**Quick Response Inputs and Outcomes in the Apparel Industry: an Example from a South African Retailer.**



March 13, 2017


## Abstract

This paper provides a two-tier framework for empirically analysing Quick Response on a product level. The first part of the framework suggests retail metrics based on the characteristics of Quick Response to allow comparison between supply chains in terms of their adherance ot the strategy. The second section of the framework lays out a methodology for quantifying the benefits of Quick Response by comparing product level performance of Quick Response products to those on traditonal lead times. The suggested methodology is applied to data from a large South African clothing retailer as an example.

# Introduction

Traditionally apparel retailers have sourced their products from external suppliers in developing countries who, due to both cheaper labour costs and the labour-intensive nature of textile and clothing manufacturing, can produce goods at much cheaper prices than local manufacturers. This practice creates lead times, the duration of time elapsed between the order being placed and the supplier delivering the products, that are often six months or higher. These long lead times necessitate retailers making buying decisions long before the season has begun. While this is not an issue in many industries, the demand for fashion products is volatile and largely unpredictable.

There is a plethora of product-level characteristics that influence demand such as consumer preferences over colour, fit, style, pattern, brand name and material composition, all of which are constantly changing based on fashion trends. Predicting these trends and consumer demand is difficult and forecasting errors are costly. Incorrect forecasts lead to losses in the form of leftover stock which have to be sold at marked down prices or, in converse, early stock outs which represent missed sales. As retailers are forced to order their stock for each season months before it begins, all of the supply decisions are made long before they can observe demand. Apparel retailers, therefore, have no way to react.

The main strategy to mitigate this risk is called Quick Response (QR). Rather than attempting to improve demand forecasts, retailers implement supply chain systems that allow them to make buying decisions once they have more information. Increased levels of communication, facilitated by technology, throughout the value chain coupled with shorter lead times due to local manufacturing create versatile and efficient supply chains that allow retailers to respond to consumer demand in a way that is impossible with traditional lead times. Short lead times allow for buying decisions to be made closer to the season at which point trends are easier to predict. Additionally, they make in-season replenishment possible, allowing retailers to order smaller quantities of each product at the beginning of the season and only restock products that are selling out. If lead times are short enough, new products can be designed during the season informed by sales data.

The literature suggests that these benefits should, in most cases, outweigh the increased costs associated with compressing lead times (García, 2014; King and Moon, 1999). However, there is no conclusive empirical evidence of this being true. As a consequence of company data at the product level not being publicly available, most of the empirical papers, to date, have relied on simulated data or have compared the performance of QR retailers to traditional retailers and have been unable to find significant differences. Furthermore, company level analysis has a number of problems. Firstly, the sample size will necessarily be small based on the number of firms in the industry. Secondly supply chain strategies are just one of many company level characteristics that contribute to performance. Finally, even QR firms often use a mix of Quick Response and traditional lead times because demand for basic clothing items is less difficult to predict. In order to control for retailer level variation, a product level performance analysis should be conducted on products with quick response and traditional lead times both sold by the same firm.

This paper provides an empirical framework by which quick response retailers can be evaluated to determine how well the strategy is being implemented as well as a methodology for comparing quick response and traditional products using appropriate retail performance metrics. Data from a major South African retailer is used to carry out the methodology as an example. The retailer sources products locally as well as internationally. Some of the locally manufactured products have traditional lead times and some are Quick Response. This provides an opportunity to compare these groups of products on retail metrics to determine how QR products compare to traditional lead time products.

ANOVA and OLS regression analysis is used to compare the groups and to test for significant differences first in the theoretical characteristics of QR and secondly in performance metrics. While this analysis follows as closely to the proposed empirical framework as is possible, limitations in the data prevent some metrics from being calculated.

This is the first paper to analyse Quick Response in South Africa's apparel industry. From the results it appears that the retailer has successfully reduced lead times which is a positive sign. Unfortunately, the retailer has not adapted their buying behavior to capitalize on the benefits of QR. This can be seen by the low order frequency and high inventory levels of the QR products.

Conclusions cannot be drawn about the effectiveness of quick response as the retailer is not currently implementing the strategy in full. The negligible differences in performance between the QR and non-QR products is likely due to improper implementation.

The paper is structured as follows: section 1 summarises the current literature regarding global value chains, the South African clothing industry and quick response. In Section 2 there is a recommended list of metrics that are to be used to evaluate retailers on their implementation of quick response as well as metrics to quantify the benefits. The description of the data and exploratory statistics can be found in section 3. Section 4 outlines the methodology and models used to evaluate adherence to quick response and test for the benefits. The results of the empirical work can be found in section 6. Section 7 concludes the paper.

# 1 Literature Review

The literature review is subdivided into three sections. The first focuses on global value chains and the apparel industry as a buyer driven market. Subsection two is concerned with the implementation and benefits of Quick Response in apparel retail. Subsection 3 is a summary of the empircal papers in the literature.

## 1.1 Global Value Chains

Understanding global value chains in the apparel industry and how the necessity for more flexibility and speed is changing the nature of these value chains provides context for this paper.

Generally the global value chains in labour intensive consumer goods industries are coordinated by lead firms that manage globally dispersed networks of manufacturers. These firms coordinate and control the value chain but outsource the majority of the manufacturing to offshore firms (Gereffi and Frederick, 2010). The apparel industry is no exception.

For decades the primary method of competition was through price, allowing for imports from developing countries to dominate even with the relatively long lead times. The manufacturing of textiles and clothing is very labour intensive, has relatively low fixed/start-up costs and uses simple technology. Due to labour being the primary cost, most global retail and textile manufacturing happens in developing countries with cheap labour (Tybout, 2000; Gereffi and Frederick, 2010; Staritz and Morris, 2015).

The primary method by which apparel firms outperform their competition is through their ability to differentiate their product in the eyes of the consumer (Gereffi, 1999). This is in contrast to many other industries where the main method of competition is through improvements in production methods or through technological innovation.

## 1.2 Quick Response

Quick response and fast fashion are terms used to describe a retailer's ability to react to market trends and have their supply levels better match the unpredictable demand. Zara, the largest fashion retailer in the world is also the world leader in fast fashion (García, 2014). Traditionally, fashion research has focussed on predicting consumer demand but due to the high level of volatility and complexity of the systems underpinning demand for fashion products it is essentially impossible (Christopher and Lee, 2004). Due to the chaotic nature of the demand, it is much more fruitful to focus on developing structures and systems within the supply chain that can respond to demand in real time rather than attempting to predict it months in advance.

A fundamental requirement of this system is a large quantity of quality data that is communicated in real time from the retail stores to the buyers and suppliers so they can replenish stock as inventory starts to run low (Caro and Martínez-de Albéniz, 2015). Additionally, the business must have a very agile supply chain that has short lead times, allowing for quick replenishment before stock outs occur (Christopher et al., 2004).

The primary goal of any supply chain system is to have supply match demand (Fisher and Rajaram, 2000). The fundamental difference between quick response and traditional sourcing strategies is the ability to implement in season replenishments (Mattila et al., 2002). A wide range of products are sourced at low quantities prior to the season at which point there is little information about consumer demand for each product. Products that are in high demand are replenished during the season and ones that aren't selling quickly are not restocked. In this way retailers are reacting to consumer demand in real time rather than trying to predict it in advance (King and Moon, 1999). Replenishment orders are based upon reestimations of consumer demand grounded in sales data and are, therefore, far more likely to be accurate.

