteq\mathbb{G}\cup\mathbb{S}; \\ & \mathbb{D}\cap\mathbb{T}=\mathbb{T}\cap\mathbb{P}=\mathbb{P}\cap\mathbb{D}=\varnothing. \end{aligned} \tag{7}$$

The first constraint in Formulation (7) states that dedicated and traditional flexible technologies handle generic designs only, whereas 3D printing can handle both generic and 3D-specific designs. The second constraint enforces that each design is assigned to one production technology only. Next, we make four observations about the trade-offs that are in play for the firm's assortment decision.

First, $\mathcal{G}(\mathbb{D},\mathbb{T},\mathbb{P})$ in Equation (4) shows that the gross profit opportunity associated with each technology, which is determined by the corresponding unit gross margin and the market share of each product handled by the technology, should motivate the firm to assign designs to technologies with high gross margins. It is not uncommon in today's manufacturing practice that dedicated technology yields a higher gross margin than flexible technologies, while traditional flexible technology, if not handling too many products, should have a higher margin than 3D printing. However, when a technology offers superior product quality, and thus affects the market shares of products assigned to it, the firm may favor the technology even when the unit gross margin is not high.

Second, $\mathcal{M}(\mathbb{D},\mathbb{T},\mathbb{P})$ in Equation (5) shows that the mismatch cost of each technology increases in the market share covered by the technology; traditional flexible technology and 3D printing enjoy the demand-pooling benefit enabled by their capacity flexibility, which means that, as the market share coverage increases, their mismatch costs increase at a slower speed than that of dedicated technology. However, the unit capacity/production cost of traditional flexible technology weakly increases in the number of products it handles, whereas the unit capacity/production of 3D printing is constant based on its natural flexibility. Thus, as far as the mismatch cost is concerned, the firm should prefer to assign products to traditional flexible technology or 3D printing; 3D printing is especially useful for a large number of products.

Third, $\mathcal{F}(\mathbb{D},\mathbb{T},\mathbb{P})$ in Equation (6) shows that, different from gross profit and mismatch cost, the fixed adoption cost and product development cost are not affected by the market share of each design in the assortment. The fixed cost is affected only by the size of each technology set in the assortment portfolio, and lower product development costs make the firm more inclined to choose a larger assortment.

Finally, the constraints in Formulation (7) suggest that the design freedom of 3D printing, represented by set $\mathbb{S}$, can be an important reason for the firm to adopt 3D printing because it offers more design options to choose from.

5. Assortment Structure

In this section, we characterize the structural properties of the firm's optimal assortment portfolio by solving the problem formulated in (7). The structural properties presented in this section and results in the ensuing sections hold when there exist multiple optimal solutions. Since the problem requires the determination of multiple sets, we compare designs selected for different technologies: first, between 3D printing and the two conventional technologies; then, between dedicated technology and traditional flexible technology; and finally, between the overall assortment and the designs not included in the assortment.

5.1. 3D Printing versus Conventional Technologies

We first compare designs selected for 3D printing and for conventional technologies.

Proposition 1 *Let* $(\mathbb{D}^*, \mathbb{T}^*, \mathbb{P}^*)$ *be the optimal assortment portfolio. Then:*
(i) For any $i \in \mathbb{D}^*$ *and any* $j \in \mathbb{G} \cap \mathbb{P}^*$*,* $\mathsf{v}_i \geq \mathsf{v}_j$*;*
(ii) For any $i \in \mathbb{T}^*$ *and any* $j \in \mathbb{G} \cap \mathbb{P}^*$*,* $\mathsf{v}_i \geq \mathsf{v}_j$*.*

Recall that v_i and v_j represent the popularities of design i and design j, respectively. Proposition 1(i) implies that, within the generic set $\mathbb{G}$, the designs handled by dedicated technology should be more popular than the designs handled by 3D printing. This represents an *ordered* structure between the two technologies. To see the rationale behind this property, let us consider a given assortment portfolio and focus on two designs in the generic set, $i, j \in \mathbb{G}$, with $\mathsf{v}_i > \mathsf{v}_j$. Consider three possible cases of assigning i and j between dedicated technology and 3D printing: (1) $i \in \mathbb{D}$ and $j \in \mathbb{P}$; (2) $i \in \mathbb{P}$ and $j \in \mathbb{D}$; and (3) $i, j \in \mathbb{P}$. Case (1) and Case (3) satisfy the ordered structure but Case (2) does not. Everything else being fixed, among the three cases, Case (1) and Case (3) respectively result in the lowest and highest aggregate popularity handled by 3D printing, with Case (2) falling in between. Note that, from Equation (5), the square root form of mismatch costs indicates that there are economies of scale in the aggregate market share handled by a capacity of any technology. Due to economies of scale and the pooling effect brought by 3D printing's natural flexibility, $\mathcal{G} - \mathcal{M}$ is quasi-convex in the aggregate popularity handled by 3D printing among the three cases. Adding the fixed cost $\mathcal{F}$, we can conclude that Case (2), which violates the ordered structure, can be "improved" by Case (1) or Case (3). Following a similar deduction, if an assortment portfolio violates the ordered structure between $\mathbb{D}$ and $\mathbb{P}$, we can apply the aforementioned approach to product pairs violating the ordered structure in an iterative fashion and improve the firm's profit.

Proposition 1(ii) confirms that, the ordered structure within the generic set $\mathbb{G}$ also holds between traditional flexible technology and 3D printing. To see the rationale, let us consider an assortment portfolio with design $j \in \mathbb{T}$, design $i \in \mathbb{P}$, and $\mathsf{v}_i > \mathsf{v}_j$, which violates the ordered structure. We will show that we can construct ordered structure assortment portfolios for the same overall assortment that dominates this portfolio. Consider two possible scenarios of set $\mathbb{T}$ size: (1) set $\mathbb{T}$ is relatively small and the corresponding unit capacity/production cost of handling $\mathbb{T}$ is low, and (2) set $\mathbb{T}$ is relatively large and the corresponding unit capacity/production cost is high. Under Scenario (1), the firm can improve its profit by exchanging the assignment of design i and design j, i.e., letting the more cost-efficient traditional flexible technology handle the more popular design i and 3D printing handle the less popular design j. Doing so will not affect the unit capacity/production cost of traditional flexible technology because there is no change in $|\mathbb{T}|$. Under Scenario (2), the firm's profit can be improved by moving all the designs in set $\mathbb{T}$ to set $\mathbb{P}$. Doing so creates a greater demand-pooling effect without affecting 3D printing's unit capacity/production cost, and significantly reduces the supply-demand mismatch cost. Hence, under either scenario, an assortment portfolio that violates the ordered structure between $\mathbb{T}$ and $\mathbb{P}$ can be further improved, and cannot be optimal.

A noteworthy message from Proposition 1 is that the ordered structure holds regardless of the quality level of 3D printing. That is, 3D printing should be used to handle the less popular designs even if it delivers higher quality than conventional technologies. The quality of 3D printing indeed affects the cut-off point between the "more popular" designs and the "less popular" designs, but the ordered structure will always hold.

Note that the ordered structure between conventional technologies and 3D printing applies only to designs in the generic set. If 3D-specific designs are selected into the optimal assortment, they can be more popular than designs handled by conventional technologies. The ordered structure property and the design freedom of 3D printing corroborate various industry observations. For example, experts claim that 3D printing should be used to produce low-volume and long-tail products (Smith, 2015; Pooler, 2017). The ordered structure property supports this recommendation if the low-volume products (i.e., less popular products) are generic designs. In other examples, 3D printing can be used to produce highly popular products (i.e., high-volume products) if they are 3D-specific designs, e.g., the jewelry firm Titan benefits from 3D printing's design freedom.

5.2. Dedicated Technology versus Traditional Flexible Technology

We now compare designs selected for dedicated technology and for traditional flexible technology.

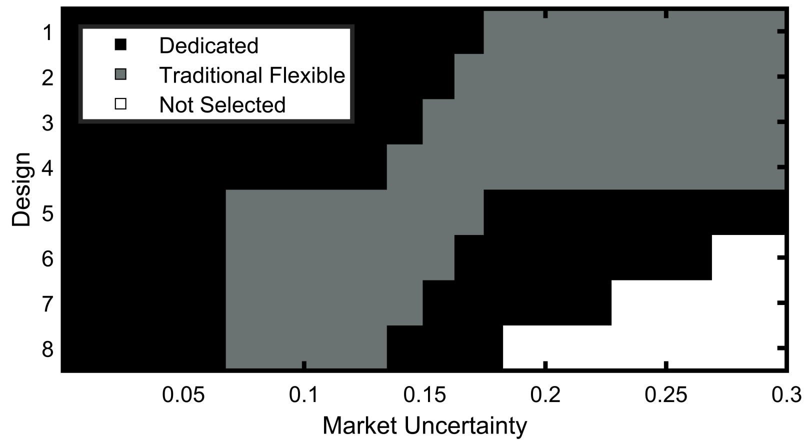
Proposition 2 *Let* $(\mathbb{D}^*, \mathbb{T}^*, \mathbb{P}^*)$ *be the optimal assortment portfolio. If* $\mathbb{T}^* \neq \varnothing$*, then for any* $i \in \mathbb{D}^*$*, either* $\mathsf{v}_i \geq \max\{\mathsf{v}_j : j \in \mathbb{T}^*\}$*, or* $\mathsf{v}_i \leq \min\{\mathsf{v}_j : j \in \mathbb{T}^*\}$*.*

Proposition 2 implies that any design handled by dedicated technology should be either more popular or less popular than all the designs handled by traditional flexible technology. In other words, if two designs are assigned to traditional flexible technology, then designs with popularity falling in between those of the two designs should also be handled by traditional flexible technology. This pattern represents a *clustered* structure of traditional flexible technology. To see the rationale, consider three designs $i, j, k \in \mathbb{G}$ with $\mathsf{v}_i > \mathsf{v}_j > \mathsf{v}_k$, and three possible cases of assigning those designs between dedicated technology and traditional flexible technology: (1) $i \in \mathbb{D}$ and $j, k \in \mathbb{T}$; (2) $j \in \mathbb{D}$ and $i, k \in \mathbb{T}$; and (3) $k \in \mathbb{D}$ and $i, j \in \mathbb{T}$. Case (1) and Case (3) satisfy the clustered structure but Case (2) does not. Everything else being fixed, the three cases have the same size of $\mathbb{T}$ and thus the same unit capacity/production cost for traditional flexible technology. Among the three cases, Case (1) and Case (3), respectively, lead to the lowest and highest aggregate popularity pooled within the traditional flexible capacity, whereas Case (2) falls in between. Similar to what has been shown for Proposition 1(i), the convexity of $\mathcal{G} - \mathcal{M}$ makes Case (2) dominated by either Case (1) or Case (3). The rationale for the local clustered structure among three designs can be applied repeatedly to explain the global clustered structure.

