An Empirical Analysis of Sell-through in a Fashion Setting

Flores, J.E.[1], Boada, P. [2], Moscoso, P.[3]

[#]*Department of Operations Management, IESE Business School – University of Navarra*
Camino del Cerro del Aguila 3, 28023 MAdrid. Spain

[1]jeflores@iese.edu

[2]pboada@iese.edu

[3]pmoscoso@iese.edu

***Abstract*— Sell-through is a widely used performance metric in retail supply chains, but limited empirical research exists about its validity for that purpose, given its dependence on many different variables. This study analyses to what extent sell-through is influenced by fixed store attributes (e.g. store size), and what impact on this metric operational management decisions (e.g. replenishment) have. Using data collected from a fashion retailer, a sales model was developed to estimate the statistical contribution of the different types of impacts to sell-through. Results of the study provided strong empirical evidence that fixed store attributes such as store size can impact significantly sell-through levels. Operational management decisions also have a statistically significant impact on sell-through, but to a much smaller extent. This makes sell-through more valuable for compare performance when fixed store attributes are not differential.**

***Keywords*—** *Fashion industry, sell- through ratio, empirical analysis, sales estimates*

1. Introduction

Matching demand and supply at the point of sales is a key goal for fashion companies, as this will mitigate the cost of stock clearances and reduce opportunity costs of lost sales. It is a challenging goal, however, as demand usually is highly uncertain and supply chain lead times are traditionally long, making sales forecast difficult [1]. On the demand side competition has become more global and price intense over the years, and consumers more strategic in their buying behavior. On the supply side companies have tried to achieve economies of scale in production, while making their assortments more dynamic. This has resulted in complex global multi-echelon supply chains that need to be managed carefully [2].

International Journal of Supply Chain Management
IJSCM, ISSN: 2050-7399 (Online), 2051-3771 (Print)

Consequently, avoiding the demand-supply mismatch has received mayor attention both in research and industrial practice. Specifically in apparel retailing, three fundamental types of decisions have been analyzed in this regard: (1) which products to design and how many different ones (assortment); (2) how much and when to produce/buy of a particular product (sourcing); and (3) how to distribute inventory over the network of warehouses and stores (distribution) [3].

In this paper we will focus on the last type of these decision problems, the distribution. We are particularly interested in the last step of the supply chain, the allocation and distribution of merchandise to stores, and on how the supply-demand matching performance of stores can be measured and evaluated. Stores are the point in the supply chain where demand-supply mismatches received the highest attention in practice as corrective actions are difficult and costly.

The specific purpose of our study is to empirically analyze the meaningfulness of a metric that has been extensively used in retailing to assess how well demand and supply have been matched: the sell-through ratio [4]. This ratio is sometimes also referred to as sell-out or retail turnover. Sell-through is usually defined as the ratio of the quantity of merchandise sold divided by the quantity purchased, or more precisely, the fraction of all units of a given product shipped to the store since the beginning of the season that have actually been sold at a given date. The ratio can be calculated for individual SKUs or entire categories, for example, as well as for single stores or entire countries.

This research purpose originated from the collaboration with a Spanish mid-size fashion retailer that used the sell-through metric for the performance evaluation of its stores. The company called the metric "Sales Effectiveness" and based part of the management incentives on this metric. This company has provided us the data for the analysis. The data is from the fall-winter 2011-12 season. We wanted to investigate for this particular case which variables impact the sell-through of a store, and how the relation among these variables looks like. The company had two main concerns regarding sell-through as a performance metric. First, it is a ratio that through its numerator (sales) is known to be affected by store attributes such as size or location, which are outside the direct management influence of a store or merchandise manager [5]. The question was how important this impact is in the specific case under study. Secondly, a store could improve its sell-through by reducing the quantities shipped, but on the expense of increasing lost sales. Therefore, it would be interesting for a fashion retailer to complement the information provided by sell-through with an estimate of the sales potential of a given store, i.e an estimate of its sales potential adjusted for fixed store attributes (those attributes that remain fixed over the season such as, for example, size).