The benefit of purchasing in advance is the ability to source the goods from the most cost effective manufacturer regardless of geographical location. This is the opportunity cost of quick response.

In season replenishment is only possible with short lead times and is most effective when buyers have up to date and accurate point of sales data. Traditional lead times are around 6-8 months which would make replenishment impossible. In order to react to consumer demand, retailers require lead times to be as short as possible. Zara, the industry leader in quick response, have been operating on lead times of 15 days or fewer for more than 10 years (Barnes et al., 2006).

However, short lead times on their own aren't sufficient to allow a retailer to reap the benefits of a reactive supply system. Replenishment decisions must be informed by data on product sales. Firms must be able to update their original estimates of consumer demand for the season by observing consumer demand for the beginning of the season.

### 1.2.1 Benefits

Preseason forecasts of demand for fashion products have been shown to be inaccurate roughly 50% of the time. These errors lead to large losses due to products having to be sold at marked down prices and forgone sales due to stock outs. For basic apparel products, for which demand is more certain, there is far less risk involved in forecasting sales (Fisher and Raman, 1996). Given that shorter lead times come at a cost, only higher risk "fashion" products that have an unpredictable demand should be sourced from suppliers that can guarantee short lead times (King and Moon, 1999).

The primary goal of quick response is to have the stock on hand more accurately reflect consumer demand. This should result in fewer and less drastic stock outs and left over stock. Reducing these has a direct, positive impact on profit as stock outs represent sales that did not occur due to lack of inventory. Furthermore, since left over stock is sold at a marked down price, sometimes below cost, profits are clearly diminished.

In addition, the longer a firm can wait before making a replenishment decision the more information they have to inform that decision and the less likely they are to make a forecasting error. This is especially true when the decision can be made after some portion of consumer demand has already been observed.

## 1.3 Empirical Literature

The vast majority of the literature on quick response and fast fashion focuses either on the theoretical benefits that should arise from more responsive supply chains or on the methodology of implementation, taking the benefits as a given.

Although quick response in the apparel industry has become the gold standard that many retailers around the world attempt to implement, there is little empirical evidence of its benefits. Part of the problem is that product level retail data on sales, losses due to markdowns and profit margin are not available to researchers. For this reason, the empirical literature has mostly been limited to analysis conducted on publicly available, firm level, financial data.

Firm level studies, comparing quick response fashion retailers to their traditional counterparts, have been carried out for UK and USA firms. Neither identified any statistically significant difference in financial performance between the groups across a plethora of performance metrics (Barnes et al., 2006). These findings, however, do not constitute definitive evidence against quick response as the sample sizes are inherently low when conducting a firm level analysis. Additionally, it is difficult to isolate the effect of Quick Response due to the variety of other firm level variables that cannot be controlled for. Studies of this kind face further limitations because they are unable to know how strictly the firms adhere to the Quick Response strategy and how efficiently they implement it. A firm that claims to be QR may not in reality be a QR firm.

Nonetheless, most firms who have adopted quick response, still source some portion of their offering on traditional lead times. Basic products, such as white t-shirts, that are less subject to volatility and unpredictable demand can be more safely purchased in advance (Abernathy et al., 1999).

### 1.4 Contribution to the Literature

This paper draws on previous empirical and theoretical work to suggest metrics and methodology to evaluate QR implementation at the product level. Additionally, a framework for quantifying the benefits of Quick Response is outlined. Finally this paper is the first paper to analyse of the effectiveness of QR implementation of a South African firm.

## 2 Metrics

This section contains a list of the retail performance metrics best suited to analysing the characterisitcs and benefits of quick response. The following is a template made up of the ideal metrics to empirically test and quantify the benefits of quick response.

Many brick-and-mortar stores, especially in South Africa, have not yet invested in data management systems. Preference is given to metrics that use basic data that most companies would record. Due to the limitations of our data, it is not possible to calculate all of these metrics for the South African retailer. They are still included as they are the metrics that should be calculated when the data is anavailable.

### 2.1 Quick Response Characterisitcs

#### Lead Time

Short lead times are the primary requirement for Quick Response. Long lead times prevent a firm from reacting to demand and make replenishing stock impossible. Long lead times make Quick Response impossible. With lead times, the shorter they are, the more reactive a retailer can be.

#### Orders

Firms with short lead times do not have to purchase their entire season's inventory before it has begun. They are able to purchase smaller quantities initially because replenishing stock during the season is possible due to shorter lead time. Being able to purchase lower quantities of each product means there is the opportunity to stock a wider variety of products. The retailer can then replenish the succesful products and not replenish the ones that don't sell.

This means that Quick Response products will be ordered in lower quantities especially at the begining of the season compared to products on traditional lead times. QR order quantities should be equal to the minimum level of inventroy required to support operations until the next order date (Zinn and Charnes, 2005).

Calculating order quantity and frequency products should give an indication of whether the extent to which they are Quick Response products.

#### Average Stock on Hand

Inventory levels are another indicator of whether a product is on traditional lead times or is a Quick Response product. A direct consequence of frequent small orders is that inventory levels will be lower on average as well as being more consistent throughout the season (Zinn and Charnes, 2005).

## 2.2 Performance Metrics

The following is a template made up of the ideal metrics to empirically test and quantify the benefits of quick response. As well as the data required to calculate these metrics. Most brick and mortar stores, especially in South Africa, do not invest in systems that make recording and analysing data easy. Some of these we are able to calculate from the data used but many are not possible due to the lack of reliable/complete data.

#### Lost Sales

Periods in which retailers are out of stock equate to forgone sales. During these periods demand is unobserved but we can assume in most cases it is non zero (Nahmias, 1994). It is clear that these periods represent a loss to the retailer however quantifying this loss is no easy task. A rough estimate can be made by forecasting demand based on sales during the time in which there was inventory available and demand was therefore observed (Mattila et al., 2002). Nahmias & Smith (1994) recommend controlling for seasonality to improve estimation accuracy. A problem inherent in this estimation is that stockouts in one product-colour combination will likely boost sales in others as consumers may substitute a different item for the unavailable one (Mattila et al., 2002).

Regardless of the difficulty, it is imperative to consider lost sales when evaluating the effectiveness of supply chain management. Even utilising a simple estimate of lost sales is preferable to ignoring them (Mattila et al., 2002; Nahmias, 1994).

#### Average Mark-Down Rate

Average markdown percentage is the mean difference between the planned selling price and actual selling price. When stock does not sell at its original price retailers are forced to reduce the price, sometimes even below cost, to recoup their investment in the inventory. The percentage of apparel items sold at reduced price has been as high as 33% in America (Fisher and Raman, 1996). Unsold products and products sold at lower prices obviously reduce profit. Consequently, the analysis of the average mark down becomes an important performance metric to consider.

### Gross Margin Return on Inventory Investment

Gross margin return on inventory investment is a retail metric that measures the gross profit generated per rand invested in inventory. A product with a higher GMROI represents a more profitable allocation of corporate assets as the same investment in inventory leads to more gross profit (Sweeney, 1973). Additionally, this metric allows for the comparison of products with different sales volume, mark-up and average inventory levels.

$$GMROI = \frac{p \times S - wc \times N - M}{wc \times \bar{I}} \tag{1}$$

where
$p$ = retail selling price;
$S$ = total sales;
$wc$ = wholesale cost;
$N$ = total units purchased;
$M$ = value of losses due to markdown; and
$I$ = average inventory.

