Essays on Consumer Returns and Environmental Sustainability in Operations Management

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ESSAYS ON CONSUMER RETURNS AND ENVIRONMENTAL SUSTAINABILITY IN OPERATIONS MANAGEMENT

by

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Submitted in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy in Business Administration
Darla Moore School of Business
University of South Carolina

2023

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ACKNOWLEDGMENTS

I would like to express my deepest gratitude to my advisors, Dr. Olga Perdikaki and Dr. Mark Ferguson. They have been incredible mentors, supporting me through all of the highs and lows of my time as a Ph.D. student. The COVID-19 pandemic was an especially testing time, but their support helped greatly through this period. Their guidance on research projects has been hugely valuable to me and the freedom that they allowed me has helped me grow tremendously as a researcher. I am also most grateful for all the support and advice that they have provided me while I was on the job market. Funding was another concern during the latter years of my Ph.D., and yet again, Mark and Olga found sources to help me financially. This helped greatly with staying focused on my work while also widening my horizons. I would also like to extend my gratitude to Olga for constantly being there for me both as a mentor and a friend.

Next, I would like to thank the other members of my dissertation committee, Dr. Michael Galbreth and Dr. Pelin Pekgün. Mike has been a great mentor and co-author over the past few years. I have learned a lot from him on how to approach and carry out research projects, especially regarding highlighting the practical relevance of one’s work. Pelin has been a constant source of encouragement during my time at USC. I am grateful for all of her valuable feedback on my research projects. Pelin also provided me with the opportunity to work with the MSBA program at USC, which I am very thankful for. I would also like to thank Dr. Keith Skowronski, Dr. Blair Flicker, and Dr. Necati Tereyağoğlu, for always listening to my innumerable worries and for providing me with the most wonderful advice. Dr. Guangzhi Shang obtained
the data for the third essay of this dissertation, for which I am very grateful. I would
never have been able to complete my Ph.D. without the support of Marcelo Frias,
Julia Witherspoon, Cindye Cotton, Leslie Jenkins, and Carla Watson. They have
helped me with innumerable administrative issues and always done so with a smile.

The successful completion of this journey would not have been possible without
the support of my friends. Dr. Sanghoon Cho, Dr. Justin Kistler, Mackenzie Volk,
and Devin Davidson essentially became my family in South Carolina. Their support
has been unwavering and I could never have asked for better friends. The other PhD
students (past and present) at the Moore School created a great environment for
me to thrive in, for which I am very grateful. Riddhi D’Souza has been a constant
supporter all the way from Bangalore – thank you for always listening. I would also
like to thank Dr. Eric Friedlander for helping me move from Chapel Hill to Columbia,
and for being a dear friend during my time in Chapel Hill. Soccer and DnD have
helped a lot with staying sane during my Ph.D., so I am thankful to all who have
been a part of these two communities.

My parents, Hema and Balaram, have been my strongest pillars, showering me
with love and encouragement throughout this journey. They have had to put up with
ridiculous amounts of complaining from me, but have always listened patiently. Their
advice at various points during my Ph.D. has been invaluable and I could never have
done this without them. I am also grateful to my aunt, Usha, for all her love and
support. Hannah Catron has listened to my rambles about work, always encouraged
me to push on, and been a constant ray of optimism, for which I am most thankful.
Abstract

Consumer returns and environmental sustainability greatly impact the operational decisions that firms make. Focusing on consumer returns, lenient return policies aid consumers with resolving uncertainty but impose additional reverse logistics costs on retailers. The current retail landscape has largely eliminated the possibility of offering more stringent return policies since consumers have come to expect such policies as a given. This has driven retailers to look for innovative solutions while still offering costly free return policies. With respect to environmental sustainability, a number of operational decisions have been examined in the academic literature. These have ranged all the way from examining closed loop supply chains to understanding the impact of operational decisions in varied contexts such as food waste and energy markets.

While returns and sustainability have been jointly examined in the context of closed loop supply chains, in this dissertation, we look at how they independently manifest in unique ways in the apparel industry as well as in the context of crowdfunding. Specifically, in Chapter 2, we examine whether an online apparel retailer can maximize profits by encouraging the seemingly deleterious consumer practice of bracketing. In Chapter 3, we compare two commonly used supply chain approaches to apparel retail (fast fashion and the traditional approach) in terms of environmental impact. We shift gears in Chapter 4, where we empirically examine whether business ventures with a sustainability orientation achieve higher success than those without such an orientation in a crowdfunding setting.
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Chapter 1
Overview

Consumer returns and environmental sustainability have become crucial to operational decision-making across a wide array of industries. The growth of online retail has put consumer returns at the forefront of retailers’ minds, while the desperate need to redress environmental harm has made sustainability considerations integral to many businesses. Consumer returns and environmental sustainability have also been intertwined in the context of circular business models and closed loop supply chains. Such models treat consumer returns as a fundamental part of their operations and use them to reduce environmental impact. While closed loop supply chains and the circular economy have received a great deal of academic attention (Guide Jr and Van Wassenhove, 2009; Govindan et al., 2015; Agrawal et al., 2019), in this dissertation, we focus on how consumer returns and environmental sustainability independently manifest in unique ways in two different contexts: the apparel industry and crowdfunding.

Consumer returns play a significant role in the retail sector, significantly impacting retailers’ decisions and profits. In 2022, $816 billion worth of merchandise was returned by consumers, representing approximately 16% of total retail sales in the US (National Retail Federation, 2022). This pervasiveness of consumer returns is driven heavily by the adoption of lenient return policies by retailers. More specifically, the common use of free return policies i.e., full refund and free reverse shipping, has allowed consumers to resolve uncertainty while bearing very minimal financial risk. While such policies aid consumers and potentially increase sales, they impose heavy
costs on retailers as returned products need to be inspected, cleaned, and potentially re-shelved – in some cases, retailers end up having to discard returned products since the processes involved in re-shelving the product are too costly. Thus, retailers face the daunting task of designing return policies to balance the risk that consumers bear and the costs incurred from returns. In the context of online retail, consumers typically bear a higher risk since they are able to resolve uncertainty only after they physically receive the product i.e., some measures of uncertainty remain unresolved at the time of purchase. This has resulted in a higher prevalence of consumer returns in online retail. The COVID-19 pandemic has led to further growth in online retail (Koetsier, 2022), thereby bringing the problem of consumer returns to the forefront of discussion in online retail.

The operations literature has examined the optimality of various return policies under a number of different scenarios (Shulman et al., 2009; Su, 2009; Akçay et al., 2013; Shang et al., 2017), often prescribing that free returns are sub-optimal for retailer profits. Yet, we observe that free return policies are very common among retailers. The prevalence of free return policies is more so in the case of online apparel retailers, where consumer uncertainty about the physical fit (size) of the product is extremely hard to resolve prior to receiving the product and trying it on. According to a consumer survey by Narvar, over 30% of returns are due to the size or fit being wrong (Narvar, 2019). This suggests that consumers value free returns to a point where retailers must accept it as a necessary evil. While some retailers have begun exploring the use of tools such as virtual fitting rooms and advanced analytics to reduce uncertainty regarding size, consumers themselves adopt strategies to reduce size uncertainty. One such practice is bracketing, where consumers order multiple sizes of a product with the ex ante intention of returning some of them (Balaram et al., 2022). While this practice greatly alleviates consumers’ concerns about size, it imposes fairly high costs on retailers. In Chapter 2, we study how a retailer can
use price to influence consumer bracketing behavior and examine whether setting prices that encourage bracketing can be profit maximizing for the retailer. We do so by taking a game-theoretic approach, where a monopolist retailer interacts with a heterogeneous mass of consumers. We characterize our results based on three key model parameters: 1) the reverse logistics cost borne by the retailer, 2) the level of size uncertainty associated with the apparel product, and 3) the hassle cost borne by consumers when returning the product. Chapter 2 has been published in Naval Research Logistics\(^1\).

The increasing importance of addressing environmental harm has resulted in businesses integrating environmental, health, and safety concerns into their decision making (Kleindorfer et al., 2005). This has been accompanied by growing academic attention on sustainability in business, especially in operations management. The sustainable operations literature has spanned topics such as closed loop supply chains, sustainable product design, and environmental regulation (Agrawal et al., 2019). Yet, there exist a number of avenues for improving environmental outcomes through better operational decisions and regulation. The apparel industry, which accounts for 10% of the world’s carbon footprint and is the second largest polluter of fresh water globally (Dottle and Gu, 2022), is especially rife with problems that require addressing. A common theme across criticisms of the apparel industry is the throw-away culture that has been encouraged by various decisions made by apparel retailers. These criticisms have been especially focused towards fast fashion retailers as they are believed to have perpetuated the consumer culture of “single-use purchases”, which results in a dangerously high amount of apparel being sent to landfills or incinerated (U.S. Environmental Protection Agency, 2020b). The operational decisions that have been attributed with encouraging this consumer culture are 1) the production of less durable apparel products and 2) very frequent assortment changes.

\(^1\)Throughout this dissertation, we cite this paper as Balaram et al. (2022).
While the criticisms of these operational decisions associated with fast fashion are certainly justified, there are environmental gains achieved through other operational aspects of the fast fashion business model. Fast fashion retailers are characterized by quick response capabilities, which allow them to better match supply and demand. When compared to retailers that lack quick response capabilities, fast fashion retailers typically have lower levels of leftover inventory at the end of selling seasons. With many retailers typically incinerating unsold inventory (Lieber, 2018), it is clear that the superior matching of supply and demand can help with achieving positive environmental outcomes. In Chapter 3, we use an infinite-horizon game to compare the environmental impacts of the fast fashion approach and the traditional approach to apparel retail. These are the two most common supply chain approaches to apparel retail, and differ in terms of product durability and quick response capabilities. Fast fashion is characterized by less durable products and the presence of quick response capabilities, while the traditional approach produces more durable products and lacks quick response capabilities. Our results help reshape the rhetoric around the environmental impact of fast-fashion and provide insights into how existing policy (New York State Senate, 2021; Chakraborty et al., 2022) needs to be revamped to ensure that it does not lead to worse environmental outcomes than the status quo.

As mentioned earlier, the academic literature has examined sustainability in business from a variety of angles, yet early stage funding for ventures with a sustainability focus has received limited attention. The general belief has been that traditional venture capitalists are put off by such ventures (Petruzzelli et al., 2019; Böckel et al., 2021). More recently, crowdfunding has emerged as an avenue for such business ventures to obtain early stage funding. Crowdfunding is defined as “the efforts by entrepreneurial individuals and groups – cultural, social, and for-profit – to fund their ventures by drawing on relatively small contributions from a relatively large number of individuals using the internet, without standard financial intermediaries” (Mollick,
2014). It is largely due to this more democratic (small donations from many individuals) structure that crowdfunding has been deemed a promising avenue for ventures that also take into account environmental outcomes. In Chapter 4, we use data from the rewards-based crowdfunding platform Kickstarter to examine whether a sustainability orientation results in better financial and marketing success for crowdfunding campaigns. Our results have significant implications for both campaign creators and crowdfunding platforms.
Chapter 2
Bracketing of Purchases to Manage Size Uncertainty: Should Online Retailers be Worried?

2.1 Introduction

2.1.1 Research Motivation

A fundamental difference between brick-and-mortar and online retail channels is the ability of the consumer to physically assess the characteristics of the product prior to purchase. While product descriptions allow online consumers to gather information about digital attributes, many non-digital attributes can be evaluated only through experience (Lal and Sarvary, 1999). This is especially relevant in the apparel industry, which provides the context for our research, and for which online sales account for 25% of total revenues (Gallino and Moreno, 2018).

Without the ability to physically interact with the product, online apparel consumers cannot fully ascertain the match between their expectations and the characteristics of the product (Ofek et al., 2011). In general, this pre-purchase uncertainty can be divided into two components: (i) Size uncertainty, which captures uncertainty regarding how well a given size of the product fits a particular consumer’s body, and (ii) Preference uncertainty, which captures all other uncertain product characteristics, e.g., the feel, comfort, and style of the apparel.

Since size and preference uncertainty cannot be fully resolved without physically
interacting with the product, many online apparel retailers have chosen to offer free returns (meaning, specifically, a full refund with no return shipping charge), enabling consumers to assess the product in-home before making the final decision to keep it. That is, free returns enable consumers to order apparel, try it on, and return it without incurring any monetary cost. Amazon, Zappos, and Running Warehouse are a few examples of online apparel retailers offering free returns. Amazon’s Prime Wardrobe allows consumers to order multiple apparel items, while offering free returns within a try-on period (Thomas, 2017). Zappos also offers free returns with a very generous return window of 365 days. Many omnichannel retailers, including Nordstrom and Macy’s, also offer free returns. Such generous policies have enabled consumers to turn their “living rooms into dressing rooms” (Banjo, 2013) by ordering multiple sizes of an apparel item with the ex ante intention of returning some of them. This practice is commonly referred to in the retail industry as bracketing, and its impact on retailers is the primary focus of this study. Narvar (2017) finds that nearly 50% of apparel consumers will bracket at least some of their online purchases.

While the term bracketing is sometimes used as a general term for the practice of ordering multiple products with the intention of returning some of them, in this study we use its most common (and literal) meaning, which is related specifically to size uncertainty. With bracketing, a consumer makes her best determination of size (e.g., shoe size 8), and then she “brackets” that with one size smaller and one size larger (sizes 7.5 and 8.5) in order to ensure that she receives her best fit size. The smaller size (7.5 in the example) is the lower “bracket” and the larger size (8.5) is the upper “bracket” (see Figure 2.1). This notion of ordering additional items as “brackets” has been described in the popular press (Mull, 2021) and is consistent with our categorization of consumer uncertainties – bracketing can completely resolve size uncertainty¹ (i.e. one of the three will be the correct size choice), but it does not

¹Other order quantities might also be used by consumers seeking to reduce size uncertainty.
address preference uncertainties such as feel and comfort.

In contrast to its benefits to consumers, bracketing imposes a heavy cost on retailers. The condition of returned apparel is labor-intensive to assess, and it is also highly variable. Many returned apparel items are liquidated at a steep discount, donated, or even discarded. This creates an interesting dilemma in retail operations. Consumers expect free returns, and they are increasingly using bracketing to assess sizing in apparel. Retailers enjoy the additional net sales that may result from bracketing, but they also have to bear the substantial costs of returns while being unable (or at least unwilling) to explicitly discourage returns via a restocking fee (Shang et al., 2017). Executives at Narvar provide further credence for the prevalence of bracketing and the unique problems imposed by size uncertainty by stating that improper fit was one of the primary reasons that the number of returned packages increased by 70% between 2019 and 2020 (Kapner, 2021).

The goal of this study is to provide new insights into the practice of bracketing and its impact on an online apparel retailer’s pricing strategy and profit. To the best of our knowledge, ours is the first study to model the phenomenon of consumer

Our focus is on the bracketing approach, which eliminates size uncertainty by placing an upper and a lower bracket around a size (thus guarding against sizing errors on either side). We discuss the implications of ordering a different number of sizes in Section 2.3.5.
bracketing. We provide a preview of our main results in the following subsection.

2.1.2 Summary of contributions

Our results provide insights into how and when a retailer should discourage, or perhaps encourage, bracketing through pricing. We characterize our results based on the three crucial parameters in the return process: the retailer’s reverse logistics cost, the product’s match probability (how likely it is that a single selected size fits the consumer), and the hassle cost that the consumer bears when returning the product. We show that when the product’s match probability is moderate, consumers’ hassle cost is low, and retailer’s reverse logistics cost is low, rather than attempting to deter consumers from bracketing, a retailer should set a price that encourages bracketing since this can drive higher profits. We also provide representative examples of apparel categories that correspond to different parametric regions to facilitate the application of the insights gleaned from our model.

In addition to our main results, we provide analyses of four model extensions, which enable us to provide insights into more retail scenarios. In our main model, price is the only endogenous variable for the retailer. Our first extension considers an additional lever with which a retailer might respond to bracketing: investment in efforts to eliminate size uncertainty (e.g., establish physical showrooms, adopt virtual online fitting technologies, etc. (Cordero, 2010; Gao and Su, 2017)). Similar to our pricing analysis, we find that the retailer should not always invest to eliminate size uncertainty. Indeed, there are cases in which the retailer can benefit from size uncertainty (and the higher bracketing behavior it engenders) if it sets its price accordingly. We also provide some insights into how the retailer’s willingness to make the investment will depend on its reverse logistics cost and the hassle cost that consumers bear when returning. Once again, this helps us fine tune our suggestions for retailers selling various apparel categories.
In a second extension, we relax our assumption that consumers are homogeneous in their hassle costs by considering two consumer segments, each with a different hassle cost (low and high). This segmentation provides the retailer with an additional pricing strategy that encourages one segment to bracket, while discouraging the other. We find that this strategy outperforms that of discouraging bracketing altogether in certain scenarios, but on the whole the insights from our main model do not change. In a third extension, we consider a price-taking retailer that influences consumer bracketing by controlling the hassle cost that consumers incur when returning products. We find cases where increasing the hassle cost up to a threshold is optimal for the retailer. Finally, in a fourth extension we allow for the retailer to use two endogenous levers, price and hassle cost, to influence consumer bracketing. We find that there are cases in which the retailer can benefit from completely eliminating consumers’ hassle cost. We also observe that when size uncertainty is relatively low, the retailer can achieve higher profit by increasing consumers’ hassle cost while also shifting from encouraging to discouraging bracketing.

2.1.3 Relevant Literature

Our work builds on the existing literature on consumer product returns and retailers’ strategies to manage and/or limit these returns. For a detailed overview of the literature on consumer returns, readers are referred to Abdulla et al. (2019). In the context of online retail, free returns allow consumers to resolve uncertainty regarding a product’s characteristics. Early work in this area focused on different return policies and their effect on reducing both consumer risk and opportunism (Davis et al., 1995; Hess et al., 1996; Chu et al., 1998; Davis et al., 1998). From an operations angle, Su (2009) examined the impact of full and partial refund policies on supply chain performance, Altug and Aydinliyim (2016) studied strategic purchase deferrals in the context of online retail, and Shulman et al. (2010) studied the impact of product returns on a
reverse channel structure. In a subsequent study, Shulman et al. (2011) studied the effect of competition on restocking fees and equilibrium prices, given consumer uncertainty. Esenduran et al. (2022) look at how firms’ optimal prices and return policies vary when they offer customized products. Shang et al. (2017) showed that, when the extent of “wardrobing” (the practice of opportunistically buying and returning products) is high, pricing that induces further wardrobing can actually lead to higher retailer profits. Akturk et al. (2021) examine how and when customer profiling and product tracking should be used to counter opportunistic and fraudulent consumer returns.

A common theme in the research described above is that full refunds are not always theoretically optimal. However, from the empirical work of Petersen and Kumar (2009) we know that returns should not necessarily be avoided, since returns are positively associated with future purchases up to a threshold, and there exists an optimal (non-zero) level of returns for the profit maximizing retailer offering free returns. In a subsequent paper, Petersen and Kumar (2015) show that a retailer’s profit is positively affected by incorporating customers’ perceived risk and product return behavior in their resource allocation schemes.

In practice, most online retailers continue to offer free returns. This reality suggests a need to complement analytical work on the theoretically best return policy with research that takes free returns as a given, i.e. acknowledges that free returns are “table stakes” for many online retailers. Retailers need guidance on how to make the best of a challenging marketplace, in which free returns are a standard consumer expectation and practices like bracketing are becoming part of the online retail landscape.

From a modeling perspective, our work builds upon standard monopolist models of consumer uncertainty and product returns (Akçay et al., 2013; Altug and Aydinliyim, 2016; Su, 2009; Shulman et al., 2009; Shang et al., 2017) by including a more granular
representation of uncertainty. Specifically, we disentangle the broader concept of uncertainty into two components: size uncertainty and preference uncertainty. This allows us to tease out the specific impact of size uncertainty on returns – an aspect that is of particular relevance for apparel retailers. Using this decomposition of uncertainty, we build a stylized model to study the effect of bracketing on a retailer’s profit. Several recent papers have considered the idea that consumers make multiple purchases to resolve uncertainty, albeit not in the bracketing sense that we examine in this chapter. Shulman et al. (2010) account for the possibility that consumers may exchange for a product that better matches their preferences, but they do not compare simultaneously ordering multiple sizes (bracketing) vs. sequentially ordering. That is, they do not account for the fact that bracketing, as opposed to exchanging, can limit the hassle cost borne by the consumer but also increase the number of returns processed by the retailer. Guo (2006) considers the act of purchasing multiple products, termed “multiple buying,” to hedge against pre-consumption uncertainty, but they do not consider product returns. In their setting, consumers buy multiple products (for example, a PC and a Mac to account for virus attacks on the PC), and choose to use one or the other depending on the state of the system. Hence, “multiple buying” does not impose a cost on retailers to process the returned items as bracketing does. Finally, while our focus is on a monopolist setting, consumer returns have also been studied in competitive settings where different return policies can be used by firms to differentiate themselves from competitors (McWilliams, 2012; Huang et al., 2018).

2.2 Model and Analysis

We consider a monopolist online retailer selling a single product available in multiple sizes to a mass of consumers normalized to 1. The retailer sets the per unit selling price $p$ and allows free returns. Specifically, at the consumer’s discretion the retailer
will bear the full cost of a return, $k$, and provide a full refund back to the consumer. The parameter $k$ is a unit cost and encapsulates all costs involved in the reverse logistics process (shipping, inspection, cleaning, restocking, etc), net of any salvage value. In other words, irrespective of whether the retailer restocks returned units, passes returned products back to a manufacturer, or disposes of returned units itself, it will incur some unit cost $k$ to process a return\(^2\). We refer to $k$ as the reverse logistics cost. Consumers are heterogeneous in their valuation $v$ of all product characteristics other than size (e.g., color, feel, comfort) and each consumer’s valuation $v \sim U[0, 1]$ is unknown ex-ante (only its distribution is known), since characteristics such as the feel of a product are generally unknown until the consumer actually experiences the product. We refer to $v$ as preference uncertainty. Consumers also face size uncertainty, which is the uncertainty regarding the physical fit of the product i.e. is the selected size the appropriate one? We assume that there is only one best fit size for the consumer. For example, T-shirts may come in sizes S, M, L, XL, and only one of these sizes fits a particular consumer. We denote by $\beta$ ($0 < \beta < 1$) the match probability and define it as the likelihood that the consumer’s single “best guess” size will fit satisfactorily. A high (low) $\beta$ indicates a low (high) size uncertainty. We treat $\beta$ as a product-specific characteristic and hence consider it to be the same for all consumers. For example, products with more size granularity, such as shoes, have considerable variability in sizing depending on the brand and style. A consumer who usually wears size 9.5 can often fit into a 9 or 10 depending on the brand and/or style. On the other hand, products such as undershirts are far more standard in their sizing. It is less likely that a consumer who usually wears a size M will prefer size S or L across brands and/or styles. Thus, we incorporate size uncertainty into our model using a product-specific approach, rather than a consumer-specific one. Given this

\(^2\)Each of these means through which a return is processed may impose a different cost on the retailer, but this is generally a product-specific cost. For example, undergarments are hard to restock and thus impose a higher $k$ than a product such as a winter coat, which is easier to restock.
product-specific nature of the match probability, we assume that it is known ex-ante to both the retailer and consumers. That is, both retailers and consumers know that products such as undershirts have a higher match probability than others such as shoes or dresses. Finally, we limit our analysis to the case of full market coverage by imposing a base valuation of $V = 3$ throughout the chapter as a sufficient condition\(^3\) to ensure all consumers will make a purchase in equilibrium (although they may end up returning the purchased item(s) for a refund). We do so in order to focus our analysis on the manner in which purchases are being made (i.e. bracketing behavior) rather than the overall extent of market participation when valuations are relatively low. We discuss the implications of relaxing this assumption of full market coverage in Section 2.3.5.

2.2.1 Consumer actions

Consumers can choose to eliminate size uncertainty by bracketing, i.e. ordering multiple sizes of the product and keeping, at most, the one size that fits. More specifically, consumers order their “best guess” size, and they also order one size above and one size below (for a total of three products ordered – see Figure 2.1). We assume that one of these three sizes will fit. Consumers incur a non-negative hassle cost, $h \in [0, 1]$, when returning products to capture the fact that the return process can be a cumbersome endeavor (Indeed, 51% of consumers indicate that a key reason for their disappointment during the return process was that “it was too much of a hassle to return the package” (Narvar, 2017)). We assume that all consumers incur the same hassle cost (this assumption is relaxed in Section 2.3.2). If the realized $v$ is satisfactorily high, consumers who engage in bracketing will choose to keep the best-fit product and obtain a utility of $V + v - p - h$. Otherwise, consumers will return all

\(^3\) $V \geq 3$ ensures full market coverage and we set $V$ to be the lower bound. Derivation of the condition is available from the authors.
products and obtain a utility of $-h$. In the former scenario, the retailer receives a profit $p - 2k$, and in the latter, it ends up with $-3k$.

Alternatively, consumers may choose not to bracket, but instead buy only a single size of the product (referred to as *buying single*). In this case, there is a $(1 - \beta)$ probability that a consumer will order the incorrect size. Among these consumers, those who realize a low valuation $v$ will return the product and obtain a utility of $-h$. Consumers with higher valuations, however, will prefer to exchange the product for the correct size. For example, a consumer might order a size 6 shoe (her expected size) and find that she likes it very much in terms of style, etc. (i.e. her $v$ is high), but it is simply too large. She subsequently exchanges this for a 5.5 to obtain the right size. By doing so, such consumers obtain a utility of $V + v - p - \delta h$, where $1 < \delta < 2$ is a scalar that captures the exchange cost. Given the prevalence of bracketing in practice, we posit that $\delta$ must be larger than 1, i.e. consumers are experiencing a considerably higher inconvenience and disutility when exchanging (otherwise bracketing would not be a common occurrence). This is driven, for example, by retailers often requiring consumers to place altogether new orders when exchanging a product (Owens, 2021).

Another possible explanation for the additional disutility of exchanging is that the consumer is unable to use the product until she eventually receives the right size, thus incurring additional disutility. On the other hand, when she brackets, she ensures that she will receive the right size in her initial order. We impose the condition $\delta < 2$ to ensure that the additional hassle cost to exchange is not higher than the cost of the simple return itself. This reasonable assumption on $\delta$ also provides a substantial improvement in model tractability. The retailer’s profit from a return is $-k$, while that from an exchange is $p - k$. For parsimony, we do not impose any additional cost associated with the forward shipping of the correct size (imposing such a cost would not change the results).

Turning now to those consumers who do find a size match (probability $\beta$), these
consumers can choose to keep the product and obtain a utility of $V + v - p$. In that case the retailer receives a profit of $p$. Alternatively, if their realized valuation $v$ isn’t high enough, they can return the product and obtain a utility of $-h$. In this scenario, the retailer’s profit is $-k$.

The sequence of events in this single-shot game, along with the payouts described above, are shown in Figure 2.2. The solid vertical lines indicate nodes where the consumer makes a choice. The filled-in circle indicates a node where a random choice, outside the consumer’s control, is made. The retailer acts as a Stackelberg leader and sets the price $p$. Initially, consumers do not know their inherent valuation of the product $v$. Since all consumers have the same information at the start of the game, all consumers choose the same action from among the options of bracketing and buying single, based on the price offered (we account for heterogeneity in the first stage of the game in Section 2.3.2). Consumer heterogeneity enters the model in the decision to keep or return the product, given $v$. If consumers have chosen to bracket,
they realize their valuation $v$ and either return or keep the best-fit product based on this valuation (recall that the two products that do not fit are always returned). The indifference point between returning and keeping the best-fit product is given by $v_1 = p - V$. Consumers whose $v$ is larger than $v_1$ will keep, while the rest will return.

On the other hand, if consumers choose to buy single, there is a probability $\beta < 1$ of obtaining the right size. For consumers that do buy the best-fit size, the choice between returning and keeping the product again depends on their realized valuation $v$. This indifference point is given by $v_2 = p - V - h$. Having obtained the product and realized their valuation $v$, those consumers with $v > v_2$ keep the product, while the rest return it. The remaining $1 - \beta$ fraction of consumers obtains a size mismatch and faces the decision between exchanging for the right size and returning the product without an exchange. The indifference point between these actions is given by $v_3 = p + (\delta - 1) h - V$. Those consumers with $v > v_3$ (i.e. a sufficiently high valuation) will exchange for the right size, while the rest return the product without an exchange. Given our interest in how firm actions can shift consumers across different behaviors, we focus on the case where some positive mass of consumers will prefer each action (keep, return, exchange). In other words, we assume that $v_1$, $v_2$ and $v_3$ are in $[0, 1]$ i.e. $3 + h \leq p \leq 4 - (\delta - 1) h$. Given that $1 < \delta < 2$, this simplifies to $3 + h \leq p \leq 4 - h$, implying that we must have $h \in [0, \frac{1}{2}]$ in order for a feasible price to exist. Thus, for the remainder of the chapter, we restrict our attention to $h \leq \frac{1}{2}$. We provide a summary of our model assumptions in Table 2.1.