The clustered structure implies three possible popularity rankings between designs in $\mathbb{D}^*$ and designs in $\mathbb{T}^*$: (a) dedicated technology produces the most popular designs and traditional flexible technology produces the least popular designs; (b) dedicated technology produces the least popular designs and traditional flexible technology produces the most popular designs; (c) dedicated technology produces the most and the least popular designs and traditional flexible technology produces moderately popular designs. Ranking (a) is, perhaps, the most intuitive one and has been recognized in practitioners' discussions regarding how flexible technology should be used (Bowman and Kogut, 1995). We show in the following numerical example that ranking (b) and ranking (c) can also emerge in the optimal assortment portfolio.

Example 1 *Set* $a_D = a_T = 0$ *and* $a_P = \infty$*. Let* $\mathbb{G} = \{1, 2, 3, 4, 5, 6, 7, 8\}$ *with* $\mathsf{v}_i = 0.055 - 0.005 \cdot i$*,* $\lambda = 1$*,* $p_D = p_T = q_D = q_T = 10$*,* $c_D = r_D = 2$*,* $c_T(n) = r_T(n) = 2.3$ *for* $n \leq 4$ *and* 3 *for* $n > 4$*,* $d_D = d_T = 0.01$*. Figure 1 depicts how the optimal portfolio changes as market uncertainty* σ *increases.*

Figure 1 **Example 1 Illustration**



In Example 1, we focus on the two conventional technologies by assuming an infinite adoption cost for 3D printing. In Figure 1, the horizontal axis represents market uncertainty σ and the vertical axis indicates designs 1–8 with design 1 being the most popular and design 8 being the least popular. The dark/grey color indicates that the design is selected for dedicated/traditional flexible technology. When $\sigma \in [0, 0.068)$, all the designs are produced by dedicated technology, which is a special case of ranking (a). When $\sigma \in [0.068, 0.134)$, ranking (a) holds. When $\sigma \in [0.134, 0.182)$, ranking (c) holds; when $\sigma \in [0.182, 0.3]$, ranking (b) holds. The overall observation is that, under a higher market uncertainty, the firm tends to assign designs with higher popularities to traditional flexible technology to focus on reducing the mismatch cost for the more popular designs, while excluding the less popular designs from the flexible capacity to maintain capacity/production efficiency.

5.3. Overall Assortment

In the assortment planning literature, it has been shown in many settings that the optimal assortment should comprise the most popular product variants (e.g., van Ryzin and Mahajan, 1999; Cachon et al., 2005; Cachon and Kök, 2007; Kök and Xu, 2011). In this subsection, we show that when technology choice is considered jointly, some nuance is introduced to the "most popular" structure. The next proposition compares designs included and designs not included in the optimal overall assortment.

Proposition 3 *Let* $(\mathbb{D}^*, \mathbb{T}^*, \mathbb{P}^*)$ *be the optimal assortment portfolio and* $\mathbb{A}^* \equiv \mathbb{D}^* \cup \mathbb{T}^* \cup \mathbb{P}^*$ *be the corresponding overall assortment. Then the following hold:*

(i) For any $i \in \mathbb{G} \cap \mathbb{A}^*$ *and any* $j \in \mathbb{G}/\mathbb{A}^*$, $\mathsf{v}_i \geq \mathsf{v}_j$*;*

(ii) For any $i \in \mathbb{S} \cap \mathbb{A}^*$ *and any* $j \in \mathbb{G} \cup \mathbb{S}/\mathbb{A}^*$, $\mathsf{v}_i \geq \mathsf{v}_j$*;*

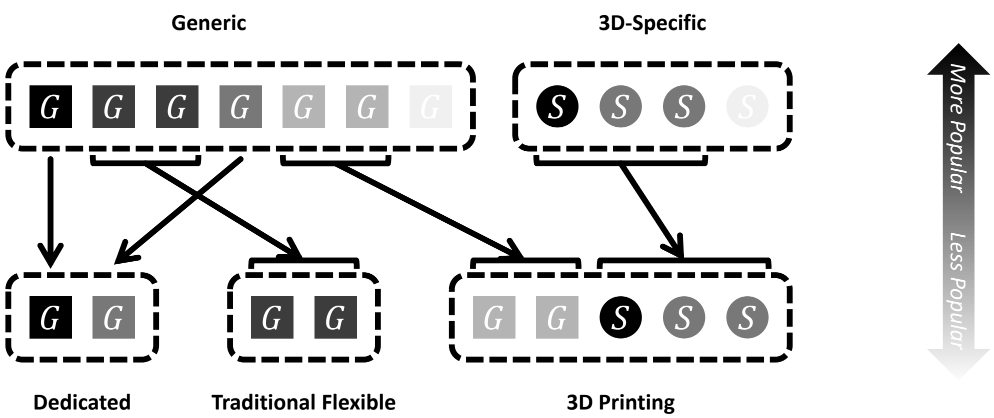
(iii) If $\mathbb{G} \cap \mathbb{P}^* \neq \varnothing$*, then for any* $i \in \mathbb{A}^*$ *and any* $j \in \mathbb{G} \cup \mathbb{S}/\mathbb{A}^*$, $\mathsf{v}_i \geq \mathsf{v}_j$*.*

Proposition 3(i) states that, within the generic set $\mathbb{G}$, any design included in the assortment should be more popular than any design not selected. This is because, if a less popular design instead of a more popular design is selected, we can always improve the firm's profit by either replacing the less popular design with the more popular one or removing the less popular one from the assortment. However, it is possible that a design selected from the generic set is less popular than a more popular 3D-specific design not included in the assortment because the former, when handled by a conventional technology, is not replaceable by the latter. Proposition 3 (ii) states that any 3D-specific design selected should be more popular than any designs (generic or 3D-specific) not selected. This is because a less popular 3D-specific design selected for 3D printing is replaceable by a more popular generic design, and thus the firm's profit can be improved by such a replacement or by removing the less popular 3D-specific design.

Proposition 3(i)–(ii) imply that the "most popular" structure holds within each individual design set, $\mathbb{G}$ and $\mathbb{S}$, to which we refer as the *enclosed most popular* structure. However, the "most popular" structure does not necessarily hold for the overall set of designs, $\mathbb{G} \cup \mathbb{S}$, because, as mentioned above, a generic design inside the assortment may be less popular than a 3D-specific design outside the assortment. Proposition 3 (iii) states that the *overall most popular* structure holds if 3D printing is utilized to handle at least one generic design. This result is due to the ordered structure established in Proposition 1 and the natural flexibility of 3D printing. Specifically, under the stated condition, 3D printing must be handling the least popular generic design within the assortment. If any design, generic or 3D-specific, outside the assortment is more popular than the least popular generic design handled by 3D printing, then the firm's profit can be improved by letting 3D printing handle the more popular design instead or removing the least popular generic design from the assortment, which follows the same logic of the above discussion for Proposition 3(i).

Propositions 1–3 jointly describe the structural properties that must be satisfied by the optimal assortment portfolio. Figure 2 provides an illustration of what a general optimal assortment portfolio should look like. Interestingly, the structure means that the problem formulated in (7), which is originally combinatorial, now collapses into an algebraic one where only several integers are the decision variables. Namely, the firm only needs to decide $|\mathbb{D}|$, $|\mathbb{T}|$, $|\mathbb{P} \cap \mathbb{G}|$, $|\mathbb{P} \cap \mathbb{S}|$, and the number of designs in $\mathbb{D}$ that are more popular than designs in $\mathbb{T}$; then the assortment portfolio can be fully characterized by applying the above structural properties. This simplification facilitates the analytical and numerical studies presented in the following sections.

Figure 2 **The General Structure of Optimal Assortment Portfolio**



6. Product Variety

A frequently discussed issue regarding 3D printing is its impact on product variety, i.e., the number of products offered. Although it is widely believed that 3D printing will significantly increase a firm's product variety, this is not always the case in practice. For instance, a very limited number of 3D-printed products can be found from Nike and IKEA (only around ten different products observed in the Omedelbar collection with fewer than five 3D-printed ones).[6] Admittedly, this can be attributed to the fact that 3D printing is still under development. We nevertheless seek to understand how the underlying characteristics of 3D printing may influence product variety.