### Gross Margin Return on Inventory Investment - Lost Sales

Gross margin return on inventory investment minus lost sales, a metric proposed by Mattila and King (2002), is intended to capture the benefits of quick response by incorporating forgone sales into the GMROI equation. Unfortunately, this metric requires weekly estimates of lost sales during stock outs.

$$GMROILS = \frac{p \times S - wc \times (N + L) - M}{wc \times \bar{I}} \tag{2}$$

where
$p$ = retail selling price;
$S$ = total sales;
$wc$ = wholesale cost;
$N$ = total units purchased;
$L$ = estimated lost sales for the period;
$M$ = value of losses due to markdown; and
$I$ = average inventory.

This equation takes into account, gross profit, losses due to markdowns, missed sales due to stock outs and accounts for high inventory levels. All of the theoretical benefits of Quick Response are quantified by this metric. Comparing QR products with non QR product using GMROILS would provide an estimate of the value created by Quick Response (Mattila et al., 2002).

## 3 Data

Unlike previous analyses on QR and fast fashion, this analyse has the benefit of using product-level data of a large South African retail firm. This is the first analysis of its kind in this regard. In line with the dashboard of metrics described in Section 2, the descriptive statistics of the fundamental variables and their relationships with one another are reported herein.

## 3.1 The Dataset

The data are from one of the biggest South African clothing retailers. The retailer sells products sourced from two external suppliers as well as their own locally manufactured 'in-house' brand. According to the retailer, a number of the locally manufactured products are on quick response lead times according to the retailer. The dataset contains information on 288 ladies wear and 142 girls wear products over a 30-week period during the 2017 financial year. However not all products are sold throughout the period as some are introduced in later weeks. Once introduced, all products are in stock until the end of the period.

253 of the 430 products are sourced from external suppliers and the remaining 177 are manufactured in-house. One external supplier provides only ladies wear and the other exclusively provides girl's wear. Of the in-house products, 100 are on traditional lead times while the remaining 77 make up the company's quick response range. Table 1 below shows the summary statistics for the variables of interest in the data set.

Note that lead times are calculated as the time in days from the date that the order was placed with the supplier to the date on which the order was delivered to the retailer. In instances where two or more orders were placed for a single product, the mean lead times for all orders are used as that products lead time.

In addition markup is calculated as the difference between selling price and cost price over the cost price. Average markdown is defined as the total loss due to selling products at reduced prices divided by the full price value of goods. Average stock on hand is calculated as the mean value of inventory during the weeks in which the product was being sold.

## 3.2 Limitations

There are two major limitations of the dataset. As mentioned in the literature review, two of primary benefits of QR are reduction in losses due to mark downs and a reduction in stock outs resulting in fewer forgone sales. The retailer was unable to provide data on losses due to markdown for the majority of the in-house products.

The second limitation is that the retailer did not experience any stock outs throughout the 30 week period. This makes it impossible to draw conclusions about the relative frequency of stock outs between the groups. This also means that there were no lost sales due to stock outs. Since GMROILS is simply the GMROI minus lost sales and lost sales is equal to zero, GMROILS is equal to GRMOI. Hence, only the latter is reported.

## 3.3 Exploratory Data Analysis

This section explores the data by analysing the descriptive statistics of each relevant variable contained in the data set and comparing the differences in distributions between the groups. Table 1 contains summary statistics describing the data.

Table 1: Summary Statistics

| **Variable** | **Mean** | **Std. Dev.** | **N** |
|---|---|---|---|
| Ladies | 0.67[1] | 0.471 | 428 |
| In House Quick Response | 0.18 | 0.38 | 428 |
| In House Traditional | 0.23 | 0.422 | 428 |
| 1st Selling Week | 5.68 | 5.48 | 428 |
| Price | 219.6 | 93.14 | 428 |
| Cost | 95 | 40 | 428 |
| Number of Orders | 1.83 | 1.46 | 428 |
| Average Order Quantity | 2137 | 1083.8 | 428 |
| Lead Time[2] | 130.9 | 65 | 428 |
| Orders Per Month | 0.29 | 0.19 | 428 |
| Average Weekly Sales | 27598 | 34703 | 428 |
| Markup | 0.56 | 0.036 | 428 |
| GMROI | 1.44 | 0.857 | 428 |
| Average Markdown[3] | 0.19 | 0.23 | 296[4] |
| Average Stock on Hand[5] | 2968185 | 3227837 | 428 |

1 67% of the products are from the ladies department

2 Measured in days

3 The average percentage reduction in price

4 Markdown information was missing for many of the in house products

5 Measured in rand value

The average price of all the products in the dataset is R219.6, which is relatively low. Lead times are 131 days on average which is approximately 4.4 months. The average markup is 56% and the average markdown is 19%. For the data set, the mean gross margin return on inventory investment is 1.44. This means that, on average, for every rand spent on purchasing inventory, the firm generates R1.44 in gross profit.

Table 2 displays the means for each of the four product groups.

Table 2: Means by Group

| Variable | Supplier 1 | Supplier 2 | In-House QR | In-House Traditional |
|---|---|---|---|---|
| Ladies | 1 | 0 | 0.70 | 0.66 |
| 1st Selling Week | 5.3 | 5.1 | 8.5 | 4.6 |
| Price | 275 | 181.1 | 185.2 | 184.8 |
| Cost | 117.88 | 84.32 | 77.08 | 78.71 |
| Number of Orders | 1.95 | 1.87 | 1.55 | 1.82 |
| Average Order Quantity | 2350 | 1623 | 2024 | 2300 |
| Lead Time[1] | 165.4 | 175 | 37.6 | 107.4 |
| Orders Per Month | 0.3 | 0.28 | 0.27 | 0.28 |
| Average Weekly Sales | 41027 | 16429 | 19252 | 20777 |
| Markup | 0.57 | 0.532 | 0.58 | 0.572 |
| GMROI | 1.63 | 1.26 | 1.27 | 1.39 |
| Average Markdown[2] | 0.16 | 0.24 | 0.15[3] | 0.25 |
| Average Stock on Hand[4] | 416472 | 193572 | 208138 | 250346 |

1 Measured in days

2 The average percentage reduction in price

3 Markdown data was only available for 30% of the in house products

4 Measured in rand value

In Table 2, we see that the QR products were introduced approximately three weeks later than the other products, on average. The average number of orders is lower for QR products but as the difference in orders per month is negligible, this difference is probably due to them being introduced later.

Interestingly, the locally manufactured products have lower average cost prices than the international supplier's products. It is surprising because the South African clothing industry has traditionally not been able to compete with Chinese imports due to the higher cost of South African labour (Morris and Einhorn, 2008).

Furthermore, lead times are significantly lower for the two in-house groups, with the QR group having an average lead time of just 37.6 days. This is to be expected as one of the requirements of the Quick Response strategy is short lead times. By comparison, the world leaders in quick response, Zara, have lead times of 15 days or fewer (Barnes et al., 2006). Supplier 1 sells roughly double the quantity per product compared to the other 3 groups but also has roughly double the average stock on hand.

Supplier 1 has the highest GMROI, meaning that on average, a rand spent on inventory from this supplier generates more gross profit than the other groups. However, caution must be taken when interpreting the average markdown ratios as the retailer was not able to provide markdown data for 70% of the in house products.

Figure 1, contains a scatter plot matrix made up of scatter plots for each pair of the eight variables of interest, as well as kernel density plots that show the distribution of each variable. Within each scatter plot, red dots represent quick response products and the green dots represent all the other products.