The initial choice between bracketing and buying single is made by comparing the expected utilities from each of these actions. The expected utility from bracketing is

$$\mathbb{E}[U_B] = v_1 (-h) + (1 - v_1) \left(3 + \frac{1 + v_1}{2} - p - h\right) \quad (2.1)$$

And the expected utility from buying single is

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Table 2.1  Key model assumptions.

<table>
<thead>
<tr>
<th>Assumption</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$V = 3$</td>
<td>Ensures full market coverage and results in a more tractable model. Implications of relaxing this assumption are discussed in Section 2.3.5.</td>
</tr>
<tr>
<td>$1 &lt; \delta &lt; 2$</td>
<td>$\delta &gt; 1$ to capture the additional hassle of exchanging as opposed to returning. $\delta &lt; 2$ to ensure that the additional hassle cost to exchange is not higher than the cost of the simple return itself.</td>
</tr>
<tr>
<td>$3 + h \leq p \leq 4 - h$, $h \leq \frac{1}{2}$</td>
<td>Focus the analysis on the most interesting case, when a positive mass of consumers takes each possible action – keep, return, and exchange.</td>
</tr>
</tbody>
</table>

\[
\mathbb{E}[U_S] = \beta \left[ v_2 (-h) + (1 - v_2) \left( 3 + \frac{1 + v_2}{2} - p \right) \right] \\
+ [1 - \beta] \left[ v_3 (-h) + (1 - v_3) \left( 3 + \frac{1 + v_3}{2} - p - \delta h \right) \right] \tag{2.2}
\]

Let $p_1$ be the price that makes a consumer indifferent between bracketing and buying single (i.e. $\mathbb{E}[U_B] = \mathbb{E}[U_S]$). We characterize consumer behavior through the following result.

**Lemma 1.** Consumers’ actions depend on the match probability, hassle cost, and cost of exchange as follows:

(a) When the match probability is high ($\beta \geq \frac{\delta - 1}{\delta}$), or hassle cost is high ($h \geq h_T$), purchase occurs only through buying single.

(b) When the match probability is moderate ($\left(\frac{(3-\delta)(\delta-1)}{(4-\delta)\delta} < \beta < \frac{\delta - 1}{\delta}\right)$, and hassle cost is low ($h < h_T$), consumers prefer bracketing for prices below $p_1$, and buying single for prices above $p_1$. Furthermore, $p_1$ is decreasing in $\beta$.

(c) When the match probability is low ($\beta \leq \frac{(3-\delta)(\delta-1)}{(4-\delta)\delta}$), purchase occurs only through bracketing.

Proofs of all technical results are provided in Appendix A.
The results in Lemma 1 confirm intuition i.e. they show that the parameters divide the problem space in a logical fashion. From part (a) of Lemma 1, we see that when the likelihood of obtaining the right size on a single order is sufficiently high, or the hassle of returning the product is sufficiently high, consumers do not resort to bracketing. The bound on the match probability $\frac{\delta - 1}{\delta}$ is increasing in the cost that the consumer incurs when exchanging the product. Hence, as the cost of exchanging increases, consumers are less likely to buy single. Part (b) of Lemma 1 indicates that for moderate values of the match probability and for low hassle cost, consumers prefer bracketing when the retail price is sufficiently low, and prefer buying single otherwise. As expected, as the match probability increases, bracketing becomes a less attractive option for consumers and they are willing to bracket only when the price is sufficiently low. Thus, the price at which consumers are indifferent between bracketing and buying single is decreasing in the match probability. From part (c), we see that for low values of the match probability, consumers purchase only by bracketing. Given the high likelihood of obtaining the wrong size when ordering a single size, the consumer action of buying single is dominated by bracketing. Throughout the remainder of the chapter, we refer to the parametric region defined by part (a) of Lemma 1 as the Only Single region, since it defines the context in which consumers will only purchase by buying single. We refer to the region defined in part (b) of Lemma 1 as the Choice region, since for these parameters consumers will choose either to bracket or to buy a single size after observing the price $p$. Similarly, the parametric region defined by part (c) of Lemma 1 is called the Bracketing Only region, since it defines the context (low match probability) in which bracketing is the only way that a purchase will occur. A graphical representation of the behavior established in Lemma 1 is presented in Figure 2.3.

Part (b) of Lemma 1 shows that consumers’ bracketing behavior can be influenced by the retailer’s pricing strategy. We next explain how the retailer can use pricing to
Lemma 2. Within the Choice region, the retailer can use price to influence consumers’ bracketing behavior since consumers are more likely to keep the product if they choose to bracket rather than buy single.

To understand the result in Lemma 2, consider the fact that if consumers choose to bracket in the first stage as opposed to buy single (the choice between bracketing and buying single exists only in the Choice region), the probability that they will keep the product is higher. This implies that consumers are more likely to end up paying the price $p$ if they choose to bracket. As a result, consumers prefer to bracket only for a low enough price, ceteris paribus, and will buy single otherwise.

Having established the utility maximizing consumer actions, based on the event sequence in Figure 2.2, we now provide guidance on how a retailer should price to encourage or discourage the practice of bracketing. Unless otherwise mentioned, we focus on the interesting region: in which a purchase might occur through either bracketing or buying single depending on price (the Choice region).
2.2.2 The retailer’s problem

In the Choice region, the retailer can induce consumers to bracket by setting the price in $[3 + h, p_1]$, or it can set the price in $[p_1, 4 - h]$, in which case all consumers will buy single. The profit from encouraging consumers to bracket is given by:

$$
\Pi_B = (p - 2k) \left( \int_{v_1}^{1} dv - 3k \int_{0}^{v_1} dv \right) \tag{2.3}
$$

The optimal price when maximizing (2.3) is $p^*_B = 3 + h$, and the resulting optimal profit is $\Pi^*_B = 3 - h(h + k + 2) - 2k$.

Next, we consider the profit from encouraging consumers to buy single:

$$
\Pi_S = \beta \left( \frac{p}{1 - \beta} \int_{v_2}^{1} dv - k \int_{0}^{v_2} dv \right) + (1 - \beta) \left( \frac{p - k}{1 - \beta} \int_{v_3}^{1} dv - k \int_{0}^{v_3} dv \right) \tag{2.4}
$$

The price that maximizes the profit defined in (2.4) is $p^*_S = p_1$, and the resulting optimal profit is

$$
\Pi^*_S = \frac{h(\delta(1 - \beta)((2\beta - 1)\delta + 2) - 1)(8((1 - \beta)\delta - 1) - h(1 - (1 - \beta)(2 - \delta)\delta))}{4(1 - (1 - \beta)\delta)^2}
- \frac{k(2(1 - \beta)\delta - \beta h ((1 - \beta)\delta^2 - 1) - 2)}{2((1 - \beta)\delta - 1)} \tag{2.5}
$$

The following result provides a key insight into the retailer’s preferences in the Choice region.

**Proposition 1.** In the Choice region, the retailer finds it optimal to price such that consumers will bracket when the reverse logistics cost is sufficiently small i.e. $k < \bar{k}$. This upper bound on the reverse logistics cost is affected by the other model parameters as follows:
(a) $\bar{k}$ is decreasing in the match probability $\beta$.

(b) $\bar{k}$ is decreasing in the hassle cost $h$.

(c) $\bar{k}$ is increasing in the exchange cost $\delta$.

From Proposition 1, we see that the retailer realizes higher profits by encouraging consumers to bracket rather than buy single when the reverse logistics cost is sufficiently small. This runs counter to the idea that a returns-intensive consumer behavior like bracketing is necessarily detrimental to a retailer’s profit. This result can be understood as follows. Recall that bracketing eliminates some of the losses in sales due to a size mismatch, which subsequently results in a gain in net purchases. The gain in net purchases occurs because the utility from exchanging a product (conditional on buying single) is always less than that from keeping a product (conditional on bracketing). Simply put, exchanging is more of a hassle for consumers than bracketing. As long as the revenue from the additional net purchases offsets the reverse logistics costs that arise due to a larger number of returns, the retailer finds it more profitable to price such that consumers will bracket. This finding is relevant for retailers that have efficient reverse logistics operations in place and/or sell products that are easier to reshelve (i.e. have a low $k$). Proposition 1 shows that such retailers can, in fact, achieve higher profits by pricing to encourage bracketing instead of deterring it.

To better understand when bracketing is optimal for the retailer, we also analyze how the upper bound $\bar{k}$ is affected by the other model parameters. From part (a) of Proposition 1, we see that bracketing is less likely to be optimal as the match probability increases. Higher values of $\beta$ make buying single more attractive for consumers. The retailer, in turn, experiences fewer returns and is also able to increase demand, thus resulting in better outcomes when encouraging buying single. Part (b) of Proposition 1 shows that as the hassle cost $h$ increases, bracketing is less likely
to be optimal. Given that consumers are guaranteed to incur the hassle cost when bracketing, higher values of $h$ result in lower demand, thus hurting the retailer’s profit. Finally, from part (c) of Proposition 1, we see that bracketing is more likely to be optimal as the exchange cost increases, since a higher exchange cost decreases the attractiveness of buying single to consumers.

To summarize our findings thus far, a graphical representation of the optimality of bracketing (in terms of the hassle cost $h$ and the match probability $\beta$) is shown in Figure 2.4. Note that $k = 0.8$ and $\delta = 1.8$. Further, in the region marked B (S), bracketing (buying single) is optimal for the retailer.

Figure 2.4 Optimal retailer outcomes in the Choice region.

Figure 2.4 shows that pricing to encourage bracketing is preferred for comparatively low hassle cost and match probability. A low hassle cost suggests that consumers do not view the process of returning a product to be particularly cumbersome. A relatively low match probability is associated with a high likelihood of obtaining a
size mismatch and requesting an exchange. Thus, both conditions make the practice of bracketing an attractive prospect for consumers. The retailer enjoys some additional net purchases when consumers bracket, and when the reverse logistics cost is sufficiently low, the revenue from these additional net purchases offsets the cost that arises due to a larger mass of returns.

Proposition 1 and Figure 2.4 provide guidance on when a retailer should encourage or discourage bracketing within the Choice region. Our insights are framed in terms of the key contextual elements of match probability, return hassle cost, exchange cost, and reverse logistics cost. Next, we examine how each of these key model elements can impact the retailer’s optimal profit. We begin by considering the case where consumers will bracket (Proposition 2) and then the case where consumers will buy single (Proposition 3). For Propositions 2 and 3, we do not limit our attention to the Choice region since, unlike in Proposition 1, we are interested in characterizing how the retailer’s profit changes throughout the entire parametric region.

**Proposition 2.** When bracketing is the optimal outcome (i.e. in the Only Bracketing region, or in the Choice region with \( k < \bar{k} \)), the retailer’s profit is decreasing in the hassle cost \( h \).

The hassle cost has an inverse relationship with the profit from bracketing. Given that consumers are guaranteed to incur the hassle cost when bracketing, this action becomes less attractive for higher values of the hassle cost, and reduces the attractiveness of encouraging bracketing for the retailer. The match probability \( \beta \) and the exchange cost \( \delta \) do not impact the profit since these parameters are inconsequential to consumers when they choose to bracket.

Next, we consider the case where buying single is the optimal outcome for the consumers.

**Proposition 3.** When buying single is the optimal outcome (i.e. in the Only Single
region, or in the Choice region with \( k > \bar{k} \), the retailer’s profit is

(a) increasing in the match probability \( \beta \); 

(b) increasing and then decreasing in the hassle cost \( h \); 

(c) decreasing in the exchange cost \( \delta \).

Proposition 3(a) shows that the retailer’s profit when consumers buy single is always increasing in the match probability. This is intuitive since a higher match probability results in fewer returns due to a size mismatch, and thus higher profits for the retailer. Figure 2.5 provides a complete illustration of the retailer’s profit as a function of the match probability. Note that buying single becomes profit-maximizing for the retailer for sufficiently high \( \beta \). The upper envelope of the plot is the optimal profit. The shaded region depicts the Choice region. We set \( k = 0.8 \), \( h = 0.3 \), and \( \delta = 1.8 \).

![Figure 2.5 Retailer profit for both outcomes as a function of the match probability.](image)

In Figure 2.5, we observe that the retailer’s profit eventually starts to increase in the match probability as per Proposition 3(a). At first, profit is flat (unaffected by \( \beta \)). For low values of \( \beta \), we are in the Only Bracketing region, where \( \beta \) is a completely inconsequential parameter since consumers will always eliminate size uncertainty by
bracketing. As $\beta$ increases, we enter the Choice region (the shaded area in Figure 2.5). Within the Choice Region, we observe the profit from buying single to be increasing in $\beta$, and this eventually exceeds the profit from bracketing. This has two implications for retailers that undertake strategies to improve the match probability of a product. First, for low match probability products, only sufficiently large improvements in the match probability will result in increased profits. Second, when such large improvements are made, they must be accompanied by a switch in the pricing strategy. More specifically, the retailer must switch to a higher pricing strategy that encourages buying single. If the retailer does not make this pricing switch, the retailer will not realize higher profits from the higher $\beta$.

We see that the profit from buying single is non-monotone in the hassle cost $h$ (Proposition 3(b)). More specifically, the profit is initially increasing and subsequently starts to decrease in the hassle cost. Davis et al. (1998) observe a similar relationship between profit and hassle cost in an environment in which bracketing is absent. Our result shows that this non-monotonicity persists, even when considering the emerging consumer practice of bracketing. This relationship is driven by the following mechanisms. When $h$ is low, the retailer prices such that some positive mass of consumers will return the product. As $h$ increases, the optimal price $p^*_S$ drops, and a larger fraction of consumers will choose to keep the product. This is true even for those consumers who obtain a mismatch, since consumers will prefer to exchange rather than return, given that the retailer reacts to an increase in $h$ by dropping the price to a very appealing level. Thus, in this low hassle context, the decrease in net returns drives profits higher as $h$ increases. Beyond a certain threshold level of $h$, consumers will not bracket and the retailer’s optimal price is such that all consumers that obtain a match keep the product. The mass of consumers that request an exchange (as opposed to return) after a mismatch is decreasing in $h$ which drives profit down. Thus, we observe the more intuitive relationship that higher hassle costs
negatively impact profits. Figure 2.6 combines Proposition 2 and Proposition 3(b) to provide a complete illustration of the retailer’s profit as a function of hassle cost. We set $k = 1.2$, $\beta = 0.3$ and $\delta = 1.8$ in Figure 2.6, and the upper envelope of the plot denotes the optimal profit. We further examine this complex relationship between profit and hassle cost in Sections 2.3.2, 2.3.3, and 2.3.4.

The results summarized in Figure 2.6 point to actionable insights for retailers, given that the hassle cost is a consumer characteristic over which the retailer can exert some influence. Although reducing the hassle (moving from right to left in Figure 2.6) when it is already high can lead to higher profits, such reductions when the hassle is already moderate can in fact be detrimental to the retailer. Indeed, retailers who currently have return policies that impose a lower hassle cost on consumers (e.g. convenient return shipping options) can benefit from increasing consumers’ hassle cost, due to the dynamics explained in Proposition 3. For example, allowing returns at fewer physical locations, or with a limited set of shipping providers, could mildly increase the hassle cost, and we show that this can drive higher retailer profits.

We summarize the insights from our main model by providing four examples of apparel categories that have a high/low match probability and impose a high/low reverse logistics cost on the retailer (shown in Table 2.2). The profit enhancing
strategy for a retailer selling each of these products is provided in parentheses.

Table 2.2  Representative examples of apparel categories.

<table>
<thead>
<tr>
<th>$\beta$</th>
<th>Low</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>Running shoes (Strongly encourage bracketing)</td>
<td>Undergarments (Discourage bracketing)</td>
</tr>
<tr>
<td>High</td>
<td>Basic T-shirts (Encourage bracketing)</td>
<td>Customized T-shirts (Strongly discourage bracketing)</td>
</tr>
</tbody>
</table>

We begin in Table 2.2 by characterizing apparel categories based on the reverse logistics cost, $k$, they impose on a retailer. Both running shoes\textsuperscript{4} and basic T-shirts are products that are relatively easy for retailers to inspect, clean and reshelve, suggesting that they are low $k$ products. On the other hand, undergarments impose a high $k$ on the retailer since they are difficult to reshelve. Similarly, customized T-shirts are extremely hard to resell given that they have been customized to a particular consumer’s preferences.

Table 2.2 also categorizes products based on the match probability $\beta$. For example, T-shirts in general are a high $\beta$ product, since they come in largely standardized sizes (S, M, L, XL) with small variation across brands and designs. This differs from categories such as running shoes and undergarments, which require a more precise fit for consumers to be willing to keep the product. Furthermore, the increased granularity in sizing for these categories makes it more likely that there are more pronounced differences in size across brands and designs. It is likely that a consumer fits into shoes of sizes 8.5, 9 and 9.5 across brands and designs, but far less likely that a consumer fits into T-shirts of sizes S, M and L depending on the brand and design.

\textsuperscript{4}Since we assume that consumers are only trying on the items to ascertain size as they would in a store, it is reasonable to assume that running shoes are not going to require a great deal of inspection and cleaning upon return.
There is currently little consensus among retailers regarding which contextual factors are the most critical in determining the impact of bracketing on profits. While it is reasonable to conjecture that the match probability of a product (\( \beta \)) should drive a retailer’s openness to bracketing, our findings suggest a more nuanced approach. In fact, it is the reverse logistics cost (\( k \)) that should be the primary driver of a retailer’s decision to encourage or discourage bracketing. From Table 2.2, we see that a retailer selling a low \( k \) product (e.g. running shoes and basic T-shirts) should encourage bracketing, while a retailer selling a high \( k \) product (e.g. undergarments and customized T-shirts) should discourage bracketing. The match probability, on the other hand, impacts the decision of how strongly the retailer must encourage/discourage bracketing (i.e. \( \beta \) affects \( \tilde{k} \)). For example, while both running shoes and basic T-shirts are low \( k \) products, a retailer selling the former category (with a lower match probability) should more strongly encourage bracketing. Similarly, while undergarments and customized T-shirts are high \( k \) products, and thus bracketing should be discouraged, a retailer selling the latter category (with a higher match probability) should discourage bracketing more strongly.

To demonstrate the applicability of our findings, consider two online apparel retailers – ThirdLove and Running Warehouse. ThirdLove, an online retailer specializing in bras, is a representative example of a retailer selling a low \( \beta \), high \( k \) product, while Running Warehouse, an online retailer specializing in running shoes, is an example of a retailer selling a low \( \beta \), low \( k \) product. Our findings indicate that retailers such as ThirdLove should work towards discouraging bracketing, while those such as Running Warehouse should in fact strongly encourage bracketing. From the perspective of consumers’ hassle cost, Running Warehouse achieves no gain by increasing the hassle cost, but ThirdLove may benefit from making the return process mildly more inconvenient for consumers, since the benefit from more consumers keeping the product can outweigh the negative impact of higher hassle costs in some cases (see Figure
2.3 Model extensions and checks for robustness

In this section, we consider four different model extensions, as well as discuss the robustness of our results after relaxing some of the assumptions of the main model. First, in Section 2.3.1, we consider a scenario in which the retailer can invest to completely eliminate size uncertainty. Next we consider three alternative formulations of the hassle cost parameter. In Section 2.3.2, we allow for the hassle cost to be heterogeneous across consumers. In Section 2.3.3, we endogenize the hassle cost and assume that the price is fixed. This is reflective of scenarios in which a retailer may have very low control over price, and instead uses the hassle cost to impact consumer bracketing. In Section 2.3.4, we allow for the retailer to choose both price and hassle cost jointly to impact consumer bracketing. Finally, in Section 2.3.5, we discuss how the relaxation of the assumptions of full market coverage and 3-size bracketing impact our results.

2.3.1 Size Uncertainty Elimination

ThirdLove has undertaken strategies to improve the match probability of their bras, thereby reducing consumers’ need to bracket. These strategies include the provision of blogs on sizing as well as the use of advanced analytics to provide personalized recommendations to consumers. Further examples of strategies that online retailers implement to eliminate size uncertainty include the use of virtual fitting rooms (Nuwer, 2014) or online fitting tools such as True Fit and Shoefitr. Of course, these improvements come at a cost (purchase of advanced analytics tools, development of software that measures size and body proportions, purchase of virtual fitting room software, etc). In this extension to the main model, we consider the scenario in which the retailer (as opposed to the consumer through bracketing) can, through
an investment in technology, eliminate size uncertainty entirely. By endogenizing
size uncertainty, we are able to contribute to the literature on retailers’ fit-revealing
strategies (Chen and Xie, 2008; Shulman et al., 2009; Gu and Xie, 2013; Gallino and
Moreno, 2018) by studying whether and under what conditions an online retailer
should invest in such strategies, as opposed to allowing consumers to manage size
uncertainty through bracketing.

We assume that the product has an inherent match probability $\beta_0 < 1$, such that
the value of $\beta$ with no investment by the retailer is $\beta_0$. The retailer can eliminate
entirely the size uncertainty associated with the product (i.e. set $\beta = 1$) by investing
in strategies such as those discussed above and incurring a fixed cost $C$. We assume
that such retailer actions can result in the complete elimination of size uncertainty,
which enables a clean comparison with bracketing, the consumer action to completely
eliminate size uncertainty. We treat the investment cost $C$ as a fixed cost to adopt
virtual fitting rooms or other analytics-based tools. Since the size uncertainty is
completely eliminated if the retailer makes the investment, consumers would no longer
consider bracketing or incur any size mismatch. We restrict our attention and analysis
to that part of the Choice region where bracketing is the optimal outcome for the
retailer in our main model.

The retailer’s profit when it decides to make the investment and eliminate size
uncertainty is given by:

$$\Pi_I = -k \int_0^{v_2} dv + p \int_{v_2}^1 dv - C \tag{2.6}$$

where $v_2$ (from Section 2.2) is the valuation of a consumer who is indifferent between
keeping and returning the product having obtained a size match after choosing to
buy single. $\Pi_I$ is maximized at $p_I^* = v_2 = 3 + h$.

The alternate strategy for the retailer is to leave the match probability as is
($\beta = \beta_0$) and price to encourage bracketing. The retailer’s profit under such a scenario
is given by (2.3).
Comparing the profits in (2.3) and (2.6) yields the following result. Note that the initial match probability does not play a role in this result since the cost of eliminating size uncertainty is independent of this parameter.

**Proposition 4.** There exists a threshold investment cost, $\bar{C}$, below which it is optimal for the retailer to make the investment to eliminate size uncertainty. This threshold cost is

(a) increasing in the reverse logistics cost $k$;

(b) increasing in the hassle cost $h$.

Proposition 4 establishes the existence of a bound on the fixed cost, below which the retailer should make the investment to push $\beta$ to 1. From part (a), we see that an increase in the reverse logistics cost leads to an increase in the threshold cost $\bar{C}$, i.e. retailers with less efficient reverse logistics processes and/or selling items that are harder to reshelve (higher $k$) are more likely to make the investment to eliminate size uncertainty. ThirdLove has attempted to eliminate size uncertainty by offering a mobile app for consumers, as well as using advanced analytics to provide consumers suggestions on the right undergarment size to order. Given the relatively high reverse logistics cost that undergarments are expected to impose on ThirdLove, their strategy of eliminating size uncertainty is in line with our results. Proposition 4(b) establishes that an increase in the return hassle cost borne by consumers drives an increase in the threshold cost $\bar{C}$. This means that a retailer who has a more consumer-friendly return process (lower $h$) is less likely to invest in eliminating size uncertainty.

In summary, Proposition 4 suggests that, if the retailer has the opportunity to invest to eliminate size uncertainty altogether, this option is more attractive if the retailer has less efficient reverse logistics processes, and/or strict or cumbersome return policies for consumers.
2.3.2 Heterogeneous hassle costs

In this alternative formulation of the hassle cost parameter, we explore the possibility that hassle costs might vary across consumers. To maintain tractability, we divide consumers into two categories in terms of their return hassle. Specifically, a fraction \( \alpha \) of consumers incurs a low hassle cost \( L \), and the remaining consumers incur a high hassle cost \( H \) when returning the product\(^5\). Each consumer segment behaves independently of the other and makes their decisions in the same manner as described in Section 2.2. We denote the threshold prices (below which each consumer segment brackets and above which they buy single) as \( p_L \) for the low hassle segment, and \( p_H \) for the high hassle segment. We restrict our attention to the Choice region so that both consumer segments could be encouraged to bracket for a sufficiently low price (as established in Lemma 1). It can be shown that \( p_H < p_L \) in this parametric region. The optimal consumer actions for each segment are shown in Figure 2.7.

The retailer is now faced with three possible pricing strategies: (1) Set \( p \in [3 + H, p_H] \) and make both segments bracket, (2) set \( p \in [p_H, p_L] \) and make the high hassle segment buy single, while the low hassle segment continues to bracket, (3) set \( p \in [p_L, 4 - H] \) and make both segments buy single. Strategies (1) and (3) can be thought of as “pooling” strategies since both consumer segments choose the same action, while strategy (2) is a “separating” strategy since each segment chooses a different action\(^6\). Although a complete characterization of the retailer’s optimal selection from across these three strategies is analytically intractable, we use numerical

\(^5\)While \( \alpha \) might be difficult to estimate in practice, we suggest that the retailer could also use the fraction of frequent returners to estimate \( \alpha \). Some retailers closely track consumer return behavior with the intention of banning those consumers that abuse free return policies (Peterson, 2018). It seems reasonable to assume that these consumers often have a lower hassle cost of returning. Altug et al. (2021) make a similar assumption in the context of differentiating between “renters” and “honest returners”.

\(^6\) Readers might be familiar with the terms pooling and separating strategies from the context of signaling games. Although we adopt the same terminology, our setting is one of perfect information, and we use these terms simply to describe whether all consumers take the same action (pooling) or each segment takes a different action (separating).
Figure 2.7 Optimal consumer actions, by price, for both consumer segments.

experiments to provide several insights.

Figure 2.8 (where we set $k = 0.8, \alpha = 0.5, L = 0.2, \delta = 1.8$) summarizes our numerical results. Region I: Encourage both segments to bracket; Region II: Encourage high hassle segment to buy single and low hassle segment to bracket; Region III: Encourage both segments to buy single. In that figure we see that bracketing continues to be the optimal outcome (Region I) for most of the Choice region. More specifically, *ceteris paribus*, the strategy of encouraging bracketing is more attractive for the retailer as long as the match probability is sufficiently low. The separating strategy of making the high hassle cost segment buy single and the low hassle cost segment bracket tends to be more attractive as the match probability increases and when the difference in hassle costs between the two segments is high (Region II). The strategy of encouraging both segments to buy single tends to benefit from a high match probability and a smaller difference between the hassle costs of the two segments (Region III). The overarching implication of this heterogeneous hassle cost analysis is that bracketing remains the preferred retailer outcome for products with a low match probability, which is consistent with the findings from Section 2.2.
The following result provides insights on the impact of the size of the low hassle cost segment of consumers, \( \alpha \), on the retailer’s profits.

**Proposition 5.** Under heterogeneous hassle costs, the retailer’s optimal profit in the Choice region depends on \( \alpha \) in the following manner:

(a) When it is optimal to encourage both segments to bracket (Region I of Figure 2.8), the optimal profit is independent of \( \alpha \).

(b) When it is optimal to employ the separating strategy (Region II of Figure 2.8), the optimal profit is decreasing in \( \alpha \).

