Fast Fashion: Business Model Overview and Research Opportunities

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Fast fashion is a business model that offers (the perception of) fashionable clothes at affordable prices. From an operations standpoint, fast fashion requires a highly responsive supply chain that can support a product assortment that is periodically changing. Though the underlying principles are simple, the successful execution of the fast-fashion business model poses numerous challenges. We present a careful examination of this business model and discuss its execution by analyzing the most prominent firms in the industry. We then survey the academic literature for research that is specifically relevant or directly related to fast fashion. Our goal is to expose the main components of fast fashion and to identify untapped research opportunities.

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1. Introduction

The global apparel industry has experienced a compound annual growth rate of 4.3% since 2000, reaching a market size of USD 1.7 trillion in 2012 (Euromonitor International 2013). The growth has not only been in terms of revenue. The number of pieces of clothing purchased per capita increased from 9.0 in 2000 to 13.9 in 2012 worldwide, and in countries like the United Kingdom it has increased from 18.7 to 29.5 over the same period (Euromonitor International 2013). Part of the growth embedded in these figures has been attributed to the

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emergence of new industry players – collectively known as "fast-fashion retailers" – which have seen an explosive expansion since the turn of the century. In fact, stores like Hennes and Mauritz (H&M) from Sweden and Zara – the flagship brand of Inditex from Spain – have established themselves as recognized brands (Interbrand 2013) and have grown to become the largest apparel retailers in the world, see Figure 1.

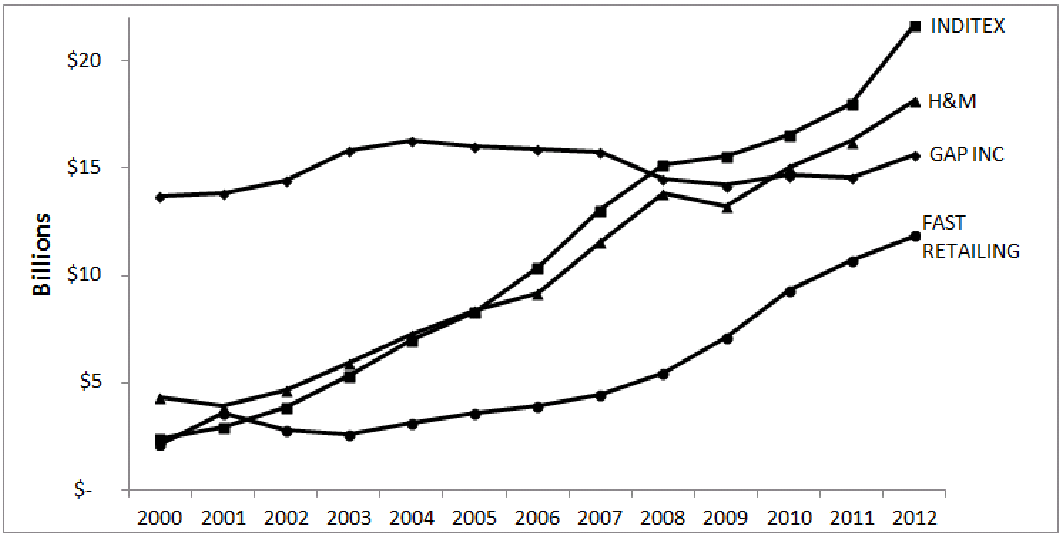

Figure 1: Select specialty apparel retailer revenues in 2000-2012. Source: annual reports.

Fast fashion brought fresh air into the textile and apparel industries and it quickly struck a chord with the consumer. From a management and economics perspective, fast fashion has been the long-awaited realization of "lean retailing" with items produced in small batches and within short lead times. Moreover, fast fashion's reliance on near-shore production has given a lifeline to an otherwise dying industry in developed countries (Abernathy et al. 2006, Doeringer and Crean 2006). On the other hand, fast fashion has been associated with a disposable culture and its social responsibility is constantly under scrutiny (Siegle 2011, Cline 2012).

Fueled by the success and growth of fast-fashion retailers, the term *fast fashion* has become ubiquitous and it has been used indiscriminately to describe almost any specialty apparel retailer below a certain price threshold, spanning stores like Old Navy and Chico's that have almost nothing in common besides the fact that they sell clothes. Hence, given the prominent role of fast fashion in the last decade, it is worth asking: which retailers are fast fashion and how do they operate? To find an answer to this question, in section 1.1 we first follow a qualitative approach based on online sources and then in section 1.2 we provide a more precise academic definition and we postulate metrics to measure "degrees" of fast fashion.

1.1 Which firms are fast fashion and how do they operate?

The Wikipedia entry for *fast fashion* lists 21 firms.[1] The list is quite diverse, but most of the firms have the following in common. First, they are specialty apparel retailers with brick & mortar stores and some online presence. Second, they are not "haute couture" or trend-setters but rather fashion followers that target the mid-to-low price range. To elaborate a more definite list of firms, we performed a frequency count using the Factiva database. We first searched for all the media publications in the last two years that contained the exact phrase "fast fashion" and we looked for brand names to form a preliminary list. Then, for each brand, we counted in how many of these media publications the brand was mentioned. A ranking of the brands that appeared in at least 20 publications is shown in Table 1 and a word-cloud representation is shown in Figure 2. As a form of validation, we performed the same frequency count using all the PDF documents available through Google that contained the exact phrase "fast fashion". The corresponding ranking using the latter is also reported in Table 1.

	number of appearances in Factiva search		number of appearances in PDF online search	
Specialty apparel retailer	rank	% appearances	% appearances	rank
H&M	1	31.7%	41.0%	2
Zara/Inditex	2	29.2%	45.9%	1
Gap	3	11.9%	18.2%	3
Uniqlo/Fast Retailing	4	9.9%	9.4%	8
Topshop	5	9.3%	13.7%	4
Forever 21	6	7.5%	11.2%	6
Mango	7	4.3%	12.4%	5
Wet Seal	8	3.2%	0.6%	16
Benetton	9	3.1%	10.1%	7
New Look	10	2.8%	6.2%	9
Esprit	11	2.8%	4.7%	10
C&A	12	1.9%	4.7%	11
American Apparel	13	1.2%	2.6%	13
Urban Outfitters	14	0.9%	2.8%	12
Peacocks	15	0.5%	1.1%	15
Charlotte Russe	16	0.5%	0.2%	17
Armani Exchange	17	0.3%	1.5%	14

Table 1: Frequency count of specialty apparel retailers in media publications that mention fast fashion (data retrieved 26-Aug-2013). The search in the Factiva database was among 7,587 articles published in the last two years that mentioned fast fashion. The PDF search was among 466 PDF files available to download in Google.com that mentioned fast fashion.

[1] `http://en.wikipedia.org/wiki/Fast_fashion`, accessed January 17, 2014

Figure 2: Word-cloud representation of fast-fashion specialty retailers based on number of appearances in Factiva search (cf. Table 1). The figure was generated by wordle.net.