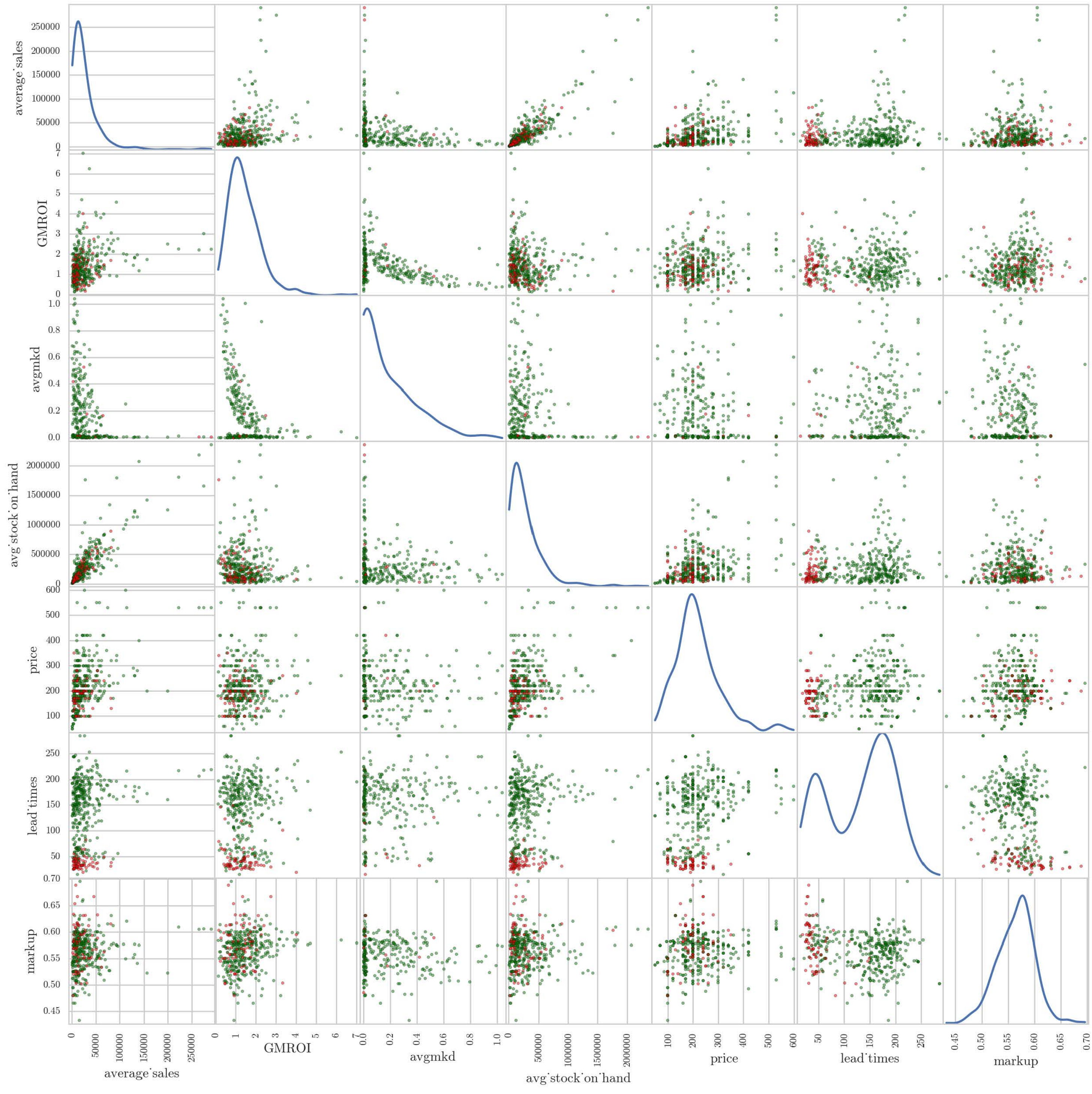


Figure 1: Scatter Matrix

The most apparent relationship within the data is the positive correlation between average stock on hand and average sales. This suggests that the buyers are purchasing larger quantities of the goods that sell in higher quantities.

From the lead time scatter plots it appears that the quick response products have much shorter lead times than the other products. This is confirmed by the difference in means displayed in Table 2. That is the reason for the bimodal shape of the lead time kernel density plot.

The figure shows that markdown is negatively related to GMROI. This is unsurprising since selling items at a lower price reduces gross profit for a given unit of inventory.

Contrary to expectations, the quick response products do not appear to differ from the rest of the products in any meaningful way. Furthermore, there seem to be no other meaningful relationships amongst the metrics.

### 3.4 Graphs & Plots

The box plot below (Figure 2) shows the distribution of lead times for each of the four product groups. It is clear that the quick response product range outperforms the other three groups. As noted, this is expected given the design of the quick response supply chain.

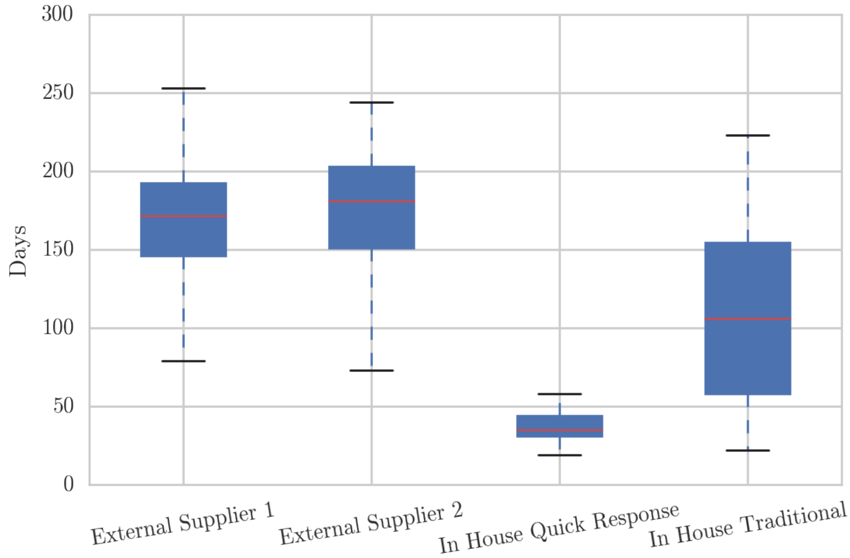


Figure 2: Lead Times

Both of the in-house product ranges significantly outperform the external suppliers, however, the average lead times are considerably shorter for the quick response group. The traditional group has shorter lead times than the external suppliers simply because the manufacturing is done locally rather than internationally.

This confirms that the retailer has, thus far, correctly implemented the lead time strategy of the QR model correctly. The difference in lead times is the core feature that allows for this analysis. The retailer must have implemented the quick response strategy successfully to enable inferences to be drawn from this data about quick response in general. Nonetheless, this does not negate the need for improvement in their QR implementation, as shorter lead times allow for even more versatility.

Figure 3 and 4 display the frequency and size of orders placed by the retailer for each of the 4 groups. We expect that quick response products will have more variation in order frequency as some goods should never be replenished and others should be replenished frequently. The quick response range should also have lower average order quantity. The key benefit of short lead times is being able to order in smaller quantities therefore reducing the risk of having large amounts of inventory that is not in demand.