We think we made two main corresponding contributions with this study. First of all, we confirmed that sell-through is conditioned substantially by the store size, and therefore is better suited as a metric to compare cases where this variable does not change. Secondly, we developed further a mathematical model to estimate the impact of different variables on the sales of stores. The model allows estimating what we called "normalized sales" of a store, i.e. sales that are adjusted for store size and week of the season. This means that a store that performs well with regard to this normalized sales, is doing better than it would be expected given its size and the season trend. We then analyzed empirically the relation of these variables using data from a mid-size Spanish fashion retailer.

From here on the paper is organized as follows. Section 2 provides a review of the relevant literature. In Section 3 we develop a model for the empirical analysis of sell-through and its underlying variables. In Section 4 the data and the empirical results are reviewed. Section 5 summarizes the conclusions, research limitations, and suggests topics for further research.

2. Literature Review

The objective of supply chain management is to make supply meet demand [6]. The mismatch of supply and demand is costly to all members involved in a supply chain. It will produce lost sales through stock-outs and markdowns due to high inventories. Many management initiatives and techniques, such as quick response or fast fashion, have been developed to cope better with the demand uncertainty [3]. These practices have been analyzed extensively in the operations management literature, mostly in the form of analytical models, and less often through empirical work. However, in industrial practice a big majority of apparel buying and production is still done upfront, based on forecasts.

A traditional performance metric widely used in practice of how well supply matches demand is the sell-through ratio [7]. Sell-through is the percentage of units of a product shipped which are actually sold over a period of time, for example a day or a season. Sell-through has been also used extensively as a metric or information base to coordinate and evaluate the collaboration of different players along a supply chain and accordingly it can be measured at different points of the supply chain [8]. Sell-through data from supply chain partners have also been used by manufacturers for the monitoring of the introduction of new products [9].

A retailer's sell-through will depend on its ability to place the right amount of inventory in the right place at the right time and at the right price so as to maximize the ratio of quantity sold to quantity purchased. During the full-price selling period, the main focus of sell-through optimization is on distributing the inventory correctly over the time and network [3]. During the sales period, price reductions are typically used to push up the sell-through level [10].

Improving sell-through leads therefore to the generic problem of allocating inventory from a central warehouse to several locations (eg. stores) satisfying separate demand streams. This particular problem has received significant attention in the literature. The optimal allotment of stock over time is mathematically still an open question for most distribution systems, however. For the case of stochastic demand, inventory policies described in the literature are based on approximate analysis, and their performance depends on the problem data. When demand is assumed to be deterministic, very effective heuristics with data-independent worst-case performance bounds for setting reorder intervals exist, however [11]. Caro and Gallien (2010) [12] provided a complete review of general literature about stochastic demand models for inventory management in distribution networks.

The many ways in which in-store inventories can influence store sales have also been explored in detail [5]. The authors concluded that for the aggregated category demand, the influence of inventories on sales is small compared to fixed store attributes or seasonality. Particularly, store size was found to have a substantial effect on demand. But for the product market shares within a category the impact of inventories can be substantial, as store size does not play a role any more. Specifically, they differentiate between direct and indirect effects among the variables of inventories and sales. The first ones are given when the availability of more inventories in a store leads to more sales, for example, due to customers seeing more of the product or the product having a better assortment. The indirect effects occur when sales and inventories are still positively associated, but not by a causal effect, but rather through a common driver that increases (or decreases) both variables at the same time, such as, for example, store size.

Regarding the optimization of distribution decisions, the main studies carried out are based on dynamic programming, e.g. [13], [14] among others. Those works assume stochastic demand and describe the relationship between shipments, inventory at the warehouse, and inventory at each store. Additional studies exist that tried to improve sell-through by a better prediction of sales using empirical models (e.g. [15]), or analytical models (e.g. [16]). Alternative tailored solutions for a particular case (Zara) are provided in [4].

Several researchers have approached the problem of improving sell-through also from the perspective of assortment decisions, i.e. what products should be offered along the season in the stores. An extensive literature review of assortment models can be found in [17].