The first remark from Table 1 is that the firms in the top 10 are the same in both lists except for Wet Seal, which is a newcomer in the fast-fashion market so it appears more often in the Factiva search because the articles are more recent. Second, from Table 1 and Figure 2 it is clear that H&M and Zara stand out with a number of appearances that outshines the rest. Therefore, it is safe to say that these two specialty retailers embody what fast fashion is or at least they are widely recognized as the exemplary representation of fast fashion. H&M is a rather secretive company that does not disclose its operations but the annual report describes H&M's business concept as "fashion and quality at the best price" (H&M 2012). On the other hand, Zara has been repeatedly studied and its mode of operation has been widely documented, see Ferdows et al. (2002), Ghemawat and Nueno (2003), McAfee et al. (2004), Lewis et al. (2004) or Caro (2012).

Zara – and H&M to a similar extent – have undertaken a radical change to the design cycle in order to provide fashion almost on demand. Specifically, these retailers have chosen to work at the item level – which includes all the sizes and colors of a given garment – rather than using collections. They can do this because they do not have a wholesale channel that is demanding a full collection, and they control the retail point of sales. Such control structure allows them to avoid batching thousands of products together. In particular, it is no longer necessary to design together products with quick and slow supplier lead times. In the words of H&M: "The time from an order being placed until the items are in the store may be anything from a few weeks up to six months. The best lead time will vary. For high-volume fashion basics and children's wear it is advantageous to place orders further in advance. In contrast, trendier garments in smaller volumes have to be in the stores much quicker" (H&M 2007).

Overall, the lead time of each product in the assortment depends on where it fits in the *fashion triangle* (see Figure 3). At the bottom of the triangle are basic products. These items are the perennial products that are present at the store year after year with slight variations in design, such as a grey pullover or a white t-shirt. Basics are typically sourced in large quantities from low-wage countries and have long lead times. The center of the triangle is composed of fashion-basics or updated classics, which represent "basics with a feel for fashion" (H&M 2010). Fashion-basics have some fashion component – e.g., a non-traditional cut or a special trim – but they are produced as basics in varying volume. The line between basics and fashion-basics can be blurry. Moreover, since they share the same lead times, they tend be lumped in one category (which for ease of exposition we refer to as basics). At H&M, basic items roughly represent 70% or more of the product assortment. At Zara, basics have increased from less than 20% in the late 90's to 40% or more nowadays.

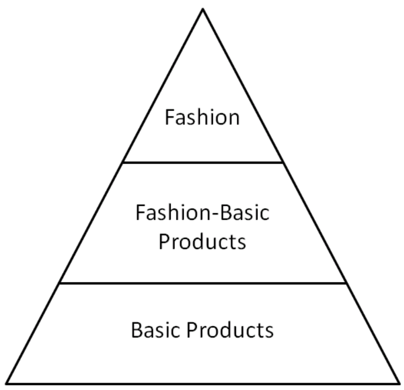

Figure 3: The fashion triangle. Based on Abernathy et al. (1999).

The top section of the fashion triangle corresponds to the (true) fashion products. For these items, H&M and Zara have typically used *quick-response* production to reach stores as soon as possible, thereby allowing them to respond to nascent demand trends first, so as to provide and capture more value from the consumers. This requires them to accelerate the production phase – using near-shore suppliers close to market in countries such as Portugal, Morocco, Bulgaria, Romania or even Turkey – and also the design phase, by directing the creative aspects towards a commercial need to reduce design iterations, and by using standard methods and materials to reduce efforts on samples. As a result, the total design-to-market time for an item to be launched in January can be reduced to a mere 6 weeks if the appropriate fabric is used and the go decisions (authorizations to move from sample to industrialization) are not delayed. In a way, they are like a surfer that is able to catch a wave before any other notices it. Figure 4 compares the planning process of fashion versus basic products (this figure also serves as a comparison with respect to a more traditional collection-based retailer that only carries basic items). The coexistence of fashions and basics calls for a dual supply chain. Moreover, the two types of products play different marketing roles. The fashion products generate customer traffic, sometime even playing the role of a loss leader, whereas the basics bring in the revenue.

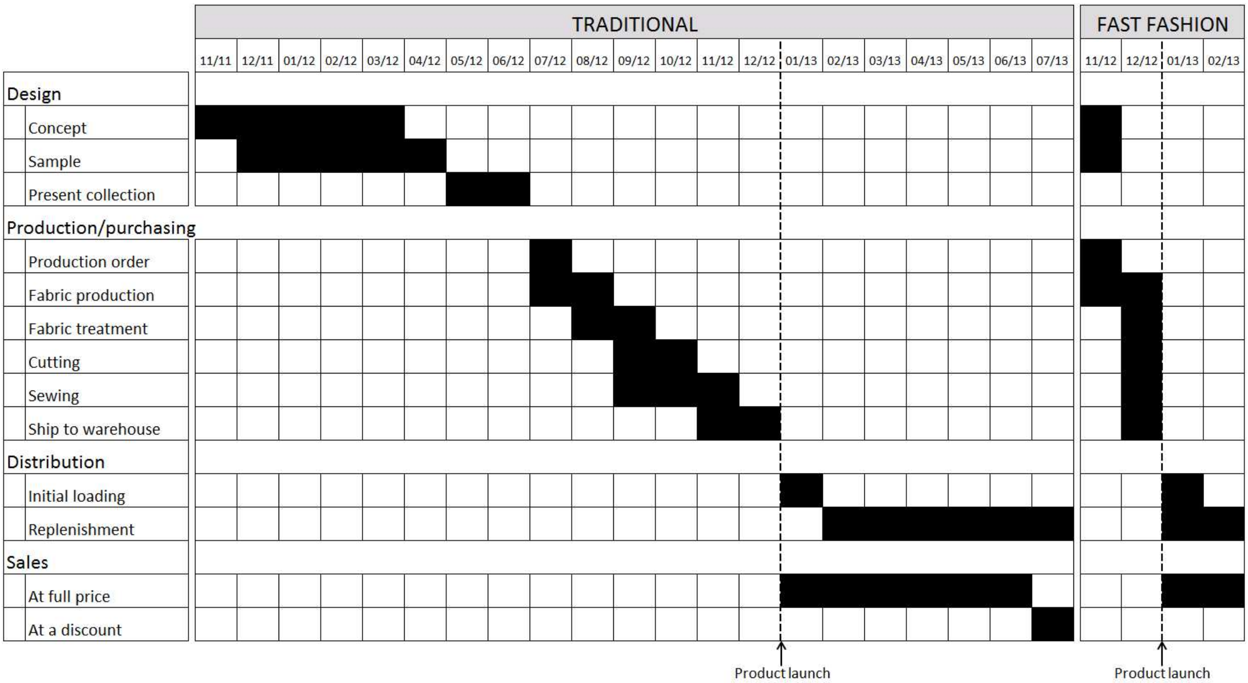

Figure 4: Traditional vs. fast-fashion design-to-sales processes for a product introduced in January 2013. Source: Caro and Martínez-de-Albéniz (2013).

An important advantage of working at the item level is that it gives the freedom to introduce products in the store continuously, not only twice a year. This implies that the utilization of all resources – designers, factories, distribution – can be balanced better over time, avoiding unnecessary peaks twice a year (see Figure 5). Costs and response times can thus be reduced. The frequent assortment changes are also necessary for fashion items to keep up with the trends. Indeed, a retailer like H&M "buys items on an ongoing basis throughout the season to optimise fashion precision" (H&M 2011). Therefore, fast-fashion retailers combine supply chain agility to respond quickly, and constant product introductions to attract variety-seeking/fashion-conscious customers. It is these two key features –

operational agility and time-based variety – that we use next to measure the execution of the fast-fashion business model.