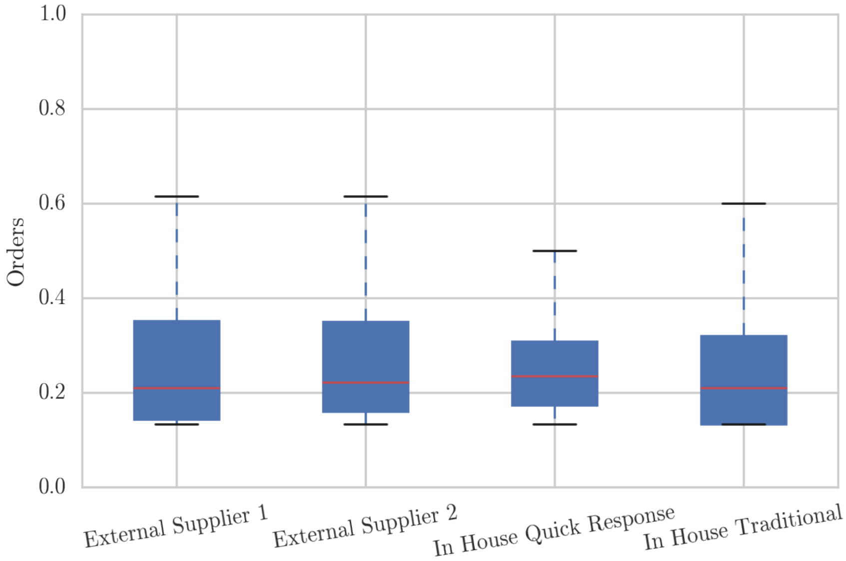


Figure 3: Number of Orders, from Supplier, per Month

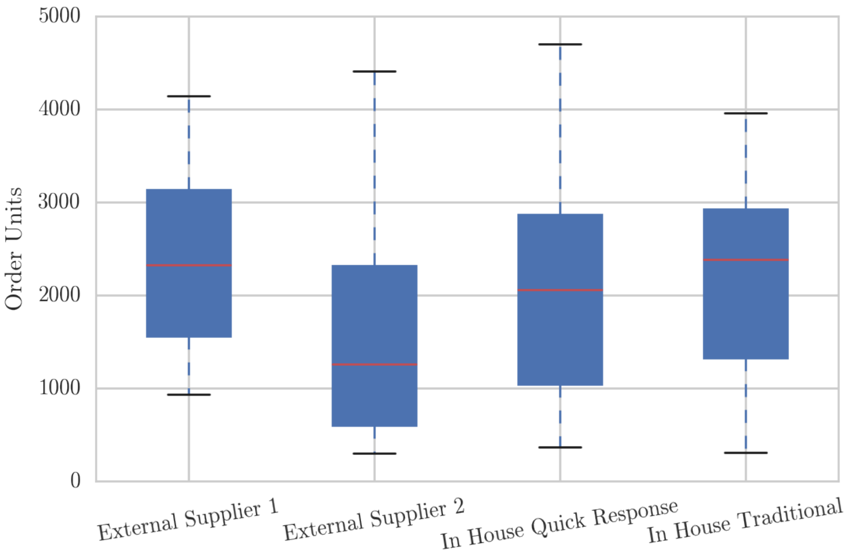


Figure 4: Average Order Quantity

Interestingly, the QR group does not appear to have significantly smaller order quantities or a larger number of orders per month. This may be an indication that the retailer is failing to correctly implement the quick response strategy.

The following two box plots (Figure 5 & Figure 6) show the pricing and mark-up distributions. The literature suggests that there is a cost associated with implementing quick response because local manufacturing is often more costly. The South African textile and clothing industries are not globally competitive (Morris and Einhorn, 2008). It would therefore be unsurprising to see lower markups on the in-house product groups as costs are likely higher. Contrary to expectations though, Table 2, above, illustrated that the in-house products have lower average prices.

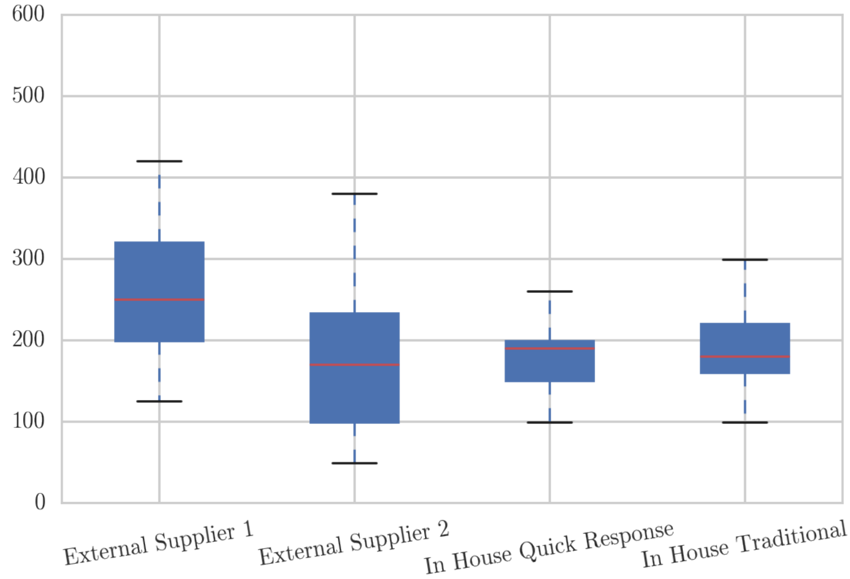


Figure 5: Price

Across all the suppliers there seems to be very little variation in the percentage mark-up with the majority of products falling within the 50% - 60% range. The pricing distribution reveals that the majority of products fall below the R400 price point. This indicates that the retailer is relatively low cost.

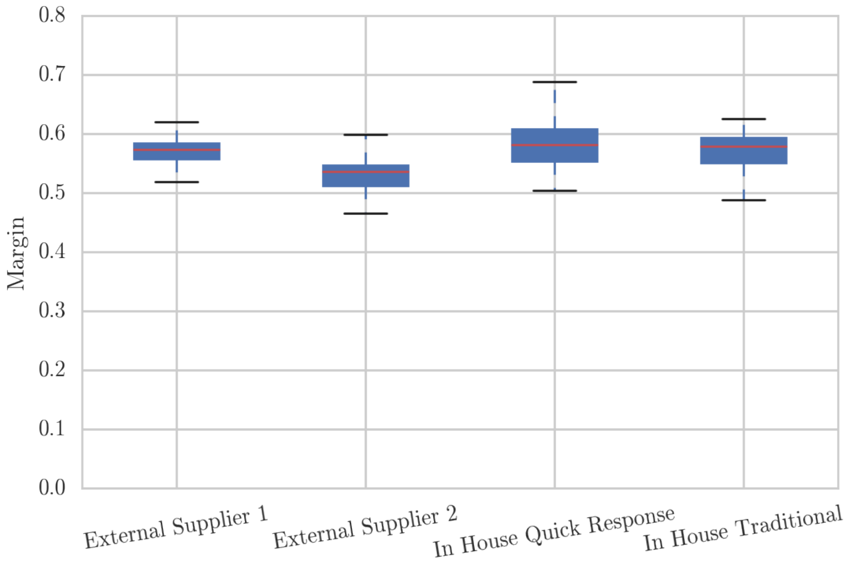


Figure 6: Gross Profit Margin

Figure 7 gives a breakdown of the average markdown of sales prices broken down by supplier type. However, since the retailer could not provide markdown information for the majority of the in-house products, it would not be sensible to draw conclusions about the distribution.