Finally, competitive pressure on retailers has led to a closer consideration on how to leverage best the stores (selection of locations and the store management) as a source of competitive advantage [18].

Considering the wide use of sell-through as a performance indicator both in industrial practice and the literature, our paper tries to analyze if sell-through is a valuable metric to evaluate the management performance of a store. To do this, we need to empirically analyze the different variables impacting sell-through of a store, and understand to what extend and in what form their impact takes place. As sell-through is given by the relation of shipments to sales, this analysis extends to variables impacting the store sales and the inventory on-hand. On one hand there are management decisions at the store level such as, for example, visual merchandising, the store layout or the product assortment, which are known to have a substantial impact on the store sales.

But on the other hand, it is also known that fixed store attributes which are beyond the management control of store and merchandise managers, particularly store size [5], can have as well an important impact on the sales of a store. But to the best of our knowledge no empirical studies like this exists on sell-through, and no empirical results are available that tell fashion retailers to what extend their sell-through performance depends on these different variables, and particularly, to what extend it depends on management decisions not given by the fixed attributes of a store. As we explain in the next section, we will do this analysis by developing a sales estimation model that we then can compare with effective sell-through data from the company.

3. Model Description

The aim of our research is to empirically study the variables impacting the sell-through achieved by a store, in order to determine if the sell-through ratio is a valuable indicator of the store’s management performance. As sell-through is (generally) defined as the percentage of units shipped which are actually sold over a period of time, our research requires understanding which factors impacts sell-through, and in which form. The store’s management performance will be the result of the decision taken by the store or merchandise manager, which typically decides the replenishment of the stores (among other things).

This research objective can be summarized in the following research question:

To what extent is the sell-through ratio of a store conditioned by fixed store attributes (particularly store size), and what is the impact of operational management decisions (particularly replenishment) on this ratio?

The answer of this question will shed light on how valuable sell-through is for the evaluation of the performance management of a store. If sell-through is chiefly conditioned by store attributes outside the control for the managers, it would not be a fair metric to compare the performance of different stores (in the same way as store sales are not a fair metric to compare different stores). We could answer this research question by analyzing the statistical relation between store size and sell-through for a specific case (and we do this in section 4). But that would not allow us to study the relations of the variables underlying sell-through (sales and shipments), and we would not develop knowledge about the impact on sell-through of the variables under management control, such as replenishment.

Therefore, we developed a mathematical model that allowed us to study this research question in detail. Based on the previous literature review we identified the key variables that have an impact on the sell-through ratio of a store. They are depicted in figure 1 in a summarized way. Consider a retailer that sells I fashion products over a network of S stores during T weeks. The distribution decisions and replenishments are made every week t, and each product i is carried in the store s until it is sold or the season is over. Each store s will receive merchandise at the beginning of a week t, will carry an in-store inventory equal to the ending inventory in the previous week plus these receptions, and achieve certain sales in the week t.

Sales of a store depend on numerous factors. For our analysis, the important ones are (1) how much inventory it has on hand in the store, (2) specific store attributes such as size or location, and (3) what week of the season we are in. While the relation between week and store with the variable sales is unidirectional, the interrelation of sales and inventory on hand is obviously bidirectional, as the more is sold the less inventory will be available, and the other way around. As mentioned earlier, inventories levels may have a direct impact on store sales (i.e. the more inventory the more sales), for example, through product availability, but both variables of sales and inventories are also receiving indirect impacts from the variables store size or season week.

The resulting sell-through ratio of shipments over sales will be given then by the ratio of shipments to sales. The shipments are depended on (4) the replenishments policy followed, which can depend itself on the week and store, and (5) the available stock in the central warehouse.