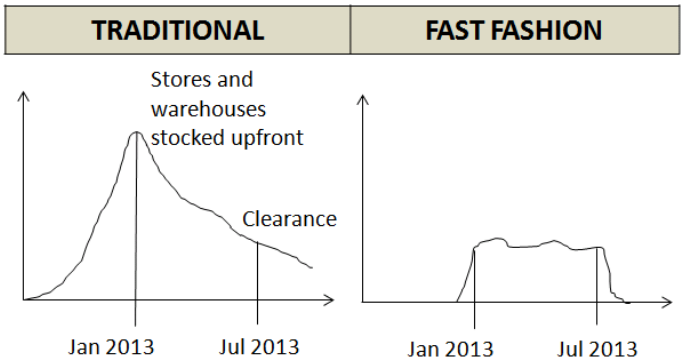

Figure 5: Resource (designers, factories, distribution) utilization in a typical season.

1.2 Defining and Measuring Fast Fashion.

Based on the discussion above, fast fashion can be defined as a business model that combines three elements: (i) quick response; (ii) frequent assortment changes; and (iii) fashionable designs at affordable prices. Note that the first two elements are fundamentally operational and allow the execution of fast fashion, whereas the last element represents the value proposition that the operational backend strives to deliver. Though this definition is quite broad, it does put a boundary and it leaves out several (fashion) retailers that sometimes are mistaken as being fast fashion. For instance, the fashion powerhouse Prada sells at a much higher price point – and the responsiveness of its supply chain is unclear – so it would not be fast fashion according to our definition. On the other end, there are many retailers that sell at affordable prices but they do not qualify as fast fashion either. For instance, Old Navy has very competitive prices but lacks quick response capabilities; or in the case of Chico's, the assortment is refreshed regularly but the products are mostly basics and fashion-basics (Chico's 2012).

The first two elements in our definition – namely, quick response and frequent assortment changes – characterize a fast-fashion supply chain, and for that reason we devote more attention to them in this book chapter and we postulate metrics to measure their effectiveness. Since the purpose of quick response is to reduce markdowns and stockouts, its effective implementation should lead to a better gross margin and less inventory. Therefore, an appropriate metric to measure the effectiveness of quick response is the gross margin return on inventory (GMROI), which is defined as the ratio between the gross margin and the average, where both quantities are measured at the aggregate firm level. The GMROI metric is largely used among retailers but several other ratios could serve the same purpose. For instance, Hausman and Thorbeck (2010) use Operating Income/Inventory as a markdown/stockout performance metric.

Measuring the dynamic assortment capability is less straightforward. Ideally, one would want to monitor and keep track of the product assortment on display at the stores, but collecting this data is impractical. Instead, we resort to the online stores in the USA. Specifically, for each specialty apparel retailer we considered the "new arrivals" of the Women's section and counted how many items were less than a week old. In other words, we counted the number of products that had become available less than a week ago. We disregarded variations in color and prints to only count those products that were really new introductions. Then, we took the average over a 20-week period.[2]

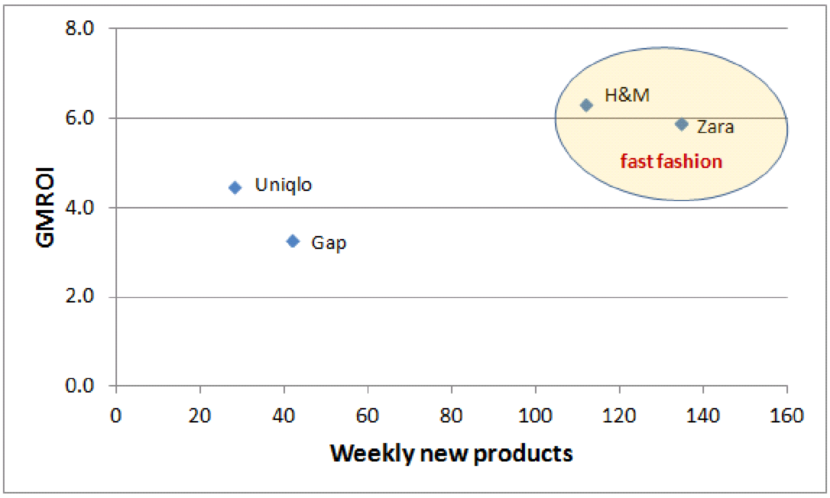

Figure 6: GMROI versus the average number of weekly new products introduced by mid-to-low price specialty apparel brands. GMROI is a 5-year average. For Zara and Uniqlo we report the GMROI of the holding company (Inditex and Fast Retailing, respectively).

In Figure 6 we plot the GMROI versus the weekly number of new arrivals for the top 4 specialty retailers in Table 1, which are publicly traded companies (the three retailers that follow on the list are privately held). It is noteworthy that Figure 6 confirms that H&M and Zara are "in a different ball game" compared to Gap and Uniqlo. Not only do H&M and Zara have better dynamic assortment capabilities – in the order of 120 new product introductions per week on average – but they also get more margin out of their inventory, roughly 50% better GMROI, which speaks to their ability to respond quickly with the right

[2]Zara has a separate section for Women in their teens (TRF), which we included in the count. The other retailers in the study have a single section for Women that includes teenagers.

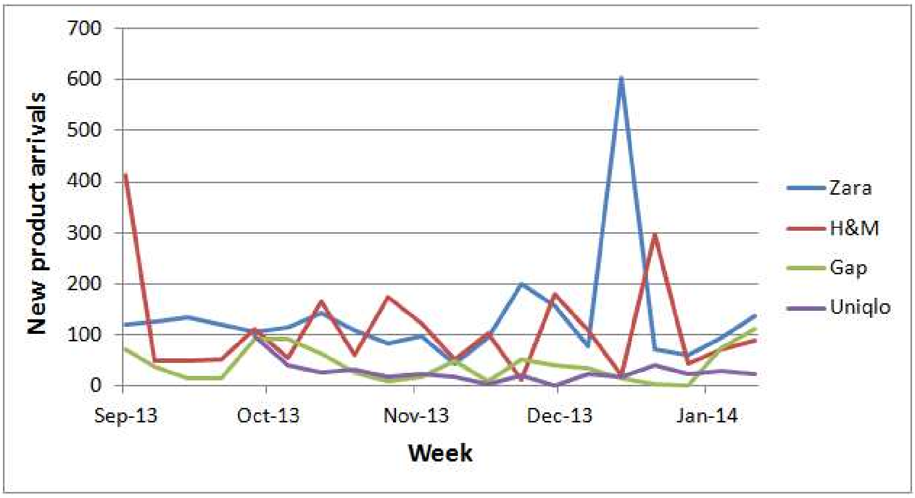

Figure 7: Weekly new arrivals in the Women section in Fall 2013.

product/quantity so markdowns are less of an issue.[3] It is also interesting to observe from Figure 6 that, though there is not a straight correlation between new arrivals and GMROI, there does seem to be a few local "sweet spots". In fact, H&M and Uniqlo introduce less products than their nearest competitor (Zara and Gap, respectively) and manage to achieve a higher GMROI. Finally, Figure 7 shows the new arrivals over the 20-week period considered. Both Zara and H&M have big spikes when a new season is launched, but during the season Zara's assortment rotation tends to be more stable with a standard deviation of 37 new products versus 53 for H&M.