We define product variety as the size of the optimal overall assortment, $|\mathbb{A}^*|$. In case there are multiple optimal overall assortments, product variety is defined as the size of the largest optimal overall assortment.

6.1. The Impact of Design Freedom

In our model, 3D printing's design freedom is embodied by the existence of $\mathbb{S}$, which, in addition to $\mathbb{G}$, offers the firm more potential designs that can be provided to the market. However, the following proposition shows that a larger number of potential designs does not necessarily result in the firm's offering a larger assortment.

Proposition 4 *Consider non-empty design sets $\mathbb{G}$ and $\mathbb{S}$. Let h be the most popular design in $\mathbb{S}$. Suppose $\underline{\mathbb{A}}^*$ is the (largest) optimal overall assortment given $(\mathbb{G}, \varnothing)$, i.e., $\mathbb{S}$ is unavailable, and $\overline{\mathbb{A}}^*$ is*

[6] Nike's offering of the 3D-printed footware product line is limited, although it offers a full spectrum of sizes within a product line. In our model, shoes of various sizes but sharing a common design would be considered as one product, because consumer size data can be meshed with the master prototype data during the production stage.

the (largest) optimal overall assortment given $(\mathbb{G}, \mathbb{S})$*, i.e.,* $\mathbb{S}$ *is available. Consider nontrivial cases with* $\underline{\mathbb{A}}^* \neq \varnothing$*. There exists a threshold* $\hat{\mathsf{v}}$ *such that, if* $\mathsf{v}_h > \hat{\mathsf{v}}$*, then* $|\underline{\mathbb{A}}^*| \geq |\overline{\mathbb{A}}^*|$.

Proposition 4 implies that the introduction of a 3D-specific set with highly popular designs may reduce the firm's product variety. This outcome can be explained by the cannibalization of market share introduced by 3D-specific designs. If the 3D-specific set consists of highly popular designs, then including some of those designs in the assortment will significantly cannibalize the market shares of generic designs. Based on the enclosed most popular structure in Proposition 3 (i)–(ii), the firm will adjust its assortment by keeping the most popular designs from the 3D-specific set and the generic set and abandoning some less popular generic designs to alleviate the intensified cannibalization caused by the introduction of 3D-specific designs. When the existence of a 3D-specific set, i.e., the design freedom advantage, is the only reason that the firm adopts 3D printing, then such a technology adoption may reduce product variety offered by the firm. This may explain why firms like Nike and IKEA offer only a small assortment size even with 3D printing.

Note that, theoretically speaking, if the firm is able to add a very popular design to $\mathbb{G}$, product variety may also decrease. However, in many industries, introducing a new, significantly popular design is increasingly difficult for conventional technologies that have been around for a long time. For example, the jewelry industry has been sticking to basic designs for years (Hill, 2018). By contrast, 3D printing, a new technology with design freedom, has the potential to invigorate design creativity in many industries and give rise to novel and exciting designs and products.

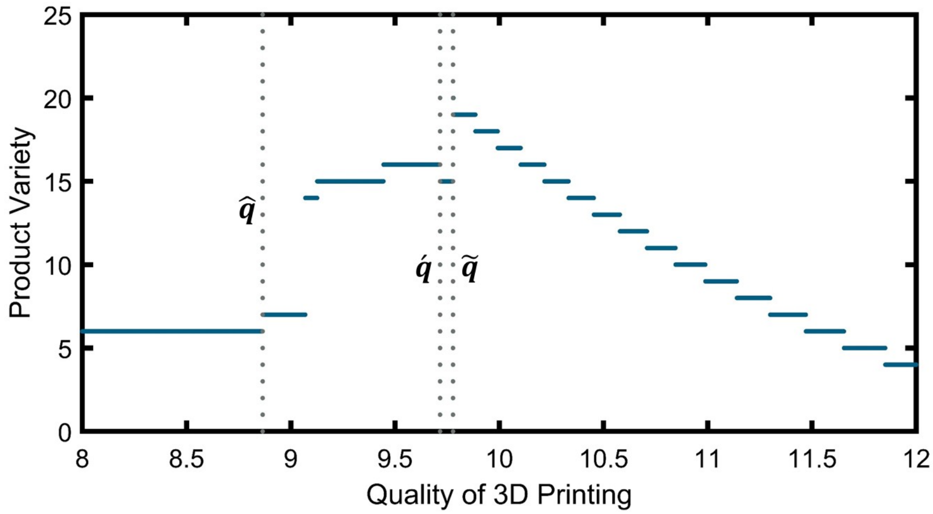
6.2. The Impact of Quality Distinction

Recent research has been striving to improve the quality of 3D printing outputs to match or exceed that of conventional technologies. For instance, breakthrough progress has been made in solving porosity problems and expanding the types of materials that 3D printing can handle (Hojjatzadeh et al., 2019; Pham et al., 2019). We next discuss the impact of improving 3D printing quality on product variety.

Proposition 5 *With* $\mathbb{G}$*,* $\mathbb{S}$*, and all the other parameters fixed, as* q_P *increases:*
(i) A threshold $\hat{q}$ *exists such that 3D printing should be adopted if and only if* $q_P \geq \hat{q}$*;*
(ii) The firm's profit under optimal assortment portfolio increases;
(iii) A threshold $\tilde{q}$ *exists such that product variety decreases for* $q > \tilde{q}$*.*

Proposition 5(i)–(ii) confirm that improving 3D printing's quality promotes the adoption of this technology and improves the firm's profit. Proposition 5(iii) shows that product variety can decrease if 3D printing's quality improvement passes a threshold. When the quality of 3D printing

Figure 3 **Example 2 Illustration**



is low, improving the quality of 3D printing would make 3D-printed products more attractive to consumers. The firm can improve profit by including more 3D-printed products to increase market coverage. However, when the quality of 3D printing is very high, the firm can keep increasing its profit by using fewer 3D-printed products (high-quality, high-popularity) to serve a significant portion of its market share while saving on the product development cost.

We can observe how increasing 3D printing's quality influences product variety from the following numerical example:

Example 2 *Let* $\mathbb{G} = \{1, 3, 5, \cdots, 39\}$ *and* $\mathbb{S} = \{2, 4, 6, \cdots, 40\}$ *with* $\mathsf{v}_i = 0.5$ *for* $i \leq 4$ *and* $\mathsf{v}_i = 0.2$ *for* $i \geq 5$. *In addition,* $\lambda = 1$, $\sigma = 0.1$, $q_D = q_T = 10$, $a_D = a_T = a_P = 0$, $d_D = d_T = 0.1$, $d_P = 0.03$, $p_D = p_T = p_P = 10$, $c_D = r_D = 2$, $c_T(n) = r_T(n) = 2 + 0.05 \cdot (n-1)$, $c_P = r_P = 2.5$. *Figure 3 depicts how product variety changes as* q_P *increases.*

Interestingly, in Example 2, the curve of product variety is non-monotonic in the quality of 3D printing and may increase and then decrease multiple times (see Figure 3). Thresholds $\hat{q}$ and $\tilde{q}$ in Proposition 5 and another threshold $\acute{q}$ are presented in the figure. As q_P increases to pass $\hat{q}$, 3D printing is adopted, which triggers an increase in product variety. As q_P increases to pass $\acute{q}$, product variety decreases to save product development cost. As q_P increases to pass $\tilde{q}$, the quality improvement of 3D printing triggers a major design-to-technology reassignment: from using 3D printing and conventional technologies jointly to using 3D printing only. This reassignment leads to another increase of product variety. Going beyond $\tilde{q}$, product variety decreases in q_P, and can even fall below the level when 3D printing is not adopted.

6.3. The Impact of Natural Flexibility

Although design freedom and quality improvement may lead to lower product variety, the natural flexibility characteristic of 3D printing always increases product variety. The next proposition, by muting the design freedom and quality distinction characteristics of 3D printing, focuses on the impact of natural flexibility on product variety.

Proposition 6 *Set $a_D = 0$ and $a_T = \infty$. Let $\mathbb{S} = \varnothing$, $q_D = q_P$, $p_D = p_P$, and $d_D = d_P$. There exists a threshold $\hat{a}$ such that:*
(i) 3D printing is adopted if and only if $a_P \leq \hat{a}$;
(ii) The (largest) optimal overall assortment $\mathbb{A}^*(a)$ is piecewise constant over $[0, \hat{a}] \cup (\hat{a}, \infty)$;
(iii) $|\mathbb{A}^*(a_1)| \leq |\mathbb{A}^*(a_2)|$ for $a_1 > \hat{a}$ and $a_2 \leq \hat{a}$.

Proposition 6 considers a scenario in which 3D printing does not offer design freedom (i.e., $\mathbb{S} = \varnothing$) and entails the same quality, price, and product development cost as conventional technologies. Under this scenario, the only characteristic that distinguishes 3D printing is its natural flexibility, i.e., capacity flexibility with constant unit capacity/production cost. Proposition 6 shows that product variety will increase when 3D printing becomes profitable for adoption. In the absence of design freedom and quality distinction, the reason that the firm adopts 3D printing is the demand-pooling benefit enabled by its natural flexibility. That is, by assigning more designs to 3D printing, the firm can reduce the mismatch cost without increasing the unit capacity cost. This benefit enables the firm to further increase the profit by including more designs in the assortment. Naturally, the optimal assortment as a function of 3D-printing adoption cost remains constant and changes only when the firm adjusts its technology adoption decision. Although Proposition 6 is shown under the assumption that dedicated technology is readily available ($a_D = 0$) and traditional flexible technology is unavailable ($a_T = \infty$), we can numerically verify that the results hold when traditional flexible technology is available ($a_T < \infty$).