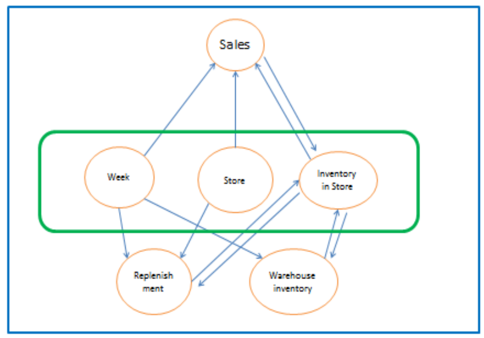

Figure 1 – Key variables behind sell-through

In order to study the impacts of the different variables on sell-through (the answer to our research question), we need to estimate the effect of inventories on sales, but adjusting these sales for other effects in figure 1. To do so, we will compare sales estimates adjusted for fixed store attributes and season trends with effectively measured sell-through data of the case firm. In this study we will analyze the sell-through ratio cumulatively over a selling season, i.e., we define sell-through as the ratio of cumulative sales to cumulative shipments, starting from the beginning of the season.

Consequently, we need to develop a model to estimate such "adjusted sales". Our empirical model for predicting sales uses a two-step least squares (2-SLS) approach, similar to previous empirical models used for similar purposes (see [15], [5]). In the first step we developed a predicting sales model disaggregating the different contributions that explain the behavior of sales for each store and week of the season. We control for store heterogeneity (size) and seasonality through fixed effects. Doing so, allows us then to study how variances of other variables resulted in sales variances. That is, in the second step we calculated the portion of sales that is not explained by store size, or season week. We will name those sales as "normalized-sales". In a last step we then tested the relation of these normalized sales and the sell-through ratios. This will reveal the impact of the underlying variables on sell-through.

The estimation of the normalized sales was done at the level of main product categories (i.e. textile and footwear in our case), as those aggregated sales are supposed to follow a log-normal distribution with heteroscedasticity (different variabilities in the sub-populations). This was done following the methodology used in Boada and Martínez-de-Albéniz, 2014 [5], that is, we took into account endogeneity and heteroscedasticity supposing that the log-normal distribution is such that the variance is proportional to category sales. The difference to this previous model is that we used directly a variable that accounts for store size instead of the store fixed effects, in order to control specifically for store size, which was found out to have a critical impact in that previous study. We did this using the sum of total sales, including all SKUs, all categories, and all weeks. It is important to note that the store size variable is a store-characteristic variable with no seasonality, and therefore uncorrelated to season trends or time variability. In fact, total revenues could be used instead, obtaining the same result.

According to the model described we introduced the following key variables: $sales_{t,s}^{C}$, $inventory\ level_{t,s}^{C}$ and $receptions_{t,s}^{C}$. All of them are variables aggregated by category at week *t* in store *s*, i.e. $sales_{t,s}^{C}$ represents the cumulative (C) sales at the week (*t*) for the store (*s*). We then built the model in Eq. (1):

$$\log\left(Sales_{t,s}^{C}\right) \sim \alpha^{C} Size_s + \alpha_t{}^{C} + \varepsilon_{t,s}^{C} \qquad (1)$$

Where α_t is a time fixed effect dummy variable that controls for seasonality and the term $\alpha^{C} Size_s$ captures the size effect of the store. Note that $\varepsilon_{t,s}^{C}$ includes all other factors such as inventory level dependence [5], retail manager decisions, store characteristics different form size, display features, etc. That is, with this model we try to separate the impact of store size and week of the season, from the rest of the variables. As most strategic management decisions related to the store, such as, for example, visual merchandising, assortment, or layout don't change (significantly) during the season, the residual is expected to depend chiefly on the replenishment policy applied.

As mentioned, the second step consisted in comparing the normalized sales performance of the stores to their sell-through rate. We defined the normalized-sales as follow:

$$\frac{\varepsilon_{t,s}^{C}}{\sqrt{Var_{t,s}^{C}}} \equiv normalized\ sales_{t,s}^{C} \qquad (2)$$

Where the term $Var_{t,s}^{C}$ is the variance calculated following the Boada and Martínez-de-Albéniz, 2014 [5] approach (i.e. taking into account the specificities of such a sales distribution of competing products). We could also take other definitions for normalized sales such as the term $Sales_{t,s}^{C} - \exp(\alpha^{C} Size_s + \alpha_t)$, however, we obtained similar results and conclusions. Given the above definition of normalized sales, these can be positive or negative. A store with high normalized sales for a given week is a case where sales are higher than expected (given its fixed store attributes) and vice versa. The total amount of normalized sales of the season for a store can be an indication of whether a store has had a successful or poor sales performance along the season.