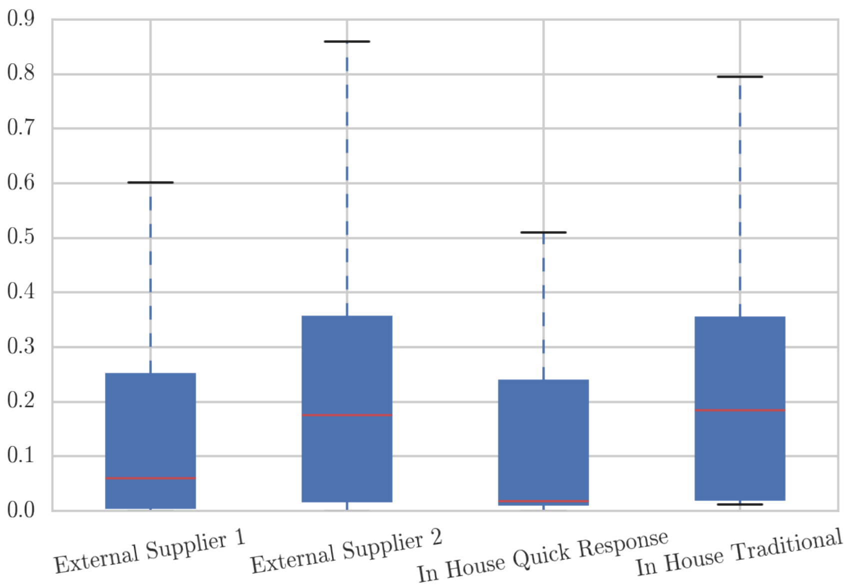


Figure 7: Average Markdown

Figure 8 shows sales grouped by supplier over the thirty-week period, starting in week 12. Sales are highest in the middle of this time period and drop off significantly at the end. The products sourced from "External Supplier 1" have a much higher sales volume as was seen in Table 2. The QR range clearly does not outperform the other groups in terms of sales. This is surpising because the QR products should more closely match consumer demand and therefore have higher sales on average.

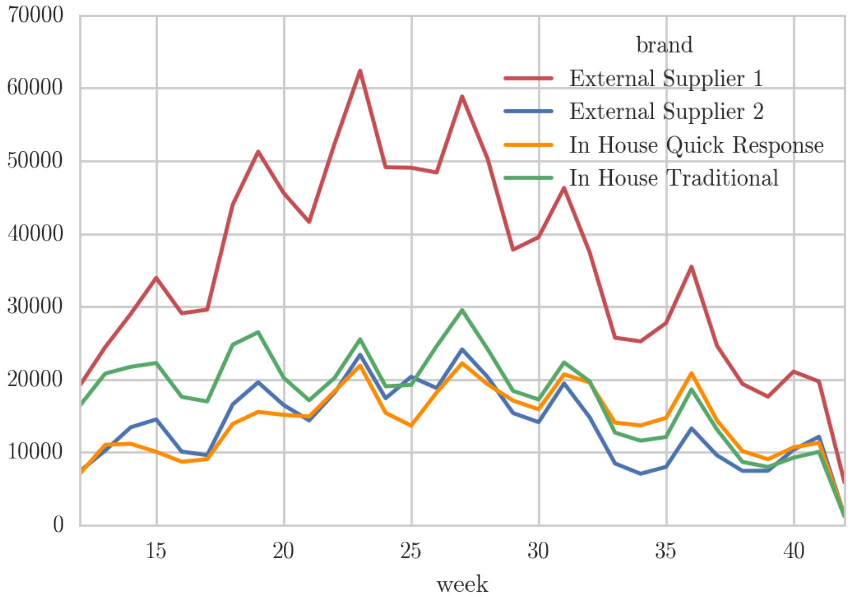


Figure 8: Sales Volume Over Time

Figure 9 shows the average value of inventory during the same period. As expected the QR group range has lower inventory levels at the start of the period. As more goods are introduced throughout and others are replenished during the period, the inventory levels converge to the levels of the other groups.

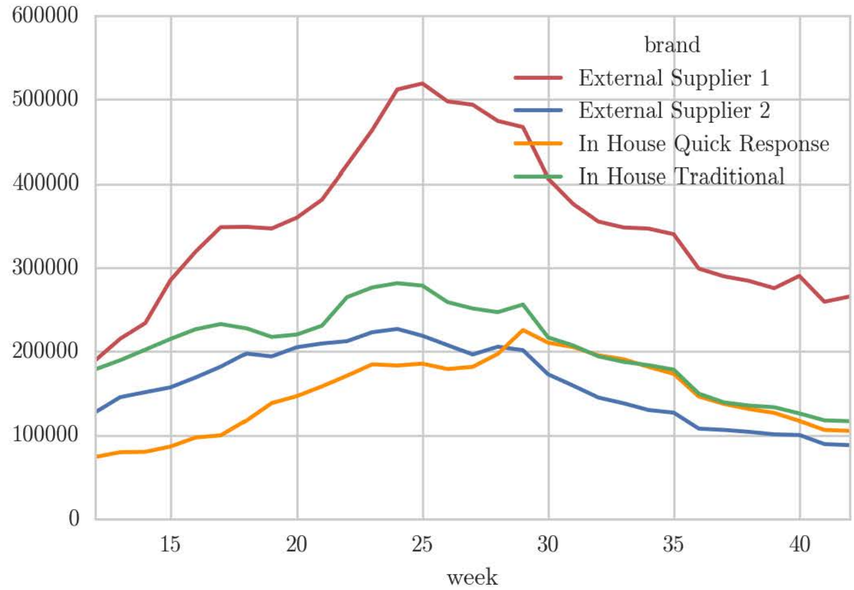


Figure 9: Stock on Hand, Over Time

# 4 Methodology

The aim of the following analysis is twofold. The first objective is to investigate the extent to which the retailer has implemented quick response. By comparing the QR product range to the other three product ranges, using the metrics outlined in Section 2.1, the retailer's effectiveness will be evaluated. In order to draw conclusions about the benefits of quick response from the performance of the retailer's QR product range, it is crucial to know that the strategy has been implemented correctly according to the theory.

Once this is understood, section two of the analysis can begin. Using ANOVA and OLS regression analysis, it is possible to test for relationships between the quick response characteristics, such as lead time, and the performance metrics suggested in section 2.2. ANOVA statistics determine whether the means between grouops are significantly different from one another. This is done by comparing the groups individual variation to the variation between the groups. As the question of interest is in the individual differences between the four product groups, the ANOVA analysis will be supplemented with Tukey's HSD (Honest Significant Difference) test which allows for accurate pairwise comparisons of means when there are more than two groups .

Due to data limitations that have already been highlighted, calculating the GMROILS is not possible. This is due to the lack of stock outs experienced by the retailer across the 30-week period. This is unfortunate as the GMROILS is an ideal metric for quantifying the benefits of QR and, as a consequence of these limitations, has to be omitted from the analysis

## 4.1 Quick Response Characteristics

The three characteristics that are analyzed are, lead time, average stock on hand and order frequency. These are all metrics on which QR products should differ from those on traditional lead times.

### Lead Time

$$\begin{aligned} LeadTime_i = \beta_0 + \beta_1 Ladies_i + \beta_2 InHouseQR_i + \\ \beta_3' InHouseTraditional_i + \epsilon_i \end{aligned}$$

The linear model above is estimated using OLS to determine the effect that the different dummy variables have on lead time. It is expected that both of the in-house dummies will have significant, negative, coefficients as they are produced locally.

### Average Stock on Hand

For average stock on hand an ANOVA analysis is carried out to compare the means of the four product groups. The aim is to identify whether the QR products have significantly lower average inventory levels. based on the literature, it is expected that the Quick Response products should have less stock on hand.