We highlight that, although natural flexibility always increases product variety, traditional flexibility, contrary to common belief (e.g., Bownman and Kogut, 1995), does not necessarily lead to increased product variety. The next example shows that, when dedicated technology is already available and 3D printing is unavailable, the adoption of traditional flexible technology can reduce product variety.

Example 3 *Set $a_D = 0$ and $a_P = \infty$. Let $\mathbb{G} = \{1,2,3\}$. Fix $\mathsf{v}_1 = \mathsf{v}_2 > \mathsf{v}_3$, $d_D = d_T$, $q_D = q_T$, $p_D = p_T$, r_D, and c_D. There exist thresholds $\hat{a}$, $\underline{\sigma}$, $\overline{\sigma}$, $\overline{d}$ and increasing functions $\underline{c}(\cdot)$, $\overline{c}(\cdot)$, $\underline{r}(\cdot)$, $\overline{r}(\cdot)$ such that, if (i) $\underline{c}(\cdot) < c_T(\cdot) < \overline{c}(\cdot)$, $\underline{r}(\cdot) < r_T(\cdot) < \overline{r}(\cdot)$, (ii) $\underline{\sigma} < \sigma < \overline{\sigma}$, and (iii) $d_D, d_T < \overline{d}$, then $(\mathbb{D}^*, \mathbb{T}^*, \mathbb{P}^*) = (\{1,2,3\}, \varnothing, \varnothing)$ when $a_T \geq \hat{a}$ and $(\mathbb{D}^*, \mathbb{T}^*, \mathbb{P}^*) = (\varnothing, \{1,2\}, \varnothing)$ when $a_T < \hat{a}$.*

In Example 3, when traditional flexible technology is too costly for adoption ($a_T \geq \hat{a}$), the firm will use dedicated technology to handle all three designs; when traditional flexible technology can be adopted inexpensively ($a_T < \hat{a}$), the firm will use traditional flexible technology to handle the two most popular designs and exclude the least popular design from the assortment. To understand the rationale, we compare all four assortment portfolios under $a_T < \hat{a}$ that require the use of traditional flexible technology and satisfy the clustered structure (Proposition 2): $(\varnothing, \{1,2,3\}, \varnothing)$, $(\{1\}, \{2,3\}, \varnothing)$, $(\{3\}, \{1,2\}, \varnothing)$, $(\varnothing, \{1,2\}, \varnothing)$, and provide reasons to conclude that the first three assortment portfolios cannot be optimal under the given set of conditions. First, $(\varnothing, \{1,2,3\}, \varnothing)$ is out of consideration because a 3-flexible capacity is too expensive ($c_T(3) > \underline{c}(3)$). Second, $(\{1\}, \{2,3\}, \varnothing)$ is not considered because design 1 already faces a considerably variable demand, given the market uncertainty ($\sigma > \underline{\sigma}$), and is better handled by the flexible capacity. Next, $(\{3\}, \{1,2\}, \varnothing)$, which lets dedicated technology handle the least popular design, leads to a significant increase in the mismatch cost that outweighs the gross profit of the least popular design. Therefore, with traditional flexible technology, the firm is better off focusing on serving pooled demand from the two most popular designs and offering lower product variety than without traditional flexible technology.

7. The Value of 3D Printing

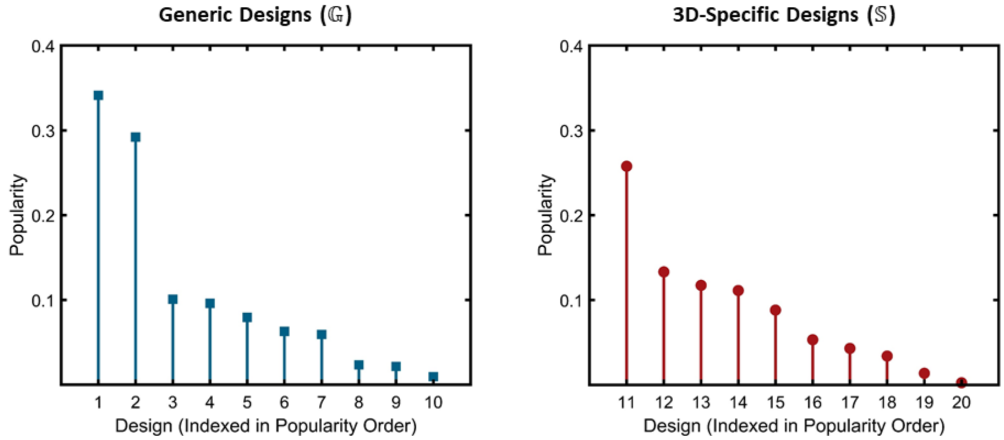
In this section, we investigate the value of 3D printing. It is straightforward that 3D printing adds more value to the firm when it has lower costs or higher quality, and when the market becomes more uncertain. Hence, in this section, we focus on the less obvious question: How does the value of 3D printing depend on the firm's endowed potential designs?

7.1. Numerical Study Setup

In practice, the popularities of product designs often follow a "long tail" pattern (Elberse, 2008): A few very popular designs coexist with a large number of niche designs, and the latter can accumulate to a considerable total market share. We simulate this pattern by drawing the popularities of different designs from an exponential distribution. To be specific, we generate samples of $\mathbb{G}$ and $\mathbb{S}$ according to the following steps:

Step 1. Let $|\mathbb{G}| = n_G$, $|\mathbb{S}| = n_S$. (n_G, n_S) take three pairs of values, $\{(5,15), (10,10), (15,5)\}$;

Figure 4 **An Instance of Generated $\mathbb{G}$ and $\mathbb{S}$**



Note. $n_G = n_S = 10$, $\mu = 0.1$.

Step 2. Let number μ take a value from $\{0.02, 0.1, 0.5\}$;

Step 3. Draw n_G values and n_S values independently from the exponential distribution with rate $\frac{1}{\mu}$, and treat them as the design popularities in $\mathbb{G}$ and $\mathbb{S}$, respectively. Thus, μ is the expectation of popularities.

Figure 4 illustrates an instance of generated popularities for $\mathbb{G}$ and $\mathbb{S}$. We follow this process to generate $100,000$ samples of $\mathbb{G}$ and $\mathbb{S}$ for each of the nine combinations of (n_G, n_S) and μ, and thus a total of $900,000$ samples are generated. For each sample, we calculate the Gini indices of design popularities in $\mathbb{G}$ and in $\mathbb{S}$. The Gini index has been broadly adopted in the economics literature (e.g., Yitzhaki, 1979 and Kopczuk, 2010) to measure income inequality. We borrow it to measure how unevenly the popularities are distributed in each of the two sets, which will be the focus of our study. A higher Gini index means that the popularities are less evenly distributed. Specifically, the Gini indices we use are defined as:

$$\text{Generic Set Gini Index} = \frac{\sum_{i\in\mathbb{G}}\sum_{j\in\mathbb{G}}|\mathsf{v}_i - \mathsf{v}_j|}{2\sum_{i\in\mathbb{G}}\sum_{j\in\mathbb{G}}\mathsf{v}_j}, \tag{8}$$

$$\text{3D-Specific Set Gini Index} = \frac{\sum_{i\in\mathbb{S}}\sum_{j\in\mathbb{S}}|\mathsf{v}_i - \mathsf{v}_j|}{2\sum_{i\in\mathbb{S}}\sum_{j\in\mathbb{S}}\mathsf{v}_j}. \tag{9}$$

Table 2 summarizes the parameters used in this numerical study. Given that the total number of parameters is great in our model, we vary the parameters related to 3D printing while fixing the others. For each sample of $\mathbb{G}$ and $\mathbb{S}$, we examine the firm's profit under all combinations of the parameters.

Table 2 Parameters Used in the Numerical Study

Fixed Parameters									
λ	p_D, p_T, & p_P	c_D & r_D	$c_T(n)$ & $r_T(n)$	a_D	a_T	d_D	d_T	q_D	q_T
1	10	2	$2+0.1\cdot(n-1)$	0	0	0.1	0.1	10	10

Varied Parameters				
σ	c_P & r_P	a_P	d_P	q_P
0.1, 0.3	2.5, 3	0, ∞	0.05, 0.1	9, 10, 11

Note that the adoption cost of 3D printing, a_P, can be either 0 or ∞, which respectively correspond to the two cases that 3D printing can be adopted or never adopted. Given $\mathbb{G}$, $\mathbb{S}$, and a combination of other parameters, we let π_0 be the optimal profit when $a_P=0$ and π_∞ be the optimal profit when $a_P=\infty$, and define

$$\text{Improvement Index} = \begin{cases} \frac{\pi_0-\pi_\infty}{\pi_0+\pi_\infty} & \text{if } \pi_0>0 \\ 0 & \text{if } \pi_0=0 \end{cases} \tag{10}$$

to measure the value of 3D printing to the firm.[7] The improvement index is a number between 0 and 1. It equals 0 when 3D printing does not bring any additional profit to the firm and equals 1 when 3D printing can turn a nonviable business (zero profit) into a profitable one (the firm always obtains a non-negative profit because it can opt to choose an empty assortment).

7.2. Numerical Results

We focus on investigating the impacts of three sets of parameters representing the potential designs' characteristics: the Gini indices of generic and 3D-specific sets, which measure the popularity distribution unevenness; (n_G,n_S), which measure the availability of potential designs; and μ, which measures the mean popularity of potential designs.