We calculated the total performance during the season using aggregated normalized sales (AN.sales):

$$AN.sales_s{}^{C} = \sum_{t=1}^{T} normalized\ sales_{t,s}^{C} \qquad (3)$$

It is important to note that the actual numerical value of the aggregated normalized sales is not as important as its relation to the actual performance of the store in the context of its specific market. The important contribution of this new variable is that within a specific market (or product category), we can conclude that stores with higher aggregated normalized sales performed comparatively better than those with lower values of this variable. But as each market (or product category) has a different variability, comparing aggregated normalized sales between different markets will be less revealing.

We then estimated an ordinary least squares (OLS) to test if there is a significant linear relation between the aggregated normalized sales and the sell-through. We firstly estimated the impact of the store size on sell-through using Eq. (4).

$$\text{Sell Through}_s^C \sim \beta \log(\text{Size}_s) \quad (4)$$

Sell Through_s^C is the final sell-through for each store and category. On the other side, β is the coefficient for the size variable, that is, Size_s. We also estimated the impact of AN.sales on sell-through using Eq. (5), where θ is the linear coefficient for the aggregated normalized sales.

$$\text{Sell Through}_s^C \sim \theta\, \text{AN.Sales}_s^C \quad (5)$$

We later included both variables together to estimate their contribution on the final sell-through fluctuation in Eq. (6).

$$\text{Sell Through}_s^C \sim \beta \log(\text{Size}_s) + \theta\, \text{AN.Sales}_s^C \quad (6)$$

4. Data Analysis and Results

4.1 Case and data description

The data used to test the abovementioned model were supplied by a mid-size Spanish fashion retailer with stores in Spain, Portugal, and France. The company started in the year 2004 and currently sells through over 50 points of sale (own operated and wholesale). They essentially operate a traditional business model of two collections per year. They have a central warehouse in Madrid (Spain), from where they distribute weekly to all points of sale with a lead time of 1-3 days. We analyze in this paper specifically distribution and sales data from the fall-winter 2011-12 season.

We have used data for 17 weeks (no weeks with products on sale or discounts were included) of the fall-winter 2011/12 season in 17 different stores. The stores were selected together with the company management to get a best possible representation of their sales network. Two categories are studied: footwear and textile, which were the most representative product categories in terms of sales (Table 1 summarizes the relevant category statistics). To study the data at the category level eliminates concerns about inter-product cannibalization.

Table 1 - Data overview (units)

Main Categories	Number of SKU	Average Weekly Sale	Average Stock	Average Selling Price	Number of stores
Footwear	135	83	651	68	17
Textile	289	150	1263	97	17

We can see the evolution of category sales, inventory levels, and receptions in figure 2.

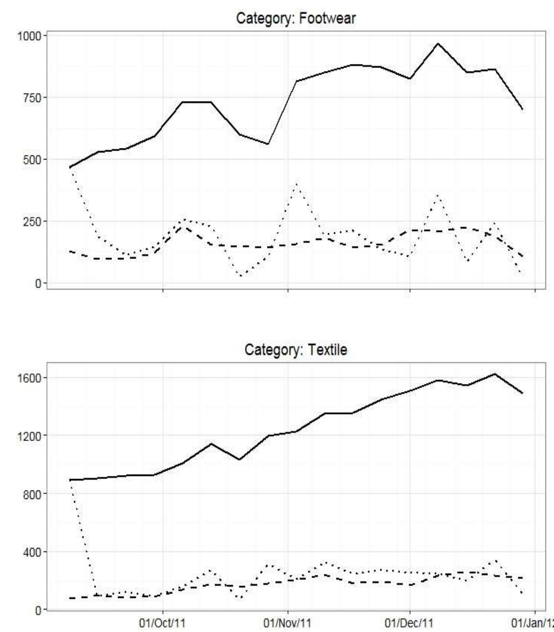

Figure 2 - Evolution of category inventory levels (solid line), sales (dashed line) and receptions (dotted line) in number of units over the 17 weeks.