(c) When it is optimal to encourage both segments to buy single (Region III of Figure 2.8), the optimal profit is decreasing in \( \alpha \) when \( k \) is large, and increasing in \( \alpha \) when \( k \) is small.
From Part (a) of Proposition 5, we see that the size of the two segments is immaterial to the retailer’s profit when encouraging both segments to bracket (Region I of Figure 2.8). Given that both segments behave identically and have the same indifference points when bracketing, the size of each segment does not affect the retailer. As the match probability and difference in hassle costs increase (Region II of Figure 2.8), it is optimal for the retailer to employ the separating strategy. Part (b) of Proposition 5 states that the retailer’s profit is decreasing in the size of the low hassle segment. The low hassle segment chooses to bracket and thereby imposes a higher reverse logistics cost on the retailer. This overrides the gain in net purchases that is achieved via bracketing, thereby resulting in an inverse relationship between profit and the size of the low hassle segment. Finally, for sufficiently high values of the match probability and for small differences between the hassle costs of the two segments, the retailer is better off encouraging all consumers to buy single (Region III of Figure 2.8). Under this pooling strategy, the retailer’s profit is non-monotone in $\alpha$. When the reverse logistics cost $k$ is low, we observe that the profit is increasing in the size of the low hassle segment. On the other hand, when $k$ is large, the profit is decreasing in the size of the low hassle segment. This is driven by the following mechanism: First, consider those consumers that obtain a size match. The fraction that returns the product is higher for the low hassle segment (of size $\alpha$), and thus a larger $\alpha$ implies a higher loss in revenue. Second, consider those consumers that obtain a size mismatch. The fraction that exchanges the product is higher for the low hassle segment (of size $\alpha$), and thus a larger $\alpha$ implies a higher gain in revenue. Third, recall that size mismatches will always impose a reverse logistics cost on the retailer irrespective of whether the consumer exchanges or returns the product. When $k$ is large, the loss in revenue from low hassle consumers who return the product of the correct size outweighs the gain in revenue from low hassle consumers who exchange the product to obtain the correct size. Thus for large $k$, the profit is decreasing in $\alpha$. 

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Similarly, when $k$ is small, the opposite holds and hence the profit is increasing in $\alpha$.

![Figure 2.9 Optimal retailer profit as a function of the match probability $\beta$ when the cost of exchange is high.](image)

Next, we numerically illustrate how the retailer’s profit is affected by the match probability $\beta$. In Figure 2.9 (where we set $\alpha = 0.5, L = 0.2, \delta = 1.8, k = 1$), we see that the heterogeneity in the hassle cost does not lead to different dynamics from the main model in terms of the retailer’s profit and the match probability, and we see that an improvement in the match probability does not always translate to higher profits. More specifically, only a sufficiently large improvement in the match probability makes buying single attractive enough for consumers, thereby driving higher profits by limiting the volume of returns that the retailer has to process.

### 2.3.3 Endogenous hassle cost – A price-taking retailer

In this section, we consider a setting in which the retailer acts as a price-taker i.e. the retailer does not set the price. Instead, the retailer has control over the hassle cost $h$, and uses this as a lever to impact bracketing behavior. We assume that the price $p$ is determined exogenously, and that there is an initial hassle cost $h_0 \in [0, 1/2]$ associated with making returns to this retailer. The retailer can choose to alter this hassle cost to any value $h \in [0, 1/2]$ by incurring a quadratic cost $c(h - h_0)^2$, where $c > 0$. Note that consumers only observe the final hassle cost $h$ set by the retailer.
In this fixed price and endogenous hassle cost setting, consumers behave as follows. For low values of the match probability \( \beta \), consumers will only bracket. When the match probability \( \beta \) is moderate, consumers choose between bracketing and buying single based on the hassle cost. This is analogous to the Choice region described in Section 2.2.1. By setting the hassle cost below a threshold \( \bar{h} \), the retailer can induce consumers to bracket, and by setting the hassle cost above this threshold, it can push consumers to buy single. Finally, for high values of \( \beta \), consumers will only buy single. This behavior is illustrated in Figure 2.10.

![Figure 2.10](image)

**Figure 2.10** Possible actions through which purchase may occur in the case of endogenous hassle cost and fixed price for \( \delta = 1.8 \).

As in Section 2.2, we focus on the Choice region, i.e. the region in which the retailer can impact consumer behavior using hassle cost as a lever. The key insights regarding the optimal hassle cost are summarized in Proposition 6.

**Proposition 6.** When it is optimal for the retailer to encourage bracketing, the retailer should make the following adjustments to hassle cost:
(a) Leave the hassle cost as is when the initial hassle cost is below consumers’ threshold to bracket i.e. if \( h_0 \leq \bar{h} \), \( h^* = h_0 \).

(b) Decrease hassle cost down to the consumers’ threshold if the initial hassle cost is above this threshold i.e. if \( h_0 > \bar{h} \), then \( h^* = \bar{h} \).

When it is optimal for the retailer to encourage buying single, the retailer should make the following adjustments to hassle cost:

(c) Increase the hassle cost to the consumers’ threshold if the initial hassle cost is below this threshold i.e. if \( h_0 < \bar{h} \), then \( h^* = \bar{h} \).

(d) Weakly decrease the hassle cost if the initial hassle cost is above this threshold i.e. if \( h_0 \geq \bar{h} \), then \( h^* = \max\{\bar{h}, h\} \).

Proposition 6 (a) shows that when the hassle cost is sufficiently low to begin with, the retailer is better off leaving the hassle cost as is when encouraging bracketing. On the other hand, for a high initial hassle cost, a price-taking retailer is better off decreasing the hassle cost to encourage bracketing (part (b)). In this case, the retailer reduces the hassle cost up to the point that consumers prefer bracketing over buying single. Any further decrease in the hassle cost will only result in a decrease in the retailer’s profit. Interestingly, when encouraging consumers to buy single, the retailer finds it optimal to increase the hassle cost when the initial hassle cost is very low (cf Proposition 6 (c)). This is driven by the fact that the retailer can reduce the mass of returns by encouraging buying single as opposed to bracketing. This reduction in returns is achieved by increasing the hassle cost that consumers incur and making bracketing excessively costly to consumers, which subsequently pushes consumers to buy single instead. If the initial hassle cost is high and buying single is optimal for the retailer, the retailer can increase profits by decreasing the hassle cost.
We also explored the conditions under which the retailer would encourage/discourage consumers to bracket versus buy single, and we find that these are consistent with the conditions identified in our main model. In essence, encouraging bracketing is optimal for the retailer as long as the reverse logistics cost is sufficiently small, while encouraging buying single is optimal when the reverse logistics cost is high. We also observe a similar relationship between the retailer’s optimal profit and the match probability $\beta$ to that from the main model (cf Proposition 3 and Figure 2.5). Detailed analysis is available upon request.

In Figure 2.11, we present a numerical example (analogous to Figure 2.4 from the main model) to illustrate the optimality of the two approaches (bracketing versus buying single) in the Choice region. In this example, we set $\delta = 1.8$, $h_0 = 0.1$, $k = 0.1$, $c = 3$. In the B (S) region, bracketing (buying single) is optimal for the retailer. As in the main model, we observe that encouraging bracketing is typically optimal for
the retailer for lower values of the match probability since this eliminates the large fraction of returns without purchases. For higher values of the match probability, the retailer faces fewer returns when consumers buy single, and thus prefers to set a hassle cost that encourages buying single.

The key takeaways from our analysis of a price-taking retailer that can use hassle cost as a lever to impact bracketing are as follows. First, when encouraging consumers to bracket, the retailer never finds it optimal to increase the hassle cost. In fact, the retailer should leave the hassle cost as is so long as the initial hassle cost is low (i.e. below consumers’ threshold hassle cost for bracketing). Second, the retailer can, under certain conditions, benefit from increasing the hassle cost when encouraging consumers to buy single. Third, as in the main model, the retailer finds it optimal to encourage bracketing when the reverse logistics cost is low, and when the match probability is relatively low.

2.3.4 Endogenous price and hassle cost

So far, we have assumed that the retailer could influence consumer behavior only through one lever - either price or hassle cost. We now consider the case where the retailer can simultaneously use both price and hassle cost as levers to influence consumer behavior. As in section 2.3.3, we assume that the retailer’s return policy imposes an initial hassle cost $h_0$ on consumers. The retailer can adjust this hassle cost to any $h \in [0, \frac{1}{2}]$ by incurring a cost of $c(h_0 - h)^2$, where $c > 0$.

The following result characterizes the price and hassle cost that the retailer should set when it is optimal to make consumers bracket.

**Proposition 7.** When it is optimal to encourage consumers to bracket, the retailer’s optimal price and hassle cost are as follows

(a) $p = 3, h = 0$, when $c \leq \frac{k+2}{2h_0}$.
(b) \( p = \frac{2ch_0 + 6c - k + 4}{2c + 2}, \ h = \frac{2ch_0 - k - 2}{2c + 2}, \) when \( c > \frac{k + 2}{2h_0}. \)

From Proposition 7 part (a), we see that if the cost of adjusting the hassle cost is low the retailer can benefit by completely eliminating consumers’ hassle cost while encouraging bracketing. When this cost is high, we see that it is optimal for the retailer to impose some hassle cost (lower than \( h_0 \)) on consumers when they return the product (Proposition 7 part (b)).

Note that Proposition 7 does not establish the optimality of bracketing over buying single. Instead, Proposition 7 identifies the price and hassle cost that the retailer would choose if encouraging bracketing was the optimal strategy for the retailer. Next, we numerically verify that there are instances where the strategies described in Proposition 7 are indeed optimal (see Figure 2.12). We set \( k = 0.8, \ \delta = 1.8, \) and \( c = 3.5 \) in this example.

![Figure 2.12](image)

**Figure 2.12** Optimal retailer actions under endogenous versus exogenous hassle cost.

Figure 2.12a provides a complete characterization of the optimal strategies for the retailer when it has control over both price and hassle cost. We see that for sufficiently small values of the match probability \( \beta \) and the initial hassle cost \( h_0 \), the retailer is better off pricing to encourage bracketing while also completely eliminating consumers’ hassle cost; a strategy consistent with Proposition 7 (a). For high values of the initial hassle cost, we see that the retailer is better off with only a partial
reduction in hassle cost; a strategy in line with Proposition 7 (b). For sufficiently high values of the match probability, we see that it is optimal for the retailer to increase the hassle cost and push consumers to buy single.

Comparing this endogenous \( p \) and \( h \) (Figure 2.12a) setting with the exogenous \( h \) setting from Section 2.2 (Figure 2.12b), we observe a few instances where the retailer can actually benefit by increasing consumers’ hassle cost and pushing consumers to buy single as opposed to bracketing. This is in line with the findings from Proposition 6.

### 2.3.5 Checks for robustness

In all of the models presented thus far, we assumed full market coverage to maintain analytical tractability. By relaxing this assumption and allowing for consumers to choose between bracketing, buying single, and not ordering the product at all, we find through numerical analysis (available from the authors) that our key insights continue to hold qualitatively. Consumers continue to bracket for a low match probability and a low hassle cost, while a high match probability or hassle cost ensures that consumers will refrain from bracketing. We also continue to observe that the retailer finds it optimal to encourage bracketing for relatively low match probabilities within the Choice region. Further, when encouraging bracketing, the retailer largely finds it optimal to completely eliminate consumers’ hassle cost. It is only in scenarios where the initial hassle cost is high that the retailer finds it optimal to partially decrease consumers’ hassle cost while encouraging bracketing. As in Sections 2.3.3 and 2.3.4, we find instances where the retailer can benefit from increasing consumers’ hassle cost while encouraging consumers to buy single.

In a second robustness check, we relax our definition of bracketing as the common consumer practice of ordering a size up and a size down from the size that they think they need, resulting in consumers ordering exactly three sizes when bracketing. It is
also possible that consumers can completely eliminate size uncertainty by ordering only two sizes – the size they expect that they need and one size smaller (bigger). In such a scenario, our numerical analysis indicates that all our key insights continue to hold qualitatively, and bracketing becomes optimal for a wider range of parameters. Alternatively, there may be situations in which sizing is so granular that consumers must order more than three sizes to eliminate size uncertainty. In such a situation, our key insights continue to hold, and the parametric region where bracketing is the optimal strategy for retailers becomes smaller than that under our main definition of bracketing. All numerical analyses described in this subsection are available from the authors upon request.

2.4 Conclusion

The debate of whether or not to offer free returns seems to have become moot, particularly in online apparel retail. Consumers have come to expect free returns to such an extent that we see online retailers resigning themselves to the reality that offering such a policy is a cost of doing business. In fact, some online retailers (Zappos, Running Warehouse, and Amazon, through their Prime Wardrobe service, are a few examples) are beginning to embrace the practice of bracketing, and accept the resultant reverse logistics costs, in order to allow consumers to resolve their fit uncertainty at home. This new retail reality motivated our investigation of how retailers can best respond to the “new normal” of free returns and consumer bracketing. Our work is the first to model the phenomenon of bracketing and study its implications for retailer profitability. By considering key characteristics of bracketing and the return process, including a product’s match probability (i.e. size uncertainty), consumers’ hassle costs, and a retailer’s return logistics cost, we provide several novel insights. First, we show how and why price can be used as a tool, under certain conditions, to influence consumers’ bracketing behavior. More specifically, we show that when con-
sumers’ hassle cost is low and the product’s match probability is moderate, consumers are willing to bracket for sufficiently low prices, and will prefer buying a single size otherwise. This is because the likelihood of actually incurring the price (by keeping the product) is higher when consumers choose to bracket, which makes them more price sensitive. Secondly, retailers can increase profits by using price to encourage bracketing when the product’s match probability is moderate, the retailer’s reverse logistics cost is low, and/or consumers’ hassle cost is low. For moderate levels of the match probability, consumers are more inclined to bracket, and the quantity of net purchases is higher, resulting in a higher profit for the retailer. Similarly, when the reverse logistics cost is low, the retailer can more easily bear the cost of more returns, and hence realize higher profits from the gain in net purchases due to bracketing. A low hassle cost suggests that consumers do not view the process of returning a product to be particularly cumbersome, and hence the practice of bracketing becomes an attractive prospect for consumers, which increases demand and thereby the retailer’s profit.

We also show that an increase in the product’s match probability is only beneficial to the retailer when the increase is large enough to enable the retailer to shift consumers away from bracketing and into buying single. Similarly, marginal reductions in the hassle cost are not always beneficial to the retailer, particularly when the retailer prices such that consumers prefer to buy a single size rather than bracket.

In an extension, we examine whether and under what conditions an online retailer should invest in technology and tools to eliminate size uncertainty as opposed to allowing consumers themselves to evaluate sizing through bracketing. We find that there is a threshold investment cost below which the retailer should make the investment, and this threshold is higher for retailers who face high reverse logistics costs and/or offer higher-hassle return processes.

In three subsequent model extensions, we consider alternative formulations of
the hassle cost. First, we assume that a fixed fraction of consumers incur a low hassle cost, with the remaining consumers incurring a higher hassle cost. Under such heterogeneous hassle costs, the retailer can employ one of three strategies: two pooling strategies in which all consumers either bracket or buy single, and a separating strategy in which the low hassle segment brackets and the high hassle segment buys single. We demonstrate that the presence of this heterogeneity does not change the primary insights from our main model, although we are able to comment on how the sizes of these two consumer segments impact the retailer’s profit.

In our second hassle cost extension, we model hassle cost as an endogenous variable, subject to an investment cost, and treat the price to be exogenously determined. We find that when encouraging bracketing is optimal for the retailer, it is largely better off leaving the hassle cost as is. The retailer would reduce the hassle cost only when that cost is significantly high to begin with. On the other hand, when it is optimal for the retailer to encourage consumers to buy single, we identify conditions under which the retailer can benefit by increasing the hassle cost.

In a final extension, we allow the retailer to choose both price and hassle cost. We find that it can be optimal for the retailer to encourage bracketing and completely eliminate consumers’ hassle cost if the cost of doing so is sufficiently small. We also find that for higher values of the product’s match probability, the retailer is better off shifting from encouraging bracketing to encouraging buying single, while also increasing consumers’ hassle cost.

We see several promising research directions in the area of bracketing, and our model can provide a foundation for future inquiry into this important phenomenon in online retail. Specifically, our framework includes the essential aspects of the business context: size uncertainty, return hassle, and reverse logistics costs. One limitation of this research is our focus on a single-product setting. Relaxing this assumption through horizontally differentiated products might provide additional insights, al-
though for tractability some other model elements may need to be simplified. Second, a competitive model using a simplified analytical framework could be a promising direction for future research, since it could lend insights into the competitive necessity of free returns given the realities of bracketing. A competitive model may also be useful to study how quality differences across retailers can manifest in differing attitudes towards encouraging bracketing. Finally, a supply chain setting where the online retailer is buying goods from a manufacturer and the manufacturer buys back all of the returned goods could also be a promising direction with potentially interesting supply chain implications. Studies exploring these directions could be a valuable complement to the insights provided in this chapter.
Chapter 3
Is Fast Fashion Really Killing the Planet? A Comparison to Traditional Apparel Supply Chains

3.1 Introduction

Traditional apparel retailers such as The Gap and Abercrombie & Fitch are characterized by long lead times and three selling seasons (winter, spring, summer-autumn) per year (O’Byrne, 2017). Beginning with Zara in Spain, apparel retailers such as Boohoo, H&M, and Benetton have employed a “fast fashion” approach to apparel retail. This approach is characterized by quick response, frequent assortment changes, and lower prices\(^1\)(Caro and Martínez-de Albéniz, 2015). Greater vertical integration (Ghemawat et al., 2003; Ferdows et al., 2004), more localized production\(^2\), and delayed final production are among the strategies that provide fast fashion retailers with quick response capabilities, and help better match supply with demand (Fisher and Raman, 1996). In other words, the fast fashion approach provides retailers with more accurate demand forecasts.

Despite this superior ability to match demand and supply, the fast fashion ap-

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\(^1\)As Caro and Martínez-de Albéniz (2015) point out, the price point is not truly a defining factor of fast fashion retailers. While all fast fashion retailers attempt to provide “fashionable designs at affordable prices”, there are a number of retailers that lack the operational capabilities of fast fashion that also price products fairly low. Caro and Martínez-de Albéniz (2015) provide the example of Old Navy, who lack quick response capabilities but provide very competitive prices.

\(^2\)Zara and Benneton have their main production facilities close to their headquarters (Camuffo et al., 2001; Ferdows et al., 2004)
approach has received a great deal of criticism due to its perceived environmental impact. Butler (2018) and Schlossberg (2019) are just two among a myriad of publications in the popular press that report on the environmental impact of fast fashion. While quick response typically results in less unsold inventory (Recer, 2017), its reliance on delayed production often requires expedited shipping, which may result in a higher environmental impact. Another facet of fast fashion is the production of less durable products. This lower product durability can be attributed to the following reasons. First, fast fashion retailers typically have rapidly changing assortments which are built around a consumer culture of “single-use purchases” (Zarroli, 2013; Butler, 2018). Less durable products result in more frequent purchases. Second, the intense pressure to shorten lead times can pressure manufacturers to skip quality controls (Stanton, 2018). While the popular press (Stanton, 2018; Friedman, 2022) and regulatory bodies (Chakraborty et al., 2022) have focused on this lower product durability, it has received limited academic attention.

The aforementioned facets of the fast fashion approach (i.e., quick response capabilities and the production of less durable products) can affect its environmental impact in opposing directions. On one hand, fast fashion’s quick response capabilities can reduce the amount of unsold inventory at the end of the selling season which can subsequently lower its environmental impact. On the other hand, the lower durability of fast fashion products can result in more frequent purchases and more units being discarded by consumers, which often end up in landfills. Specifically, the U.S. Environmental Protection Agency (2020b) reports that over 9 million tons (70% of total apparel waste generated) was landfilled in 2018. Thus, it is not clear how the fast fashion approach compares to a more traditional approach in terms of total environmental impact. Surprisingly, there has been no comparison in the extant literature between the two approaches.

We seek to fill this gap by comparing the environmental impact of the fast fashion
approach, which produces lower quality products but has quick response capabilities, and the traditional approach, which produces more durable products but incurs longer lead-times. More specifically, we study how the total environmental impact is jointly affected by differences in product durability and quick response. Our goal is to compare the choices from commonly observed supply chain structures rather than what some prescriptive model says those structures should be. Thus, we compare these approaches in their current forms (despite some perceived inefficiencies) as opposed to providing guidance on how firms should optimally behave under a given approach (e.g., choosing the optimal level of inventory or product durability). Doing so requires that we start with some basic premises rather than endogenizing them as decision variables, which we feel are well supported in both the business news outlets and in empirical findings. We provide further justification of these basic premises in Section 3.3 but summarize them here:

1. Because of their longer lead times, traditional supply chains carry larger amounts of safety stock than fast fashion supply chains.

2. Fast fashion supply chains choose lower product durability levels than traditional supply chains.

We model the lower product durability of fast fashion by making the number of periods for which a customer gains utility from owning it smaller than for a traditional supply chain product. To do so, we take a stylized approach and consider the best-case scenario for fast fashion (from a durability perspective) in which the product lifetime under fast fashion is half of the lifetime of the traditional approach. One may ask why one half, why not one third, two thirds, etc. We acknowledge that this choice is a simplification made for tractability, but we expect the directional effects of our results to be consistent if we were to consider different relative product lifetimes.
across the two approaches. The first order effects only require that the lifetime be shorter.

We model interactions between a monopolistic firm and a heterogeneous, price-sensitive, mass of consumers through an infinite-horizon game, and compare the environmental impact of the two approaches using life-cycle analysis (LCA), a “cradle-to-grave approach for assessing industrial systems” (Scientific Applications International Corporation, 2006). Using this game-theoretic setup, we provide a more nuanced understanding of how the two approaches compare in terms of product volume in each life-cycle phase as well as their total environmental impact. Since markdown pricing is prevalent in the apparel marketplace, we account for it in our model for both supply chain strategies. Our study is the only one that incorporates markdown pricing in this stylized setting. Our numerical experiments provide a clearer understanding of 1) the different market conditions under which the fast fashion approach can be greener and 2) the extent to which changes in the parameter values impact the total environmental impact of the two approaches.

We find that the fast fashion approach has a smaller product volume in the production and the disposal phases than the traditional approach when the markdown price under the fast fashion approach is significantly higher than the markdown price under the traditional approach. For more comparable values of the markdown prices of the two approaches, the fast fashion approach has a smaller product volume in the production and disposal phases as long as the traditional approach is characterized by sufficiently high leftover inventory. We also find that the fast fashion approach has a smaller product volume in the use phase than the traditional approach, as long as the markdown price under the fast fashion approach is larger than the markdown price under the traditional approach. In terms of total environmental impact, we find a threshold on the leftover inventory under the traditional approach above which fast fashion is greener i.e., the traditional approach’s superiority in product durability is
outweighed by the fast fashion approach’s quick response capabilities. We conduct
numerical experiments using parameter estimates based on fashion industry data and
observe that the fast fashion approach can be greener even in instances where the
traditional approach targets an expected service level of just 60%. In fact, this is the
case even if fast fashion is characterized by more environmentally harmful production
and distribution processes (by a factor of 10%) than the traditional approach. When
the production phase impacts are very similar across the two approaches, fast fashion
can be greener even in instances where there is no leftover inventory under the tradi-
tional approach (a target service level of 50%). Further numerical experiments allow
us to tie the greenness of the two approaches to different apparel categories based on
the expected leftover inventory and markdown prices.

These findings call for a more balanced environmental criticism of fast fashion.
While a shift to an altogether new approach that combines quick response and high
product durability may result in superior environmental outcomes, our findings sug-
gest that the popular press should be more wary in its criticisms and regulatory bodies
need to be especially careful regarding legislation that they pass. This is particularly
important when demand uncertainty is high, since the traditional approach is typi-
cally characterized by large amounts of leftover inventory. In this case, a shift from
fast fashion to the traditional approach results in worse environmental outcomes. In
other words, the environmental positives that fast fashion achieves through supe-
rior matching of demand and supply outweigh the environmental negatives of lower
product durability. This suggests that a blanket ban on fast fashion, as is being con-
sidered by the European Union (Chakraborty et al., 2022), may well result in worse
environmental outcomes than the current situation.

We also provide guidance to policy makers by analyzing the product volume in
each life-cycle phase of a specific approach. More specifically, when firms are pro-
ducing more durable products, as per the traditional approach, policy makers should
focus on the production and disposal phases when leftover inventory is high, or the product has a high salvage value. This could take the form of incentives to push manufacturers to greener production and distribution methods, as well as improved recycling methods for end-of-life products. Whereas, a focus on educating consumers about better habits regarding washing and drying (either directly or through the firm itself) becomes imperative when both leftover inventory and the product’s salvage value are low. This is in contrast to The Fashion Sustainability and Social Accountability Act’s (New York State Senate, 2021) sole focus on the production phase. For the less durable fast fashion approach, each life-cycle phase has the same product volume in each period. This suggests that policy makers have little influence on the volumes produced from a particular phase and their choice of which phase to focus on may be better driven by factors such as per-unit cost considerations. These findings are supplemented by a global sensitivity analysis (Wagner, 1995; Denizel et al., 2009), where we examine which model parameters are the most influential on the environmental performance of the two approaches. Using a wide range of parameter values, we find that the production phase has the largest influence on the total environmental impact of both approaches. The Fashion Sustainability and Social Accountability Act aims to have apparel retailers mapping a “minimum of 50% of suppliers by volume across all tiers of production”. While this focus on holding apparel retailers accountable for the production phase impact is justifiable across a wide range of scenarios, our results suggest that a stronger push towards more environmentally friendly production and distribution processes may be necessary.

3.2 Literature Review

This work relates to two primary research streams: Operational flexibility gained via the quick response capability of the fast fashion approach and the environmental impact of operational decisions (sustainable operations). The early literature on quick
response focused on monopolist settings and highlighted the advantages gained when a firm obtains additional demand information (Fisher and Raman, 1996; Eppen and Iyer, 1997). Caro and Martínez-de Albéniz (2010) and Lin and Parlaktürk (2012) account for competition to provide further insights on the benefits of quick response. Cachon and Swinney (2009) and Swinney (2011) extend this to the setting in which customers are strategic. In their follow-up work, Cachon and Swinney (2011) explicitly model both quick response and enhanced design in the presence of strategic consumer behavior to examine whether they act as complements or substitutes, finding that they do act as complements in most cases. Calvo and Martínez-de Albéniz (2016) study the impact of quick response in the context of sourcing from multiple suppliers. Tuna and Swinney (2021) compare efficient and responsive supply chains, specifically focusing on two separate means through which responsiveness is achieved, namely nearshoring and expedited shipping. Most of the aforementioned studies focus on quick response in general and are not specific to the fast fashion context. Long and Nasiry (2022) study how quick response and design flexibility, in the context of fast fashion, interact with each other and affect a firm’s decision making regarding price, inventory, and product variety. Most of the previous work in this space assumes that there is no variation in product quality between production with and without quick response capabilities. On the contrary, evidence from practice suggests that fast fashion retailers (equipped with quick response capabilities) typically sell less durable products than traditional retailers (those without quick response capabilities). Our work builds on this previous literature in two ways. First, we account for the reduced product durability among fast fashion retailers which has significant implications for the environmental impact of the two approaches to apparel retail. Long and Nasiry (2022) account for product quality in their study of fast fashion but do not explicitly compare this approach with the traditional approach. Second, our use of an infinite-horizon model captures the substitution effect that arises due to consumers choosing
between keeping a product for its entire lifetime and repurchasing every period—a facet associated with durability. This substitution effect that arises due to the repurchase decision of consumers has been termed “inter-temporal substitutability” in the durable goods literature (Agrawal et al., 2012). Long and Nasiry (2022) use a two-period model in which consumers make their purchase decision only in the second period, but do not capture how differences in durability can affect consumers’ repurchase decisions. Another theme that is common among the aforementioned works is identifying theoretical optima in systems involving quick response. On the contrary, our goal is to model two existing systems, as they are currently observed in practice, focusing on the effects of quick response and product durability, and compare their environmental impact. In other words, our goal is not to provide prescriptions to retailers on how to improve the profitability of each strategy, but better understand the environmental impact of two supply chain approaches that are highly prevalent in the existing apparel retail landscape.

To capture this difference in durability, we draw on the durable goods literature. In his seminal piece, Coase (1972) explores the difficulty of maintaining monopolist power when consumer valuations are unknown and products are durable. This gave rise to a large stream of work comparing the strategies of selling and leasing. Early work in this area made some restrictive assumptions including infinite durability, homogenous consumers, the lack of an active used goods market, etc. Rust (1986); Anderson and Ginsburgh (1994); Waldman (1997); Porter and Sattler (1999), and Hendel and Lizzeri (2002) are among the works that relax these assumptions. Huang et al. (2001) include the aspect of concurrent leasing and selling, while accounting for the Markovian nature of decision making. While our work draws on the model setting proposed by Huang et al. (2001), we do not account for leasing as it is uncommon in apparel retailing. Instead, we combine their Markovian nature of decision making with the existence of markdown sales. Mantena et al. (2012) provide a detailed
overview of the use of durable goods models in the operations management literature.