First, for each of the nine combinations of (n_G,n_S) and μ, we compute the improvement index for all $100,000$ samples and for all parameters listed in Table 2, and average the improvement indices over sample combinations with similar Gini indices. Table 3 presents the average improvement index for any given ranges of the generic set Gini index and the 3D-specific set Gini index when $(n_G,n_S)=(10,10)$ and $\mu=0.1$. Results for all the other combinations of (n_G,n_S) and μ are similar and relegated to Online Supplement B.

[7] An intuitive measurement of improvement is percentage increase, $\frac{\pi_0-\pi_\infty}{\pi_\infty}\times 100\%$. We do not use it because it may happen that $\pi_0>0$ and $\pi_\infty=0$, leading to an infinite value. The measurement we use is well defined for any π_0 and π_∞ and is consistent with percentage increase (i.e., a larger improvement index means a larger percentage increase) when percentage increase is also well defined.

Table 3 Average Improvement Index under Given Ranges of Gini Indices

		Generic Set Gini Index								
		0–0.35	0.35–0.4	0.4–0.45	0.45–0.5	0.5–0.55	0.55–0.6	0.6–0.65	0.65–1	Overall
3D-Specific Set Gini Index	0–0.35	0.1408	0.1289	0.1178	0.1080	0.0980	0.0906	0.0807	0.0718	0.1136
	0.35–0.4	0.1452	0.1321	0.1191	0.1129	0.1037	0.0963	0.0885	0.0772	0.1173
	0.4–0.45	0.1490	0.1354	0.1253	0.1179	0.1078	0.1000	0.0905	0.0858	0.1219
	0.45–0.5	0.1545	0.1409	0.1299	0.1205	0.1119	0.1045	0.0940	0.0854	0.1260
	0.5–0.55	0.1614	0.1431	0.1357	0.1248	0.1154	0.1046	0.1020	0.0845	0.1304
	0.55–0.6	0.1649	0.1484	0.1384	0.1274	0.1219	0.1084	0.0961	0.0957	0.1338
	0.6–0.65	0.1809	0.1599	0.1426	0.1338	0.1230	0.1097	0.1046	0.1225	0.1411
	0.65–1	0.1766	0.1639	0.1507	0.1351	0.1255	0.1227	0.1053	0.0771	0.1431
	Overall	0.1531	0.1386	0.1278	0.119	0.1098	0.1013	0.0926	0.0845	0.1242

Note. $n_G = n_S = 10$, $\mu = 0.1$.

We may examine each row in Table 3. As the generic set Gini index increases, 3D printing tends to be less valuable. Recall that designs in the generic set can be produced by both conventional technologies and 3D printing. When the generic designs have more evenly distributed popularities (i.e., low Gini index), the firm can achieve a reasonable market coverage by using 3D printing to produce some designs in the assortment so as to control the mismatch cost without increasing unit capacity/production cost. When the generic designs have more unevenly distributed popularities (i.e., high Gini index), the firm can achieve a reasonable market coverage by focusing on a small subset of designs. Conventional technologies can serve as the workhorse handling the relatively small assortment as the mismatch cost and development cost are low. Hence, the value of 3D printing decreases as the generic set Gini index increases.

We next examine each column in Table 3. By contrast, 3D printing becomes more valuable as the 3D-specific set Gini index increases. This is because designs in the 3D-specific set can be handled only by 3D printing. When the 3D-specific designs have more evenly distributed popularities (i.e., low Gini index), 3D printing has to handle a large number of designs to obtain sufficient market

Table 4 Average Improvement Index under Given Potential-Design Sizes and Expectations

		Generic Set Gini Index					
		0.4–0.45			0.55–0.6		
3D-Specific Set Gini Index		n_G, n_S			n_G, n_S		
		5,15	10,10	15,5	5,15	10,10	15,5
0.4–0.45	μ = 0.02	0.4640	0.3789	0.3158	0.3962	0.2839	0.2247
	μ = 0.1	0.2536	0.1253	0.0824	0.2189	0.1000	0.0577
	μ = 0.5	0.0482	0.0141	0.0076	0.0383	0.0077	0.0029
		n_G, n_S			n_G, n_S		
		5.15	10.10	15.5	5.15	10.10	15.5
0.55–0.6	μ = 0.02	0.5480	0.4198	0.3449	0.4511	0.3201	0.2367
	μ = 0.1	0.2809	0.1384	0.0880	0.2546	0.1084	0.0650
	μ = 0.5	0.0558	0.0158	0.0082	0.0457	0.0082	0.0034

coverage. When the 3D-specific designs have less evenly distributed popularities (i.e., high Gini index), 3D printing can achieve approximately the same amount of market coverage and revenue with fewer highly popular designs and save on the product development cost. However, the effect of product development cost is small for 3D printing, which explains why the average improvement index is less sensitive to the 3D-specific set Gini index than to the generic set Gini index. It also explains some local decreasing patterns in the simulation (e.g., when the generic set Gini index is 0.65–1 and the 3D specific set Gini index increases from 0.4–0.45 to 0.45–0.5).

We further study the impacts of (n_G, n_S) and μ. Table 4 presents the average improvement indices for all nine combinations of (n_G, n_S) and μ, under four representative combinations of Gini indices. For each combination of Gini indicies (each of the four small tables), 3D printing is more valuable when the number of generic designs is smaller and the number of 3D-specific designs is larger (the first columns in the small tables), or the designs' mean popularity is low (the first rows in the small tables). The former is due to more potential design availability introduced by 3D printing in comparison with the existing, generic designs; the latter is due to the need for using 3D printing to deliver a larger assortment of low-popularity designs.

We also look into the values of the other two technologies using the same approach. The Gini index has an opposite impact on the value of dedicated technology. That is, dedicated technology is more valuable as the generic set Gini index increases and the 3D-specific set Gini index decreases. We also observe that the value of traditional flexible technology is the lowest among the three technologies. Its improvement index is over 0.01 for only 10.03% of the samples (compared with 31.99% for dedicated technology and 49.66% for 3D printing). Note that our selection of parameters deliberately make traditional flexible technology more cost-attractive than 3D printing: Its capacity and production costs increase to the same level as those of 3D printing when handling five (for low 3D printing cost) or ten (for high 3D printing cost) designs, which are sufficiently large compared with the overall sizes of the design sets. The intuition behind this observation can be explained as follows. Traditional flexible technology can be treated as a moderate technology positioned between dedicated technology and 3D printing, with more expensive total capacity/production/mismatch cost than dedicated technology (3D printing) when handling a small (large) number of designs. Adopting dedicated technology and 3D printing is thus almost sufficient and the adoption of an additional in-between technology does not bring much incremental value.

8. Extensions

In this section, we check the robustness of results using several extensions.

8.1. Endogenous Pricing

In the base model, the prices p_D, p_T, and p_P are exogenously given. One may wonder whether the insights on product assortment strategy with 3D printing apply to scenarios where the firm can adjust its prices for products made by different technologies. We extend the study to an endogenous pricing setting in which the firm determines p_D, p_T, and p_P together with the assortment portfolio decision $(\mathbb{D}, \mathbb{T}, \mathbb{P})$. The technical details of the endogenous pricing problem are presented in Appendix A.

We can prove that, under endogenous pricing, Propositions 1–3 in the base model continue to hold. It implies that the optimal assortment structure in the base model remains valid even under endogenous pricing. The reason behind the structure's robustness is that, although endogenous pricing can improve the performance of any given assortment, such an improvement would only strengthen the structural dominance that holds under exogenous pricing.

We also conduct numerical experiments to check the other results in the base model. We highlight that the impacts of 3D printing on product variety remain valid. In the base model, design freedom or improved quality of 3D printing may reduce product variety to weaken market cannibalization between products. Although smart pricing can help reduce market cannibalization, it is not strong enough to enable 3D printing's design freedom or improved quality to always increase product variety. Natural flexibility alone still enhances product variety. As to the value of 3D printing, we also observe similar implications for the popularity Gini indices as in the base model. The details of these findings can be found in Appendix A.

8.2. Make-to-Stock versus Make-to-Order

In practice, when facing a short selling season, the firm may use dedicated technology in a make-to-stock fashion and flexible technologies in a make-to-order fashion. This situation can be captured by the base model with slight modifications: (a) in Equation (5), we change the newsvendor safety factor z_D's expression from $\Phi^{-1}(1-\frac{c_D}{p_D-r_D})$ to $\Phi^{-1}(1-\frac{c_D+r_D}{p_D})$ and change the term $(p_D-r_D)\phi(z_D)$ to $p_D\phi(z_D)$ to reflect that, in a make-to-stock setting, the unit production cost of dedicated technology, r_D, is an ex ante cost instead of an ex post cost; (b) we adjust the quality levels of the two flexible technologies, q_T and q_P, to reflect the potential consumer disutility for having to wait longer for product delivery. The rest of the formulations remain unchanged. These minor changes do not affect the proofs of Propositions 1–6 or the qualitative implications of the numerical study.

8.3. Conventional-Specific Designs

Although 3D printing has been advocated as being able to handle almost any geometric shape (Stackpole, 2016), it is possible that 3D printing, still a technology in development, cannot handle some designs that conventional technologies can. For example, 3D printing cannot yet meet the high-precision requirements for certain products with very small parts (3D Supermarket, 2017). Such a situation can be captured by introducing a conventional-specific set $\mathbb{C}$ consisting of designs that could be produced only by conventional technologies. The introduction of this new design set does not affect the basic dynamics of the model, and thus all the propositions remain valid with minor adjustments. For concision, we present the details of this extension in Appendix B.