According to the relations of the key variables impacting on sell-through we assumed in our figure 1, we wanted to analyze upfront the possible relation between store size and sell-through. As we can see in figure 3, store size in terms of total sales during the season, proved to be highly related with the sell-through achieved. Specifically, the correlation turned out to be about 65% in our case.

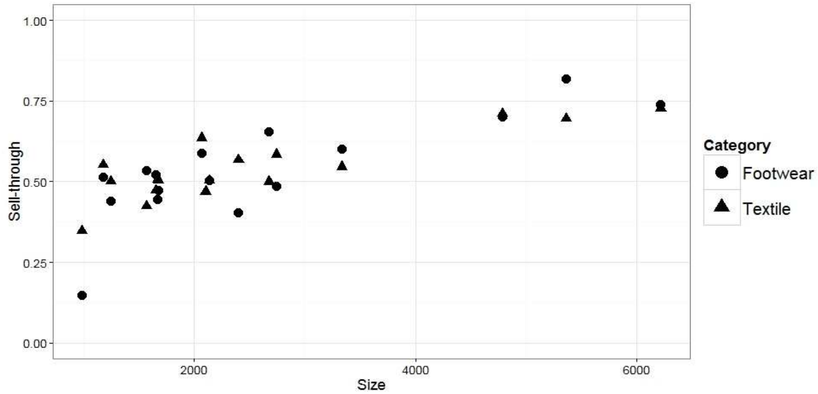

Figure 3 - Relation between sell -through and store size

Therefore, in our case we could confirm that big stores were more likely to have higher sell-through than stores with lower sales. Lower sales may occur for different reasons, such as, for example, because the store is physically smaller and cannot offer the full product assortment, or it is not situated on a main street. Because these factors are intrinsic store characteristics, they must be taken into account when judging the sales performance of a store, since, independently from the distribution decisions taken during the season, a small store will be comparatively penalized in terms of sell-through. This first result already questions using an unadjusted sell-through ratio as a store performance indicator.

4.2 Results

The model described by Eq. (1) confirmed that both store size and season week were statistically significant for both product categories. In Table 2 we show the summary of these estimates.

Table 2 - Summary of Eq. (1) estimations. Standard error inside parethesis. * Estimated using significative parameters

	Footwear	Textile
Size parameter	2.48e-04 (0.10e-04)	2.94e-04 (0.13e-04)
Number of parameters α_t	16	16
Number of sing. par α_t	11	12
Average value of α_t*	0.626	0.503
Standard error of α_t*	0.129	0.144
Degrees of freedom	247	246
R^2	0.770	0.776

Approximately 77% of the sales performance of a certain store and category were explained by the variables size and week. The variability not captured by these variables is what we call normalized sales and is chiefly associated with the management performance of the stores, since those sales are mostly related to exogenous management decisions such as inventory decisions, visual display, etc.

Using these results we estimated the relation between final sell-through and performance (aggregate normalized sales) using Eq. (4), (5) and (6). We show the results of both estimates in Table 3.

Table 3 - Summary of Eq. (3) estimation. Standard error inside parenthesis. ** (p-value<0.001),* (p-value<0.05)

	Model 4	Model 5	Model 6
Intercept coefficient	-0.988 ** (0.197)	0.561** (0.021)	-0.893** (0.186)
Size coefficient	0.198** (0.025)	-	0.188** (0.023)
AN.Sales coefficient	-	2.0E-03* (0.8E-03)	1.3E-03* (0.5E-03)
Degrees of freedom	31	31	30
R^2	0.656	0.147	0.718