The second major stream that we contribute to is that of sustainable operations. This is a wide area covering topics ranging from remanufacturing (e.g., Ferguson and Toktay, 2006) to green technology choices (e.g., Drake et al., 2016). Our work on this topic is most related to Agrawal et al. (2012), Raz et al. (2013), Tuna and Swinney (2021), Alptekinoglu and Orsdemir (2022), and Long and Nasiry (2022). These studies provide insights on the environmental impacts of decisions regarding price and/or inventory using life-cycle analysis (LCA). Our model most closely follows that of Agrawal et al. (2012) with the differences being similar to those mentioned with respect to Huang et al. (2001). Thus, we wed the topic of apparel retail with sustainable operations in the same vein that Agrawal et al. (2012) brought the sustainability angle to product leasing versus selling. Tuna and Swinney (2021) compare the environmental impacts of an efficient supply chain with two types of responsive supply chains, one where responsiveness is achieved by nearshoring and another where responsiveness is achieved via expedited shipping. We do not narrow our focus to the means through which quick response is achieved, in the context of fast fashion, since both nearshoring and expedited shipping are used in conjunction with a number of other techniques to achieve responsiveness. Alptekinoglu and Orsdemir (2022), Long and Gui (2022), and Long and Nasiry (2022) also focus on the environmental impacts of operational decisions in the apparel industry. Alptekinoglu and Orsdemir (2022) compare the strategies of mass production and mass customization in apparel retailing, and find that mass customization can result in preferred outcomes in terms of higher profits and lower environmental impact. Long and Gui (2022) analyze the impact of quick response and upcycling (the practice of using deadstock fabric to make new clothes). We do not consider upcycling in this study, but focus on the joint impact of product durability and quick response on a firm’s environmental impact. Long and Nasiry (2022) also study how decisions related to product variety
and quality, in the context of fast fashion, can impact the environment. We build on their work by accounting for inter-temporal substitutability, which governs how long consumers use the product, and account for markdown purchases, which allows for a better matching of demand and supply as well as price discrimination. They also look at how different policy decisions such as consumer education programs and the levying of production taxes can result in surprising environmental outcomes. We complement this study by providing insights on which phases of a product’s lifecycle a policy maker should focus on to minimize the total environmental impact.

Since Tuna and Swinney (2021) and Long and Nasiry (2022) have the most similar objectives, we provide a summary of how our model compares to theirs in Table 3.1. Note that neither study specifically addresses our research question.

<table>
<thead>
<tr>
<th></th>
<th>Quick response (QR)</th>
<th>Inter-temporal</th>
<th>Durability</th>
<th>Markdown pricing</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>vs traditional</td>
<td>substitutability</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Long and Nasiry (2022)</td>
<td>QR only</td>
<td>2 periods</td>
<td>✓</td>
<td>–</td>
</tr>
<tr>
<td>Tuna and Swinney (2021)</td>
<td>Both QR &amp; traditional</td>
<td>1 period</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>This work</td>
<td>Both QR &amp; traditional</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

### 3.3 Model

We model the firm-consumer interaction as a dynamic, discrete-time, sequential, infinite-horizon game. We consider an infinite-horizon game for the following reasons. First, in a finite-horizon model, the initial state has an impact on the evolution of the system and thereby the resulting equilibria. The choice of an initial state is arbitrary, but the analysis of steady-state equilibria eliminates this problem. Second, this steady-state analysis allows us to compare existing supply chain strategies employed by apparel retailers rather than study the initial choice between the traditional and fast fashion approach (which would be the focus of a two-period model...
and reflective of the decision made by new firms in the apparel space). Third, an infinite-horizon model allows us to capture the substitution effect between consumers purchasing a new product versus keeping a product for its entire lifetime – a key aspect in the multi-period durable goods literature (Huang et al., 2001; Debo et al., 2005; Agrawal et al., 2012). The firm acts as a Stackelberg leader that sets prices and consumers observe these prices before making their purchase decisions.

3.3.1 Firm and product characteristics

We consider a profit maximizing monopolist that selects one of the two following supply chain strategies: (1) the fast fashion approach or (2) the traditional approach. We use the subscripts $F$ and $T$ to denote the fast fashion and traditional approaches, respectively. The firm offers the product at a full price $p_i$ at the start of the selling season and at a markdown price $s_i (< p_i)$ later in the selling season$^3$, where $i \in \{F, T\}$ denotes the approach that the firm is following. We treat the markdown prices to be exogenous for the sake of tractability (Su and Zhang (2008) and Cachon and Swinney (2011) make the same assumption). We relax this exogenous markdown assumption in Section 3.5.1. Under the fast fashion approach, the firm has a supply chain that gives it the ability to place production orders very close to the start of the selling season – the quick response capability. This implies that the firm faces less demand uncertainty under the fast fashion approach than under the less nimble traditional approach. While our modeling framework accounts for demand uncertainty, we do not follow the common approach in the inventory management literature of modeling the uncertainty directly through a statistical distribution in a newsvendor setting. Instead, we make the following modeling assumption to capture differences in the level of demand uncertainty under the two approaches.

$^3$Markdown pricing is very common among traditional retailers in order to combat demand uncertainty but also used by certain fast fashion retailers as it is a means to price discriminate (Caro and Gallien, 2012).
Assumption 1. (a) Under the fast fashion approach, the firm can completely eliminate demand uncertainty through its quick response capabilities.

(b) Under the traditional approach, the firm cannot always do so and there is a quantity $k \geq 0$ that remains unsold at the end of the selling season.

Since our goal is to compare the traditional and fast fashion approaches as they are currently implemented, as opposed to provide guidance on how firms should optimally behave under these approaches, we treat $k$ as an exogenously determined parameter. We refer to $k$ as the leftover inventory, which is representative of (1) the demand uncertainty in a particular market and (2) the firm’s service level. For example, a high value of $k$ may correspond to a product that has highly volatile demand across selling seasons (e.g., a cocktail dress) and/or a supply chain with a high geographic spread (this results in longer lead times and thereby more uncertainty). Alternatively, a high value of $k$ may be representative of a firm that chooses to operate at a very high service level, possibly even in a market with stable demand.

From Assumption 1(a), when following the fast fashion approach, the firm is able to eliminate leftover inventory through its quick response capabilities. In practice this is not the case but we normalize the leftover inventory to 0 ($k = 0$) for the fast fashion approach. When following the traditional approach, the lack of quick response capabilities results in an inferior demand estimate at the start of the selling period. The firm uses markdown pricing under the traditional approach to make up for this inferior demand estimate but a certain amount of inventory remains unsold\(^4\). Thus, $k \geq 0$ for the traditional approach. Our modeling of leftover inventory under the traditional approach is relative to that of the fast fashion approach. We do not

\(^4\)Given that markdown pricing provides the firm with the option to sell at two price points, we also allow for markdown pricing under the fast fashion approach. This results in a more appropriate comparison between the environmental impacts of the two approaches as both of them have the opportunity to price discriminate.
consider the case of demand underestimation since retailers typically do not target service levels below 50%, which under expectation results only in negative safety stock levels.

Since fast fashion products are known to be less durable (Zarrol, 2013; Butler, 2018; Stanton, 2018), we make the following assumption regarding the lifetimes of products produced under the two approaches.

**Assumption 2.** The lifetime of units produced through the fast fashion approach is a single period, while units produced through the traditional approach have a lifetime of two periods.

The assumption of a lifetime of two periods to capture inter-temporal substitution effects has been made in the durable goods literature (Desai and Purohit, 1998; Huang et al., 2001; Agrawal et al., 2012). In the case of the two-period model used by Long and Nasiry (2022), consumers make a purchase decision only at one instance (i.e., in the second period). By considering a lifetime of two periods under the traditional approach, coupled with the infinite-horizon setting, we are able to account for consumer segments that keep the product for its entire lifetime, as well as those segments that discard the product more frequently. This makes our model more reflective of consumer behavior in practice. Long and Nasiry (2022) allow for the firm to endogenously set durability in order to maximize profit. Since our goal is not to provide firms with guidance on how durable their products should be, we treat durability to be fixed. More specifically, through Assumption 2, we consider the best-case scenario (in terms of environmental impact) for fast fashion. For tractability, we collapse the full and markdown price selling instances into a single period for both approaches.

### 3.3.2 Consumer characteristics

The mass of consumers is normalized to 1 and remains constant over time. Consumers’ valuations for the product are assumed to be heterogeneous. More specifi-
cally, each consumer is of type $v$, which is uniformly distributed over $[0, 1]$. In a given period, consumers may choose to buy the product at the full price $p_i$, or at the markdown price $s_i$, where $i \in \{F, T\}$. In order to capture the disutility associated with waiting for the product to be on markdown, we introduce the parameter $\delta \in (0, 1)$. If consumers choose to purchase the product at the full price, their per-period utility from consumption is $v$, while if the purchase is made at the markdown price, the utility from consumption is $\delta v$. High values of $\delta$ imply that consumers are more willing to wait for the product to be on markdown in a given period. Given the two period lifetime of products produced under the traditional approach, we make the following assumption regarding the salvage value of the product.

**Assumption 3.** (a) Consumers that purchased the product at the full price $p_T$ can dispose of it after a single period of use and obtain a salvage value of $r \in [0, s_T]$.  

(b) Consumers that purchased the product at the markdown price $s_T$ cannot obtain a positive salvage value.

As per Assumption 3(a), consumers may use the product only for a single period (half its lifetime) and choose to dispose of it while obtaining a salvage value of $r$. A positive salvage value $r$ represents the case where the consumer is able to sell the product in an independent used goods market such as Poshmark or Plato’s Closet. Such resale platforms typically accept products that are lightly used and in fashion. Thus, we do not allow for consumers to obtain a positive salvage value when they discard the product after two periods of use (i.e., the product’s entire lifetime). Markdowns usually occur once the product’s season of use (e.g., the summer for swimwear) is complete. This realistically allows the consumer to only use the product for the following season of use (i.e., the summer of the following year). Thus, the consumer disposes of the product two periods on from its sale. This results in the product being out of fashion and incapable of being sold for a positive salvage value (Assumption
3(b)). Under the fast fashion approach, all consumers dispose the product after a single period of use (i.e., the product’s entire lifetime) and do not obtain a positive salvage value. This choice to prevent resale under the fast fashion approach is also reflective of the policies set forth by resale platforms such as ThredUp (Dobrosielski, 2022).

3.3.3 Sequence of events

The firm follows either the traditional or fast fashion approach. For either approach, at the start of each period, the firm sets the full price $p_i$ and the markdown price $s_i$ is determined exogenously. Consumers observe these prices and choose among three alternatives: purchase at the full price, purchase at the markdown price, and remain inactive. Consumers are aware of the markdown price at the start of any period, i.e., the firm is committing to prices. This assumption is especially relevant in the apparel retail context as the prices and extent of markdowns do not vary greatly given the repeated firm-consumer interactions every selling season. Further, this assumption has been made in models in the prior literature (e.g., Elmaghraby et al., 2008, Liu and Van Ryzin, 2008, and Yin et al., 2009). Consumers maximize their net future value by incorporating a discount factor of $0 < \rho \leq 1$ in their decision making. We make the following assumption about the length of each selling season.

We treat each period to be a selling season. Each selling season is characterized by a unique set of products usually governed by the climatic season. For example, in the winter season, one would expect products such as jackets and sweaters to be sold, while in the summer season, it is more likely that T-shirts and shorts are being sold. Since we focus on a single product, we are considering a single season that is repeated every year. For more perennial products such as undergarments, the selling season may be a lot longer, but our focus on a single product eliminates comparisons across products with selling seasons of different lengths. As was the case with Assumption
2, this represents the best-case environmental scenario for fast fashion. A pictorial representation of the dynamics in a given period is shown in Figure 3.1.

![Period dynamics diagram](image)

**Figure 3.1** Period dynamics

### 3.3.4 Environmental impact

We follow a life-cycle approach (LCA) to analyze the environmental impact of the two production strategies. As in Agrawal et al. (2012) and Tuna and Swinney (2021), we consider three life-cycle phases: production \((P)\), usage \((U)\), and disposal \((D)\). The total per-period environmental impact of either approach is given by the product volume in each phase in a given period multiplied by the per-unit environmental impact of that phase. We denote the per-unit environmental impact of a phase by \(e_{i,j}\) and the product volume per-period in a given phase by \(q_{j,i}\), where \(j \in \{P, U, D\}\) denotes the phase and \(i \in \{F, T\}\) denotes the production strategy of the firm. We now describe the per-unit impact of each of these phases.

**Production phase:** This phase of the product’s life-cycle accounts for the impact of all processes involved from the sourcing of raw materials for the product up to the product reaching the customer.

**Use phase:** This phase includes the time from the purchase of the product up to its disposal (not accounting for the disposal itself). In the main model, we assume that the use phase does not contribute differently across the two approaches, i.e., \(e_{F,U} = e_{T,U} = e_U\). This assumption is relaxed in Section 3.5.2 in order to account for...
potential differences in the extent of synthetic versus natural fibers used across the two approaches (Laitala et al., 2018; Changing Markets Foundation, 2021).

Disposal phase: This phase accounts for the environmental costs of disposing the product. Under the fast fashion approach, all units are disposed of by consumers at the end of each period. Under the traditional approach, some units may be disposed of by the firm, while the rest may be disposed of by consumers. We assume that the impact of disposal is independent of whether the firm or the consumer disposes of the product. Thus, we have $e_{F,D} = e_{T,D} = e_D$.

3.4 Analysis

Using the model described in Section 3.3, we compare the fast fashion and traditional approaches in terms of their environmental impact. We analyze steady-state firm and consumer strategies that constitute subgame-perfect equilibria under the two approaches. We begin by comparing the product quantities in each life-cycle phase across the two approaches. We obtain an analytical threshold on the leftover inventory above which fast fashion is environmentally superior. Finally, we tie our results to practice using numerical experiments.

3.4.1 Fast fashion approach

Under the fast fashion approach, we model the lower durability of the product by assigning it a lifetime of a single period. As a consequence, consumers enter each period without a product, which leads to a decoupling of decisions between periods, i.e., both consumer and firm decisions in period $t$ are independent of decisions made in the past. Recall that the firm sets the price $p_F$ along with the exogenous determination of the markdown price $s_F$ at the start of each period. These prices are observed by consumers who choose between buying the product at the full price, buying the product at the markdown price, and remaining inactive. The utility that
a consumer of type \( v \) obtains from buying at the full price is \( v - p_F \), the utility from buying at markdown is \( \delta v - s_F \), while she obtains 0 if she chooses to remain inactive. Let \( v^* = \frac{p_F - s_F}{1 - \delta} \) denote the consumer who is indifferent between buying at full price and markdown, and \( v^{**} = \frac{s_F}{\delta} \) denote the consumer who is indifferent between buying at markdown and remaining inactive. Then, consumers in \([0, v^{**}]\) remain inactive, those in \([v^{**}, v^*] \) purchase the product at the markdown price, while those in \([v^*, 1]\) purchase the product at the full price\(^5\). The mass of consumers that purchases at the markdown price is \( q_{s_F}(p_F, s_F) = v^* - v^{**} \), and the mass of consumers that purchases at the full price is \( q_{p_F}(p_F, s_F) = 1 - v^* \). The firm’s per-period optimization problem is given by (3.1) and its optimal solution is presented in Table 3.2.

\[
\max_{p_F} \Pi_F = (p_F - c_F) q_{p_F}(p_F, s_F) + (s_F - c_F) q_{s_F}(p_F, s_F) \tag{3.1}
\]

The per-period environmental impact of the fast fashion approach is given by
\( E_F = (q^{P,F} \cdot e_{F,P}) + (q^{U,F} \cdot e_{U}) + (q^{D,F} \cdot e_D) \). Note that each life-cycle phase has the same product volume which is equal to the total product volume sold at both prices (full and markdown) i.e., \( q^{P,F} = q^{U,F} = q^{D,F} = q_{p_F}^* + q_{s_F}^* \).

<table>
<thead>
<tr>
<th>Table 3.2</th>
<th>Optimal solution to the maximization problem under the fast fashion approach.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full price</td>
<td>( p_F^* = \frac{1 - \delta}{2} + s_F )</td>
</tr>
<tr>
<td>Quantity sold at full price</td>
<td>( q_{p_F}^* = \frac{1}{2} )</td>
</tr>
<tr>
<td>Quantity sold at markdown</td>
<td>( q_{s_F}^* = \frac{1}{2} - \frac{s_F}{\delta} )</td>
</tr>
<tr>
<td>Profit</td>
<td>( \Pi_F^* = \frac{\delta - 4c_F(\delta - 2s_F)(\delta - 2s_F) / 48}{2})</td>
</tr>
</tbody>
</table>

\(^5\)For the ordering \( 0 \leq v^{**} \leq v^* \leq 1 \) to hold in equilibrium, we impose the following parametric condition: \( s_F \leq \frac{\delta}{2} \).
3.4.2 Traditional approach

If the firm chooses to follow the traditional approach, the product has a lifetime of two periods. To overcome the time-inconsistency problem (i.e., preferences of either consumers or the firm changing over time), we only consider subgame perfect equilibria as in Huang et al. (2001). Further, the two-period lifetime of the product imposes a Markovian structure on consumers’ decision-making. This implies that a consumer’s utility in period \( t \) is only dependent on her actions in periods \( t \) and \( t - 1 \), and the prices in period \( t \). The consumer is faced with three alternatives: (1) Purchase the product at the full price \( p_T \), (2) purchase the product at the markdown price \( s_T \), and (3) remain inactive during period \( t \). We assume that when a consumer has purchased at the full price in period \( t - 1 \), the utility from keeping the product in period \( t \) is the same as the utility from buying the product on markdown in period \( t \). Agrawal et al. (2012) make the same assumption in the context of new versus used goods. Recall that the consumer can resell the product only if she bought it at full price as per Assumption 3. Thus, she obtains an additional positive utility of \( r \) if she purchased the product at full price in period \( t - 1 \) and does the same in period \( t \), which results in a utility of \( v - p_T + r \). Purchasing at full price in period \( t - 1 \) followed by purchasing on markdown in period \( t \) (which is equivalent to keeping the product for a second period) results in a utility of \( \delta v + r - s_T \). The resulting consumer utility matrix is shown in Table 3.3. These Markovian dynamics lead us to further restrict our attention to Markov perfect equilibria. In the infinite horizon, such equilibria are those in which time dependence has dropped out altogether, implying that decisions are constant in time (Huang et al., 2001; Agrawal et al., 2012). As in Huang et al. (2001), we focus on “focal points” which are those equilibria such that the game has

---

6 Considering a separate consumer action that represents keeping the product for a second period leads to many possible orderings of the indifference points that arise in the subsequent analysis. A natural and meaningful ordering of these indifference points does not exist, which results in an overly complex model.
converged to a fixed point (in a finite number of steps) in the strategy space given some initial starting point. As mentioned earlier, the choice of a starting point does not impact steady-state equilibria.

Table 3.3 Consumers’ utilities under the traditional approach.

<table>
<thead>
<tr>
<th>Action in period ( t )</th>
<th>Action in period ( t-1 )</th>
<th>Buys at full price ( p_T )</th>
<th>Buys at markdown ( s_T )</th>
<th>Inactive</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buy at full price ( p_T )</td>
<td>( v - p_T + r )</td>
<td>( v - p_T )</td>
<td>( v - p_T )</td>
<td></td>
</tr>
<tr>
<td>Buy at markdown ( s_T )</td>
<td>( \delta v + r - s_T )</td>
<td>( \delta v - s_T )</td>
<td>( \delta v - s_T )</td>
<td></td>
</tr>
<tr>
<td>Inactive</td>
<td>( r )</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
</tbody>
</table>

We obtain these equilibria by solving the time-independent Bellman equations of the consumers and the firm. Unlike the used goods models of Huang et al. (2001) and Agrawal et al. (2012), we do not have a market clearing condition since we assume that the used goods market caters to an entirely different mass of consumers. There are 4 credible Markovian strategies that consumers may play. Those consumers of types that lie in \([v_1, 1]\) buy at full price in every period, those in \([v_2, v_1]\) buy at full price and keep the product for two periods (i.e., they buy at full price in every other period), those in \([v_3, v_2]\) buy at markdown in every period, while those in \([0, v_3]\) remain inactive. As in Huang et al. (2001) and Agrawal et al. (2012), in the infinite horizon, half of the \([v_2, v_1]\) segment purchases in each period, while the other half keeps the product for the second period of the product’s lifetime. The derivation of the indifference points \(v_1, v_2\) and \(v_3\) is shown in Appendix B.2. The per-period demand for the product at the full price is given by \(q_{p_T} (p_T, s_T) = \frac{1-\delta - p_T + (\rho+1)s_T}{1-\delta}\) and the demand at the markdown price is \(q_{s_T} (p_T, s_T) = \frac{\delta(p_T + \rho^1 - s_T(1+2\delta\rho)}{(1-\delta)^2} \). The firm maximizes its expected profit and its maximization problem is
\[
\max_{pT} \Pi_T = (p_T - c_T) q_{pT} (p_T, s_T) + (s_T - c_T) q_{sT} (p_T, s_T) - c_T k
\]
\[
s.t. \quad q_{pT} (p_T, s_T) + q_{sT} (p_T, s_T) \leq 1; \quad q_{pT} (p_T, s_T) \geq 0; \quad q_{sT} (p_T, s_T) \geq 0; \quad p_T \geq s_T
\] (3.2)

The first two terms in the objective function of (3.2) represent the firm’s profit while using markdown pricing to combat demand uncertainty (Assumption 1). This is analogous to the riskless profit from Petruzzi and Dada (1999) since the firm is perfectly able to resolve one layer of uncertainty through markdown pricing. The last term in the objective function of (3.2) represents the profit loss due to uncertainty that the firm is unable to respond to, and is analogous to the loss function from Petruzzi and Dada (1999). The first constraint ensures that the demand does not exceed the total consumer mass of 1. The second and third constraints ensure that demand at the full and markdown prices, respectively, is non-negative. Finally, we ensure that the endogenous full price \(p_T\) is above the exogenous markdown price \(s_T\).

Solving the optimization problem in (3.2), we obtain two optimal solutions, one in which there is positive demand at both prices, and another in which there is positive demand only at the full price. We focus on the former case, where demand occurs at both the full and markdown prices, since that is most reflective of the current apparel retail landscape\(^7\). This optimal solution is summarized in Table 3.4.

The per-period environmental impact of the traditional approach is given by
\[
E_T = (q^{P,T} \cdot e_{T,P}) + (q^{U,T} \cdot e_U) + (q^{D,T} \cdot e_D),
\]
where \(q^{P,T} = 1 - v_1 + \frac{v_1 - v_2}{2} + v_2 - v_3 + k\), \(q^{U,T} = 1 - v_3\), and \(q^{D,T} = 1 - v_1 + \frac{v_1 - v_2}{2} + v_2 - v_3 + k\). In computing \(q^{P,T}\) and \(q^{D,T}\), we consider three consumer segments and the leftover inventory. The first consumer segment \((1 - v_1)\) corresponds to the mass of consumers that purchases at full price in each period. This consumer segment discards the product after a single period.

---

\(^7\)For the ordering \(0 \leq v_3 \leq v_2 \leq v_1 \leq 1\) to hold in equilibrium (i.e., at this optimal solution), we impose the following parametric conditions: \(r \leq \frac{(1 - \delta)}{2p - 2\delta r^2}\) and \(s_T \leq \frac{(3p - \delta + 1)}{2sT - 2\delta r^2}\).
Table 3.4  Optimal solution to the maximization problem under the traditional approach.

<table>
<thead>
<tr>
<th></th>
<th>Full price</th>
<th>Quantity sold at full price</th>
<th>Quantity sold at markdown</th>
<th>Profit</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$p^*_T = \frac{1}{2}(1 - \delta + (\rho + 2)s_T)$</td>
<td>$q^*_p = \frac{1}{2}(1 + \frac{\rho s_T}{1-\delta})$</td>
<td>$q^*_s = \frac{1}{2}(1 - \rho(3s_T - 2r) - \frac{2s_T}{1-\delta})$</td>
<td>$\Pi^*_T = \frac{(1 - \delta)(4c_T(s_T - \delta(k + 1)) + \delta - (\delta - 2s_T)^2) + \delta \rho^2 s_T^2}{4(1 - \delta)} - \frac{2\delta \rho(2(c_T - s_T)(r - s_T) + \delta s_T - s_T)}{4(1 - \delta)}$</td>
</tr>
</tbody>
</table>

of use. The second consumer segment $(v_1 - v_2)$ represents the mass of consumers that purchases the product at full price and keeps it for its entire lifetime of two periods. The third consumer segment $(v_2 - v_3)$ represents the mass of consumers that purchases the product on markdown in every period. Finally, $k$ is the leftover inventory. In computing $q^{U,T}$, we consider the entire demand $(1 - v_3)$ for the product since the time of purchase does not change the fact that the product is in use. We do not consider $k$ in computing $q^{U,T}$ since leftover inventory is discarded by the firm and thus, is never used by consumers.

3.4.3 Comparing the fast fashion and traditional approaches

Having solved the firm’s optimization problems under the two approaches, we begin by providing conditions under which the firm can be profitable under each approach. Technical proofs are provided in Appendix B.3.

**Lemma 3.** The fast fashion approach is profitable ($\Pi^*_F > 0$) when $c_F < \frac{\delta - (\delta - 2s_F)^2}{4(\delta - s_F)}$ and the traditional approach is profitable ($\Pi^*_T > 0$) when $k < \tilde{k}$.

Lemma 3 establishes conditions under which both approaches exist. More specifically, the fast fashion approach is profitable as long as the production cost is not prohibitively high, and the traditional approach is profitable as long as the leftover
inventory is not excessive. This result is in line with the existence of both approaches in practice.

We now shift to our primary focus of comparing the two approaches in terms of their environmental impact. We begin by comparing the product volumes in each life-cycle phase across the two approaches.

**Proposition 8.** Fast fashion has a smaller product volume in the production and disposal phases under either of the following conditions:

(a) $s_F > s_T + \frac{\delta p(s_T - r)}{1 - \delta}$, or

(b) $s_F < s_T + \frac{\delta p(s_T - r)}{1 - \delta}$ and $k > \frac{p(s_T - r)}{\delta + 1} + \frac{s_T - s_F}{\delta}$

The traditional approach has a smaller product volume in the production and disposal phases when $s_F < s_T + \frac{\delta p(s_T - r)}{1 - \delta}$ and $k < \frac{p(s_T - r)}{\delta + 1} + \frac{s_T - s_F}{\delta}$.

Proposition 8 provides valuable insights into how the two approaches compare in terms of the product volume produced and disposed of in every period. While fast fashion has been associated with excessive production and disposal in the popular press, we observe a more nuanced relationship. From Proposition 8(a), we see that fast fashion produces and disposes less when the markdown price under this approach is significantly higher than the markdown price under the traditional approach. In this case, the traditional approach ends up selling a comparatively large quantity on markdown in every period, which results in large amounts produced and disposed of under the traditional approach. This scenario is reflective of markets where a firm following the traditional approach aggressively reduces prices during the markdown window in order to limit unsold inventory. From Proposition 8(b), we see that even when the markdown prices are comparable across the two approaches, fast fashion produces and disposes less when leftover inventory is high under the traditional approach. In this case, the traditional approach’s lack of quick response capabilities
is the driving factor behind its excessive production and disposal. This situation is reflective of markets where the traditional approach is characterized by a larger level of demand uncertainty – for example, products with very volatile demand (cocktail dresses), or supply chains with large geographic spread. This situation can also represent a firm operating at very high service levels under the traditional approach. The gains achieved by the superior durability of the traditional approach are restricted to scenarios where markdown prices and leftover inventory are fairly similar across the two approaches.

**Proposition 9.** *Fast fashion has a smaller product volume in the use phase when* $s_T < s_F$, *while the traditional approach has a smaller product volume in the use phase when* $s_T > s_F$.

From Proposition 9, we observe that the fast fashion (traditional) approach has a smaller product volume in use (in a given period) when the markdown price under fast fashion is larger (smaller) than the markdown price under the traditional approach. This suggests that in scenarios where a firm following the traditional approach sets markdown prices more aggressively than a firm following the fast fashion approach, the fast fashion approach results in smaller product volume in use. In other words, the quick response capabilities of fast fashion achieve greater environmental gains than the superior product durability of the traditional approach. In scenarios where the traditional approach is characterized by high markdown prices, the superior product durability of the traditional approach outweighs the environmental gains achieved by the quick response capabilities of the fast fashion approach.