9. Concluding Remarks

Views of 3D printing that accompanied the development of the technology have ranged from the belief that the technology would revolutionize the manufacturing sector to recognition of its limitations and areas for improvement. Nevertheless, the industrial utilization and scientific breakthroughs of 3D printing are growing rapidly and steadily because its novelty offers opportunities that are impossible with conventional technologies. Motivated by the rise of industry practices that use 3D printing to produce products with novel designs, this paper studies how a firm should manage its product assortment under 3D printing and conventional production technologies. We focus on three key characteristics of 3D printing: design freedom, quality distinction, and natural flexibility, and investigate how they jointly affect a firm's product assortment strategy.

We have identified several structural properties for the optimal assortment: Between 3D printing and conventional technologies, the “ordered” structure must be satisfied; between dedicated technology and traditional flexible technology, the “clustered” structure must be satisfied; between the overall assortment and the designs that are not selected, the “enclosed most popular” structure must be satisfied and, under a mild condition, the “overall most popular” structure should also be satisfied. These structural properties that impose certain popularity ordering across designs handled by different technologies reflect the joint consideration of market coverage and supply-demand mismatch cost, both of which are influenced by the three key characteristics of 3D printing. We also show that the three characteristics of 3D printing have varying impacts on a firm’s product variety decision. Design freedom or improved quality of 3D printing may reduce product variety, but natural flexibility by itself always increases product variety. Natural flexibility is further contrasted with traditional flexibility: The former always increases but the latter may reduce product variety. Finally, we demonstrate through numerical analysis that the Gini index, which is usually used to evaluate wealth inequality, can serve as a useful indicator for the value of 3D printing. The messages are useful for firms that contemplate the adoption of 3D printing and joint utilization of 3D printing and conventional technologies for developing new product assortments.

This paper focuses on the aforementioned three characteristics of 3D printing while making simplified assumptions regarding other characteristics. For example, we treat 3D printing’s speed issue as a quality factor affecting consumer valuation as well as a cost factor affecting the unit capacity cost. This is a reasonable simplification for assortment decisions. The speed issue would require more detailed modeling in an inventory management system where production lead time is a crucial parameter (see, e.g, Song and Zhang, 2020). Another appealing characteristic of 3D printing this paper does not capture is that it generates less material waste in manufacturing and thus benefits the environment. In addition, 3D printing has inspired novel business models, e.g., consumers are offered opportunities to provide their own product designs (a form of crowd sourcing). As 3D printing technology evolves and becomes a viable manufacturing technology for more and more industries, it can introduce interesting technological ramifications into many operations and supply chain problems.

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Appendix: Technical Details of Extensions

In this appendix, we present the technical details of two extensions: the firm has the pricing power (Appendix A) and some designs can be handled only by conventional technologies (Appendix B).

A. Endogenous Pricing

This section presents the technical details of Section 8.1, which discusses the case of endogenous pricing. Let $\vec{p} = (p_D, p_T, p_P)$. We formulate the firm's problem as a two-stage optimization. In the first stage,

$$\begin{aligned} &\max_{\mathbb{D},\mathbb{T},\mathbb{P}} \ \Pi(\mathbb{D},\mathbb{T},\mathbb{P}), \\ &\text{s.t. } \mathbb{D} \subseteq \mathbb{G},\ \mathbb{T} \subseteq \mathbb{G},\ \mathbb{P} \subseteq \mathbb{G} \cup \mathbb{S}; \\ &\qquad \mathbb{D} \cap \mathbb{T} = \mathbb{T} \cap \mathbb{P} = \mathbb{P} \cap \mathbb{D} = \varnothing. \end{aligned} \tag{A.1}$$

In the second stage,

$$\begin{aligned} \Pi(\mathbb{D},\mathbb{T},\mathbb{P}) := &\max_{\vec{p}} \Omega(\vec{p},\mathbb{D},\mathbb{T},\mathbb{P}), \\ &\text{s.t. } \vec{p} \geq \vec{0}. \end{aligned} \tag{A.2}$$

Following backward induction, we first optimize the firm's profit with respect to $\vec{p}$ for a given $(\mathbb{D},\mathbb{T},\mathbb{P})$ and then find the optimal $(\mathbb{D},\mathbb{T},\mathbb{P})$. This approach is equivalent to optimizing $\vec{p}$ and $(\mathbb{D},\mathbb{T},\mathbb{P})$ simultaneously, but has more expositional clarity. The formulation of $\Omega(\vec{p},\mathbb{D},\mathbb{T},\mathbb{P})$ is as follows:

$$\Omega(\vec{p},\mathbb{D},\mathbb{T},\mathbb{P}) = \mathcal{G}(\vec{p},\mathbb{D},\mathbb{T},\mathbb{P}) - \mathcal{M}(\vec{p},\mathbb{D},\mathbb{T},\mathbb{P}) - \mathcal{F}(\vec{p},\mathbb{D},\mathbb{T},\mathbb{P}), \tag{A.3}$$

where

$$\begin{aligned} \mathcal{G}(\vec{p},\mathbb{D},\mathbb{T},\mathbb{P}) =&\lambda\Bigg[(p_D - c_D - r_D)\sum_{i\in\mathbb{D}} \mathsf{s}_i(\vec{p},\mathbb{D},\mathbb{T},\mathbb{P}) \\ &+ (p_T - c_T(|\mathbb{T}|) - r_T(|\mathbb{T}|))\sum_{i\in\mathbb{T}} \mathsf{s}_i(\vec{p},\mathbb{D},\mathbb{T},\mathbb{P}) + (p_P - c_P - r_P)\sum_{i\in\mathbb{P}} \mathsf{s}_i(\vec{p},\mathbb{D},\mathbb{T},\mathbb{P})\Bigg], \end{aligned} \tag{A.4}$$

$$\begin{aligned} \mathcal{M}(\vec{p},\mathbb{D},\mathbb{T},\mathbb{P}) =&\sigma\Bigg[(p_D - r_D)\phi(z_D)\sum_{i\in\mathbb{D}} \sqrt{\mathsf{s}_i(\vec{p},\mathbb{D},\mathbb{T},\mathbb{P})} \\ &+ (p_T - r_T(|\mathbb{T}|))\phi(z_T(|\mathbb{T}|))\sqrt{\sum_{i\in\mathbb{T}} \mathsf{s}_i(\vec{p},\mathbb{D},\mathbb{T},\mathbb{P})} + (p_P - r_P)\phi(z_P)\sqrt{\sum_{i\in\mathbb{P}} \mathsf{s}_i(\vec{p},\mathbb{D},\mathbb{T},\mathbb{P})}\Bigg], \end{aligned} \tag{A.5}$$

and

$$\mathcal{F}(\vec{p},\mathbb{D},\mathbb{T},\mathbb{P}) = \Big[a_D \cdot \mathbf{1}_{\{\mathbb{D}\neq\varnothing\}} + d_D \cdot |\mathbb{D}|\Big] + \Big[a_T \cdot \mathbf{1}_{\{\mathbb{T}\neq\varnothing\}} + d_T \cdot |\mathbb{T}|\Big] + \Big[a_P \cdot \mathbf{1}_{\{\mathbb{P}\neq\varnothing\}} + d_P \cdot |\mathbb{P}|\Big]. \tag{A.6}$$

Here $\mathsf{s}_i(\vec{p},\mathbb{D},\mathbb{T},\mathbb{P})$ is the market share of product i and z_D, $z_T(|\mathbb{T}|)$, and z_P are the newsvendor safety factors, all of which depend on $\vec{p}$. In this extension, we allow consumer utility to have a general functional form with respect to prices:

$$u_{it}(\vec{p},\mathbb{D},\mathbb{T},\mathbb{P}) = v_i + \epsilon_{it} + q_D \cdot \mathbf{1}_{\{i\in\mathbb{D}\}} + q_T \cdot \mathbf{1}_{\{i\in\mathbb{T}\}} + q_P \cdot \mathbf{1}_{\{i\in\mathbb{P}\}} - f(p_D)\cdot \mathbf{1}_{\{i\in\mathbb{D}\}} - f(p_T)\cdot \mathbf{1}_{\{i\in\mathbb{T}\}} - f(p_P)\cdot \mathbf{1}_{\{i\in\mathbb{P}\}}, \tag{A.7}$$

where $f(\cdot)$ can be any (weakly) increasing function. Thus, $\mathsf{s}_i(\vec{p}, \mathbb{D}, \mathbb{T}, \mathbb{P})$ is given by:

$$\mathsf{s}_i(\vec{p}, \mathbb{D}, \mathbb{T}, \mathbb{P}) = \frac{\left(\mathsf{e}^{q_D - f(p_D)} \cdot \mathbf{1}_{\{i \in \mathbb{D}\}} + \mathsf{e}^{q_T - f(p_T)} \cdot \mathbf{1}_{\{i \in \mathbb{T}\}} + \mathsf{e}^{q_P - f(p_P)} \cdot \mathbf{1}_{\{i \in \mathbb{P}\}}\right) \cdot \mathsf{v}_i}{1 + \mathsf{e}^{q_D - f(p_D)} \cdot \sum_{j \in \mathbb{D}} \mathsf{v}_j + \mathsf{e}^{q_T - f(p_T)} \cdot \sum_{j \in \mathbb{T}} \mathsf{v}_j + \mathsf{e}^{q_P - f(p_P)} \cdot \sum_{j \in \mathbb{P}} \mathsf{v}_j}. \tag{A.8}$$

The second-stage pricing problem is non-concave and does not have a closed-form solution. However, without characterizing the optimal prices (they do not have to be unique), we can prove:

Proposition A. 1 *Propositions 1–3 still hold under endogenous pricing.*

Thus, the optimal assortment structure in the base model holds under endogenous pricing. Recall the approach to prove Propositions 1–3: Any assortment portfolio violating the stated structure can always be improved by constructing another assortment portfolio; the process iterates until an assortment portfolio satisfying the stated structure is obtained. This approach applies to the endogenous pricing setting with minor twists. That is, first, we maintain a portfolio's optimal prices when constructing the dominating assortment portfolio; second, we optimize prices for the new portfolio; the process iterates until an assortment portfolio is found with the stated structure and optimal pricing.