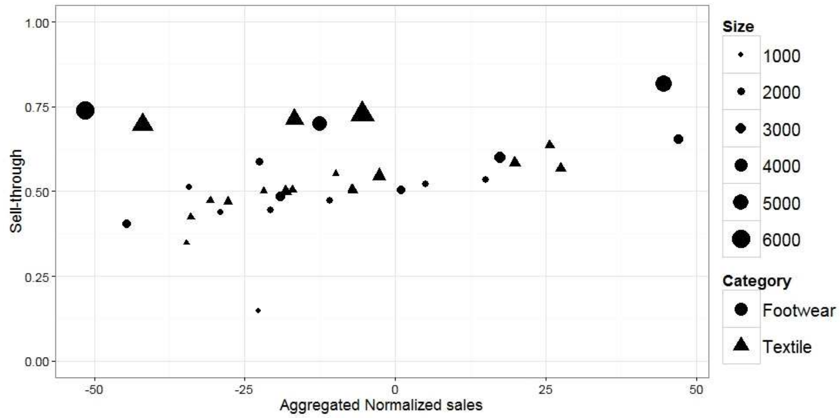

Figure 4 - Relation between final sell-through, aggregated normalized sales and size.

We can confirm from modeling Eq. (4) that the store size is highly significant and explains more than 65% of the sell-through fluctuations (see also the previous section). Moreover, an increment of 10% of the store size would increase its sell-through by 0.019 on average. Similar results are obtained with model (6) for store size. However, AN.Sales in model (5) are much less significant (at a p-value of 0.05) and we have obtained a goodness of fit R2 of only 0.147. Therefore, the explanation provided by this variable is not as important as the variability explained by store size.

When including both effects in model (6) a R2 of 0.718 resulted, but it can be concluded that most of this effect comes from changes in store size. Thus, management performance (captured with AN.Sales) statistically has a low significance in terms of explaining the sell-through variations. Figure 4 shows how sell-through is related to AN.Sales and store size for both categories. We can see how bigger stores in terms of AN.Sales are more likely to have higher sell-through.

In the view of these results, we concluded that even if we found AN.Sales to be statistically significantly related to sell-through, the managerial implications must be carefully considered given that the significance was much lower than for the store size. Specifically, statistical contribution of store size is about 65% and of AN.Sales of around 15% only. Therefore, if sell-through is used as an indicator of store management performance the strong influence of the store size need to be taken into account properly.

However, sell-through can be very useful to evaluate the management performance in cases where the effect of size is limited or nonexistent. For example, when two different replenishment policies for the same store are compared, or the sell-through of products with similar sales in the same store, or just comparisons in aggregate terms, i.e. total sales with respect to total shipments from the warehouse to stores. This corroborates the idea that in-store inventories play a strong role in helping customers choose a particular product within the assortment offered and therefore can drive sales [5].

5. Discussion

Our paper presented an empirical study of the variables impacting store sell-through using sales and inventory data of a Spanish fashion retailer. We were particularly interested in the underlying relations of these variables, and to separate the effects of variables conditioned by the store characteristics, from those under the control of management. This is determinant in order to assess the validity of sell-through as a management performance metric.

For this study we built a two steps least squares (2-SLS) model that: (1) disaggregates the different components that explain the sales of a certain store, and (2) calculates a normalized sales value that serves as an adjusted indicator of the performance of the store. Next, we statistically compared the results with the sell-through levels of each store in order to answer our research question. We concluded that there is a strong indirect effect on sell-through whereby bigger stores ultimately have comparatively higher sell-through levels than smaller ones.

6. Conclusions

We can extract several conclusions from our analysis that contribute to literature and are of interest to industrial practice. First, in our study we found that the main part of the sales fluctuations of a store is explained by store size and season week. This was captured through a fixed effects model. Second, our results confirmed that sell-through is also correlated strongly to store size and, to a lesser extent to variables under the control of management (particularly replenishment). Finally, we can conclude that sell-through is nevertheless a useful performance metric in the fashion industry when aggregated sales and shipments are compared or sales of different replenishment policies for a store.