Next, we characterize the overall environmental impact of the two approaches based on the amount of leftover inventory under the traditional approach.

**Proposition 10.** *There exists a threshold, $\bar{k}$, such that the fast fashion approach is greener if and only if* $k > \bar{k}$. *This threshold $\bar{k}$ is*
(a) Increasing in $e_{F,P}$.

(b) Decreasing\(^8\) in $e_{T,P}$.

(c) Decreasing in $e_U$ when $s_T < s_F$, and increasing when $s_T > s_F$.

From Proposition 10, we see that the fast fashion approach can have a lower environmental impact than the traditional approach. This is the case when the traditional approach is characterized by a sufficiently large leftover inventory and may occur when a firm is selling a very trend-sensitive product such as cocktail dresses. Proposition 10 reinforces the importance of the operational gains achieved via fast fashion, while also raising the need to be more cautious with claims (primarily in the popular press (Butler, 2018; Stanton, 2018; Schlossberg, 2019)) that fast fashion is always worse for the environment. On the other hand, when selling products with more stable demand, such as undershirts, we expect the traditional approach to be greener.

The threshold $\bar{k}$ is found to be increasing (decreasing) in the per-unit impact of the production phase of the fast fashion (traditional) approach. Since each approach has a unique per-unit impact for the production phase, an increase in this parameter for either approach directly hurts the environmental viability of that particular approach. The relationship between $\bar{k}$ and the per-unit environmental impact of the use phase (Proposition 10(c)) is driven by the relative product volumes in the use phase of the two approaches (cf Proposition 9). When the traditional approach has a larger volume in the use phase (i.e., when $s_T < s_F$), it is impacted more severely by a unit increase in the use phase impact. This results in a decrease in the threshold $\bar{k}$. Similarly, when the fast fashion approach has a larger volume in the use phase

\(^8\)For this relationship to hold, we impose the following ordering on the per-unit environmental impact of the three life-cycle phases: $e_{T,P} > e_U > e_D$. This assumption is in line with the findings of Niinimäki et al. (2020) and Quantis (2018).
(i.e., when $s_T > s_F$), an increase in the impact of the use phase is more pronounced for the fast fashion approach, which results in an increase in the threshold $\bar{k}$. The relationship between $\bar{k}$ and the environmental impact of the disposal phase $e_D$ is more nuanced. The mathematical analysis of this relationship is provided in Appendix B.3.

We corroborate our analytical findings with numerical experiments based on realistic parameter estimates from fashion industry data (Niinimäki et al., 2020; Quantis, 2018). We normalize the environmental impact (measured in terms of quantity of CO$_2$ produced) of the production phase under the traditional approach to 1 ($e_{T,P} = 1$). Typically, the production phase accounts for 80% of the total CO$_2$ produced in the product’s life. The use phase accounts for about 20% of CO$_2$ production so we set $e_U = 0.25$. The disposal phase accounts for about 0.1% of CO$_2$ production when incinerating products (Sandin et al., 2019), but because of the prevalence of the more harmful practice of landfilling (U.S. Environmental Protection Agency, 2020a) we set $e_D$ to be 0.05. The production cost under the traditional approach, $c_T$, is set at 0.02. We set the production cost under the fast fashion approach, $c_F$, to be $1.25 \times c_T$ (= 0.025) in order to capture 1) the higher shipping cost resulting from expedited shipping via air, and 2) the higher labor cost resulting from the fast fashion approach having some labor intensive processes carried out in nations where these costs are comparatively higher (Turkey, where the minimum wage was €318 in 2019 as opposed to €85 in Bangladesh (Business and Human Rights Resource Center, 2019; Clean Clothes Campaign, 2020)). We focus on the shipping and labor costs since they are the two biggest expenses in the production of an apparel product (NPR Planet Money, 2013) and the major costs that are expected to vary across the two approaches to apparel retail.

These numerical experiments serve two purposes. First, we show that the threshold established in Proposition 10 does not need to be very large in order for the fast fashion approach to be greener. Second, we explore the impact of other model
parameters on the environmental performance of the two approaches. In order to examine the threshold from Proposition 10, we set the markdown price under the traditional approach to be 50% more than the cost of production \((s_T = 1.5c_T)\). The salvage value that consumers may obtain by “reselling” the durable product is set at 50% of the markdown price \((r = 0.5s_T)\). Note that \(r = 0\) represents the best-case scenario in terms of environmental impact for the traditional approach, while \(r = s_T\) represents the best-case scenario for the fast fashion approach. In summary, we set the following parameter values: \(\rho = 0.2\), \(\delta = 0.1\), \(c_T = 0.0\), \(c_F = 0.025\), \(e_D = 0.05\), \(e_U = 0.25\), \(e_{T,P} = 1\), \(s_T = 0.03\), \(r = 0.015\).

\[\text{Figure 3.2} \quad \text{Ratio of } \bar{k} \text{ to total demand (under the traditional approach) as a function of the per-unit environmental impact of the production phase under the fast fashion approach.}\]

In Figure 3.2, we plot the ratio of the threshold \(\bar{k}\) to total demand under the traditional approach as a function of the per-unit environmental impact of the production phase under the fast fashion approach. We consider the ratio, as opposed to just the threshold, since this allows us to represent the threshold relative to the total demand. We observe that when the two approaches have very similar per-unit environmental impacts during the production phase, the fast fashion approach can be greener even when the traditional approach has no leftover inventory (i.e., \(\bar{k} < 0\)). This occurs when the traditional approach is characterized by aggressive markdown
pricing compared to the fast fashion approach ($s_F = 1.25s_T$). This pricing approach results in significantly more demand under the traditional approach, thereby hurting the environmental viability of the approach. When the markdown price is the same across both approaches ($s_F = s_T$), we see that expected service levels of just 60% can result in the fast fashion approach being greener despite fast fashion having a per-unit production phase impact that is 10% higher than the per-unit impact of the production phase under the traditional approach. As the per-unit impact of the production phase under the fast fashion approach increases, we observe that leftover inventory under the traditional approach needs to be fairly large for the fast fashion approach to be greener. In summary, Figure 3.2 shows that the fast fashion approach can be greener even when the traditional approach has relatively small amounts of leftover inventory (i.e., the threshold $\bar{k}$ established in Proposition 10 does not require extreme cases for realistic parameter value ranges).

Next, we examine how consumer valuation of markdowns $\delta$, leftover inventory $k$, and the markdown prices $s_T$ and $s_F$ impact the environmental viability of the two approaches. We set $e_{F,P}$ to be 25% higher than $e_{T,P}$ (i.e., $e_{F,P} = 1.25$) to account for the additional impact of expedited shipping via air, as opposed to shipping via sea. We also set the markdown price under the fast fashion approach to be 50% higher than the production cost under this approach. To maintain uniformity with the parameter values used in Figure 3.2, we continue to set the salvage value to be $r = 0.015$. Further, we set $e_{F,P} = 1.25$ and $s_F = 0.0375$. Note that the region marked FF (Traditional) denotes the parametric space where the fast fashion (traditional) approach is greener.

Figure 3.3a represents the scenario where consumers do not particularly value markdown purchases. In this scenario, we see that the fast fashion approach is relatively greener for most values of leftover inventory and the ratio of markdown prices $s_T / s_F$. The traditional approach is relatively greener only when the traditional approach
Figure 3.3 Environmentally superior supply chain approaches.

sets relatively high markdown prices compared to fast fashion and leftover inventory is low. Relatively high values of the markdown price under the traditional approach result in low overall demand under this approach. Coupling this relatively low demand with sufficiently low leftover inventory leads to the greenness of the traditional approach.

When consumers are more willing to purchase the product on markdown (Figure 3.3b), we observe that the fast fashion approach is greener for a smaller range of parameter values (i.e., the FF region has shrunk). Higher values of $\delta$ imply more purchases on markdown for the fast fashion approach. While this is also true for the traditional approach, this is offset by the fact that higher values of $\delta$ also imply that more consumers keep the product for the entire lifetime of two periods. In this high $\delta$ regime, the traditional approach has more leeway in terms of leftover inventory. In other words, when consumers are more willing to keep the product for its entire lifetime, the superior product durability of the traditional approach is more likely to outweigh the operational gains achieved by fast fashion via its quick response capabilities. As in the case of low markdown valuations, a relatively high markdown
price and low leftover inventory under the traditional approach result in superior environmental outcomes for this approach.

These numerical experiments provide further credence to the fact that the fast fashion approach can indeed result in better environmental outcomes than the traditional approach. The superiority of the fast fashion approach is seen in markets with high demand uncertainty (high \( k \)) and where firms following the traditional approach set their markdowns more aggressively (low \( s_T \) compared to \( s_F \)). We tie these parametric regions to apparel categories in order to illustrate when these two approaches are better for the environment. Low values of leftover inventory (\( k \)) represent categories with more stable demand (i.e., the firm does a reasonably good job estimating demand under the traditional approach). Swimwear and undershirts are examples of these low \( k \) categories. High values of leftover inventory (\( k \)) represent categories with more volatile demand. This volatility is typically driven by a high consumer sensitivity to trends. Cocktail dresses and jeans (different cuts go in and out of fashion reasonably fast) are examples of such trend-sensitive categories that often have large amounts of leftover inventory. While both approaches involve markdown pricing, this practice is more common under the traditional approach and is typically used to clear inventory towards the end of a selling season. Markdown pricing under the fast fashion approach can be viewed as more of a price discrimination tool to capture the low valuation segments that the traditional approach may be attracting. Product categories that are especially trend-sensitive lose value rapidly during the selling season. Given the different purpose of markdown pricing under the two approaches, we observe lower markdown prices for such categories under the traditional approach (compared to fast-fashion). Thus, such categories have low markdown price ratios (i.e., \( \frac{s_T}{s_F} \)). Cocktail dresses are a prime example of such a product category since they typically stay in vogue for very short periods and are characterized by drastic markdowns to clear leftover inventory. Similarly, swimwear is of use only during
the summer season and greatly loses value at the end of the season. On the other hand, jeans and undershirts can be used across most seasons, and allow for traditional firms to markdown less aggressively. Thus, we classify them as categories with high markdown price ratios (i.e., $\frac{s_T}{s_F}$).

Based on this characterization of apparel categories and our results thus far, we see that fast fashion is relatively greener for categories such as cocktail dresses (low $\frac{s_T}{s_F}$ and high $k$) and jeans (high $\frac{s_T}{s_F}$ and high $k$). On the other hand, the traditional approach is relatively greener for categories such as swimwear (low $\frac{s_T}{s_F}$ and low $k$) and undershirts (high $\frac{s_T}{s_F}$ and low $k$). A caveat regarding the environmental superiority of the traditional approach when selling swimwear is that consumers must sufficiently value the product on markdown (high $\delta$). In other words, swimwear products need not be too trend-sensitive since consumers would be less willing to purchase the product for use the following season. We summarize the relative greenness of each approach for different apparel categories in Table 3.5.

<table>
<thead>
<tr>
<th>Ratio of markdowns</th>
<th>Leftover inventory $k$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low</td>
</tr>
<tr>
<td>High</td>
<td>Undershirts;</td>
</tr>
<tr>
<td></td>
<td>Traditional is greener</td>
</tr>
<tr>
<td>Low</td>
<td>Swimwear;</td>
</tr>
<tr>
<td></td>
<td>Traditional is greener as long as $\delta$ is high</td>
</tr>
</tbody>
</table>

In the next section, we focus on how changes to the environmental impact of the three different phases can impact the overall environmental outcomes.
3.4.4 Where should sustainability efforts be focused?

Policy makers may encourage firms to (1) change production techniques to those with a lower environmental impact, (2) provide more information to consumers on how the product should be used to reduce environmental impact (e.g., guidelines on washing and drying), and (3) hold firms accountable for the disposal of unsold inventory. From the perspective of disposal, policy makers may also directly influence consumers’ disposal habits by encouraging them to donate or recycle as opposed to dispose products. The goal of this section is to provide guidance on where policy makers should focus their sustainability efforts.

Recall that \( q_{P,i} \), \( q_{U,i} \) and \( q_{D,i} \) are the number of units produced, in use, and disposed of in each period, respectively, under approach \( i \). The number of units in each phase (production, usage, disposal) in each period is the same under the fast fashion approach, i.e., \( q_{P,F} = q_{U,F} = q_{D,F} \). Thus, a unit decrease in environmental impact under the fast fashion approach yields the same result for all three phases. On the other hand, these quantities are not the same under the traditional approach. The following result shows where policy makers should focus their sustainability efforts.

**Proposition 11.** The production and disposal phases have the largest impact \( (q_{P,T} = q_{D,T} > q_{U,T}) \) when

(a) The leftover inventory is sufficiently large \( (k > k) \), or

(b) The leftover inventory is low and the salvage value is sufficiently high \( (k < k \) and \( r > r \)).

The use phase has the largest impact \( (q_{U,T} > q_{P,T} \) and \( q_{U,T} > q_{D,T}) \) when both the leftover inventory and salvage value are sufficiently small \( (k < k \) and \( r < r \)).

From Proposition 11(a), we see that improvements to the production and disposal phases have the most impact in markets that are characterized by large quantities
of leftover inventory. As leftover inventory gets discarded at the end of the period and thus, does not reach the end consumer, it does not contribute to the use phase. This implies that higher levels of leftover inventory contribute to higher product volumes in the production and disposal phases relative to the use phase. This result is especially relevant in the current climate given the supply chain snags caused by the COVID-19 pandemic and for apparel categories with high levels of demand uncertainty (e.g., cocktail dresses and jeans). Higher levels of demand uncertainty typically result in higher quantities of leftover inventory (Anzolin and Aloisi, 2021), thereby strengthening the need for policy makers to push firms following the traditional approach towards (i) greener production, (ii) less intensive distribution methods, and (iii) better recycling of end-of-life products.

We also see that the production and disposal phases remain most voluminous for low demand uncertainty settings as long as the salvage value of the product \( r \) is sufficiently large (Proposition 11(b)). This is driven by the fact that a high salvage value encourages consumers to keep the product for only a single period and repurchase a new product every period. This behavior ensures that the firm is producing a higher volume to cater to higher per-period demand for the product at the full price. Proposition 11(b) suggests that for an apparel category such as T-shirts (relatively low leftover inventory and high salvage value since T-shirts are likely to be purchased second hand), policy makers should focus on reducing the impacts of the production and disposal phases.

On the other hand, for categories with low levels of leftover inventory and a low salvage value (e.g., swimwear, since more intimate products are very unlikely to be purchased second hand), we see that the use phase has the greatest mass of products. This suggests that for such an apparel category, policy makers should focus on educating consumers regarding better washing and drying habits. This may be done directly through advertising or by encouraging manufacturers to provide
instructions through better labeling of products.

3.4.5 Global sensitivity analysis

To further examine how different model parameters affect the environmental impact of the two approaches, we carry out a global sensitivity analysis as described by Wagner (1995). Similar to Denizel et al. (2009), we conduct a multiple regression analysis in a large scale experimental design as this allows us to jointly test the sensitivity of a particular approach to all model parameters. In other words, rather than carrying out a single-variable sensitivity analysis for each parameter separately, we allow all model parameters to vary simultaneously.

To cover a wide range of parameter values, we set \( \delta \in \{0.1, 0.3, 0.5, 0.7, 0.9\} \) and \( \rho \in \{0.1, 0.3, 0.5, 0.7, 0.9\} \). Low (high) values of \( \delta \) correspond to low (high) consumer valuations of markdowns, while low (high) values of \( \rho \) indicate that customers place less (more) emphasis on future utility when calculating their net present value.

When selecting the range for the salvage value \( (r) \), we set the smallest value to be 0.01 and the highest value to be the largest upper bound that ensures that the indifference points, \( v_1, v_2, v_3, v^*, \) and \( v^{**} \), are interior points for the entire range of \( \rho \) and \( \delta \) mentioned in the preceding paragraph. For the sake of uniformity, we consider five values in this range (as we did with the discount parameters), which results in \( r \in \{0.01, 0.052, 0.094, 0.136, 0.178\} \). We set the markdown prices as \( s_T \in \{0.01, 0.052, 0.094, 0.136, 0.178\} \) and \( s_F \in \{0.01, 0.052, 0.094, 0.136, 0.178\} \).

For the environmental impact parameters, we set the per-unit environmental impacts of the production phase as \( e_{T,P} \in \{0.5, 0.75, 1, 1.25, 1.5\} \) and \( e_{F,P} \in \{0.5, 0.75, 1, 1.25, 1.5\} \). These parameter values cover the extreme cases of production being 50% less/more harmful than the base case that we considered in the numerical experiments in Figures 3.2 and 3.3. We follow the same approach to choose the range of values for the per-unit environmental impacts of the use and disposal phases,
which results in the following: $e_U \in \{0.125, 0.1875, 0.25, 0.3125, 0.375\}$ and $e_D \in \{0.025, 0.0375, 0.05, 0.0625, 0.075\}$. Finally, we set the leftover inventory under the traditional approach to be $k \in \{0.0, 0.1, 0.2, 0.3, 0.4\}$, where $k = 0$ would represent the case where fast fashion does not achieve any relative gains through its quick response capabilities.

These parameter values result in a full factorial design of $5^{10} = 9,765,625$ observations. Since we require combinations of values for $\delta, \rho, r, s_T$, and $s_F$ to satisfy the conditions mentioned in Footnotes 5 and 7, we only consider those combinations that meet these conditions. This also eliminates cases where $r > s_i$ and leaves us with 2,765,625 observations for our global sensitivity analysis. The dependent variables that we consider in the analysis are the total environmental impacts under the two approaches, $E_T$ and $E_F$. Summary statistics for this experimental design are shown in Appendix B.4.

We standardize all of the aforementioned parameters in order to allow for comparisons between the coefficients within a given model. The results of the two regressions are shown in Tables 3.6 and 3.7. In both regression models, we observe very high adjusted $R^2$ values (0.9619 and 0.9579) and that all the independent variables are highly significant ($p < 2e - 16$). This is expected since we are estimating the output of a model but does show that it is a good proxy.

For the fast fashion approach (Table 3.6), we observe that the per-unit environmental impact of the production phase has the largest influence on the total environmental impact. This suggests that for a very wide range of parameter values, reductions in the per-unit environmental impact of the production phase are the most fruitful. The markdown price is found to be the next most influential parameter. We observe that an increase in the markdown price reduces the overall impact of the fast fashion approach since this reduces overall demand in any period.

Similarly, for the traditional approach (Table 3.7), we observe that the per-unit
environmental impact of the production phase exerts the most influence on the total environmental impact. The second most influential parameter is the leftover inventory. This indicates that policy makers stand to gain the most by focusing on reducing the per-unit environmental impact of the production phase and pushing traditional firms to sell product categories that are typically characterized by lower levels of leftover inventory.

### 3.5 Robustness checks

In this section, we relax two of our assumptions to examine the robustness of our results. In Section 3.5.1, we allow for the firm to endogenously determine the markdown prices under both approaches. In Section 3.5.2, we consider the possibility of the use phase having different per-unit environmental impacts across the two approaches. Our results remain qualitatively consistent in both of these analyses.
3.5.1 Endogenous markdown

The model presented in Section 3.3 treats the markdown prices $s_T$ and $s_F$ to be exogenously determined. In this section, we relax this assumption by making $p_i$ and $s_i$ the decision variables in the firm’s profit maximization problem. The optimization problems under both approaches are not jointly concave in $p_i$ and $s_i$ for a particular $i$. This rules out obtaining analytical results similar to those presented in Section 3.4. Thus, we resort to numerical analyses to consider a setting where firms have complete control over markdown pricing and test the robustness of our analytical results in the exogenous markdown setting. We set the following parameter values for these numerical analyses: $\rho = 0.2$, $c_F = 0.025$, $c_T = 0.02$, $e_D = 0.05$, $e_U = 0.25$, $e_{F,P} = 1.2$, $e_{T,P} = 1$, $r = 0.015$.

![Figure 3.4 Comparison of environmental impact when markdown is endogenous.](image)

From Figure 3.4, we see that the environmental impact of the fast fashion approach remains constant across different values of consumers’ markdown valuation. This is because the firm sets prices such that the total demand under the fast fashion approach is constant in $\delta$. In other words, changes in $\delta$ only result in some consumers switching from purchasing at full price to purchasing at markdown price and vice versa. As established in Proposition 10, we observe that the traditional approach has a lower environmental impact as long as the leftover inventory is sufficiently small, and the fast fashion approach becomes relatively greener when the leftover inventory exceeds a threshold. In conclusion, accounting for endogenous markdown
does not change our key insights regarding the environmental performance of these two approaches to apparel retail.

3.5.2 Accounting for different impacts in the use phase across both approaches

In Section 3.3, we assumed that the per-unit environmental impact of the use phase was identical across the traditional and fast fashion approaches. Given that the fast fashion approach typically uses a larger amount of synthetic material as opposed to natural fibers, the washing and drying procedures may vary compared to the more natural-fiber-heavy traditional approach. While the wash and dry cycles for synthetic fibers may be less environmentally intensive, the washing of these fibers can result in the release of microplastics (Laitala et al., 2018). Thus, it is not entirely clear which of these approaches will have a larger use phase per-unit environmental impact.

To examine how our results may vary for different combinations of use phase per-unit environmental impacts for the two approaches, we carry out numerical experiments similar to those shown in Figure 3.3. We consider fairly extreme cases of differences for the per-unit environmental impacts of the use phase under the two approaches. Specifically, when fast fashion has a lower per-unit impact we set $e_{F,U} = 0.5e_{T,U}$ and when it has a higher per-unit impact we set $e_{F,U} = 1.5e_{T,U}$. The other parameter values are set as follows: $\rho = 0.2$, $c_T = 0.02$, $c_F = 0.025$, $e_D = 0.05$, $e_{U,T} = 0.25$, $e_{T,P} = 1$, $e_{F,P} = 1.25$, $s_F = 0.0375$, $r = 0.015$.

Figures 3.5a and 3.5c represent the scenario where the use phase has a higher per-unit environmental impact under the fast fashion approach compared to the traditional approach. The regions marked FF (Traditional) denote the parametric space where the fast fashion (traditional) approach is greener. The region in which fast fashion is greener shrinks when compared to Figure 3.3. In the scenario where the use phase has a smaller per-unit environmental impact under the fast fashion approach
Figure 3.5  Comparison of environmental impact for different impacts in the use phase.

compared to the traditional approach (Figures 3.5b and 3.5d), we observe that fast fashion is greener for a larger parametric region. This is in line with intuition and is qualitatively consistent with our results in Section 3.3.

3.6 Conclusion

Retailers like Zara, Boohoo, and Benetton added a new dimension to the apparel retail landscape by adopting the fast fashion approach which is characterized by quick response and rapidly changing assortments. Another facet of the fast fashion
The approach is the production of less durable products which encourages consumers to make more frequent purchases. Such changes to the product durability and their subsequent implications have led to fast fashion retailers receiving harsh criticism due to their environmental impact. This perception of the negative environmental impact of reduced product durability has also caught the attention of regulators, with the European Union proposing rules focused on product durability (Chakraborty et al., 2022). Yet, fast fashion’s use of quick response allows for the better matching between supply and demand, thereby leading to less discarding of unsold units by the retailer. Thus, it is unclear which approach truly leads to better environmental outcomes. By building a game-theoretic model to analyze whether the operational efficiencies associated with fast fashion make up for the loss in durability, we shed light on how the two approaches truly compare from an environmental perspective.

Our findings can be summarized as follows. First, we compare the volume in the production, use, and disposal phases of a product’s lifecycle across the two approaches. We find that fast fashion can, in fact, produce and dispose less than the traditional approach in a single period. This scenario occurs when the traditional approach is characterized by relatively high levels of leftover inventory or when the markdown pricing is far more aggressive under the traditional approach. This result contrasts to claims made in the popular press regarding the excesses of the fast fashion approach. With respect to the use phase, we find that the approach with lower markdowns always has a larger volume. Second, we obtain a threshold on the leftover inventory under the traditional approach below (above) which the traditional (fast fashion) approach is greener. Once again, this result contrasts to claims in the popular press and provides evidence that the operational gains achieved through quick response can indeed outweigh the negative impact of lower durability. We also present comparative statics on this threshold to examine how different parameters may impact the environmental outcomes of the two approaches, which is especially relevant given the
supply chain disruptions brought about by the COVID-19 pandemic. These disruptions have resulted in more uncertainty for geographically dispersed supply chains, which are more common for firms following the traditional approach. Further, a higher reliance on air freight, as opposed to sea freight, has resulted in the traditional approach having a higher environmental impact (per Proposition 10(b)). Our findings emphasize the importance of more cautious calls to abandon fast fashion in favor of the traditional approach when considering its environmental impact.

Third, we complement these analytical findings with numerical experiments which allows us to tie our results to specific apparel categories. We find that for categories with high levels of demand uncertainty and high markdowns (e.g., cocktail dresses), it is the fast fashion approach that is greener. On the other hand, for categories with relatively stable demand and low markdowns (e.g., T-shirts), the traditional approach is greener. This raises questions about the European Union’s approach of solely focusing on increasing durability as such a strategy may have the unwanted consequence of fast fashion firms shifting to the traditional approach. Instead, policies such as take-back legislation (to keep fast fashion retailers away from stable demand products) and penalties on disposing leftover inventory (to keep traditional retailers away from volatile demand products) seem more fruitful.

Fourth, we provide insights on where policy makers should focus their actions in terms of pushing firms and consumers towards more sustainable practices. We find that under the traditional approach, the production and disposal phases are where most gains can be achieved when demand uncertainty is high and/or the product commands relatively high prices in the secondary market. This result indicates a need to focus on greener production and distribution methods as well as better recycling of end-of-life products. On the other hand, when demand is stable and the product fails to command high prices in the secondary market, most gains are achieved in the use phase. In such a scenario, policy makers should focus on better educating
consumers on washing and drying habits. This adds more nuance to The Fashion Sustainability and Social Accountability Act’s (New York State Senate, 2021) sole focus on the production phase. As no such volume gains can be achieved under the fast fashion approach, policy makers are better off making their decisions based on cost considerations. We further back these results with a global sensitivity analysis and find that the per-unit environmental impact of the production phase exerts the most influence on the total environmental impact of both approaches. While this is in line with The Fashion Sustainability and Social Accountability Act’s focus on accountability for production phase impact, our results indicate that more stringent legislation on production and distribution processes may be necessary.

We test the robustness of our results by allowing (1) the firm to endogenously determine markdown prices and (2) different per-unit environmental impacts of the use phase across the two approaches. We find that our primary insights continue to hold. The robustness of our findings strengthens our call for a more nuanced judgment on the environmental impacts of fast fashion versus a more traditional supply chain approach to apparel retail.

Our approach to modeling the two supply chain approaches does not account for the impact of more frequent assortment changes under the fast fashion approach since our focus is on the effects of quick response capabilities and product durability on environmental performance. Our assumption of equal assortment change frequency across the two approaches represents the best-case scenario for fast fashion. We believe that accounting for more frequent assortment changes would reduce the number of scenarios where fast fashion is greener, but not necessarily eliminate such scenarios altogether.

While our model provides an important base for understanding the environmental impact of these two approaches to apparel retail, there are a number of interesting avenues for future research. First, we treat consumers to be myopic and consider a
monopolist firm. Given the importance of markdowns in a number of our results, accounting for strategic consumers as well as the inclusion of a competitive framework may be fruitful directions for subsequent studies. Second, endogenizing durability may yield results that help policy makers with regulations regarding product durability. Third, a nuanced model of product variety and consumer response to variety may lead to some interesting insights. Future studies exploring these directions could be a valuable complement to the insights provided in this chapter.
Chapter 4
The Impact of Environmental Commitment on Campaign Performance on Kickstarter

4.1 Introduction

The urgency of addressing environmental problems such as climate change and biodiversity loss has been well documented (Rockström et al., 2009; Dinerstein et al., 2019; Folke et al., 2019), yet entrepreneurs continue to struggle to obtain funds for ventures with a sustainability orientation (Petruzelli et al., 2019; Böckel et al., 2021). This has been attributed to the fact that such ventures are typically more focused on environmental and social aspects as opposed to financial returns, thereby resulting in them being deemed excessively risky by traditional investors (Hörisch, 2015; Calic and Mosakowski, 2016). Further, Moore et al. (2012) and Lehner and Nicholls (2014) suggest that entrepreneurs with a sustainability focus tend to lack knowledge of “managerial terminology” and “valuation metrics”, which creates communication gaps with traditional investors.