For example, in Proposition 1(i), we have characterized the ordered structure between dedicated technology and 3D printing. Now, under endogenous pricing, we again consider a given assortment portfolio and focus on two designs $i, j \in \mathbb{G}$ with $\mathsf{v}_i > \mathsf{v}_j$. With all the other designs fixed, we consider three assortment portfolios which differ in the assignment of design i and design j: In $(\mathbb{D}_1, \mathbb{T}_1, \mathbb{P}_1)$, $i \in \mathbb{D}_1$ and $j \in \mathbb{P}_1$; in $(\mathbb{D}_2, \mathbb{T}_2, \mathbb{P}_2)$, $i \in \mathbb{P}_2$ and $j \in \mathbb{D}_2$; in $(\mathbb{D}_3, \mathbb{T}_3, \mathbb{P}_3)$, $i, j \in \mathbb{P}_3$. With respect to design i and design j, $(\mathbb{D}_1, \mathbb{T}_1, \mathbb{P}_1)$ and $(\mathbb{D}_3, \mathbb{T}_3, \mathbb{P}_3)$ satisfy the ordered structure but $(\mathbb{D}_2, \mathbb{T}_2, \mathbb{P}_2)$ does not. Following the same rationale with Proposition 1(i), for any given $\vec{p}$, we have either $\Omega(\vec{p}, \mathbb{D}_1, \mathbb{T}_1, \mathbb{P}_1) > \Omega(\vec{p}, \mathbb{D}_2, \mathbb{T}_2, \mathbb{P}_2)$ or $\Omega(\vec{p}, \mathbb{D}_3, \mathbb{T}_3, \mathbb{P}_3) > \Omega(\vec{p}, \mathbb{D}_2, \mathbb{T}_2, \mathbb{P}_2)$. Now, let $\vec{p}_i^*$ be the optimal price vector under assortment portfolio $(\mathbb{D}_i, \mathbb{T}_i, \mathbb{P}_i)$. The following hold: 1) Either $\Omega(\vec{p}_2^*, \mathbb{D}_1, \mathbb{T}_1, \mathbb{P}_1) > \Omega(\vec{p}_2^*, \mathbb{D}_2, \mathbb{T}_2, \mathbb{P}_2) = \Pi(\mathbb{D}_2, \mathbb{T}_2, \mathbb{P}_2)$ or $\Omega(\vec{p}_2^*, \mathbb{D}_3, \mathbb{T}_3, \mathbb{P}_3) > \Omega(\vec{p}_2^*, \mathbb{D}_2, \mathbb{T}_2, \mathbb{P}_2) = \Pi(\mathbb{D}_2, \mathbb{T}_2, \mathbb{P}_2)$; 2) $\Pi(\mathbb{D}_1, \mathbb{T}_1, \mathbb{P}_1) = \Omega(\vec{p}_1^*, \mathbb{D}_1, \mathbb{T}_1, \mathbb{P}_1) \geq \Omega(\vec{p}_2^*, \mathbb{D}_1, \mathbb{T}_1, \mathbb{P}_1)$; 3) $\Pi(\mathbb{D}_3, \mathbb{T}_3, \mathbb{P}_3) = \Omega(\vec{p}_3^*, \mathbb{D}_3, \mathbb{T}_3, \mathbb{P}_3) \geq \Omega(\vec{p}_2^*, \mathbb{D}_3, \mathbb{T}_3, \mathbb{P}_3)$. As a result, either $\Pi(\mathbb{D}_1, \mathbb{T}_1, \mathbb{P}_1) > \Pi(\mathbb{D}_2, \mathbb{T}_2, \mathbb{P}_2)$ or $\Pi(\mathbb{D}_3, \mathbb{T}_3, \mathbb{P}_3) > \Pi(\mathbb{D}_2, \mathbb{T}_2, \mathbb{P}_2)$, and thus $(\mathbb{D}_2, \mathbb{T}_2, \mathbb{P}_2)$, which violates the ordered structure, must be suboptimal. By applying this approach to product pairs which violate the ordered structure, we can keep improving the firm's profit until all the designs are ordered.

The above deduction preserves the structural result from exogenous pricing to endogenous pricing, and can be applied analogously to Propositions 1(ii), 2, and 3. Since we do not have closed-form solutions for the optimal prices, we numerically examine the implications of endogenous pricing for Propositions 4–6 using the following three examples:

Example A.1 *Set* $a_D = a_T = a_P = 0$. *Let* $\mathbb{G} = \{1, \cdots, 10\}$ *with* $\mathsf{v}_i = 0.1$ *for* $i \in \mathbb{G}$ *and* $\mathbb{S} = \{11\}$ *with* $\mathsf{v}_{11} = 0.5$, $\lambda = 1$, $\sigma = 0.1$, $q_D = q_T = q_P = 10$, $c_D = r_D = 2$, $c_T(n) = r_T(n) = 2 + 0.2 \cdot n$, $c_P = r_P = 2.5$, $d_D = d_T = d_P = 0.1$, *and* $f(p) = p$. *Then:*

(i) Given potential designs $\{\mathbb{G}, \varnothing\}$, $(\mathbb{D}^*, \mathbb{T}^*, \mathbb{P}^*) = (\{1,2,3,4,5\}, \varnothing, \varnothing)$ *and* $\vec{p}^* \doteq (7.51, N/A, N/A)$.

(ii) Given potential designs $\{\mathbb{G}, \mathbb{S}\}$, $(\mathbb{D}^*, \mathbb{T}^*, \mathbb{P}^*) = (\{1,2,3\}, \varnothing, \{11\})$ *and* $\vec{p}^* \doteq (8.16, N/A, 9.12)$.

Example A.1 shows that, under endogenous pricing, design freedom may still reduce product variety. In the first numerical instance, the 3D-specific set is unavailable and product variety is 5 whereas, in the second numerical instance, the 3D-specific set containing a highly popular design is available and product variety is 4. After the highly popular 3D-specific design is added, the firm increases the price of products handled by dedicated technology. This is because the 3D-specific design helps maintain sufficient market coverage, and thus the firm can offer fewer generic designs at higher prices to save product development cost and enjoy higher margins.

Example A.2 *Let $\mathbb{G} = \{1, 3, \cdots, 9\}$ and $\mathbb{S} = \{2, 4, \cdots, 10\}$ with $\mathsf{v}_i = 0.5$ for $i \leq 4$ and $\mathsf{v}_i = 0.2$ for $i \geq 5$. In addition, $\lambda = 1$, $\sigma = 0.1$, $q_D = q_T = 10$, $a_D = a_T = a_P = 0$, $d_D = d_T = 0.1$, $d_P = 0.03$, $c_D = r_D = 2$, $c_T(n) = r_T(n) = 2 + 0.05 \cdot (n-1)$, $c_P = r_P = 2.5$. Then:*
(i) If $f(p) = p$, as q_P increases, the change in product variety is depicted in Figure A.1(i).
(ii) If $f(p) = \frac{p^2}{10}$, as q_P increases, the change in product variety is depicted in Figure A.1(ii).

In Example A.2 (i), we assume $f(p) = p$ as in the base model and observe that product variety increases as the quality of 3D printing improves. We have tested many other examples and obtained the same result. This is because, for any amount of increase in q_P, the firm can always adjust p_P up by the same amount to keep the market shares of 3D-printed products unchanged and obtain higher margins. The firm can be even more aggressive to include more 3D-printed products in the assortment. The negative effect on product development cost is dominated in this process because the pricing power endows the firm with a larger space to exploit quality improvement.

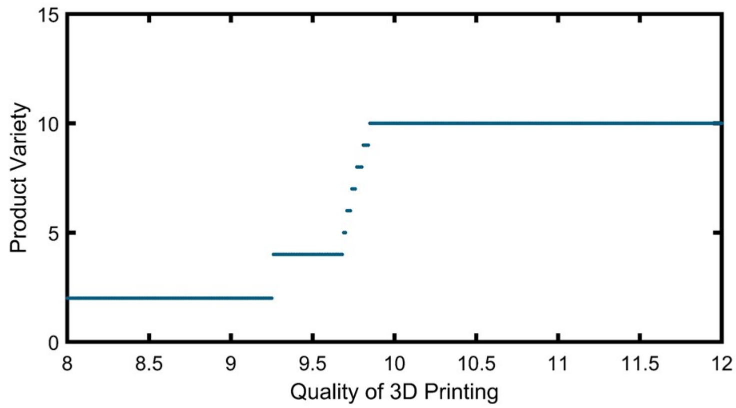
However, in practice, the disutility caused by price may not be linear. Consumers may have reference prices or mental budgets for certain categories of products and are reluctant to accept very high prices even though the quality is high. In Example A.2 (ii), we reflect this situation by assuming a convex disutility of price, $f(p) = \frac{p^2}{10}$, and observe that product variety decreases as q_P increases to pass a threshold. In this case, the firm's pricing power is restricted by the increasing price sensitivity and it cannot freely exploit quality improvement. When the quality of 3D printing is high, the firm may consider reducing its product offering to save product development cost.