The study has also several limitations that should be explored in further research, however. First, in empirical terms, the working sample is limited to one season of one company (although it confirms results from a previous study at a different company, cf. [5]). It would be therefore interesting exploring similar situations in other retail companies. Particularly, it would be interesting to have more detailed data on store management practices, such as visual merchandising, in-store inventory locations, etc., as this would allow developing similar studies to evaluate the detailed impact of these management variables on sales (sell-through). Such information would also allow studying the validity of sell-through as a performance metric in situations that are not affected by fixed store attributes.

On the side of the sales model, a further development of it would provide more information about the variables (and specific weights) that impact on the normalized sales, such as inventory levels, clearance policies, and so forth. This would allow refining the normalized sales into a valuable store performance metric to test the specific impacts on the replenishment levels of these sales.

References

[1] Christopher, M., Lowson, R., Peck, H. (2004), Creating agile supply chains in the fashion industry, International Journal of Retail & Distribution Management, 32 (8), pp. 367-376.

[2] Bhardwaj, V., & Fairhurst, A. (2010). Fast fashion: response to changes in the fashion industry. The International Review of Retail, Distribution and Consumer Research, 20(1), 165-173.

[3] Caro, F. and Martínez-de-Albéniz, V. (2013), Operations Management in Apparel Retailing: Processes, Frameworks and Optimization, SEIO 29(2), pp. 103-116.

[4] Caro, F., and Gallien, J. (2010). Inventory management of a fast-fashion retail network. Operations Research, 58(2), 257-273.

[5] Boada, P. and Martínez-de-Albéniz, V. (2014). Estimating and Optimizing the Impact of Inventory on Consumer Choices in a Fashion Retail Setting. Working paper. IESE Business School

[6] Fisher, M. and Raman, A. (1996), Reducing the cost of demand uncertainty through accurate response to early sales, Operations Research, 44 (1), pp. 87–99.

[7] (Mattila, H., King, R. and Ojala N., (2002). Retail performance measures for seasonal fashion, Journal of Fashion Marketing and Management: An International Journal, Vol. 6 Iss: 4, pp.340 – 351.

[8] Callioni, G. and Billington, C. (2001). Effective Collaboration. HP takes supply chain management to another level, OR/MS Today, October.

[9] Salmi and Holström (2004). Monitoring new product introductions with sell-through data from channel partners, Supply Chain Management: An International Journal, 9 (3), 209-212

[10] Caro, F., and Gallien, J. (2012). Clearance pricing optimization for a fast-fashion retailer. Operations Research, 60(6), 1404-1422.

[11] Muckstadt, J., R. Roundy. 1993. Analysis of multistage production systems. In Handbooks in OR and MS, Vol. 4, Graves et al. (eds.), Elsevier Science Publishers, North-Holland.

[12] Caro, F., and Gallien, J. (2010). Inventory management of a fast-fashion retail network. Operations Research, 58(2), 257-273.

[13] Graves, S. C. (1996). A multiechelon inventory model with fixed replenishment intervals. Management Science, 42(1), 1-18.

[14] Axsäter, S., Marklund, J., & Silver, E. A. (2002). Heuristic methods for centralized control of one-warehouse, N-retailer inventory systems. Manufacturing & Service Operations Management, 4(1), 75-97.

[15] Olivares, M., & Cachon, G. P. (2009). Competing retailers and inventory: An empirical investigation of General Motors' dealerships in isolated US markets. Management Science, 55(9), 1586-1604.

[16] Martínez-de-Albéniz, V., & Roels, G. (2011). Competing for shelf space. Production and Operations Management, 20(1), 32-46.

[17] Caro, F., & Martínez-de-Albéeniz, V. (2009). The effect of assortment rotation on consumer choice and its impact on competition. In Consumer-Driven Demand and Operations Management Models (pp. 63-79). Springer US.

[18] Bennison, D., Clarke, I., & Pal, J. (1995). Locational decision making in retailing: an exploratory framework for analysis. International Review of Retail, Distribution and Consumer Research, 5(1), 1-20.