The reminder of this book chapter is structured as follows. Sections 2 and 3 explore in depth the literature on quick response and dynamic assortment, respectively. In section 4 we survey papers related to the design and pricing strategies of fast-fashion retailers. We conclude the chapter in section 5 by discussing ongoing challenges for fast-fashion retailers and we identify future research opportunities.[4]

2. Sourcing and Quick Response

Quick Response (QR) was developed in the textile and apparel industry and since then it has been a prominent topic in Operations Management. QR was originally a set of standards for information exchange and supply chain management that allowed lead times to be shortened and increased supply chain efficiency (Palmer and Markus 2000). Over time, the use of

[3]Topshop and Forever 21 introduce three times more products than H&M and Zara but it is unclear whether that pays off because their GMROI is unavailable.

[4]We focus on analytical and empirical research. For more qualitative work on fast fashion, we refer the reader to Choi (2013a).

the term QR has evolved into a broader interpretation, which is conceptually very simple: postpone all risky production decisions, e.g., commit to purchases that may not be needed in case of low sales, until there is enough evidence that the market demand is there. QR thus allows to reduce finished goods excess inventory, although per-unit costs (manufacturing and shipment) may increase. The concept is related to postponement and delayed differentiation (Feitzinger and Lee 1997, Lee and Tang 1997), as QR often requires holding raw materials ready to be died, cut and sewed after item-level demand forecasts have improved.

The early literature on QR, such as Iyer and Bergen (1997) or the classic Sport Obermeyer paper by Fisher and Raman (1996), centered on a single firm and brought to light the value of early information. Further academic contributions around QR for a single firm have focused on two main issues: advanced models for demand uncertainty and in particular how forecasts are improved over time; and integrating production constraints into the decision models. In addition, competition and externalities on the supply chain have been studied as well. Finally, empirical research is a promising new field of work for QR.

2.1 Demand forecasting

Information is a key driver of QR decisions. It is widely accepted that it is impossible to forecast fashion at the item level a priori (Christopher et al. 2004). The only feasible approach is to start selling the product and use early sales data to generate more reliable forecasts. Dynamic demand models are thus required. Iyer and Bergen (1997) consider a model where demand is normally distributed with mean θ and standard deviation σ, where θ itself is unknown and follows a normal distribution with mean μ and standard deviation τ. Early sales will provide more accurate information on θ, which will help improve the demand forecast. Hence, if no information about θ is available, then demand is normally distributed with mean μ and standard deviation $\sqrt{\sigma^2+\tau^2}$. But if early sales d_1 are available, the demand forecast becomes normally distributed with mean $\mu(d_1) = \frac{\sigma^2}{\sigma^2+\tau^2}\mu + \frac{\tau^2}{\sigma^2+\tau^2}d_1$ and standard deviation $\sqrt{\sigma^2+\frac{1}{\rho}}$ where $\rho = 1/\tau^2 + 1/\sigma^2$, i.e., smaller than $\sqrt{\sigma^2+\tau^2}$. Hence, the higher $\tau^2\rho$ (i.e., the higher τ/σ), the better the forecast improvement due to observation of early sales. Fisher and Raman (1996) suggest a similar model where demand arrives in two time-windows: early and late sales follow a bivariate normal distribution and, after observing early sales, the distribution of late sales is updated. This updating scheme generally falls under the Martingale Model of Forecast Evolution (MMFE), see Heath and Jackson (1994). Other models have been used too. In particular, Lago et al. (2013) use a demand model where demand is exponentially decreasing over time, with an uncertain rate which is only revealed after the product is introduced. Demand is decreasing because inventory levels are reduced over time, thus decreasing the display, availability and consequently sale of the items. Higher rates imply that products sell out faster.

2.2 Production

The other main ingredient of QR is the consideration of production factors. Fisher (1997) provides a high level picture of the different types of supply chains, from efficient (long lead-times and rigid production schedules) to responsive (short lead-times and flexibility). If production costs are linear and there are no volume constraints, the problem is a relatively simple extension of the newsvendor model, see e.g., Martínez-de-Albéniz (2011) or Song and Zipkin (2012). The main trade-off there is to balance the higher costs of QR orders with the higher exposure to excess inventory costs of early orders. Specifically, letting q_1 be the early order quantity and q_2 the QR order quantity, and assuming that QR orders can be placed after demand D is realized, we can formulate the problem as follows:

$$\max \mathbb{E}_D \Big[p \min\{D, q_1 + q_2(D)\} - c_1 q_1 - c_2 q_2(D) \Big]$$

where p is the revenue per unit, and $c_1 \leq c_2$ the per-unit production cost of early and QR orders respectively, both less than p. It is optimal to set $q_2(D) = (D - q_1)^+$ and q_1 satisfying the critical fractile equation $Pr[D \geq q_1] = c_1/c_2$. Thus, if costs are relatively similar, QR orders will dominate, while if costs are very different, QR orders will be seldom used. Beyond this simplistic model, Fisher and Raman (1996) incorporate relevant apparel production constraints: minimum order quantities and capacity constraints. These are strong drivers of QR orders: QR capacity constraints imply that inflating early orders is desirable; minimum order quantities introduce binary decisions into the problem, which may reduce or increase early and QR orders, when the unconstrained order quantity is below the minimum. They describe an application to the Sport Obermeyer case study. Fisher et al. (2001) consider the possible cost of back-ordering between issuing and receiving the QR order, which makes the optimization problem intractable (expected profit is neither convex nor concave), so they suggest a heuristic and describe an application to a catalog retailer. A practical implementation of advanced optimization is suggested in Agrawal et al. (2002), who develop a methodology for managing a portfolio of retail products with different lead time requirements by using vendors that differ in costs and production flexibility.

2.3 Competitive implications

Given the prevalence of QR, an essential step in the analysis is to consider how the practice changes firm behavior under competition. Indeed, QR was conceived as a competitive strategy expected to change "the rules of the game", in the words of Hammond and Kelly (1990), similar to what just-in-time manufacturing had meant to the auto industry.

A key paper in this line of work is Caro and Martínez-de-Albéniz (2010). They present a two-period model where firms make inventory decisions taking into account that demand will spill-over to the competitor whenever there is a stock-out. The two-period setting allows for demand updates, which is a fundamental feature of QR. Moreover, motivated by the emergence of fast-fashion retailers and their co-existence with more traditional apparel retailers, Caro and Martínez-de-Albéniz study in particular the asymmetric game where only one firm has the QR capability while the other firm uses "slow response" (SR) and cannot leverage early demand information. The main contribution of the paper resides in the insights for the asymmetric duopoly. It is shown that in equilibrium the QR firm will stock less while the SR firm will stock more compared to the case when both firms are SR (see Figure 4 in the paper). The dynamics of this result are quite interesting. If the QR competitor committed to a high inventory level, the SR firm would actually want to stock less (see Proposition 3), but since such kind of commitment is not credible, there is an opportunity for demand spill-overs that the SR firm seizes by stocking more. These spill-overs turn out to work well for the QR competitor since it depletes inventory that would otherwise be carried over to the next period. So, by stocking less the QR competitor lets the SR firm take most of the inventory risk upfront, and even in those scenarios where demand in the initial period is high, the QR firm benefits because then it faces less competition in the last period. This effect becomes even more pronounced with demand correlation because the QR firm can also learn at the competitor's expense. Though both firms move their inventory in opposite directions, it is shown that in equilibrium the aggregate industry inventory level decreases.