Example A.3 *Consider the same numerical setup as in Section 7.1, except that n_S is fixed at 0, q_P is fixed at 10, the sample size is 1000, and the prices are not given but endogenous. We observe that product variety is always (weakly) higher with 3D printing than without 3D printing.*

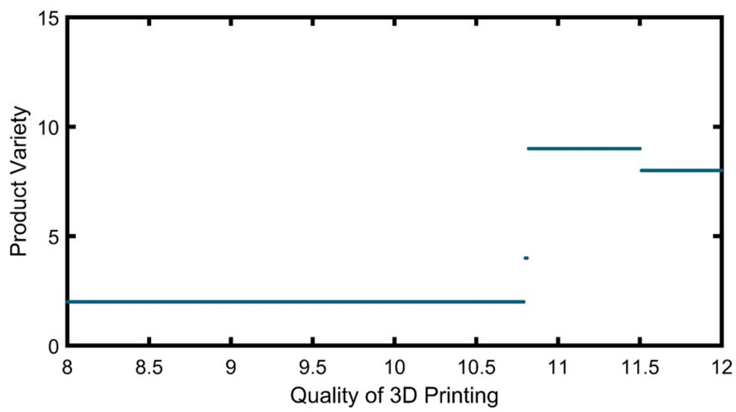
Examples A.3 confirms that, under endogenous pricing, natural flexibility by itself always enhances product variety in the absence of design freedom and quality distinction. Note that the sample size has to be small because it requires significant computational time to solve for each sample under endogenous pricing.

Example A.4 *Consider the same numerical setup as in Section 7.1, except that the sample size is 1000 and the prices are not given but endogenous. As shown in Table A.1, the value of 3D printing decreases in the generic set Gini index and increases in the 3D-specific set Gini index.*

Figure A.1 **Example A.2 Illustration**



(i)



(ii)

Table A.1 Average Improvement Index under Given Ranges of Gini Indices with Endogenous Pricing

Generic Set Gini Index

0–0.4	0.4–0.5	0.5–0.6	0.6-1
0.0683	0.0649	0.0644	0.0610

3D-Specific Set Gini Index

0–0.4	0.4–0.5	0.5–0.6	0.6-1
0.0790	0.0821	0.0858	0.0895

Example A.4 confirms our result about the value of 3D printing. Again, the sample size has to be small in light of the significant computational time. Nevertheless, the qualitative results are consistent with those derived from the base model.

B. Conventional-Specific Set

As discussed in Section 8.3, in certain situations, there may be designs that can be processed by conventional technologies but not 3D printing. In this section, we extend our base model by adding a set $\mathbb{C}$, which includes potential designs that can only be handled by conventional technologies. All the formulations in Section 4 remain unchanged, except that Formulation (7) is replaced by:

$$\begin{aligned} \max_{\mathbb{D},\mathbb{T},\mathbb{P}} \ & \Pi(\mathbb{D},\mathbb{T},\mathbb{P}), \\ \text{s.t. } & \mathbb{D} \subseteq \mathbb{G}\cup\mathbb{C},\ \mathbb{T}\subseteq \mathbb{G}\cup\mathbb{C},\ \mathbb{P}\subseteq\mathbb{G}\cup\mathbb{S}; \\ & \mathbb{D}\cap\mathbb{T}=\mathbb{T}\cap\mathbb{P}=\mathbb{P}\cap\mathbb{D}=\varnothing. \end{aligned} \tag{B.1}$$

With $\mathbb{C}$ added, all the propositions in the base model remain valid with minor changes:

Proposition B.1 *Let $(\mathbb{D}^*,\mathbb{T}^*,\mathbb{P}^*)$ be the optimal assortment portfolio. Then:*
(i) For any $i\in\mathbb{G}\cap\mathbb{D}^*$ and any $j\in\mathbb{G}\cap\mathbb{P}^*$, $\mathsf{v}_i\geq\mathsf{v}_j$;
(ii) For any $i\in\mathbb{G}\cap\mathbb{T}^*$ and any $j\in\mathbb{G}\cap\mathbb{P}^*$, $\mathsf{v}_i\geq\mathsf{v}_j$.

Proposition B.2 *The statement is the same with Proposition 2.*

Proposition B.3 *Let $(\mathbb{D}^*,\mathbb{T}^*,\mathbb{P}^*)$ be the optimal assortment portfolio and $\mathbb{A}^*\equiv\mathbb{D}^*\cup\mathbb{T}^*\cup\mathbb{P}^*$ be the corresponding overall assortment. Then the following hold:*
(i) For any $i\in\mathbb{G}\cap\mathbb{A}^*$ and any $j\in\mathbb{G}/\mathbb{A}^*$, $\mathsf{v}_i\geq\mathsf{v}_j$;
(ii) For any $i\in\mathbb{C}\cap\mathbb{A}^*$ and any $j\in\mathbb{G}\cup\mathbb{C}/\mathbb{A}^*$, $\mathsf{v}_i\geq\mathsf{v}_j$;
(iii) For any $i\in\mathbb{S}\cap\mathbb{A}^*$ and any $j\in\mathbb{G}\cup\mathbb{S}/\mathbb{A}^*$, $\mathsf{v}_i\geq\mathsf{v}_j$.

Note that, although the "enclosed most popular" property still holds, the overall most popular property does not necessarily hold because there may be $i\in\mathbb{S}\cap\mathbb{A}^*$ and $j\in\mathbb{C}/\mathbb{A}^*$ such that $\mathsf{v}_i<\mathsf{v}_j$.

Proposition B.4 *Consider non-empty design sets $\mathbb{G}$, $\mathbb{C}$, and $\mathbb{S}$. Let h be the most popular design in $\mathbb{S}$. Suppose $\underline{\mathbb{A}}^*$ is the (largest) optimal overall assortment given $(\mathbb{G},\mathbb{C},\varnothing)$, i.e., $\mathbb{S}$ is unavailable, and $\overline{\mathbb{A}}^*$ is the (largest) optimal overall assortment given $(\mathbb{G},\mathbb{C},\mathbb{S})$, i.e., $\mathbb{S}$ is available. Consider nontrivial cases with $\underline{\mathbb{A}}^*\neq\varnothing$. There exists a threshold $\hat{\mathsf{v}}$ such that, if $\mathsf{v}_h>\hat{\mathsf{v}}$, then $|\underline{\mathbb{A}}^*|\geq|\overline{\mathbb{A}}^*|$.*

Proposition B.5 *With $\mathbb{G}$, $\mathbb{C}$, $\mathbb{S}$, and all the other parameters fixed, as q_P increases:*
(i) A threshold $\hat{q}$ exists such that 3D printing should be adopted if and only if $q_P\geq\hat{q}$;
(ii) The firm's profit under optimal assortment portfolio increases;
(iii) A threshold $\tilde{q}$ exists such that product variety decreases for $q>\tilde{q}$.

Table B.1 Average Improvement Index under Gini Indices of Different Sets

Conventional-Specific Set Gini Index

0–0.35	0.35–0.4	0.4–0.45	0.45–0.5	0.5–0.55	0.55–0.6	0.6–0.65	0.65–1
0.0803	0.0755	0.0736	0.0710	0.0689	0.0676	0.0663	0.0612

Generic Set Gini Index

0–0.35	0.35–0.4	0.4–0.45	0.45–0.5	0.5–0.55	0.55–0.6	0.6–0.65	0.65–1
0.0815	0.0762	0.0728	0.0701	0.0683	0.0649	0.0644	0.0610

3D-Specific Set Gini Index

0–0.35	0.35–0.4	0.4–0.45	0.45–0.5	0.5–0.55	0.55–0.6	0.6–0.65	0.65–1
0.0696	0.0731	0.0751	0.0781	0.0790	0.0821	0.0858	0.0895

Proposition B.6 *Set $a_D = 0$ and $a_T = \infty$. Let $\mathbb{C} = \mathbb{S} = \varnothing$, $q_D = q_P$, $p_D = p_P$, and $d_D = d_P$. There exists a threshold $\hat{a}$ such that:*
(i) 3D printing is adopted if and only if $a_P \leq \hat{a}$;
(ii) The (largest) optimal overall assortment $\mathbb{A}^*(a)$ is piecewise constant over $[0, \hat{a}] \cup (\hat{a}, \infty)$;
(iii) $|\mathbb{A}^*(a_1)| \leq |\mathbb{A}^*(a_2)|$ for $a_1 > \hat{a}$ and $a_2 \leq \hat{a}$.

Proposition B.7 *Propositions B.1–B.3 still hold under endogenous pricing.*

We also conduct a numerical study in the presence of a conventional-specific set. We let $|\mathbb{C}| = |\mathbb{G}| = |\mathbb{S}| = 5$, and draw design popularities from the exponential distribution with rate 10 (and thus the expectation is 0.1). We generate 10,000 samples and combine them with the parameters displayed in Table 2. In Table B.1, we report the average improvement index in each range of the conventional-specific set Gini index, the generic set Gini index, and the 3D-specific set Gini index. We can observe that 3D printing is more valuable when the conventional-specific set Gini index decreases, when the generic set Gini index increases, and when the 3D-specific set Gini index increases.