### Order Frequency

Order frequency is another differentiating characteristic of QR. In order to determine whether the order patterns of the retailer, for their QR range, are in line with the theory of Quick Response, an ANOVA analysis is conducted. It is expected that order frequency will be higher for the QR group. The ANOVA results can be found in section 5.

## 4.2 Performance Metrics

In order to assess the performance of the QR strategy, markup, average markdown rate and the GMROI are analysed. Each metric is used as the dependent variable in an OLS looking at the difference in QR versus traditional supplier purchasing methods. A number of controls are used to try and reduce bias, including the category of apparel, price and lead time.

### Markup

$$\begin{aligned} Markup_i = {} & \beta_0 + \beta_1 Ladies_i + \beta_2 InHouseQR_i + \\ & \beta_3 InHouseTraditional_i + \beta_4 Price_i + \\ & \beta_5 LeadTime_i + \epsilon_i \end{aligned}$$

This model aims to explain the variation in markup using dummy variables for department and the two in-house product groups as well as price and lead time. The literature suggests that locally manufactured goods are not competitive compared to imports (Staritz and Morris, 2015). Therefore it would not be surprising to see a negative relationship between the in-house dummy variables and markup.

**Average Markdown**

$$\begin{aligned}Markdown_i = \beta_0 + \beta_1 Ladies_i + \beta_2 InHouseQR_i + \\ \beta_3' InHouseTraditional_i + \beta_4 Price_i + \\ \beta_5 LeadTime_i + \beta_6 Markup_i + \epsilon_i\end{aligned}$$

Markdowns are a large source of losses for traditional retailers. Reducing these losses is supposedly one of the primary benefits of QR. It is expected that the estimated coefficient on the QR dummy will be negative and statistically significant. There may be a positive relationship between markup and average markdown as a high markup could indicate a product being overpriced and therefore requring a reduction in price to incentivise consumers to buy it.

**GMROI**

$$\begin{aligned}GMROI_i = \beta_0 + \beta_1 Ladies_i + \beta_2' InHouseQR_i + \\ \beta_3 InHouseTraditional_i + \beta_4 Price_i + \\ \beta_5 LeadTime_i + \beta_6' Markup_i + \epsilon_i\end{aligned}$$

GMROI, after GMROILS is the best retail metric to evaluate the benefits of Quick Response. The relationship between GMROI and the QR dummy is expected to be positive and statistically significant. Lead time is included in the model to determine whether shorter lead times within the QR product group, further improve GMROI or not. Markup should be postiviely related to GMROI as markup influences gross margins.

# 5 Results and Discussion

## 5.1 ANOVA

ANOVA analysis is done on order frequency and average stock on hand. The aim is to test for differences between the product groups. ANOVA is prefered over OLS for these variables as we are only interested in knowing whether a difference in means exists.

Tukey Honest Significant Difference (HSD) post hoc analysis is done in conjunction with ANOVA to produce reliable comparisons between each pair of means.

The output can be found in Appendix A. Figure 10 shows the Tukey HSD output for average stock on hand and Figure 11 is the output for orders per month. Average stock on hand is significantly higher for external supplier 1 and there is no significant difference between the other three groups. This suggests that the QR products do not have smaller inventory levels than the second external supplier or the traditional in-house group.

None of the group means differ in terms of orders per month. This is a surprising result because we would expect, based on the literature, that the QR products would have more frequent orders.

This suggests that although the company refers to this product range as Quick Response, they simply have short lead times. QR requires short lead times as well as purchasing a variety of products in small quantities and then only replenishing the ones that are in demand. Having short lead times is a tool that allows retailers to reduce stock on hand and therefore risk. However, short lead times on their own will not improve GMROI or reduce the risk of markdowns. With low lead times there is no reason to order such large quantities.

## 5.2 Regression

In this section the regression output is analysed and discussed. Regressions are carried out on lead time, markup, average markdown and GMROI, respectively, based on the models outlined in Section 4. Table 3 shows the beta coefficients and standard deviations for each of the variables in each of the models.

Table 3: Regressions Output (t-statistics in parenthesis)

| | (1)<br>Lead Time | (2)<br>Markup | (3)<br>Markdown | (4)<br>GMROI |
|---|---|---|---|---|
| Ladies | -19.5*** | 0.0346*** | -0.0709** | 0.157 |
| | (4.14) | (0.003) | (0.034) | (0.104) |
| In House QR | -130.31*** | 0.033*** | -0.0033 | -0.2063 |
| | (5.24) | (0.006) | (0.07) | (0.177) |
| In House Traditional | -61.45*** | 0.023*** | 0.0294 | -0.0905 |
| | ( 4.77) | (0.004) | (0.048) | (0.123) |
| Price | | 0.000045** | 0.00043 | 0.0007 |
| | | (0.000017) | (0.00) | (0.00) |
| Lead Time | | .000061* | 0.0006 | 0.0006 |
| | | (0.000036) | (0.000) | (0.001) |
| Markup | | | -0.217 | 3.5192** |
| | | | (0.465) | (1.374) |
| Constant | 181.62*** | 0.512*** | 0.125* | -0.8292 |
| | (3.75) | (0.008) | (0.068) | (0.735) |
| N | 428 | 427 | 296 | 427 |
| $R^2$ | 0.62 | 0.318 | 0.039 | 0.065 |
| F | 230.5 | 39.34 | 2.300 | 4.865 |

### 5.2.1 Lead Time

From regression 1 in Table 3 above, it is suggest that the model explains 62% of the variation in lead-time and that all three dummy variables are significant. Ladies' products are on shorter lead times than girl's, with an average difference of 19.5 days. On average, the QR group have lead times 130 days shorter than the external supplier products. Traditional in-house products are also on shorter lead times than the external suppliers by 61 days on average.

These results are to be expected based on the large difference in means between the groups observed in Table 2. The result is also in line with theory as QR products are, by definition, on short lead times. The in-house traditional products have lower lead times than the external suppliers because they are produced locally so delivery times are shorter.

### 5.2.2 Markup

Regression 2 explains 31.8% of the variation in markup and, once again, all of the coefficients are statistically significant. Products in the ladies department have 3.46% higher margins. Profit margins are higher for both the in-house brands. The coefficients on price and lead time are statistically significant but they are not economically significant. A 100 rand increase in price only increases markup by 0.45%.

It is interesting that the in-house brand dummies are significant once lead times are controlled for. This suggests that the difference in markup between the external suppliers and the in-house brands is not simply due to these products having shorter lead times.

### 5.2.3 Markdown

It is clear that this regression model has some concerning results. This is unsurprising given the lack of data on markdowns for the in-house products. This has severely compromised the analysis with the model failing to explain even 4% of the variation in the dependant variable. This means that the independent variables, lead times, markup and supplier type, have very little effect on the average mark-down. Neither of the dummy variables for the in-house brands are significant meaning that there is not a statistically significant difference in average mark-down between the externally and internally sourced groups of products.

The only statistically significant variable is the ladies wear dummy. Womens wear products are marked down 7.1% more on average compared to girls wear. This seems reasonable as women are likely more discerning than girls, who are less likely to buy their own clothes.

### 5.2.4 GMROI

The results of the OLS regression on GMROI suggest that the variables are severely lacking in explanatory power. The group of variables included jointly explain 6.5% of the total variation in Gross Marginal Return on Investment. The dummy variable for the QR group is not significant meaning that the group of products do not have a statistically different GMROI on average. Moreover, the only statistically significant variable is mark-up. This suggests that the primary drivers of GMROI are not captured in the data.