Another important implication from the paper is that with equal costs, QR is a dominant strategy. In other words, QR is a no-brainer regardless of the competitor's actions. This adds another layer to the significance of QR and gives a stronger message to firms that are yet to adopt it. Of course, a QR firm would be better off competing against a SR firm rather than another QR firm, which confirms that QR provides a competitive advantage. What is not so obvious is that a SR firm would prefer a QR over a SR competitor. This is due to the spill-overs in the first period that can favor the SR firm, so the asymmetric scenario can be beneficial to both competitors.

It is also possible that QR might involve higher costs (e.g., due to expediting or local production). In that case, Caro and Martínez-de-Albéniz show that QR pays more for "fashion" goods while SR is better for "basic" items with low demand variability or low correlation across periods. This is an analytical confirmation of the fundamental rule that the supply chain should match the type of product (Fisher 1997). Interestingly, the paper shows that with unequal cost structures the asymmetric competitive scenario can still be preferred by both competitors, and this continues to hold true even when the firms endogenously choose their supply chains. This provides support for the co-existence of QR and SR retailers observed in practice. Nasser and Turcic (2013) analyze a similar context and also observe an asymmetric equilibrium when the competing firms offer products with an intermediate level of differentiation.

Another related paper that studies QR under competition is Lin and Parlaktürk (2012). They propose a two-period production model where two retailers compete in a Cournot setting. Namely, the market clearing price is $A - \sum_{i=1}^{2} X_i$ where A is an uncertain parameter, and X_i is the quantity brought to market by retailer i. They analyze different scenarios where none, one or both retailers have access to QR from the manufacturer, and study the manufacturer's optimal pricing strategy. They find that for the manufacturer it may be best to offer QR to just one or to both retailers. In addition, in contrast with Caro and Martínez-de-Albéniz (2010), they show that QR can hurt a retailer when demand uncertainty on the market potential (parameter A) is low. This effect is due to the fact that a retailer without QR can credibly inflate its initial order, thereby forcing the fast retailer to reduce its order, and hence its profits.

2.4 Impact on consumers and suppliers

It is worth pointing out that there are several papers studying the externalities of QR on other stakeholders within the supply chain. Cachon and Swinney (2009) study the effect of QR on strategic consumers, those that may delay their purchases until the discount season, where price is lower. They show that, by reducing the amount of early orders, QR decreases the probability of having excess inventory at the end of the season, thereby reducing the incentive of strategic consumers to wait for discounts. As a result, QR becomes even more valuable when consumers are strategic, as opposed to myopic. The opposite effect is shown in Iyer and Bergen (1997) when there is an intermediary (e.g., a retail partner such as department store) between the manufacturer using QR and customers. Indeed, the manufacturer adopting QR may lose sales from the retailer, its "sell-in" (as opposed to the "sell-out" from retailer to final consumers). This is because, without QR, the retailer may be ordering a very high sell-in and taking most of the inventory risk, while with QR, it may reduce the expected sell-in to shift all the demand risk to the manufacturer. The way to make the transition to QR profitable for both retailer and manufacturer is then to put in place quantity discount or volume commitment schemes. Krishnan et al. (2010) incorporate retailer effort considerations: the retailer usually puts an effort that can influence the pace of sales. With such model in mind, the inventory reduction associated with QR will reduce the risk of excess inventory costs, thereby requiring less effort from the retailer's part, which may switch it to competing products. As in Iyer and Bergen (1997), the final outcome is that QR may be detrimental to the manufacturer, unless new contracts (beyond flat wholesale pricing) are put place. Finally, the impact on supplier pricing has also been studied in Calvo and Martínez-de-Albéniz (2012). They present a model where a retailer makes use of dual sourcing (advance orders with a slow, efficient supplier; and QR orders with a fast, more expensive supplier). The price quotes from the suppliers are endogenous to the retailer decisions regarding procurement. Specifically, if the retailer commits to single sourcing, then prices may in equilibrium be lower than if the retailer accepts to place both early and QR orders, which results in the retailer sometimes being worse off. This implies that using QR also removes pressures for both slow and fast suppliers to keep prices low, which may deteriorate overall retailer and supply chain performance.

2.5 Empirical work

Finally, there is scarce empirical literature on QR. So far, the only exception is Lago et al. (2013) who evaluate the value of QR sourcing. They study the sales of products of a fast fashion firm over the Fall-Winter 2008 season. Each item, defined by a model and a color, may be introduced at a different time, and may be sourced from a different origin (from East Asia, South Asia, East Europe, West Europe or North Africa). Such input variability allows Lago et al. to study how product performance, measured by the speed of sales, depends on different factors. They focus on the interaction between time of design and sourcing origin. Their results confirm most of the intuitions about QR: an item with a shorter time-to-market (Europe or Africa for the company under study) sells faster; and the speed-of-sales difference between QR and slow production is higher early in the season, thereby confirming that firms can learn as the season advances. Furthermore, the paper provides quantitative estimates of the advantage of QR. Namely, a product sourced under QR sells about twice as fast compared to one sourced with long lead-times. This provides a strong business case for QR if the sourcing cost difference is small compared to the value of inventory and space at the store.

3. Dynamic Assortment

Besides QR, the other main difference between fast fashion and traditional retailing is the way assortments are managed. Indeed, for many years the industry has worked around the concept of collections. Assortments are updated twice a year: at the beginning of the calendar year, the Spring-Summer collection is introduced; at the end of the summer the Fall-Winter collection is released. This industry-wide pace of change has been supported by design (cool hunting), communication (catwalks and store mock-ups where media and wholesale customers are invited), sales and marketing (catalogs, advertising) that follow similar bi-annual patterns. As a result, assortment planning with this approach can be considered as static. The chapter by Kök et al. (2014) in this handbook discusses extensively the academic literature around that problem.

In contrast, fast-fashion players rely much less on collection advertising and wholesale channels. As a result, they are able to design, produce and distribute new products dynamically, both at the beginning and the middle of the season. This raises interesting research problems that have only been explored recently.

One line of work extends the static assortment problem to multiple periods and incorporates demand learning. The set of products that can be included into each period's assortment is typically fixed, and the focus is on balancing exploration, i.e., including a product in order to learn about its demand rate, and exploitation, i.e., including a product with high demand rate and thus high profit. Caro and Gallien (2007) is the first paper to develop such a model, using a multi-armed bandit formulation. They decouple the dynamic assortment problem into a set of single-product dynamic programs and propose an index policy such that, in each period, only the products with the highest index should be included. The index includes both information about the expected demand rate and the potential value of better information on demand. Rusmevichientong et al. (2010) include a capacity constraint and design an algorithm for the dynamic problem, where parameters are estimated in parallel with revenue generation. Sauré and Zeevi (2013) focus on the asymptotic performance of such algorithms. Farias and Madan (2011) introduce an irrevocability constraint, i.e., a product cannot be introduced again after it is removed; they design a heuristic that performs well. Alptekinoglu et al. (2011) use a locational model with unknown demand distributions that can be discovered by varying the assortment over time. All these papers assume that the demand parameters are stationary and need to be learnt.