These difficulties have been mitigated to some extent by the rapid rise of crowdfunding. Crowdfunding is defined as “the efforts by entrepreneurial individuals and groups – cultural, social, and for-profit – to fund their ventures by drawing on relatively small contributions from a relatively large number of individuals using the internet, without standard financial intermediaries” (Mollick, 2014). The global crowdfunding market size was $17.5 billion in 2021 and is expected to exceed $40 billion by 2028 (SkyQuest Technology Consulting Pvt. Ltd., 2022). The most common form
of crowdfunding is rewards-based crowdfunding, in which entrepreneurs (commonly referred to as creators) build fundraising campaigns that are targeted to supporters (commonly referred to as backers), who are given non-monetary rewards if the fundraising campaign is successful (Chakraborty et al., 2023). These non-monetary rewards typically take the form of the finished product that the backer is attempting to develop. The ability of crowdfunding to mitigate the difficulties faced by sustainability-focused ventures has been attributed to the fact that crowdfunding is more democratic than traditional investing, thereby allowing the “crowd” to pick “social ideas that it deems worthy and needed” (Lehner, 2013). There is also anecdotal evidence for the successful funding of sustainability-focused ventures through crowdfunding. For example, the crowdfunding platform Indiegogo saw an increase of around 145% in funds for greentech campaigns in 2021 (Marquis, 2021). Further, to highlight the relevance of sustainability in the context of crowdfunding, we draw attention to Kickstarter’s implementation of features that allow creators to “evaluate and reduce the environmental impact of their products at the earliest stages” (Hill, 2018).

While evidence from practice suggests that ventures with an environmental sustainability orientation are viewed favorably on crowdfunding platforms, this relationship has received limited academic attention (Böckel et al., 2021). Conceptual work in this space posits that ventures with a sustainability orientation are more likely to succeed on crowdfunding platforms than ventures without such an orientation (Hörisch, 2015), but rigorous empirical examinations are limited. Further, among the few empirical studies that do examine the success of crowdfunding ventures with a sustainability orientation, there is no consensus on whether such ventures outperform those without such an orientation. By examining the successful funding rates of campaigns on Indiegogo, Hörisch (2015) finds that “environmentally oriented projects” do not have a higher likelihood of reaching their funding goal compared to those
without such an orientation. Campaigns are classified as “environmentally oriented” if the creator selects the “Environment” category when creating the campaign on Indiegogo. The sample of crowdfunding campaigns used in this study contains only 2% that fall in the “Environment” category, which may explain the absence of any effect of environmental orientation on campaign success. On the contrary, Calic and Mosakowski (2016) examine campaigns on Kickstarter and find that those with an environmental orientation are more likely to attain their goal than campaigns without an environmental orientation. Unlike a clean categorization of environmentally oriented campaigns as in Hörisch (2015), Calic and Mosakowski (2016) rely on manually coding campaigns as environmentally oriented or not, which may not truly reflect the perceptions and beliefs of creators and backers.

The goal of this essay is to rigorously examine whether crowdfunding campaigns with an environmental sustainability orientation are more likely to be successful than campaigns without such an orientation. To do so, we take advantage of Kickstarter’s implementation of a new section on the description page of campaigns, in which creators can voluntarily make a commitment to the environment (Kickstarter, 2018). During the creation of a campaign, creators are able to choose from among five categories (long-lasting design, reusability and recyclability, sustainable materials, environmentally friendly factories, and sustainable fulfillment and distribution) and provide a description under each category regarding how their project commits to the environment on that specific front. This commitment by the creator allows for a clear delineation between campaigns that have a sustainability orientation and those that do not. Further, we use a sample of 5522 campaigns, out of which approximately 22% make a commitment to the environment – a significantly higher proportion than in the sample used by Hörisch (2015).

To examine the causal impact of sustainability orientation on campaign success, we couple coarsened exact matching with instrumental variables regression. While
we do not explicitly have a treatment applied to the crowdfunding campaigns in
our sample, we consider campaigns with some environmental commitment to be the
“treated” group, and those without any commitment to be the “control” group. Since
the assignment of campaigns to these two groups is not random, we use coarsened
exact matching to ensure that the distributions of covariates across the two groups
are similar, thereby resembling a randomized experiment (Yilmaz et al., 2022). Sub-
sequently, we account for omitted variable bias (unobserved measures of campaign
quality that may be impacting the success of the campaign as well as the sustainabil-
ity orientation of the campaign) that results in the endogeneity of the sustainability
orientation of campaigns.

The introduction of this environmental commitment section by Kickstarter also
allows us to examine how different types of information regarding environmental
commitment are being valued by backers. We look in to whether committing to
more categories results in better outcomes for campaigns, and follow this up with
an examination of whether the length of the text in the environmental commitment
section impacts campaign success.

Our results and their implications can be summarized as follows. First, we observe
that a sustainability orientation results in higher campaign success (in terms of finan-
cial funding as well as marketing). This implies that crowdfunding does lend itself
well to ventures with a sustainability orientation. From the perspective of project
creators, this result suggests that they stand to gain by incorporating concepts of
environmental sustainability into the design, production, and/or distribution of their
product. Second, we fail to observe any impact of the number of environmental com-
mitment categories that a creator commits to on campaign success. This suggests
that backers do not incrementally value the extent to which creators commit to the
environment. Third, we do not observe any impact of the length of the environmental
commitment section on campaign success. This provides further support to the argu-
ment that backers merely value the presence of a sustainability orientation but do not place value on the details regarding how a campaign is environmentally sustainable.

4.2 Related literature and theoretical background

4.2.1 Related literature

Our work contributes to the literature streams on crowdfunding and sustainability, with significant implications for (1) how sustainability measures may be implemented during new product development in the context of crowdfunding and (2) how crowdfunding platforms should implement sustainability oriented initiatives. Theoretical work on crowdfunding, specifically rewards-based crowdfunding, has focused on a number of decisions relevant to the creators of campaigns. Hu et al. (2015) examine how creators should optimally choose their product line (modeled as the quality gap between two vertically differentiated products) and prices. Chang (2020) showed that creators are better off when offering fixed funding (money is returned to backers if the goal is not met) as opposed to flexible funding (backers do not receive any refund). Chakraborty and Swinney (2021) study how a creator can signal quality to backers through campaign design aspects such as the funding target and the price of the reward. This work is extended by Chakraborty et al. (2023), where backers/consumers are strategic and distracted (i.e., they strategically choose to delay their contribution to the campaign but subsequently fail to return to the crowdfunding platform to make their contribution). They find that this distracted behavior can be mitigated when a creator offers a menu of rewards consisting of a fixed number of units sold at a low price and a limitless number sold at a higher price. Du et al. (2022) consider the possibility of creators contingently offering stimuli during the course of a crowdfunding campaign in order to improve campaign success. They show that projects making sufficient progress over time do not require any stimulus but those that have not made sufficient progress stand to gain from these stimuli (i.e., the optimal timing
for offering these stimuli follows a cut-off structure that is contingent on the progress made by the campaign). There have also been empirical examinations of a number of creator and campaign characteristics. Mollick (2014) and Bi et al. (2017) observe that social capital and preparedness of the creator act as signals of campaign quality, and positively impact the success of a campaign. These findings are supported by Kunz et al. (2017), who also find that offering multiple rewards and the extent to which creators interact with potential backers positively impact campaign success. Wei et al. (2021) find that prefunding, the sharing of information with potential backers before the funding period begins, increases the likelihood of a campaign being successful. Allon and Babich (2020) and Chen et al. (2020) provide detailed overviews of the literature on crowdfunding. In their systematic overview of the literature on sustainability in crowdfunding, Böckel et al. (2021) point out that the environmental aspect of sustainability has received scant attention. Further, there is a lack of consensus in the extent literature regarding the impact of environmental sustainability orientation on campaign success in rewards-based crowdfunding (Hörisch, 2015; Calic and Mosakowski, 2016).

We contribute to the overall stream on crowdfunding by examining whether creators benefit, through improved campaign success, from making environmental commitments in their crowdfunding campaign. Compared to earlier work examining the relationship between sustainability orientation and campaign success, we use a significantly larger and cleaner sample (our categorization of sustainability orientation is based entirely on the creator’s categorization), and more rigorous econometric techniques (we account for selection on observables and endogeneity arising from omitted variable bias). Further, our work examines the extent to which creators should commit to environmental sustainability as well as the amount of information they should provide regarding the environmental sustainability of their campaign.

The literature on crowdfunding has also examined the design of crowdfunding
platforms (Allon and Babich, 2020). Strausz (2017) and Belavina et al. (2020) examine mechanisms that platforms can implement in order to deter creator misconduct. Fatehi and Wagner (2019) consider the use of revenue-sharing contracts in crowdfunding and show that such contracts can outperform other financing options. We contribute to this stream of literature by examining Kickstarter’s implementation of a section on a campaign’s webpage in which creators may make a voluntary commitment to the environment. We find that the current implementation results in backers valuing the bare minimum in terms of environmental commitment, thus raising questions about Kickstarter’s implementation.

Finally, our work also has implications for new product development. Candogan et al. (2021) point out that product development decisions in crowdfunding have received minimal academic attention. Their study examines, both theoretically and empirically, product improvement decisions during the crowdfunding campaign. Through Kickstarter’s pre-defined dimensions of environmental commitment, we provide insights on the extent to which creators should incorporate environmental sustainability into new product development.

4.2.2 Theoretical background

Entrepreneurs have typically struggled to obtain funds for ventures with a sustainability orientation (Petruzzelli et al., 2019; Böckel et al., 2021). This has been attributed to the following reasons. First, such entrepreneurs tend to focus on the social and environmental aspects of the venture as opposed to the financial aspects, which is often unappealing to traditional investors (Hörisch, 2015). As Lehner (2013) and Lehner and Nicholls (2014) point out, social entrepreneurs are “torn between the social and commercial”. Second, such entrepreneurs often lack a formal business education and the typical experiences associated with raising funds (Choi and Gray, 2008). Due to this lack of formal training, entrepreneurs are unfamiliar with “managerial termi-
nology” and “valuation metrics”, thereby creating “cultural and cognitive distance-related barriers” which impede communication (Moore et al., 2012; Lehner, 2013; Lehner and Nicholls, 2014). Third, such ventures are typically characterized by legal and organizational structures that are unfamiliar to traditional investors, thus creating another barrier between ventures with a sustainability orientation and traditional investors (Lehner, 2013; Lehner and Nicholls, 2014). On a similar note, Austin et al. (2006) argue that such ventures struggle to obtain funds since “the nondistributive restriction on surpluses generated by nonprofit organizations and the embedded social purpose of for-profit or hybrid forms of social enterprise limits social entrepreneurs from tapping into the same capital markets as commercial entrepreneurs.”

In light of these difficulties faced by sustainability focused ventures, crowdfunding has been touted as an alternative to traditional means of financing. In building a theoretical model for crowdfunding ventures with a sustainability orientation, Lehner (2013) states that “crowd investors” tend to focus on the “ideas and core values of the firm” as opposed to “collaterals and business plans”. Further, the process of selection by the crowd (the fundamental tenet of crowdfunding) is democratic, thereby resulting in favorable funding outcomes for “social ideas” deemed worth by the crowd (Rubinton, 2011; Lehner, 2013; Belleflamme et al., 2014). Specifically in the context of rewards-based crowdfunding, Calic and Mosakowski (2016) argue that backers typically provide funds beyond the minimum required to obtain a reward since they “believe in or share the entrepreneur’s goals”. This results in funding success being “influenced by the socio-cultural values represented by the crowd”. Given that most backers on rewards-based crowdfunding platforms such as Kickstarter are in the age range of 18-44 and have considerable spending power (Morejon, 2016), the “crowd” values campaigns with a sustainability orientation.

The aforementioned theoretical basis leads us to propose the hypotheses below. As in Hörisch (2018), we consider two aspects of success – financial funding success
(ratio of amount pledged to the campaign’s goal) and marketing success (number of backers).

**Hypothesis 1a.** Campaigns with a sustainability orientation are more successful in terms of financial funding than those with no sustainability orientation.

**Hypothesis 1b.** Campaigns with a sustainability orientation achieve more marketing success than those with no sustainability orientation.

In building a framework for sustainable (environmental and/or social) entrepreneurship, Schaltegger (2002), Schaltegger and Wagner (2011), and Schaltegger et al. (2016) divide entrepreneurs into three types based on the “priority given to environmental issues as business goals”. The lowest on this spectrum are those that consider environmental issues merely as a “trustee duty”. Further along the spectrum are entrepreneurs that consider environmental issues to be “supplementary to core business goals”. The highest on this sustainability dimension are those that treat environmental issues as fundamental to their business.

In November 2018, Kickstarter implemented a voluntary section titled “Environmental Commitment” on a campaign’s webpage. As mentioned in Section 4.1, Kickstarter allows creators to announce their commitment to the environment by choosing from among five sustainability categories (long-lasting design, reusability and recyclability, sustainable materials, environmentally friendly factories, and sustainable fulfillment and distribution). Under each category, creators may provide details regarding how their product is sustainable with respect to that specific category. Combining this implementation with the aforementioned framework, we posit that campaigns which commit to a larger number of categories treat the sustainability angle as a fundamental aspect of their campaign, thereby sending a positive signal to backers. This leads us to the following formal hypotheses.
Hypothesis 2a. Financial funding success of a campaign increases with the number of environmental commitment categories mentioned on the campaign’s page.

Hypothesis 2b. Marketing success of a campaign increases with the number of environmental commitment categories mentioned on the campaign’s page.

The literature on crowdfunding has theorized that the preparedness of a campaign is positively associated with campaign success (Mollick, 2014; Bi et al., 2017; Kunz et al., 2017). Mollick (2014) draws on Chen et al. (2009), who posit that the (high) quality of a business plan presented to venture capitalists is evidence of thorough preparation on the entrepreneur’s part and typically viewed positively by venture capitalists. The argument used by Chen et al. (2009), grounded in the unimodel of persuasion (Kruglanski and Thompson, 1999), is that the relevance of the preparedness and/or passion displayed by an entrepreneur will depend on the venture capitalist’s implicit mental model about preparedness and passion. Mollick (2014) acknowledges that there may be other signaling effects at play regarding the quality of a project (star power as in Higgins et al., 2011, or legitimacy as in Zimmerman and Zeitz, 2002 and Soublière and Gehman, 2020), but empirically observes that preparedness has the dominant signaling effect. In a similar vein, Kunz et al. (2017) draw on signaling theory to posit that a variety of crowdfunding campaign characteristics (text description, images, and videos) are signals of preparedness on the creators part, and have a positive impact on campaign success.

Building on this stream of preparedness as a signal of campaign quality, we posit that the amount of information provided in a campaign’s environmental commitment section is also an indicator of preparedness. While it may not specifically signal overall quality of a campaign, we believe that it indicates preparation on the part of the campaign creator, which sends a positive signal regarding the campaign’s sustainability orientation. Given that Kickstarter’s environmental commitment section only allows creators to provide textual information, we hypothesize the following.
Hypothesis 3a. *Financial funding success of a campaign increases with the length of the text provided in the environmental commitment section on the campaign’s page.*

Hypothesis 3b. *Marketing success of a campaign increases with the length of the text provided in the environmental commitment section on the campaign’s page.*

4.3 Empirical Analysis

4.3.1 Data description

To test the hypotheses formulated in Section 4.2, we use data from the rewards-based crowdfunding platform Kickstarter. Our sample consists of Kickstarter campaigns with an end date on or after November 1st, 2018 – the time point when Kickstarter implemented the “Environmental Commitment” section. Our data collection process ended in September 2020, which resulted in the latest end date in our sample being September 26th, 2020. Further, we remove campaigns that satisfy the following criteria: 1) do not have an end date, 2) lacking information on the currency used in the campaign, 3) mismatch between currency for amount pledged and goal amount, 4) amount pledged for rewards exceeds the total amount pledged, 5) missing creator ID, 6) have a pledge-to-goal ratio under 0.1, 7) have a goal under $100. The first five criteria are merely further measures of cleaning the sample. We eliminate campaigns with relatively low pledge-to-goal ratios (criteria 6) since these may be campaigns that are inherently of a very low quality so the presence/absence of a sustainability orientation would be immaterial to the success of the campaign. Similar to Mollick (2014) and Kunz et al. (2017), we remove campaigns with unrealistically low goals (criteria 7) as the success of such campaigns may be driven solely by the fact that they have a very low goal. Some campaigns list pledge and goal amounts in currencies other than USD so we convert all pledge and goal amounts to USD as per conversion rates on the start date of the campaign. Finally, we focus on campaigns in the
Design and Technology categories since these are the only categories that are allowed to have an “Environmental Commitment” section. This results in a final sample of 5522 campaigns, out of which 4679 were successful, and 1249 commit to at least one environmental commitment category. We carry out our analysis at the campaign level i.e., the unit of analysis is the campaign.

**Dependent variables:** To measure financial funding success, we compute the ratio of the total amount pledged to the goal of the campaign (hereafter called pledge-goal ratio). Campaigns with pledge-goal ratios below 1 are those that fail to achieve their funding goal, while those with ratios of at least 1 have achieved their funding goal. Values much greater than 1 indicate that a campaign was able to receive significantly more than the amount requested by the creator. While some studies operationalize financial funding success as a binary variable capturing whether the amount pledged exceeded the goal (e.g., Calic and Mosakowski, 2016; Candoğan et al., 2021), our operationalization allows us to capture the possibility that a sustainability orientation is resulting in success far beyond merely hitting the campaign’s goal. For marketing success, we consider the number of backers that the campaign receives. This measure allows us to capture how wide the reach of a campaign is and has been used in prior crowdfunding studies (e.g., Mollick, 2014; Pitschner and Pitschner-Finn, 2014; Hörisch, 2018).

**Independent variables:** We have three independent variables that are relevant to the hypotheses mentioned in Section 4.2. In order to test Hypotheses 1a and 1b, we consider a binary variable capturing whether a campaign has an environmental commitment section or not. A value of 1 indicates that the campaign has a sustainability orientation, while 0 indicates that the campaign lacks a sustainability orientation. This approach to operationalizing sustainability orientation has been used by Schaltegger (2002), Calic and Mosakowski (2016), and Hörisch (2018). For Hypotheses 2a and 2b, the focal independent variable is the number of categories that
are listed under the environmental commitment section on a campaign’s page. Recall that Kickstarter allows creators to pick from among 5 preset categories (long-lasting design, reusability and recyclability, sustainable materials, environmentally friendly factories, and sustainable fulfillment and distribution), which results in this independent variable ranging anywhere from 1 to 5. Finally, for Hypotheses 3a and 3b, the focal independent variable is the number of words in the environmental commitment section on a campaign’s page.

**Control variables:** Campaign success is also impacted by a variety of campaign and creator characteristics. We include a number of control variables to account for these impacts. First, similar to Parhankangas and Renko (2017) and Candoğan et al. (2021), we control for *creator experience* as the number of campaigns previously posted by the creator on Kickstarter. We account for campaign characteristics, by controlling for the campaign’s *goal* (in USD), *category* (design or technology), *duration* (in days) – all of which are standard controls for campaign characteristics in the crowdfunding literature (e.g., Mollick, 2014; Blaseg et al., 2020; Candoğan et al., 2021). We also control for two reward related characteristics as they may also impact backer behavior (and thereby campaign success). First, we control for the *number of reward categories* in a campaign. Second, we control for the *median reward amount* across the reward categories in a campaign. Finally, to account for campaign quality, we include controls for the number of *images* and *videos* (e.g., Blaseg et al., 2020; Candoğan et al., 2021).

The summary statistics and correlation matrix for the aforementioned variables are provided in Appendix C.

### 4.3.2 Model Specification

The choice of whether a campaign has an environmental commitment section (i.e., gets assigned to the treatment group) or not is not random. In other words, this
choice can be affected by unobserved factors (e.g., creator familiarity with sustainable production methods). Not accounting for this could result in overestimation of the impact of a sustainability orientation on campaign success, so we use coarsened exact matching (CEM) to help assuage this concern. While CEM relies on the “matching on observables” assumption (Yılmaz et al., 2022), correlation between observed and unobserved factors can alleviate concerns regarding observed effects of interest being confounded by unobserved factors (Nandkumar and Srikanth, 2016; Karimi et al., 2021). We use the `matchit()` function in R (version 4.2.0) to carry out coarsened exact matching (Ho et al., 2011). The matching covariates that we use are the same as the control variables listed in Section 4.3.1. We do not manually specify any cutpoints for continuous matching covariates, instead allowing for coarsening to be automated by the `matchit()` function. This results in a matched sample consisting of 2972 campaigns in the control group and 1034 campaigns in the treatment group.

We consider OLS regression models to begin testing our hypotheses. In order to test Hypotheses 1a and 1b, we also need to address endogeneity concerns that may arise due to omitted variable bias. The endogenous independent variable is the sustainability orientation of the campaign (choice of whether to make an environmental commitment or not). It is likely that unobserved quality characteristics of a campaign may impact the decision to make some environmental commitment while also impacting campaign success (through the error term). For example, creators of low quality projects may consider environmental commitment as a boost to the perception of the quality of the campaign, thereby resulting in a negative omitted variable bias. On the other hand, creators may strategically choose to make an environmental commitment to send a signal of high campaign quality, analogous to quality signals being sent through high campaign goals (Chakraborty and Swinney, 2021). We address this endogeneity concern by adopting the standard two-stage least squares approach (Wooldridge, 2015) and use two instrumental variables: the frac-
tion of campaigns from the past 30 days belonging to the same category (design or technology) that have a sustainability orientation, and the fraction of campaigns from the past 30 days belonging to the other category (design or technology) that have a sustainability orientation. Regarding the exogeneity of these two instruments, we argue that the average backer is very unlikely to be sophisticated enough to calculate the extent to which environmental commitment has been made across campaigns on Kickstarter. To be able to do so would probably require the ability to scrape data on Kickstarter campaigns, which seems like an unlikely skill that most backers would possess. Further, the benefit that a backer gains from this information seems minimal, thereby making it very unlikely that even a sophisticated backer would choose to do so. Thus, we believe that the fraction of campaigns with an environmental commitment (the two instruments) would not directly affect campaign performance (both dependent variables).

These instruments are likely to be correlated with the endogenous regressor since common shocks to the system are likely to impact the sustainability orientation of many campaigns. For example, an increased awareness in Kickstarter’s implementation of the environmental commitment section through blog posts is likely to impact the sustainability orientation of a number of campaigns across Kickstarter. Statistical tests of instrument exogeneity and relevance are presented in Section 4.4.

In testing Hypotheses 2a, 2b, 3a and 3b, we believe that endogeneity arising from omitted variable bias is not a concern. While the initial decision of a sustainability orientation may be impacted by unobserved quality characteristics, it is unlikely that more detailed decisions (the number of categories that the creator commits and the length of the text in the environmental commitment section) regarding the extent of a campaign’s sustainability orientation are going to be impacted by these unobservables. It is immediately clear to backers that a campaign has a sustainability orientation when they observe the presence (or absence) of a tab titled “Environment-
tal Commitment” on the campaign’s webpage. On the other hand, backers need to scroll to the very bottom of a campaign’s page to gather information on the details of environmental commitment, thereby providing creators with many other avenues (text descriptions, images, videos, presence of different section headers) to signal quality. Thus, we posit that the key regressors are not correlated with the error term, and use standard OLS regression to test these hypotheses. In order to capture the impacts of committing to additional environmental categories and providing more detailed information regarding a campaign’s commitment (text length), we consider the sub-sample of campaigns that do have a sustainability orientation. This sub-sample consists of 1034 campaigns.

4.4 Results

The results from the regression models (with and without instruments) to test Hypotheses 1a and 1b are shown in Table 4.1. Note that we do not control for the campaign’s goal in models in which the dependent variable is the pledge-goal ratio. We find that the presence of a sustainability orientation results in both higher financial funding success and marketing success, thus providing support for both Hypotheses 1a and 1b.

We check the validity of our instrumental variables by examining whether they are weak instruments as well as carrying out the overidentifying restrictions test (J-test). The J-test is used to test the hypothesis that all instruments are exogenous under the assumption that at least one of them is exogenous. To check for weak instruments, we regress the endogenous variable (sustainability orientation) on the two instrumental variables and the set of controls, and follow this up by computing the heteroskedasticity-robust F-statistic. We obtain an F-statistic of 385.26 with 2 degrees of freedom ($p < 0.01$), which indicates that we do not have weak instruments i.e., the instruments explain sufficient variation in the endogenous regressor. To carry
out the J-test, we first obtain the residuals of the two-stage-least-squares estimation of the instrumental variables regression model. Then, we regress these residuals on the instrumental variables and the presumably exogenous regressors. Finally, we test the hypothesis that the coefficient estimates of the instruments in the above regression model are zero (i.e., the instruments and the error term are not correlated). For the model with Number of backers as the dependent variable, we obtain a J-statistic (with 1 degree of freedom) of 0.2941 \((p = 0.59)\). For the model with Pledge-goal ratio as the dependent variable, we obtain a J-statistic (with 1 degree of freedom) of 2.4862 \((p = 0.12)\). The results of the J-test indicate that the instruments are exogenous in both models. The instrumental variables regression models result in larger coefficient estimates than the OLS models, thereby indicating a negative omitted variable bias. This suggests that a sustainability orientation is being used by creators to improve backers’ perceptions of low quality campaigns.

The results from the regression models used to test Hypotheses 2a and 2b are shown in Table 4.2, and those used to test Hypotheses 3a and 3b are shown in Table 4.3. We observe that the number of environmental categories that a campaign commits to does not have a significant impact on the success of a campaign. Thus, we do not have support for Hypotheses 2a and 2b. Similarly, we fail to observe any impact of the length of the environmental commitment section on campaign success. This indicates a lack of support for Hypotheses 3a and 3b.

Our analyses indicate that backers value campaigns with a sustainability orientation (support for Hypotheses 1a and 1b) but do not pay attention to the details behind how a campaign commits to the environment (lack of support for Hypotheses 2a, 2b, 3a and 3b). From a creator’s perspective, this suggests that merely stating that a campaign has a sustainability orientation is sufficient to achieve a boost to campaign success. Considerations regarding the manner in which a campaign commits to the environment do not provide an additional boost to campaign success,
thereby implying that creators do not need to be making informed decisions regarding the sustainability attributes. For example, merely stating that a product has a long-lasting design yields the same value to a creator as a detailed description of how a particular design is long-lasting. This has significant implications for new product development as creators are not achieving any gains from making informed decisions regarding how a campaign may be committing to the different environmental dimensions defined by Kickstarter. Rather than attempting to base decisions of new product development on any of these sustainability dimensions, creators are better off taking cost considerations into their decisions regarding new product development.

While creators stand to benefit from a very superficial commitment to environmental sustainability, our results raise questions regarding Kickstarter’s introduction of the Environmental Commitment section to campaign pages. First, the positioning of this section on a campaign page possibly results in backers paying minimal attention to the details of a campaign’s sustainability orientation. Kickstarter currently has the Environmental Commitment section at the very end of a campaign’s webpage, providing backers with images, videos, general descriptions, and a discussion of the risks associated with the campaign prior to this section. Backers may suffer from reader fatigue, which has been documented in the context of medical professionals (Beg et al., 2021) and students applying for financial aid (Taylor and Bicak, 2020), since they have to evaluate a lot of information prior to the campaign’s specifics regarding sustainability orientation. Second, the lack of a mechanism to hold creators accountable to their environmental commitment may be resulting in backers devaluing the details behind a campaign’s sustainability orientation. In fact, Kickstarter’s implementation of the Environmental Commitment section may be having the unwanted consequence of encouraging creator to greenwash their campaigns, an action that has been studied in the context of corporate social responsibility (Wu et al., 2020). Thus, our results suggest that crowdfunding platforms need to be more
Table 4.1  Estimation results for the models examining impact of sustainability orientation.