Based on the theoretical benefits of QR, the insignificance of the QR group found in this model is an unsurprising result. The gains in GMROI come exclusively from reduced inventory on hand. Hence, it is framed as a reduction in risk and not any inherent improvement in profitability. In fact, often shortening lead times requires sourcing products from more expensive local suppliers which should increase costs. From the ANOVA analysis, it is clear that the retailer does not have lower inventory levels for their QR range. This means they are unable to capitalise on the primary benefit of quick response. For this reason, it is unsurprising that the QR dummy was insignificant in predicting GMROI in the above model.

# 6 Conclusion

This investigation set out with a two-tier framework to analyse Quick Response at the product level. Following this strategy, the conclusion will be divided into two sections. The first covers the dashboard of metrics that are recommended for analysing QR products. The second will summarise the findings of the analysis using the South African case study.

## 6.1 Framework

The literature provides compelling theoretical arguments for the benefits of Quick Response. There is, however, a lack of empirical evidence to support the theory. Firm level analysis does not find significant differences in performance between QR and non QR retailers. Due to restricted access to product level data, little analysis has been done to compare the performance of QR to non QR products. Analysis on the product level allows for the company level variables to be held constant making it easier to isolate the effects of QR.

To determine whether a product is produced by a quick response supply chain there are a number of metrics to measure. Lead times are the most important as without short lead times, reacting to demand is impossible. In addition, order frequency and average order value should be considered as further requirements of QR. The strategy involves buying small quantities of a wide variety of products and only replenishing the ones that sell quickly. Quick response products should therefore have higher order frequency and lower average order quantity.

The primary benefits of a more reactive supply chain come from the ability to match unpredictable levels of demand while keeping inventory levels low and therefore mitigating risk (Caro and Martínez-de Albéniz, 2015). Quick response products are expected to have a higher GMROI because average inventory will be lower due to smaller order quantity. Stock outs are also less likely to occur as inventories can be replenished as they start to run low due to short lead times. GMROILS the metric that incorporates lost sales due to stock outs into the GMROI equation should fully capture and quantify the benefit of QR.

## 6.2 Case Study

The move toward Quick Response manufacturing in South Africa should lead to a number of positive outcomes. Firstly, it will allow local manufacturers to gain a competitive advantage over cheaper foreign imports as retailers shift their focus from lowering costs to improving lead times. Secondly, retailers will likely experience improved profitability and face less risk when making buying decisions.

The case study in this paper highlights a critical issue for the evaluation of Quick Response in research. It should not be taken as given that companies that purport to operate with quick response supply chains are doing this correctly in reality. This is especially important to consider when attempting to use their performance to garner insights into the strategy's effectiveness. A thorough analysis of a retailer's adherence to the fundamental characteristics of quick response must precede any analysis of the strategies effectiveness.

The results highlight that the retailer does not appear to be fully and correctly implementing Quick Response. With short lead times they have the means with which to do so, however, they fail to reap the benefits as their initial order quantities are too high. Lead time compression is not the goal of a quick response supply chain strategy; it is one of the means by which the strategy is implemented. Short lead times allow retailers to react to the buying patterns of consumers. This allows them to buy wider, discontinue unsuccessful products, have less stock on hand and only restock products that are in high demand. This significantly reduces the risk inherent in forecasting fashion trends by delaying the supply decisions until such time as demand can be observed (Fisher and Raman, 1996).

Although the case study was unable to quantify the benefits of Quick Response, the framework and methodology have been laid out. The move toward QR in South Africa is promising as it will likely breath new life into local apparel manufacturing by giving the industry a competitive advantage over foreign imports while also, hopefully, improving the profitability of retail firms.

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# Appendix A

| group1 | group2 | meandiff | lower | upper | reject |
|---|---|---|---|---|---|
| External Supplier 1 | External Supplier 2 | -222899.6266 | -317666.1575 | -128133.0956 | True |
| External Supplier 1 | In House Quick Response | -208333.8317 | -305929.8355 | -110737.8279 | True |
| External Supplier 1 | In House Traditional | -166125.4875 | -255978.4477 | -76272.5274 | True |
| External Supplier 2 | In House Quick Response | 14565.7948 | -97320.5095 | 126452.0992 | False |
| External Supplier 2 | In House Traditional | 56774.139 | -48426.2392 | 161974.5172 | False |
| In House Quick Response | In House Traditional | 42208.3442 | -65547.8814 | 149964.5697 | False |

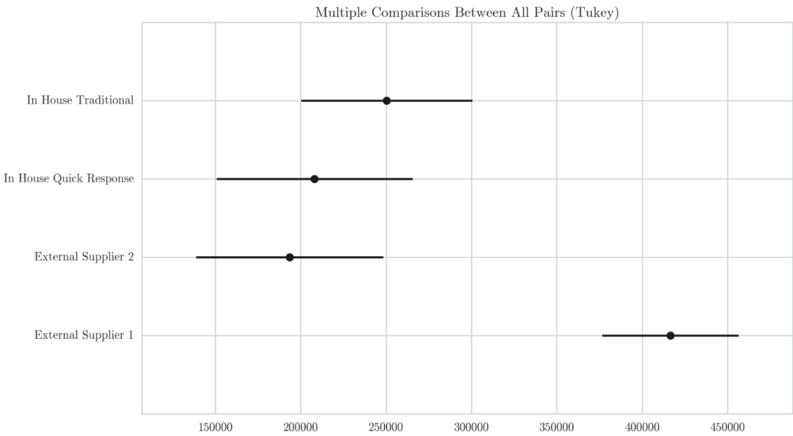


Figure 10: Average Stock on Hand

| group1 | group2 | meandiff | lower | upper | reject |
|---|---|---|---|---|---|
| External Supplier 1 | External Supplier 2 | -0.0157 | -0.074 | 0.0426 | False |
| External Supplier 1 | In House Quick Response | -0.0219 | -0.0819 | 0.0381 | False |
| External Supplier 1 | In House Traditional | -0.0194 | -0.0746 | 0.0359 | False |
| External Supplier 2 | In House Quick Response | -0.0062 | -0.075 | 0.0626 | False |
| External Supplier 2 | In House Traditional | -0.0037 | -0.0684 | 0.061 | False |
| In House Quick Response | In House Traditional | 0.0025 | -0.0637 | 0.0688 | False |

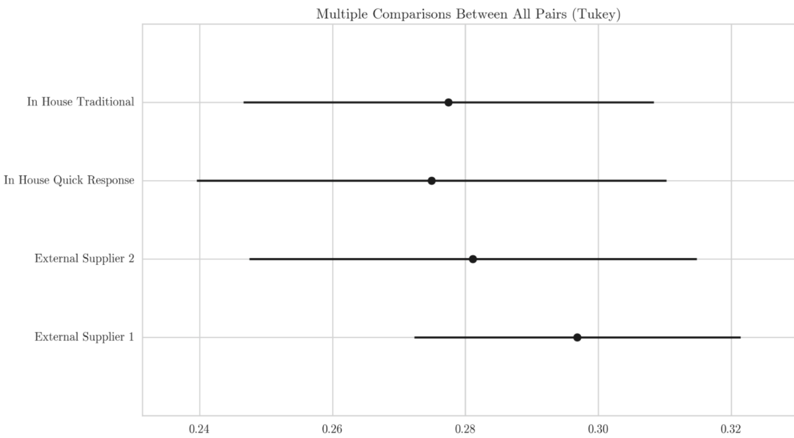


Figure 11: Orders per Month