Three important features are missing in the papers above: new products may be introduced also in the middle of the season, not all at the beginning; they cannot be introduced, removed and introduced again (Farias and Madan 2011); and demand is not stationary but typically decreases over time because, at the store, new products typically get better displays and generate more interest than older ones, everything else being equal.

Some recent papers have recognized that demand may change over time. Caldentey and Caro (2010) assume they follow a stochastic process over time, which they call the "vogue". Caro and Martínez-de-Albéniz (2012) use a satiation model where consumers progressively move away from stores that do not refresh their assortments often enough. But Caro et al. (2012) is the first paper to consider the three elements from above together in assortment planning. They take the entire set of products I as given and decide when each should be introduced over the season. The products compete for customer attention, and to capture such effect a demand attraction model is proposed: in period t, if product $i \in I$ is included in the assortment, its demand will be equal to $v_{it}/\left(v_0 + \sum_{j \in S_t} v_{jt}\right)$, where S_t is the set of product present in the assortment in period t, and v_{jt} is the attractiveness of the product in the period. Moreover, to incorporate decreasing demands over time, once introduced a product's attractiveness varies dynamically: $v_{jt} = \kappa_{j,t-intro_j} v_j$, where v_j is the attractiveness of the product when it is first introduced and $\kappa_{j,l}$ is the decay parameter that depends on the age l of the product. The focus of the paper is put on exponential attractiveness decays, i.e., $\kappa_{j,l} = \kappa_j^l$ with κ_j the decay parameter. Note that this demand model is supported by real sales data, as shown in their paper. It has also been used in describing the box office sales of movies (Ainslie et al. 2005). The parameters $v_j, \kappa_{j,l}$ are product characteristics, inputs into the model, as well as r_j the per-unit margin of product. Letting α_t denote the market size of period t, the optimization problem of Caro et al. (2012) can thus be written as an integer program:

$$
\begin{array}{lll}
\max & \displaystyle\sum_{t=1}^{T} \alpha_t \sum_{i=1}^{n} r_i \times \left(\frac{v_i \sum_{u=1}^{t} \kappa_{i,t-u} x_{iu}}{v_0 + \sum_{j=1}^{n} v_j \sum_{u=1}^{t} \kappa_{j,t-u} x_{ju}} \right) & \\
\text{s.t.} & \sum_{t=1}^{T} x_{it} \leq 1 & \forall\, i \in I, \\
& x_{it} \in \{0,1\} & \forall\, i \in I, t = 1, \ldots, T.
\end{array}
$$

Caro et al. show that the optimization problem is in general NP-complete. They propose a fluid approximation that can be solved easily and can also be used for developing heuristics. In particular, the fluid approximation is a concave nonlinear maximization problem when product margins are identical; otherwise, the problem may not be concave, but their numerical study suggests that the optimal solution can be found quickly. Some appealing insights are derived: when decays are exponential and margins identical across products, the approximation's optimal solution is to introduce the products with less decay (i.e., higher κ_j) first. This implies that basic products, with stable demand, should be introduced in the beginning of the season. In contrast, fashionable products for which customer interest quickly drops should be spaced over the entire season and used to refresh the assortment. Moreover, Caro et al. show that the heuristics based on the fluid approximation generally perform very well, even when margins are not identical.

The framework presented in Caro et al. (2012) can be extended to capture most of the realities of fast fashion. In particular, rather than taken the set I of possible products as a given, it is important to let the retailer decide whether a new product should be designed and introduced in the middle of the season, depending on the most recent information. In other words, the model should incorporate closed-loop controls into the assortment decision. Çınar and Martínez-de-Albéniz (2013) propose a dynamic programming formulation to allow for such closed-loop decisions. Instead of binary introduction decisions, they allow for continuous amounts of products u_{it} to be introduced in category $i \in I$ in period t. These depend on the current attractiveness present in category i in period t, denoted x_{it}. As a result, the profit-to-go of the retailer in period t, J_t, can be written as $J_{T+1} \equiv 0$ (terminal condition) and

$$\begin{aligned} J_t\Big((x_{it})_{i\in I}\Big) = \max_{u_{1t},\ldots,u_{nt}\geq 0} \quad & \frac{\sum_{i\in I} r_i y_{it}}{v_0 + \sum_{i\in I} y_{it}} - \sum_{i\in I} c_{it}u_{it} + \beta\mathbb{E}\left[J_{t+1}\Big((x_{it+1})_{i\in I}\Big)\right] \\ \text{s.t.} \quad & y_{it} = x_{it} + u_{it} && \forall i \in I \\ & x_{it+1} = \tilde{\varepsilon}_{it} y_{it} && \forall i \in I \end{aligned}$$

The decay of attractiveness is similar to Caro et al. (2012), since attractiveness randomly decays with parameter $\tilde{\varepsilon}_{it}$; this extends the deterministic decay κ_j of Caro et al. However, the way of assortment attractiveness can be increased is quite different. Caro et al. improve the value of the assortment by introducing new products $i \in I$, at a date specified up-front. In contrast, Çınar and Martínez-de-Albéniz can increase the attractiveness of an existing category $i \in I$, continuously and as a function of the latest information about how much decay there has been in category i's attractiveness. The model provides some insights that are complementary to Caro et al. (2012). When category margins are identical, the problem is well behaved. Again, products that decay less will be used early in the season, even if their introduction cost is higher, while products that are cheaper but decay faster should be used more at the end of the season.

The two models above open a number of interesting research opportunities. Mainly, the nature of dynamic demand evolution needs to be better understood. Real data shows that indeed individual product sales decrease over time, as new products are introduced into the assortment. However, the detailed process of how this happens is unclear: is the age of the product the determinant decay factor? Or is it because of the decrease of inventory availability over time, as Lago et al. (2013) suggest? Furthermore, there are other drivers of demand that need to be incorporated to the demand model, such as pricing or display. The increasing amount of available point-of-sales data should definitely spark more empirical work on these questions.

4. Pricing Strategy and Fashionable Design

Fast-fashion retailers mostly sell products at affordable prices – i.e., they sell "inexpensive fashion" – so the posted prices at different retailers are usually within the same price range.[5] Therefore, the main difference in pricing strategies across fast-fashion retailers is whether they use in-season promotions and markdowns or not. H&M is an example of the former whereas Zara follows the latter and avoids price changes during the selling season. Regardless of the in-season policy, fast-fashion retailers usually have well-announced clearance sales at the end of the regular season in which markdowns are introduced to liquidate stock and free up space for the new season.

The theoretical research on pricing for fast fashion has centered on price positioning and pricing strategies. On the former, Caro and Martínez-de-Albéniz (2012) present a model in which firms compete on price and product "freshness". Specifically, an inter-temporal utility model is introduced to account for product satiation. The satiation effect is incorporated through a retention factor that captures the carryover effect of consumption from one period to the next. In plain words, the retention factor measures how fast the consumer is willing to consume again. Offering a less satiating product – i.e., one with a lower carryover effect – is costly but it attracts more customers. When firms are symmetric, it is shown that there is a product strategy that is mostly dominant and firms can essentially ignore competition. However, this no longer holds if a firm breaks the symmetry by improving its processes to offer a fresher product. An important finding is that firms price incorrectly and are worse off when they ignore product satiation. Moreover, firms should aim at developing capabilities to offer less satiating products more efficiently, but since all firms have the same incentive, major improvements might be needed to guarantee an increase in profits. Interestingly, depending on the current cost structure and the magnitude of the improvements, all firms

[5] Note that H&M, and especially Zara, have deviated from the "affordable" pricing strategy to enter Asian countries – most notably Japan and China – where they are perceived as high-end European brands that signify status and therefore consumers are willing to pay a price premium.

can be better off after a "product war". This result is in contrast to price wars, which always hurt profits. Caro and Martínez-de-Albéniz (2009) present a variation of this model that relates satiation to assortment rotation, which is how fast-fashion retailers counteract product satiation in practice.