<table>
<thead>
<tr>
<th></th>
<th>Dependent variable:</th>
<th>Number of backers</th>
<th>Pledge-goal ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td><strong>OLS</strong></td>
<td><strong>IV</strong></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Sustainability orientation</td>
<td>76.738** (35.443)</td>
<td>412.914*** (93.991)</td>
<td>0.878 (0.573)</td>
</tr>
<tr>
<td>No. of images</td>
<td>12.215*** (1.081)</td>
<td>12.302*** (1.087)</td>
<td>0.138*** (0.015)</td>
</tr>
<tr>
<td>No. of videos</td>
<td>-1.307 (16.436)</td>
<td>-3.188 (16.449)</td>
<td>-0.274 (0.235)</td>
</tr>
<tr>
<td>Goal ($)</td>
<td>0.009*** (0.002)</td>
<td>0.009*** (0.002)</td>
<td>0.026 (0.446)</td>
</tr>
<tr>
<td>Category (Tech)</td>
<td>17.076 (31.349)</td>
<td>16.776 (31.284)</td>
<td>0.036 (0.445)</td>
</tr>
<tr>
<td>Median reward amount</td>
<td>-0.911*** (0.103)</td>
<td>-0.904*** (0.101)</td>
<td>0.003* (0.002)</td>
</tr>
<tr>
<td>No. of reward categories</td>
<td>9.771*** (2.790)</td>
<td>9.700*** (2.800)</td>
<td>0.087* (0.048)</td>
</tr>
<tr>
<td>Project duration</td>
<td>7.309*** (1.555)</td>
<td>7.264*** (1.555)</td>
<td>0.121*** (0.038)</td>
</tr>
<tr>
<td>No. of past projects</td>
<td>34.268*** (6.099)</td>
<td>33.509*** (6.054)</td>
<td>0.839*** (0.165)</td>
</tr>
<tr>
<td>Constant</td>
<td>-306.914*** (54.661)</td>
<td>-390.004*** (61.461)</td>
<td>-3.468*** (1.263)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-5.402*** (1.493)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>4,006</td>
<td>4,006</td>
<td>4,006</td>
</tr>
<tr>
<td>R²</td>
<td>0.125</td>
<td>0.092</td>
<td>0.063</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.123</td>
<td>0.090</td>
<td>0.061</td>
</tr>
<tr>
<td>Residual Std. Error</td>
<td>764.534 (df = 3996)</td>
<td>778.586 (df = 3996)</td>
<td>14.383 (df = 3997)</td>
</tr>
<tr>
<td>F Statistic</td>
<td>63.294*** (df = 9; 3996)</td>
<td>33.369*** (df = 8; 3997)</td>
<td></td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01
Table 4.2  Estimation results for the models examining impact of number of environmental categories committed to.

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Number of backers</th>
<th>Pledge-goal ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>No. of environmental categories</td>
<td>3.666 (22.798)</td>
<td>−0.362 (0.386)</td>
</tr>
<tr>
<td>No. of images</td>
<td>19.290*** (1.810)</td>
<td>0.188*** (0.030)</td>
</tr>
<tr>
<td>No. of videos</td>
<td>−57.819** (28.630)</td>
<td>−0.735 (0.485)</td>
</tr>
<tr>
<td>Goal ($)</td>
<td>0.006* (0.003)</td>
<td></td>
</tr>
<tr>
<td>Category (Technology)</td>
<td>118.943 (74.649)</td>
<td>0.404 (1.261)</td>
</tr>
<tr>
<td>Median reward amount</td>
<td>−0.935*** (0.249)</td>
<td>−0.005 (0.004)</td>
</tr>
<tr>
<td>No. of reward categories</td>
<td>−1.316 (7.312)</td>
<td>0.003 (0.123)</td>
</tr>
<tr>
<td>project_duration</td>
<td>7.104** (2.901)</td>
<td>0.093* (0.049)</td>
</tr>
<tr>
<td>creator_created_count_updated</td>
<td>48.486*** (9.585)</td>
<td>1.236*** (0.162)</td>
</tr>
<tr>
<td>Constant</td>
<td>−251.793* (137.446)</td>
<td>−1.113 (2.329)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Observations</th>
<th>1,034</th>
<th>1,034</th>
</tr>
</thead>
<tbody>
<tr>
<td>R²</td>
<td>0.147</td>
<td>0.092</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.139</td>
<td>0.085</td>
</tr>
<tr>
<td>Residual Std. Error</td>
<td>979.720 (df = 1024)</td>
<td>16.606 (df = 1025)</td>
</tr>
<tr>
<td>F Statistic</td>
<td>19.564*** (df = 9; 1024)</td>
<td>13.057*** (df = 8; 1025)</td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01

wary of the manner in which they introduce features that encourage various players to consider environmental sustainability in the crowdfunding landscape.

4.5 Conclusion

Crowdfunding has been touted as a promising avenue for generating funds for ventures with a sustainability (both environmental and social) focus. Anecdotally, this is evidenced by the dramatic increase in greentech campaigns in the crowdfunding space (Marquis, 2021). Further, Kickstarter’s implementation of an Environmental
Table 4.3  Estimation results for the models examining impact of length of the environmental commitment section.

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Number of backers</th>
<th>Pledge-goal ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Commitment section word count</td>
<td>0.126 (0.317)</td>
<td>−0.007 (0.005)</td>
</tr>
<tr>
<td>No. of images</td>
<td>19.216*** (1.818)</td>
<td>0.191*** (0.031)</td>
</tr>
<tr>
<td>No. of images</td>
<td>−58.246** (28.647)</td>
<td>−0.716 (0.485)</td>
</tr>
<tr>
<td>Goal ($)</td>
<td>0.006* (0.003)</td>
<td></td>
</tr>
<tr>
<td>Category (Technology)</td>
<td>119.530 (74.490)</td>
<td>0.423 (1.258)</td>
</tr>
<tr>
<td>Median reward amount</td>
<td>−0.939*** (0.249)</td>
<td>−0.004 (0.004)</td>
</tr>
<tr>
<td>No. of reward categories</td>
<td>−1.476 (7.323)</td>
<td>0.010 (0.123)</td>
</tr>
<tr>
<td>Project duration</td>
<td>7.089** (2.895)</td>
<td>0.095* (0.049)</td>
</tr>
<tr>
<td>No. of past projects</td>
<td>48.565*** (9.587)</td>
<td>1.231*** (0.162)</td>
</tr>
<tr>
<td>Constant</td>
<td>−249.605* (127.393)</td>
<td>−1.607 (2.158)</td>
</tr>
</tbody>
</table>

Observations: 1,034 1,034  
R²: 0.147 0.093  
Adjusted R²: 0.139 0.086  
Residual Std. Error: 979.657 (df = 1024) 16.599 (df = 1025)  
F Statistic: 19.581*** (df = 9; 1024) 13.180*** (df = 8; 1025)  

Note: *p<0.1; **p<0.05; ***p<0.01

Commitment section on the web pages of crowdfunding campaigns indicates that platforms are also interested in providing a space for the funding of sustainability-focused ventures (Hill, 2018). Yet, the academic community has not studied the success of such campaigns in much detail (Böckel et al., 2021). The extant literature has also failed to reach a consensus on whether a sustainability orientation impacts campaign success (Hörisch, 2015; Calic and Mosakowski, 2016). Our work aims to rigorously examine the impact of a campaign’s sustainability orientation on its success, and also provide more nuance on how details regarding a campaign’s sustainability orientation
are being perceived by backers.

To carry out this empirical examination, we scrape data from Kickstarter following their implementation of the Environmental Commitment section. We begin by carrying out coarsened exact matching to ensure that our comparison of campaigns with and without a sustainability orientation is fair based on observed campaign characteristics. Next, we account for endogeneity arising from omitted variable bias by using 2-SLS and instruments. We find that a sustainability orientation does result in improved campaign success (both in terms of financial funding and marketing). This provides support to the argument, established in the conceptual literature on sustainability and crowdfunding, that the democratic nature of crowdfunding lends itself well to ventures that have a sustainability orientation. Interestingly, we fail to observe any support for campaign success being positively impacted by more detailed descriptions of a campaign’s environmental commitment. We measure this using two metrics: 1) the number of pre-defined (by Kickstarter) environmental commitment categories mentioned on a campaign’s page, and 2) the number of words provided by the campaign creator in the environmental commitment section.

These findings suggest that backers merely value the mention of a sustainability orientation and do not focus on the specifics regarding how a campaign commits to the environment. While we do not specifically examine the mechanism that results in such backer behavior, we posit that it may be attributed to the following reasons. First, Kickstarter’s positioning of the Environmental Commitment section on a campaign’s page is such that this section is not receiving the intended level of attention from backers. The current implementation involves this section placed at the very bottom of the campaign’s webpage, possibly inundating backers with other information and resulting in reader fatigue. Second, the lack of a mechanism through which creators are held accountable for their commitments, which may result in backers placing minimal value on the details behind a campaign’s environmental commitment.
From a creator’s perspective, our findings suggest that the mere mention of a sustainability orientation is enough to result in improved campaign success. In the new product development stage, other considerations such as cost should take precedence over environmental considerations. From a platform’s perspective, there needs to be a rethink of how to implement changes geared towards sustainability. First, the positioning of an environmental commitment section on a campaign’s page may have significant impacts on backer behavior. Second, mechanisms through which creators are held accountable for their sustainability claims may help reduce potential greenwashing.

Our work is among the first forays into sustainability and crowdfunding, and provides a foundation for future work in this space. A detailed examination of the mechanisms resulting in the aforementioned backer behavior is the most natural starting point for future work. A behavioral study of how individuals respond to different platform strategies of encouraging sustainability orientation (e.g., positioning of an environmental commitment section on a campaign’s page, more structured guidelines on how creators provide information on sustainability orientation, inclusion of sustainability related information in the primary description of the campaign) is also a fruitful direction for future work. A deeper textual analysis (potentially using techniques such as Latent Dirichlet allocation) may provide a more nuanced understanding of backer behavior and merits further exploration.

Our work also has some shortcomings that may be addressed in future work. First, certain types of campaigns lend themselves better to an environmental sustainability orientation. For example, the “ECOKIND Cleaning Tablets : Fragrance Free Product Expansion” campaign (https://bit.ly/41wPNyT) inherently has a sustainability focus. On the other hand, the “Cat Ladder Feline Furniture” campaign (https://bit.ly/2EO0btp) does not naturally lend itself to a sustainability orientation. Our analysis fails to capture these differences and focuses solely on the type
of information (about sustainability orientation) provided by the creator. Our findings essentially establish a lower bound on the value of crowdfunding platforms for funding ventures with a sustainability orientation. Building on this to establish how campaigns that solely focus on environmental sustainability are valued in the crowdfunding space is a fruitful direction for future work. The use of behavioral experiments would be the most natural approach to overcoming this shortcoming. Second, the descriptions of environmental commitment in our sample vary drastically in terms of content. The use of an advanced text mining approach to filter campaigns with a superficial environmental commitment may help with better understanding how backers value campaigns’ sustainability orientation.
In this dissertation, we examine how consumer returns and environmental sustainability manifest in the apparel industry as well as crowdfunding. In Chapter 2, we investigate how an online apparel retailer can use price to influence consumer bracketing behavior (the practice of ordering multiple sizes of a product with the ex-ante intention of returning some of them), and whether encouraging bracketing can be profit maximizing. Through a game-theoretic model, we show that consumers are willing to bracket for relatively low prices, while they prefer to sequentially resolve size uncertainty for high prices. While conventional wisdom suggests that consumer returns hurt retailers’ profits, we show that pricing to encourage bracketing can be beneficial to certain retailers. More specifically, retailers selling products that have low reverse logistics costs and a high level of size uncertainty should set relatively low prices, thereby encouraging bracketing. Our work is the first to examine this consumer practice and its implications for retailers’ strategies, thus creating a foundation for future work to build upon. The examination of a competitive setting in which retailers may encourage/discourage bracketing is a natural next step. Empirically examining how consumers value the strategy of bracketing versus retailer strategies to reduce size uncertainty is also an interesting avenue for future work.

In Chapter 3, we continue to focus on the apparel industry, but shift gears to look into the environmental impacts of two commonly used supply chain approaches to apparel retail – the traditional approach and fast fashion. These two approaches differ in terms of (1) product durability and (2) ability to match supply and demand.
The traditional approach achieves an environmental positive in terms of durability while fast fashion does so in terms of its ability to better match supply and demand. Using an infinite-horizon game, we obtain a threshold on per-period leftover inventory above (below) which the fast fashion (traditional) approach is environmentally superior. Through numerical experiments, we show that fast fashion is generally greener for products that command higher markdowns under the traditional approach. Further, we provide prescriptions to policy makers regarding which life-cycle phases they should focus their sustainability efforts on. We observe that in most cases, the production phase is the most fruitful. The interesting exception is products that are characterized by low levels of leftover inventory and command a low salvage value – policy makers should instead focus on reducing the impact of the use phase of such products. Through this work, we build on the growing literature on the environmental impact of fast fashion and the larger apparel industry. Our findings help with providing nuance to both existing rhetoric around fast fashion and current policy. Combining the focus of Chapters 2 (consumer returns) and 3 (environmental sustainability), specifically in the apparel industry, is an interesting avenue for future work. The emergence of circular business models in the apparel industry (e.g., For Days) provides credence to the fact that this is a space that deserves academic attention.

Continuing to focus on sustainability in operations management, in Chapter 4, we study the performance of crowdfunding campaigns with an environmental sustainability orientation. Business ventures that jointly focus on traditional metrics and sustainability have typically struggled to appeal to standard funding sources. The emergence of crowdfunding has provided such ventures with an alternative source for funding, but its viability remains unclear. Anecdotal evidence suggests that crowdfunding can benefit such ventures but thorough and rigorous academic analysis has been minimal. Using data from the rewards-based crowdfunding platform Kickstarter, we empirically examine whether campaigns with a sustainability orientation are more
successful than campaigns without such an orientation. We observe that campaigns with a sustainability orientation do indeed receive more funding (in terms of total dollar amount) as well as appeal to more backers. Interestingly, we also find that backers do not place value on the type of information provided by campaign creators regarding environmental sustainability. In other words, it is merely the presence of some environmental commitment that is valued, while details regarding how a campaign commits to the environment are deemed unimportant. While this work establishes that crowdfunding is indeed a valuable avenue for campaigns with a sustainability orientation, there remains a lot of room for future work in this space. A better understanding of how backers value campaigns that entirely focus on the environment would help with constructing a more nuanced narrative around crowdfunding as an avenue for societal good. An examination of the impact of measures (implemented by crowdfunding platforms) that hold creators accountable for their claims regarding sustainability warrants academic attention as well. Another interesting angle to this problem is the impact of the rearrangement of campaign information on campaign success. More specifically, studying how backers respond to the provision of sustainability orientation in different positions on a campaign’s webpage would provide a useful base for crowdfunding platforms to base their sustainability initiatives around.
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Appendix A

Supplement for Chapter 2

Conditions to ensure the indifference points lie in [0, 1]:

The indifference point between keeping and returning after bracketing is
\[ v_1 = p - 3. \]

The indifference point between keeping and returning following a size match after buying single is
\[ v_2 = p - 3 - h, \]
and that between exchanging and returning following a size mismatch is
\[ v_3 = p + (\delta - 1) h - 3. \]
For any \( h \in [0, 1] \) and \( \delta \in [1, 2] \), we have
\[ v_2 \leq v_1 \leq v_3. \]
When \( p \geq 3 + h \), we have \( v_2 \geq 0 \). When \( p \leq 4 - (\delta - 1) h \), we have \( v_3 \leq 1 \). Since \( \delta \leq 2 \), we have all three indifference points in [0, 1] by restricting \( p \) to be in \([3 + h, 4 - h]\) and \( h \leq 1/2 \).

Proof of Lemma 1:

Let \( E[U_{diff}] = E[U_B] - E[U_S] \) and
\[
p_1 = \frac{h(\delta^2(1-\beta) - 2(1-\beta)\delta(h+4)+h+8)}{2(1-(1-\beta)\delta)}
\]
be the solution to \( E[U_{diff}] = 0 \). Thus, \( p_1 \) is the threshold price at which consumers are indifferent between buying single and bracketing.

(a) \( E[U_{diff}] \) is increasing in \( p \) when \( \beta \geq \frac{\delta-1}{\delta} \). Further, the threshold price \( p_1 > 4 - h \) when \( \beta \geq \frac{\delta-1}{\delta} \). Hence, the utility from buying single is always higher than that from bracketing when \( \beta \geq \frac{\delta-1}{\delta} \). When \( \beta < \frac{\delta-1}{\delta} \), \( E[U_{diff}] \) is decreasing in \( p \). It can be shown that \( p_1 \leq 3 + h \) when \( h \geq h_T \), where \( h_T = \min\{1/2, \frac{2(1-(1-\beta)\delta)}{1-(1-\beta)\delta^2}\} \).

Thus, the utility from buying single is always higher than that from bracketing when \( \beta < \frac{\delta-1}{\delta} \) and \( h \geq h_T \). In summary, consumers will purchase a single size when \( \beta \geq \frac{\delta-1}{\delta} \) or \( h \geq h_T \).

(b) As mentioned above, \( E[U_{diff}] \) is decreasing in \( p \) when \( \beta < \frac{\delta-1}{\delta} \). It can be shown
that as long as \( \frac{(3-\delta)(\delta-1)}{(4-\delta)\delta} < \beta < \frac{\delta-1}{\delta} \) and \( h < h_T \), the threshold price \( p_1 \), at which consumers are indifferent between bracketing and buying single, is in \([3+h, 4-h]\). Since bracketing yields a higher utility for \( p < p_1 \), consumers choose to bracket for lower prices. Beyond the threshold price \( p_1 \), buying single yields a higher utility, and consumers buy single for \( p > p_1 \).

(c) Recall that \( \mathbb{E}[U_{\text{diff}}] \) is decreasing in \( p \) when \( \beta < \frac{\delta-1}{\delta} \). For \( \beta \leq \frac{(3-\delta)(\delta-1)}{(4-\delta)\delta} \), it can be shown that \( p_1 > 4-h \). This implies that the utility from bracketing will always exceed the utility from buying single in this region. Thus, consumers prefer bracketing to buying single for \( \beta \leq \frac{(3-\delta)(\delta-1)}{(4-\delta)\delta} \).

\[ \square \]

Proof of Lemma 2:

We consider a product exchange to be equivalent to keeping the product since the consumer pays price \( p \) when keeping or exchanging. Let \( P[\text{Keep} | \text{Bracket}; p] \) and \( P[\text{Keep} | \text{Buy single}; p] \) be the conditional probabilities of keeping the product at any feasible price \( p \) given that consumers have chosen to bracket and have chosen to buy single, respectively. Then \( P[\text{Keep} | \text{Bracket}; p] = 1 - v_1 = 4 - p \) and \( P[\text{Keep} | \text{Buy single}; p] = \beta (1 - v_2) + (1 - \beta) (1 - v_3) = 4 - p + h \left[ 1 - (1 - \beta)\delta \right] \). For \( \beta < \frac{\delta-1}{\delta} \), we have \( P[\text{Keep} | \text{Buy single}; p] - P[\text{Keep} | \text{Bracket}; p] = h \left[ 1 - (1 - \beta)\delta \right] < 0 \). Thus, \( P[\text{Keep} | \text{Bracket}; p] > P[\text{Keep} | \text{Buy single}; p] \) for any \( p \) in the Choice region.

\[ \square \]

Proof of Proposition 1:

The optimal profit from bracketing is \( \Pi_B^* = 3 - h(h + k + 2) - 2k \) and the optimal profit from buying single is \( \Pi_S^* = \frac{h((1-\beta)(2\beta-1)\delta+2)\delta-1+(1-\beta)(2-\delta)\delta)}{4(1-(1-\beta)\delta)^2} - \frac{k(2(1-\beta)\delta-h((1-\beta)\delta^2-1)-2)}{2((1-\beta)\delta-1)} \).

We define \( \Pi_{\text{Diff}} = \Pi_B^* - \Pi_S^* \), which is linear and decreasing in \( k \). The solution to \( \Pi_{\text{Diff}} = 0 \) is given by
We now present the derivatives of $\tilde{k}$ with respect to the model parameters.

(a) 

$$\frac{\partial \tilde{k}}{\partial \beta} = \frac{h (2(\beta - 1)\delta + 1)^2 \left( h \left( (\beta - 1)^2 \delta + 2\beta - 1 \right) + 1 \right) \left( h^2 + 2h - 3 - A \right) \left( 2(\beta - 1)\delta + 2 \right)^2}{4((\beta - 1)\delta + 1)^4 \left( h ((\beta - 1)\delta^2 + 2(\beta - 1)\delta + \beta + 2) + 2(\beta - 1)\delta + 2 \right)^2} + \frac{h \left( (\beta - 1)\delta^2 h + 2(\beta - 1)\delta (h + 1) + \beta h + 2h + 2 \right) B}{4((\beta - 1)\delta + 1)^4 \left( h ((\beta - 1)\delta^2 + 2(\beta - 1)\delta + \beta + 2) + 2(\beta - 1)\delta + 2 \right)^2}$$

where

$$A = \frac{h((\beta - 1)\delta((2\beta - 1)\delta + 2) + 1)(-8(\beta - 1)\delta + h((\beta - 1)(\delta - 2)\delta - 1) - 8)}{4((\beta - 1)\delta + 1)^2}$$

and

$$B = \left( h \left( (\beta - 1)(\delta - 2)\delta \left( (\beta - 1)^2 \delta + 3\beta - 2 \right) + 1 \right) - 4((\beta - 1)\delta + 1) \left( \delta \left( 2(\beta - 1)^2 \delta + 4\beta - 3 \right) + 1 \right) \right) \left( 2(\beta - 1)\delta + 2 \right)^2$$

The denominator is always positive. The numerator is cubic in $h$. The smallest root is negative and thus irrelevant. The largest root, $h_1$ is positive, while the third root is zero. Since the leading term of the numerator is positive, the numerator is negative in $(0, h_1)$ and positive for $h > h_1$. Recall that $h < h_T$ and it can be shown that $h_1 > h_T$ in the Choice region. Thus, the numerator is negative. this implies that $\frac{\partial \tilde{k}}{\partial \beta} < 0$.

(b) 

$$\frac{\partial \tilde{k}}{\partial h} = \frac{h^2 \left( (\beta - 1)\delta^2 + 2(\beta - 1)\delta \right) \left( (\beta - 1)\delta((\beta - 1)\delta(2(\beta(\delta - 2) - \delta + 4) - 10) - 12) - 5 \right) \left( 2(\beta - 1)\delta + 2 \right)^2}{8((\beta - 1)\delta + 1)^3 \left( h ((\beta - 1)\delta^2 + 2(\beta - 1)\delta + \beta + 2) + 2(\beta - 1)\delta + 2 \right)^2} + \frac{h^2 \left( (\beta - 1)\delta(\beta - 1)\delta(2(\beta(\delta - 2) - \delta + 4) - 10) - 12) - 5 \right) \left( 2(\beta - 1)\delta + 2 \right)^2}{8((\beta - 1)\delta + 1)^3 \left( h ((\beta - 1)\delta^2 + 2(\beta - 1)\delta + \beta + 2) + 2(\beta - 1)\delta + 2 \right)^2} + \frac{4h(1 - (1 - \beta)\delta)((\beta - 1)(\delta((\beta - 1)\delta(2(\beta(\delta - 2) - \delta + 4) - 10) - 12) - 5) \left( 2(\beta - 1)\delta + 2 \right)^2}{8((\beta - 1)\delta + 1)^3 \left( h ((\beta - 1)\delta^2 + 2(\beta - 1)\delta + \beta + 2) + 2(\beta - 1)\delta + 2 \right)^2} - \frac{4((\beta - 1)\delta + 1)^2 \left( (\beta - 1)(11\beta - 4)\delta^2 + 18(\beta - 1)\delta + 3\beta + 14 \right) \left( 2(\beta - 1)\delta + 2 \right)^2}{8((\beta - 1)\delta + 1)^3 \left( h ((\beta - 1)\delta^2 + 2(\beta - 1)\delta + \beta + 2) + 2(\beta - 1)\delta + 2 \right)^2}$$

The denominator of the above derivative is negative in the Choice region. The numerator is quadratic in $h$ and has real roots only when it is concave. Let $h_2$
and $h_3$ be the roots of the numerator. The smaller root $h_2$ is negative, while
the larger root $h_3$ is greater than $h_T$ in the Choice region. Thus, the numerator
is positive in the Choice region. This implies that $\frac{\partial k}{\partial h} < 0$.

\[(c)\]

$$\frac{\partial k}{\partial \delta} = \frac{h P^2 (1 - \beta)(C((\beta - 1)\delta + 1)((2\beta - 1)\delta((\beta - 1)\delta + 2) + 1) - h((\beta - 1)\delta D((\beta - 1)\delta + 2) - 1))}{4((\beta - 1)\delta + 1)^4 (h ((\beta - 1)\delta^2 + 2(\beta - 1)\delta + \beta + 2) + 2(\beta - 1)\delta + 2)^2} + \frac{(1 - \beta)h \left(2E\beta(1 - (1 - \beta)\delta)^2(\delta(2 - (1 - \beta)\delta) - 1)\right)(2(\beta - 1)\delta + 2)^2}{4((\beta - 1)\delta + 1)^4 (h ((\beta - 1)\delta^2 + 2(\beta - 1)\delta + \beta + 2) + 2(\beta - 1)\delta + 2)^2}$$

where

$$C = 2h + 2 + (\beta - 1)\beta\delta^2 h + 2(\beta - 1)\delta(h + 1) + \beta h,$$

$$D = \delta(2\beta(\delta - 1) - \delta + 2) - 2,$$

$$E = h^2 - \frac{h((\beta - 1)\delta((2\beta - 1)\delta + 2) + 1)(-8(\beta - 1)\delta + h((\beta - 1)(\delta - 2)\delta - 1) - 8)}{4(1 - (1 - \beta)\delta^2)} + 2h - 3,$$

and

$$P = (2(\beta - 1)\delta + 2)$$

The denominator is clearly positive. The numerator is cubic in $h$ with a negative
coefficient for the leading term. One of the roots is 0 and we denote the other
two as $h_4$ and $h_5$, where $h_4 < 0 < h_5$. It can be shown that $h_5 > h_T$ in the
Choice region, which implies that the numerator is positive in the Choice region.
Thus, $\frac{\partial k}{\partial \delta} > 0$. \qed

Proof of Proposition 2:

The optimal profit from bracketing is $\Pi_B^* = 3 - h(h + k + 2) - 2k$ in both the
Only Bracketing and Choice regions. $\frac{\partial \Pi_B^*}{\partial h} = -2h - k - 2 < 0$. Hence, the profit is
decreasing in $h$. \qed
Proof of Proposition 3:

The optimal profit from buying single in the Choice region is given by

\[
\Pi^*_S,\text{Choice} = \frac{h(\delta(1 - \beta)((2\beta - 1)\delta + 2) - 1)8((1 - \beta)\delta - 1) - h(1 - (1 - \beta)(2 - \delta)\delta))}{4(1 - (1 - \beta)\delta)^2} - \frac{k (2(1 - \beta)\delta - \beta h ((1 - \beta)\delta^2 - 1) - 2)}{2((1 - \beta)\delta - 1)}
\]

The optimal profit from buying single in the Only Single region is given by

\[
\Pi^*_S,\text{OnlyS} = 3 + h - (1 - \beta)\delta(h + 3)h - (1 - \beta)k
\]

(a)

\[
\frac{\Pi^*_S,\text{Choice}}{\partial\beta} = \frac{h (\delta k ((\beta - 1)^3\delta^3 + (\beta - 1)(3\beta - 2)\delta^2 + \beta\delta + \beta - 2) + k)}{2(1 - (1 - \beta)\delta)^3} + \frac{h (\delta (4\delta (2(\beta - 1)^3\delta^2 + (6\beta - 5)(\beta - 1)\delta + 5\beta - 4) + h + 4))}{2(1 - (1 - \beta)\delta)^3} + \frac{h (\delta ((1 - \beta)(\delta - 2)\delta h (\delta ((\beta - 1)^2\delta + 3\beta - 2) + 2)))}{2(1 - (1 - \beta)\delta)^3}
\]

The denominator is negative in the Choice region. The numerator is linear and decreasing in \(k\). Let the root of the numerator be denoted by \(k_1\). It can be shown that \(k_1 < 0\) in the Choice region. This implies that the numerator is negative in the Choice region. Hence, the profit from buying single is increasing in \(\beta\) in the Choice region.

\[
\frac{\Pi^*_S,\text{OnlyS}}{\partial\beta} = \delta h(h + 3) + k > 0
\]

Hence, the profit from buying single is increasing in \(\beta\) in the Only Single region.

(b)

\[
\frac{\Pi^*_S,\text{Choice}}{\partial h} = \frac{h + ((\beta - 1)\delta + 1) (8(\beta - 1)\delta + (\beta - 1)\delta^3(\beta(k + 8) - 4) + \beta k + 4)}{2(1 - (1 - \beta)\delta)^2} + \frac{(\beta - 1)\delta h(4 - (\beta - 1)\delta)(\delta(2\beta(\delta - 2) - \delta + 4) - 6))}{2(1 - (1 - \beta)\delta)^2}
\]
The denominator is positive. The numerator is linear and increasing in $k$. Let the root of the numerator be denoted by $k_2$. It can be shown that $k_2 < 0$ in the Choice region. This implies that the numerator is positive in the Choice region. Hence, the profit from buying single is increasing in $h$ in the Choice region.

$$\frac{\Pi_{S, \text{OnlyS}}^*}{\partial h} = 1 - (1 - \beta)\delta(2h + 3).$$

This derivative is linear and decreasing in $h$. Let $h_6$ be the root of the derivative. We begin by analyzing the portion of the Only Single region defined by $h \geq h_T$ and $\beta < \frac{\delta - 1}{\delta}$. It can be shown that $h_6 < h_T$, which implies that the derivative is decreasing in this parametric region.

Next, we analyze the portion of the Only Single region defined by $\beta \geq \frac{\delta - 1}{\delta}$. In this case, $h_6$ can lie in $[0, 1/2]$, which implies that the profit from buying single is increasing for $h < h_6$ and decreasing for $h > h_6$.

(c)

$$\frac{\Pi_{S, \text{Choice}}^*}{\partial \delta} = \frac{(\beta - 1)h(h - (\beta - 1)\delta h)((\beta - 1)\delta + 2)(\delta(2\beta(\delta - 1) - \delta + 2) - 2))}{2(1 - (1 - \beta)\delta)^3} + \frac{(\beta - 1)h((\beta - 1)\delta + 1)\left(-8\delta + (\beta - 1)\delta^2(\beta(k + 8) - 4) + 2\delta(\beta(k + 8) - \beta k + 4)\right)}{2(1 - (1 - \beta)\delta)^3}$$

The denominator is negative in the Choice region. The numerator is linear and increasing in $k$. Let the root of the numerator be denoted by $k_3$. It can be shown that $k_3 < 0$ in the Choice region. This implies that the numerator is positive in the Choice region. Hence, the profit from buying single is decreasing in $\delta$ in the Choice region.

$$\frac{\Pi_{S, \text{OnlyS}}^*}{\partial \delta} = -h(1 - \beta)(h + 3) < 0.$$ This implies that the profit from buying single is decreasing in $\delta$ in the Only Single region.

Proof of Proposition 4:

The profit when the retailer makes the investment to eliminate size uncertainty so that consumers buy single is shown in (2.6). This profit is maximized at $p_I^* = 3 + h$, and the resulting optimal profit is $\Pi_I^* = 3 + h - C$.  

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When the retailer does not make any investment to eliminate size uncertainty and consumers bracket, its optimal profit is
\[ \Pi^*_B = 3 - h(h + k + 2) - 2k. \]
Note that the match probability is now \( \beta = \beta_0 \) in all expressions hereafter.

Let \( \Pi_{\text{Diff}, I} = \Pi^*_I - \Pi^*_B \). This difference is linear and decreasing in \( C \). The solution to \( \Pi_{\text{Diff}, I} = 0 \) is given by \( \bar{C} = h(h + k + 3) + 2k. \) Thus, the retailer is better off making the investment to eliminate size uncertainty as long as \( C < \bar{C}. \)

We now prove the comparative statics shown in this result.

(a) \( \frac{\partial \bar{C}}{\partial h} = h + 2 > 0. \) Thus, the threshold cost is increasing in \( h. \)

(b) \( \frac{\partial \bar{C}}{\partial k} = 2h + k + 3 > 0. \) Thus, the threshold cost is increasing in \( h. \)

Proof of Proposition 5:

The optimal profits from the pooling strategy to encourage all consumers to bracket, the separating strategy, and the pooling strategy to encourage all consumers to buy single are shown in (A.1), (A.2), and (A.3) respectively.

\[ \Pi^*_{\text{B,Pool}} = -H(H + k + 2) - 2k + 3 \quad \text{(A.1)} \]

\[ \Pi^*_{\text{Sep}} = \frac{H \left( 2\alpha((\beta - 1)\delta + 1)^2 - (\beta - 1)\delta((2\beta - 1)\delta + 2) - 1 \right) - 8(\beta - 1)\delta + H((\beta - 1)(\delta - 2)\delta - 1) - 8}{4(1 - (1 - \beta)\delta)^2} \]
\[ - k \left( 4\alpha + (\beta - 1)\delta^2 H(\alpha(\beta - 1) + 2(\beta - 1)\delta - 1) + \alpha(\beta H + \alpha H - \beta H + 2) \right) \quad \text{(A.2)} \]

\[ \Pi^*_{\text{S,Pool}} = \frac{F \left( 2\alpha((\beta - 1)\delta + 1)^2 + (\beta - 1)(\delta - 2)\delta - 1 \right) - 2(\alpha - 1)H((\beta - 1)\delta + 1)^2}{4((\beta - 1)\delta + 1)^2} \]
\[ - k \left( 1 - \beta(\alpha((\beta - 1)\delta + 1) + (\beta - 1)(\delta - 2)\delta - 1) - 2(\alpha - 1)H((\beta - 1)\delta + 1)) \right) \quad \text{(A.3)} \]

where \( F = 8(\beta - 1)\delta - L((\beta - 1)(\delta - 2)\delta - 1) + 8. \)

We now present the comparative statics of the three profit functions with respect to \( \alpha. \)

(a) \( \frac{\partial \Pi^*_{\text{B,Pool}}}{\partial \alpha} = 0. \) Thus, the threshold cost is independent of \( \alpha. \)
\[
\frac{\partial \Pi^{*}_{\text{Sep}}}{\partial \alpha} = \frac{1}{2} \left( (\beta - 1) \delta^2 H^2 - (\beta - 1) \delta H(2H + k + 8) - \frac{\beta Hk}{(\delta - 1)\delta - 1} - H(H + k + 8) - 4k \right).
\]

This derivative is linear and decreasing in \( k \). Let the root be denoted by \( k_4 \).

It can be shown that \( k_4 \) is less than the value of \( k \) that makes the separating strategy optimal in the Choice region. This implies that the derivative is negative when the separating strategy is optimal, and thus, the optimal profit from the separating strategy is decreasing in \( \alpha \).

\[
\frac{\partial \Pi^{*}_{\text{Sep}}}{\partial \alpha} = \frac{1}{2} \left( H - L \right) \left( (\beta - 1)((\delta - 2)\delta - 1) - 2(4(\beta - 1)\delta + \beta k + 4) \right).\]

This derivative is linear and decreasing in \( k \). Let the root be denoted by \( k_5 \). It can be shown that \( k_5 > 0 \) in the Choice region. Thus, the derivative is positive for \( k < k_5 \) and negative for \( k > k_5 \). It can be shown that there are feasible instances of the parameters that satisfy the optimality of this pooling strategy as well as both \( k < k_5 \) and \( k > k_5 \).

Proof of Proposition 6:

Recall that within the Choice region, consumers bracket for \( h \leq \bar{h} \) and buy single for \( h > \bar{h} \), where \( \bar{h} = \frac{2(4-p)(1-(1-\beta)\delta)}{(1-\beta)(2-\delta)\delta - 1} \). The profit from bracketing is \( \Pi_B = (4-p)p - c(h-h_0)^2 - kp + k \). \( \Pi_B \) is concave and quadratic in \( h \), with \( h = h_0 \) as the critical point. As long as \( h_0 < \bar{h} \), it is optimal to set \( h^* = h_0 \). Given the concavity of \( \Pi_B \), when \( h_0 > \bar{h} \), it is optimal to reduce the hassle cost to the boundary point \( \bar{h} \) i.e. \( h^* = \bar{h} \). This establishes parts (a) and (b) of Proposition 6.

The profit from buying single is \( \Pi_S = p(h-p+4-(1-\beta)\delta h) - c(h-h_0)^2 + k((\beta(h-p+4) - 1) \). \( \Pi_S \) is concave and quadratic in \( h \). The critical point is \( h = \frac{2ch_0 + \beta k - (1-\beta)\delta p + p}{2c} \).

We restrict our attention to \( k < \frac{\delta p - p - \beta \delta p}{\beta} \) to eliminate the case of the critical point, \( h \), being larger than the upper bound on \( h \) (i.e. \( p - 3 \)). This limits the complexity of our analysis and is representative of scenarios where the reverse logistics cost is not excessively high. Thus, the retailer’s optimal choice for the hassle cost is \( \max\{\bar{h}, \underline{h}\} \).

Given our restriction on \( k \), it can be shown that the only case in which the retailer
would increase the hassle cost is when \( h_0 < \bar{h} \). This establishes parts (c) and (d) of Proposition 6. Note that the retailer leaves the hassle cost as is if \( h_0 = \max\{\bar{h}, \bar{h}\} \).

Proof of Proposition 7:

The retailer’s problem is

\[
\max_{p, h} \quad (p - 2k) \int_{v_1}^{1} dv - 3k \int_{0}^{n} dv - c(h - h_0)^2
\]

s.t.

\[
p \geq 3 + h,
\]

\[
h \geq 0,
\]

\[
h \leq h_T,
\]

\[
p \leq p_1
\]

Let \( \mu_1, \mu_2, \mu_3 \) and \( \mu_4 \) be the multipliers for the constraints in the retailer’s maximization problem. This function is jointly concave in \( h \) and \( p \) since the eigenvalues of the Hessian are \(-2\) and \(-2c\). The KKT conditions are

\[
k - \mu_1 + \mu_4 + 2p - 4 = 0
\]

\[
2c(h - h_0) + \mu_1 - \mu_2 + \mu_3 = 0
\]

\[
\mu_1 (3 + h - p) = 0
\]

\[
\mu_2 (-h) = 0
\]

\[
\mu_3 (h - h_T) = 0
\]

\[
\mu_4 (p - p_1) = 0
\]

It can be shown that there are two solutions that satisfies the above KKT conditions, the non-negativity of the multipliers as well as the constraints defined in the retailer’s maximization problem. These two solutions are
(a) \( p = 3, h = 0, \mu_1 = 2 + k, \mu_2 = 2 - 2c h_0 + k, \mu_3 = 0, \mu_4 = 0 \). Note that the non-negativity of \( \mu_2 \) holds only when \( c \leq \frac{k+2}{2h_0} \).

(b) \( p = \frac{2c h_0 + 6c - k + 4}{2c + 2}, h = \frac{2c h_0 - k - 2}{2c + 2}, \mu_1 = \frac{c(2h_0 + k + 2)}{c+1}, \mu_2 = 0, \mu_3 = 0, \mu_4 = 0 \). Note that the non-negativity of \( h \) holds only when \( c \geq \frac{k+2}{2h_0} \). \( \square \)


Appendix B

Supplement for Chapter 3

B.1 Summary of model parameters

Table B.1 provides a summary of the notation used for the parameters in the models for the fast fashion and traditional approaches. \( i \in \{F, T\} \) denotes the approach (fast fashion or traditional) adopted by the firm.

<table>
<thead>
<tr>
<th>Notation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \delta )</td>
<td>Discount factor associated with consumers’ valuation of markdowns</td>
</tr>
<tr>
<td>( \rho )</td>
<td>Discount factor incorporated by consumers when computing net future value</td>
</tr>
<tr>
<td>( s_i )</td>
<td>Markdown price set by the firm under approach ( i )</td>
</tr>
<tr>
<td>( c_i )</td>
<td>Production cost under approach ( i )</td>
</tr>
<tr>
<td>( e_{i,P} )</td>
<td>Per-unit impact of the production phase under approach ( i )</td>
</tr>
<tr>
<td>( e_U )</td>
<td>Per-unit impact of the use phase</td>
</tr>
<tr>
<td>( e_D )</td>
<td>Per-unit impact of the disposal phase</td>
</tr>
<tr>
<td>( k )</td>
<td>Leftover inventory at the end of a selling season</td>
</tr>
<tr>
<td>( r )</td>
<td>Salvage value that consumers obtain when they discard the product after using it for a single period (under the traditional approach)</td>
</tr>
</tbody>
</table>
B.2 Derivation of equilibrium consumer strategy under the traditional approach

Let BF, BM and I denote the single period action of buying at full price, buying on markdown and remaining inactive, respectively. We denote the action of a consumer whose valuation is \( v \) in period \( t \) as \( a^t(v) \). We suppress the subscript \( T \) to denote the traditional approach throughout this section. For any price path \( \{ p^t, t \geq 0 \} \), a consumer of type \( v \) solves the following utility maximization problem

\[
V_v(a_0) = \max_{a} \sum_{t=1}^{\infty} \rho^t U[a^t(v); a^{t-1}(v), p^t],
\]

where \( U[a^t(v); a^{t-1}(v), p^t] \) is the utility obtained in period \( t \) when consumer \( v \) plays action \( a^t(v) \) in period \( t \) given the full price \( p_t \) and her action \( a^{t-1}(v) \) in period \( t - 1 \). As per Blackwell (1965), this problem can be solved by deriving the Bellman equations through backward induction since the strategy space is finite and the per-period utility is bounded. The net present value functions are defined as

\[
V_t^v[a^{t-1}(v), p^t] = \max_{a^t(v) \in \{BF, BM, I\}} U[a^t(v); a^{t-1}(v), p^t] + \rho V_{t+1}^v[a^t(v), p^{t+1}].
\]

As in Huang et al. (2001) and Agrawal et al. (2012), we define the reaction function as \( R_t^v[a^{t-1}(v), p^t] = a^t(v)^* \), where \( a^t(v)^* \) is the solution to the previous equation.

Table 3.3 shows the nine possible two period consumer strategies. As per Huang et al. (2001), at the focal point, consumer \( v \)'s time independent Bellman equation is

\[
V_v[a(v), p] = \max_{a(v) \in \{BF, BM, I\}} U[R_v(a(v)), p] + \rho V_v[R_v[a(v), p], p].
\]

The periodicity of two ensures that permutations of consumer strategies do not lead to distinct strategies (for example, BFBM is not a different strategy to BMBF). This leaves us with six distinct strategies: BFBF, BFBM, BFI, BMBM, BMI, II.

We prove that BFI and BMI are not credible strategies. We begin with the proof for BFI. Let us assume that BFI is a credible strategy. This implies \( R_v[BF, p] = I \) and \( R_v[I, p] = BF \) for some \( v \). \( R_v[BF, p] = I \) implies that \( r + \rho V_v[I, p] > v - p + r + \rho V_v[BF, p] \). This simplifies to \( U_v[I; I, p] > U_v[BF; I, p] \) which implies \( R_v[I, p] = I \). This is a contradiction, thereby showing that BFI is not a credible strategy.
Next, we move to the strategy BMI. Assume that BMI is a credible strategy. This implies $R_v[BM, p] = I$ and $R_v[I, p] = BM$ for some $v$. $R_v[BM, p] = I$ implies that $\rho V_v[I, p] > \delta v - s + \rho V_v[BM, p]$. This simplifies to $U_v[I; I, p] > U_v[BM; I, p]$ which implies $R_v[I, p] = I$. This is a contradiction, thereby showing that BMI is not a credible strategy.

This leaves us with four possible strategies at the focal point. They are BFBF, BFBM, BMBM, II. We compute the net present values at the focal point using the Bellman equations as follows: The highest $v$ consumers play BFBF and their net present value is obtained by solving $V_v[BF, p] = v - p + r + \rho V_v[BF, p]$. This yields $V_v[BF, p] = \frac{v - p + r}{1 - \rho}$. The next highest valuation consumers play BFBM. We solve the following pair of equations to obtain their net present value: $V_v[BF, p] = \frac{v(\delta + \rho)r - s - \rho v}{1 - \rho^2}$ and $V_v[BM, p] = \frac{v(1 + \delta r - p + \rho(s - r))}{1 - \rho^2}$. Consumers with a lower valuation play BMBM and their net present value is obtained by solving $V_v[BM, p] = \delta v - s + \rho V_v[BM, p]$, which results in $V_v[BM, p] = \frac{\delta v - s}{1 - \rho}$. Finally, consumers with the lowest valuation play II, and their net present value is $V_v[I, p] = 0$.

Let the consumer of type $v_1$ be indifferent between BFBF and BFBM, the consumer of type $v_2$ be indifferent between BFBM and BMBM, and the consumer of type $v_3$ be indifferent between BMBM and II. These indifferent points are obtained by solving the following equations. Note that in each equation, consumers enter a period in the same state. (Huang et al., 2001; Tilson et al., 2009; Mahmoudzadeh, 2022). In other words, in the first equation consumers enter a period with a product (play BF) and in the other two equations consumers enter without a product.

$$\frac{v_1 - p + r}{1 - \rho} = \frac{v_1(\delta + \rho)r - s - \rho p}{1 - \rho^2},$$

$$\frac{v_2(1 + \delta \rho) - p + \rho(s - r)}{1 - \rho^2} = \frac{\delta v_2 - s}{1 - \rho},$$
\[ \delta v_3 - s = 0. \]

The resulting expressions for the three indifference points are

\[ v_1 = \frac{p - s - r\rho}{1 - \delta} \]

\[ v_2 = \frac{p + \rho r - 2\rho s - s}{1 - \delta} \]

\[ v_3 = \frac{s}{\delta} \]

Consumers in \([v_1, 1]\) play BFBF, those in \([v_2, v_1]\) play BFBM, those in \([v_3, v_2]\) play BMBM, and consumers in \([0, v_3]\) play II. Note that we have \(0 \leq v_3 \leq v_2 \leq v_1 \leq 1\) in equilibrium.

As pointed out by Huang et al. (2001) and Agrawal et al. (2012), by restricting our attention to a focal point, in any period, half of the consumers playing BFBM will purchase the product at full price while the other half keeps the product for its second period of use. Thus, in equilibrium, the demand at the full price is

\[ q_p(p, s) = 1 - v_1 + \frac{(v_1 - v_2)}{2} = \frac{1 - \delta - \rho r + (\rho + 1)s}{1 - \delta} \]

and that at markdown is

\[ q_s(p, s) = v_2 - v_3 = \frac{\delta(p + \rho r - s)(1 + 2\delta)}{(1 - \delta)\delta}. \]

### B.3 Proofs of results

**Proof of Lemma 3:**

The optimal profit under the fast fashion approach is

\[ \Pi^*_F = \frac{\delta - 4c_F(\delta - s_F) - (\delta - 2s_F)^2}{4\delta}. \]

\(\Pi^*_F\) is linear and decreasing in \(c_F\). The solution to \(\Pi^*_F = 0\) is given by

\[ c_{F_1} = \frac{\delta - (\delta - 2s_F)^2}{4(\delta - s_F)}. \]

Then, \(\Pi^*_F > 0\) when \(c_F < c_{F_1}\).

The optimal profit under the traditional approach is
\[ \Pi_T^* = \frac{(1 - \delta) (4c_T(s_T - \delta(k + 1)) + \delta - (\delta - 2s_T)^2)}{4(1 - \delta)\delta} + \frac{\delta \rho^2 s_T^2 - 2\delta \rho(2(c_T - s_T)(r - s_T) + \delta s_T - s_T)}{4(1 - \delta)\delta} \]

\( \Pi_T^* \) is linear and decreasing in \( k \). The solution to \( \Pi_T^* = 0 \) is given by

\[ \tilde{k} = \frac{(1 - \delta) (4c_T(s_T - \delta) + \delta - (\delta - 2s_T)^2)}{4c_T(1 - \delta)\delta} + \frac{\delta \rho^2 s_T^2 - 2\delta \rho(2(c_T - s_T)(r - s_T) + \delta s_T - s_T)}{4(1 - \delta)\delta} \]

Then, \( \Pi_T^* > 0 \) when \( k < \tilde{k} \).

Proof of Proposition 8:

Under the fast fashion approach, the per-period volume in any phase is given by

\[ q^j,F = 1 - v^{**} = 1 - \frac{s_F}{\delta^*} \]

where \( j \in \{P,U,D\} \) denotes the life-cycle phase.

Under the traditional approach, the per-period volumes in the production (\( q^{P,T} \)) and disposal (\( q^{D,T} \)) phases are identical and given by

\[ q^{P,T} = q^{D,T} = 1 - v_1 + \frac{v_1 - v_2}{2} + v_2 - v_3 + k = 1 + k - \frac{\rho(s_F - r)}{1 - \delta} - \frac{s_T}{\delta}. \]

\( q^{P,F} - q^{P,T} \) is linear and decreasing in \( k \). The solution to \( q^{P,F} - q^{P,T} = 0 \) is given by

\[ k_1 = \frac{\rho(s_F - r)}{\delta + 1} + \frac{s_T - s_F}{\delta}. \]

(a) Recall that we have \( k \geq 0 \) from Assumption 1. \( k_1 < 0 \) when \( s_F > s_T + \frac{\delta \rho(s_F - r)}{1 - \delta} \).

This implies that when \( s_F > s_T + \frac{\delta \rho(s_F - r)}{1 - \delta} \), we have \( q^{P,F} < q^{P,T} \) for all \( k \).

(b) When \( s_F < s_T + \frac{\delta \rho(s_F - r)}{1 - \delta} \), we have \( k_1 > 0 \). Then, \( q^{P,F} < q^{P,T} \) only if \( k > k_1 \).

Based on (b) above, \( q^{P,F} > q^{P,T} \) only when \( s_F < s_T + \frac{\delta \rho(s_F - r)}{1 - \delta} \) and \( k < k_1 \).

Since \( q^{P,F} = q^{D,F} \) and \( q^{P,T} = q^{D,T} \), the same relationships hold for the disposal phase.

Proof of Proposition 9:
From the proof of Proposition 8, we know that the per-period volume in the use phase under the fast fashion approach is $q_{U,F} = 1 - \frac{s_F}{\delta}$.

Under the traditional approach, the per-period volume in the use phase is $q_{U,T} = 1 - v_3 = 1 - \frac{s_T}{\delta}$.

$q_{U,F} - q_{U,T} = \frac{s_T - s_F}{\delta}$, which is clearly positive (negative) for $s_T > (<) s_F$. Thus, $q_{U,F} > q_{U,T}$ for $s_T > s_F$ and $q_{U,F} < q_{U,T}$ for $s_T < s_F$.

Proof of Proposition 10:

The total environmental impact under the fast fashion approach is given by $E_F = (q^{P,F} \cdot e_F,P) + (q^{U,F} \cdot e_U) + (q^{D,F} \cdot e_D) = \left(1 - \frac{s_F}{\delta}\right)(e_{F,P} + e_U + e_D)$.

The total environmental impact under the traditional approach is given by $E_T = \left(q^{P,T} \cdot e_{T,P}\right) + (q^{U,T} \cdot e_U) + (q^{D,T} \cdot e_D) = e_{T,P} + e_U + e_D + k(e_D + e_{T,P}) - \frac{s_T(e_D + e_{F,P} + e_U)}{\delta} - \frac{\rho(e_D + e_{T,P})(s_T - r)}{1 - \delta}$.

$E_F - E_T$ is linear and decreasing in $k$. The solution to $E_F - E_T = 0$ is $\bar{k} = e_{T,P} \left(1 - \frac{v^{F-T}}{1 - \frac{s_F}{\delta}}\right) + e_U \left(1 - \frac{s_T}{\delta} + \frac{s_F - \delta}{\delta}\right) - e_D \left(1 - \frac{v^{F-T}}{1 - \frac{s_F}{\delta}} + \frac{s_F - \delta}{\delta}\right) - \frac{\rho(e_D + e_{F,P})(s_T - r)}{\delta}$. This implies that $E_F < E_T$ for $k > \bar{k}$.

Next, we prove the relationships between $\bar{k}$ and the environmental impact parameters.

(a) $\frac{\partial \bar{k}}{\partial e_{F,P}} = \frac{\delta - s_F}{\delta(e_D + e_{T,P})}$. Recall that we impose the condition $s_F < \frac{\delta}{2}$ for the consumer indifference points under the fast fashion approach to satisfy the ordering $0 \leq v^{**} \leq v^* \leq 1$. We have $\frac{\partial \bar{k}}{\partial e_{F,P}} > 0$ for any $s_F < \frac{\delta}{2}$, which implies that $\bar{k}$ is increasing in $e_{F,P}$.

(b) $\frac{\partial \bar{k}}{\partial e_{T,P}} = \frac{(e_D + e_{F,P})(s_F - \delta) + e_U(s_F - s_T)}{\delta(e_D + e_{T,P})^2}$. The denominator is positive for all feasible parameter values. The numerator is linear and decreasing in $s_T$. Its root is $\tilde{s}_T = \frac{s_F(e_D + e_{F,P} + e_U) - \delta(e_D + e_{F,P})}{e_U}$, which is negative for all feasible parameter values. Thus, the numerator is negative for all feasible parameter values. This implies $\frac{\partial \bar{k}}{\partial e_{T,P}} < 0$. 

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(c) \( \frac{\partial \bar{k}}{\partial e_U} = \frac{s_T - s_F}{\delta(e_D + e_T,P)} \). The denominator is clearly positive for all feasible parameter values. The numerator is positive when \( s_T > s_F \) and negative when \( s_T < s_F \).

Thus, \( \frac{\partial \bar{k}}{\partial e_U} > 0 \) when \( s_T > s_F \), and \( \frac{\partial \bar{k}}{\partial e_U} < 0 \) when \( s_T < s_F \).

**Relationship between \( \bar{k} \) and \( e_D \):** \( \bar{k} \) is increasing in \( e_D \) when \( s_T < M \), and decreasing in \( e_D \) when \( s_T > M \), where \( M = \frac{s_F(e_F,P - e_T,P + e_U) - \delta(e_F,P + e_T,P)}{e_U} \).

**Proof:** \( \frac{\partial \bar{k}}{\partial e_D} = \frac{(e_F,P - e_T,P)(s_F - \delta + e_U(s_F - s_D))}{\delta(e_D + e_T,P)^2} \). The denominator is clearly positive for all feasible parameter values. The numerator is linear and decreasing in \( s_T \). The root of the numerator is \( \hat{s}_T = \frac{s_F(e_F,P - e_T,P + e_U) - \delta(e_F,P + e_T,P)}{e_U} \). Thus, \( \frac{\partial \bar{k}}{\partial e_U} > 0 \) for \( s_T < \hat{s}_T \), and \( \frac{\partial \bar{k}}{\partial e_U} < 0 \) for \( s_T > \hat{s}_T \).

**Proof of Proposition 11:**

Under the traditional approach, the per-period volumes in the production \( (q_{P,T}) \) and disposal \( (q_{D,T}) \) phases are identical and given by \( q_{P,T} = q_{D,T} = 1 + k - \frac{\rho(s_T - r)}{1 - \delta} - \frac{s_T}{\delta} \).

The per-period volume in the use phase is given by \( q_{U,T} = 1 - \frac{s_T}{\delta} \).

\( q_{P,T} - q_{U,T} \) is linear and increasing in \( r \). The solution to \( q_{P,T} - q_{U,T} = 0 \) is \( r = s_T - \frac{(1 - \delta)k}{\rho} \). Recall that the salvage value \( r \) is a non-negative quantity \( (r \geq 0) \).

(a) It can be shown that \( r < 0 \) when \( k > \bar{k} \), where \( \bar{k} = \frac{\rho s_T}{1 - \delta} \). This implies that \( q_{P,T} > q_{U,T} \) when \( k > \bar{k} \).

(b) When \( k < \bar{k} \), we have \( q_{P,T} > q_{U,T} \) if \( r > r \) since \( q_{P,T} - q_{U,T} \) is linear and increasing in \( r \).

The fact that \( q_{P,T} < q_{U,T} \) when \( k < \bar{k} \) and \( r < r \) directly follows from above.

Since \( q_{P,T} = q_{D,T} \), the above relationships hold between the use and disposal volumes as well.

**B.4 Summary statistics for the global sensitivity analysis**

The summary statistics for the experimental design mentioned in Section 3.4.5 are shown in Table B.2.
Table B.2 Descriptive statistics for experimental design.

<table>
<thead>
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<th>Mean</th>
<th>St. Dev.</th>
<th>Min</th>
<th>Max</th>
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<td>0.354</td>
<td>0.500</td>
<td>1.500</td>
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<tr>
<td>$e_{F,P}$</td>
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<td>0.500</td>
<td>1.500</td>
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<tr>
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## Appendix C

### Supplement for Chapter 4

Table C.1  Summary statistics.

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<td>No. of videos</td>
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<tr>
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<td>0.04*</td>
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<td>4. No. of environmental categories</td>
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<td>8. No. of images</td>
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<td>9. No. of videos</td>
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* denotes \( p < 0.05 \)