A separate stream of literature has focused on how to price fashion or seasonal products when consumers are forward-looking, in the sense that they anticipate the usual markdown policy used by retailers and might wait until prices goes down. The consumers' logic is quite simple: if nobody buys early, then the retailer will be forced to decrease prices. Su and Zhang (2008) show that a price commitment strategy in which the retailer makes a credible commitment not to lower prices can be effective in deterring consumers' strategic behavior. An alternative and equally effective strategy is allowing markdowns but rationing capacity (Liu and van Ryzin 2008). The latter resembles Zara's practice of having limited production to create shortages and induce consumers to buy at the regular season price. In the same vein, Liu and van Ryzin (2011) study rationing strategies when consumers can learn over repeated seasons and Yin et al. (2009) analyze strategies that restrict inventory display in order to create a perceived sense of scarcity.

Fashionable design is the last element of fast fashion that has not been discussed so far. This subject has been almost absent in the operations literature, and for a good reason since design is the part of retailing that has remained closer to an art rather than a science, at least until now. One paper that does deal with design at a high level is Cachon and Swinney (2011). This paper looks at whether the quick-response and (enhanced) design capabilities of a fast-fashion retailer are strategic complement or substitutes under the presence of forward-looking consumers. Though there are some exceptions, for the most part the paper shows that the two elements are strategic complements, which confirms that fast fashion is really an "all or nothing" proposition.

The economics and marketing literature has delved further into the drivers and dynamics of fashion. Sproles (1981) provides a comprehensive survey of the different – and sometimes competing – perspectives that try to explain the "fashion process". These perspective differ on the level at which the fashion process takes place (individual or societal) and whether the factors driving the process are endogenous or exogenous. Miller et al. (1993) categorize the different perspectives in a conceptual framework, which they formalize mathematically in a system of difference equations that are able to explain several of the fashion trends described in the literature. Pesendorfer (1995) provides an alternative model of fashion cycles in which fashion designs are used as a signaling device in a matching game. Consumers adopt fashions to show that they are "in" and the widespread adoption leads to lower prices, giving the firm selling fashion an optimal time for innovation. Kuksov and Wang (2013) build on the signaling idea and show that in equilibrium consumers randomize over designs, which explains fashion's "unpredictability". From an empirical standpoint, not too many attempts have been made to validate the theoretical findings. A few exceptions are Yoganarasimhan (2012) and Martínez-de-Albéniz and Sáez-de-Tejada (2014) who use decades of data to analyze the presence of fashion cycles in the choice of names for newborns and Nunes et al. (2012) who study how fashion designs evolve based on the feedback from critics and reviewers. The lack of data is frequently cited as a reason that has prevented further empirical studies, but this is likely to change with the recent surge of social media where fashion dynamics can be tracked more easily (e.g., see Wang et al. 2013).

5. The Evolution of Fast Fashion

We began this chapter by noting that fast fashion has changed the industry dynamics significantly in recent years. We have outlined the set of practices that characterize fast fashion: sourcing with quick response and assortment planning with dynamic in-season introductions. Beyond these intrinsically operational levers, fast-fashion retailers have adopted alternative pricing and product strategies. We have discussed in detail all these elements in this chapter. But this overview would not be complete without a discussion on the current trends around the fast-fashion phenomenon, as well as the related research questions that arise from its evolution. Indeed, the fast-fashion model keeps evolving. There are numerous trends that retailers must take into account and that are affecting the operational implementation of fast fashion.

5.1 Leveraging business analytics

Business analytics is one trend that seems poised to grow in importance. It has gained notoriety with the copious amount of data that has become available lately, but the underlying concepts and techniques are not new to retailing. Good examples include Smith et al. (2001) and Fisher and Raman (2010). Though data-driven decision making is arguably relevant to any retailer, it is becoming a necessity for fast-fashion retailers that want to excel operationally, and in particular want to scale their internal processes to sustain continued growth. Zara, for instance, has taken up the challenge and since 2005 it has embedded model-based decision making into its daily operations. Caro et al. (2010) and Caro and Gallien (2010) describe a model developed and implemented at Zara to optimize the allocation of scarce inventory across its global network of stores. An interesting feature of the model – and quite unique to Zara – is how the model accounts for the interaction between the inventory levels of the different sizes of a given garment. The model aims at keeping the key sizes in stock to avoid negative customer perception and to ensure that the overall product remains on display. The use of the model led to a 3-4% increase in sales.

Zara has also ventured into business analytics to optimize clearance sales. Caro and Gallien (2012) describe in detail the implementation of a model-based decision support system for markdowns at Zara. Though this is a classic revenue management problem, there are at least two distinguishing characteristics: (i) the model considers multiple items which contrast with most of the literature that focuses on a single item; and (ii) the lack of in-season price response data poses a challenge that is overcome by leveraging past season data combined with an adaptive procedure. The model was tested in a controlled field experiment with a symmetric design in which half of the assortment in Ireland was priced using the model and half was priced manually. The same happened in Belgium but with the opposite pricing methods. The rest of Western Europe was priced manually and was used a baseline. Using double differences to control for confounding effects, it is shown that the model increased clearance revenue by 6%, which amounted to $90M in 2008.

Despite some isolated efforts, there is room for more research focused on business analytics in fast fashion. In particular, it would be interesting to see how business analytics can enhance the fundamental operational capabilities that define fast fashion, even more so as retailing evolves rapidly and steadily to cater to omni-channel consumers.

5.2 Creating or following fashion trends

The most intriguing changes are happening in the design space. What initially gave birth to the fast-fashion model was the rapid and unpredictable changes of what customers want. These fickle trends are getting more numerous and shorter. Thus, quickly identifying a nascent trend becomes vital to retailers. Currently, fast-fashion players rely mostly on own sales data and competitor intelligence – i.e., paying attention to their new releases, in particular to determine whether these are successful – as an input for design. But this means that the original design decision, whether it was internal or at a competitor, was a wild guess that was not customer-driven. This may change: we have seen some design crowdsourcing platforms appear, a form of open innovation (Salfino 2013). For example, Threadless was started in 2000 and now boasts a community of over 2 million creators that can post their print designs on the Threadless website. Each week, the company selects the most voted designs for production, i.e., printing over T-shirts, hoods, tops, etc. The designer is rewarded with USD 2,000, plus additional payments for every reprint (Pozin 2012). Over 500,000 designs have been submitted to date and 1% of them have been chosen for production. ModCloth uses a similar model, except that designs are not only prints, but full product specifications including fabric, cut, etc. This online retailer was started in 2002, and currently gathers 700 independent designers and suppliers, who create and keep ownership of original product designs. Once a design is ready, it is posted on modcloth.com and online customers can rate it. Successful products are then manufactured; this task's responsibility falls on the designers/suppliers (Indvik 2013). Similar initiatives have been tried out of apparel retailing too. The Danish toy company Lego experienced in 2006-2012 with DESIGN byME, an online platform where users could submit their brick construction designs and Lego would custom produce them (Lego 2012). Popular designs could then inspire mass production designs. Furthermore, it is worth noting that the examples above introduce a pure pull logic into the design process, where design is only approved after sufficient people have endorsed it.[6]

Models with a clear push logic also exist. For example, JustFab is a subscription service for shoes and accessories where users initially take a test to learn their fashion preferences, and later on are offered customized assortments that fit their tastes (Chang 2011). The company's role is thus to curate new designs that each user will like. Since the assortment is constantly renewed and prices are rather low, some investors have called this subscription model "the new fast fashion" (Reuters 2013). Another business model known as *flash sales* also has a push logic and borrows elements of fast fashion. Flash sale websites offer "one deal a day" in which a selection of fashion items are sold at a discount for a very short period of time (usually less than a day). Imposing a narrow time window serves the same purpose than limiting inventory: it creates a perceived sense of scarcity and stimulates impulsive buying. Numerous websites – e.g., Zulily, Gilt Groupe, Ideeli, Net-a-Porter, Vente Privée or Privalia – adopted this business model; so many, that the market could be drying up (Roof 2014).

From a research perspective, these changes open numerous research opportunities. Models can be developed to understand what is the best way to capture demand trends. Clearly, different approaches have different impacts in terms of demand forecast accuracy (e.g., using votes or "likes" from Facebook provides a less accurate picture than pre-orders with full payment), reach (e.g., online will reduce access costs to the consumers but will also be less targeted than physical displays at a store) and costs (e.g., virtual displays are cheaper

[6]In manufacturing, a pull system is make-to-order, whereas a push system is make-to-stock.

than real samples that require production). There are also interesting problems regarding the allocation of costs and profits, especially when retailers are the ones collecting revenues while designers are incurring the fixed costs of design, and design quality is hard to codify, so engineering effective incentive systems is a challenge.[7] Finally, understanding better how consumers dynamically choose between current styles and future ones is another interesting direction of work (Lobel et al. 2013, Bernstein and Martínez-de-Albéniz 2014).

5.3 Sourcing and corporate social responsibility

There are also various developments on the production side of fast fashion. Deciding where to produce a garment usually depends on three aspects: (i) there are technical capabilities that are product-specific, e.g., treatment of leather requires significant expertise and access to water; (ii) lead time requirements may eliminate some possible sourcing origins, although nowadays air transportation has mostly removed such constraints; and finally (iii) cost competitiveness, including materials costs, energy costs, wages and freight charges, provides the last and perhaps most important element for decision-making. Thus, determining the optimal sourcing strategy becomes a complex task, especially when most of these factors change over time. For example, wage developments in China are triggering the offshoring of production to countries such as Vietnam, Cambodia or Bangladesh (Roland Berger 2011).

Offshoring for purely economic motives raises ethical questions: it is not always clear that working conditions are appropriate. For instance, the Rana Plaza factory collapse in April 2013 showed that workplace safety standards were not being followed (The Economist 2013). Moreover, the search for low costs is usually credited as one of the reason that has pushed factories into non-compliance, with consumers' appetite for fast fashion getting much of the blame (Lamson-Hall 2013). In fact, the Rana Plaza incident immediately put H&M on the spot for being the largest exporter of clothing from Bangladesh, even though it was not directly involved with that factory (Kerppola et al. 2014). Fast-fashion retailers have been taking note, and in response are developing corporate social responsibility (CSR) policies, e.g., Inditex has a code of conduct and responsible practices, and a committee of ethics, see Inditex (2012). It is not clear how to implement such CSR measures and what control mechanisms and incentives work best. Indeed, even when CSR policies exist, they are difficult to enforce, especially when there is limited visibility as work is offshored and subcontracted. Laudal (2010) identifies sector-specific variables that drive the risk of violating CSR standards, which suggests that regulation may be more effective than individual-firm actions.

[7] Chan et al. (2013) present a method to codify and identify styles in product designs. It works well for design patents, but it might be less applicable to fashion due to the lack of IP protection.

Besides literature in business ethics, there is some nascent research in operations on these subjects – including Babich and Tang (2012), Guo et al. (2013) and Kim (2013) – but much more is needed.

These ethics concerns are starting to be shared by some consumers. Siegle (2011) and Cline (2012) point out that fast fashion is unsustainable by nature as it encourages disposability, low durability, low quality, the loss of craftsmanship and ultimately uniformity. Some hard indicators can support this observation, e.g., Allwood et al. (2006) point out that consumers in the United Kingdom throw away 30 kg of clothing and textiles per capita each year, on average. Beyond economics, in a review of Siegle's book, Anderson (2011) states that "our bulimic passion for fashion is symptomatic of a broader malaise. Disposability, instant gratification, the idea that impulses are there be indulged, regardless of impact – these sentiments permeate our lives." Some retailers are taking a similar position. For instance, Zady states that it "began with a grand vision: to combat the fast-fashion craze by providing a platform for only those companies that care about timeless style and solid construction" (Zady.com 2013); it sells products with a traceable origin. Adidas is supporting a community project in Brazil to design bags and caps with favela-inspired graphics (Clarke 2013). These critiques of fast fashion raise the question of how to make the entire business model more sustainable. Recycling is one option (Salfino 2014). From the research standpoint, there is already some work on this topic, e.g., Choi (2013b) examines how to use carbon footprint taxation to encourage local sourcing. But this is a broad research line that should be further explored, in connection with the work on closed-loop supply chains (Daniel et al. 2002).

Furthermore, if retailers continue to search for the current-day lowest-cost options, garment manufacturers choosing to close down high-wage operations and ramp up low-wage ones will experience inefficient investments (capacity installation, employee training and skill development). And it is not only a matter of costs: moving away from a region may have irreversible consequences. For instance, we have worked with an Italian jeans manufacturer that can no longer source and treat denim fabrics in Italy because most of the suppliers disappeared during the offshoring waves in the 1990s and 2000s. Similarly, there are few suppliers with QR capabilities left in Spain, after most retailers moved their QR operations to Portugal, North Africa and East Europe. It thus seems necessary to shape dynamic sourcing strategies that pay attention to cost dynamics and longer term implications, i.e., that a region's capabilities are being shaped by the retailer's sourcing decisions.

5.4 Beyond apparel

We would like to conclude this chapter by discussing how fast-fashion practices can be extended beyond apparel retailing. The general ideas behind this phenomenon apply to any industry where numerous new products appear every day and consumers are searching for novelty. One such industry is food (grocery stores and restaurants). There, the fast-fashion formula would amount to changing offers and menus to satisfy customers' desire for new tastes and to providing the items from on-the-spot sources, as opposed to long-planned supplies, e.g., fresh preparations where ingredients are combined at the last minute. Some companies already have such capabilities, e.g., Seven Eleven Japan (Matsuo and Ogawa 2007). Another such example could be consumer electronics. A fast-fashion electronics manufacturer or retailer would have to significantly reduce the time between new product introductions, and be able to install flexible production capacity so as to respond quickly to demand, with low supply chain inventories. Interestingly, releases of smartphones have been more and more frequent, and product upgrades have less to do with technology breakthroughs and more with simple added functionalities and aesthetics (Knowledge @ Wharton 2013). Many other industries may also be ripe for a fast-fashion revolution.

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