

ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL

**ASSESSING THE IMPACT OF PROMOTIONS ON SALES:
A QUANTITATIVE APPROACH FOR A LARGE-SCALE RETAILER'S
SALES PERFORMANCE**

Ph.D. THESIS

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Department of Management

Management Programme

JULY 2022

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JULY 2022

İSTANBUL TEKNİK ÜNİVERSİTESİ ★ LİSANSÜSTÜ EĞİTİM ENSTİTÜSÜ

**PROMOSYONLARIN SATIŞLAR ÜZERİNDEKİ ETKİSİNİN
DEĞERLENDİRİLMESİ: BÜYÜK ÖLÇEKLİ BİR PERAKENDECİNİN
SATIŞ PERFORMANSINA İLİŞKİN KANTİTATİF BİR YAKLAŞIM**

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To my family,



FOREWORD

This doctoral thesis contains the results of my research undertaken at the Department of Management at the Graduate School of İstanbul Technical University. This research was also realized within the data science framework of the RD projects completed at Migros Ticaret AŞ. R&D Department. Moreover, I was funded by the Turkish Higher Education Council's 100/2000 Priority Areas Doctoral Scholarships during my studies. I would have never finished my studies without the assistance of these three institutions. Therefore, I want to thank them for their support.

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TABLE OF CONTENTS

	<u>Page</u>
FOREWORD	ix
TABLE OF CONTENTS	xii
ABBREVIATIONS	xiii
SYMBOLS	xv
LIST OF TABLES	xvii
LIST OF FIGURES	xix
SUMMARY	xxi
ÖZET	xxiii
1. INTRODUCTION	1
1.1 Sales Promotions	1
1.1.1 Types of sales promotions	3
1.1.1.1 Trade promotions / retailer promotions	3
1.1.1.2 Price - non price promotions	5
1.1.2 Theories of price promotions	6
1.1.3 Research question and significance	10
2. LITERATURE REVIEW	13
2.1 Early Studies on Sales Promotions	13
2.2 Price Promotions Research Stream and emerge of Quantitative Analysis in Price Promotion Research	14
2.3 Recent Developments in Price Promotions Research	17
3. METHODOLOGY	21
3.1 Empirical Context and Data	21
3.1.1 Empirical context	21
3.1.2 Econometric framework	24
3.1.2.1 Univariate mean level and volatility modelling	25
3.1.2.2 Autoregressive distributed lag models	27
3.1.2.3 SUR estimation	29
3.1.3 Data	31
3.1.3.1 Data and feature creation	32
3.1.3.2 Feature creation	32
3.1.3.3 Data preprocessing	35
4. EMPIRICAL FINDINGS	41
4.1 Price Promotions Effects on Mean Level and volatility of Sales Trend	41
4.2 Price Promotions' Effects on Brand/Category Level	46
4.2.1 Diagnostic tests	48
4.2.2 Post estimation analysis	52
4.2.2.1 Category - brand own effects	59
4.2.2.2 Category switching effects	60
4.2.2.3 Within category effects	61
4.2.2.4 Seasonal effects	62

5. CONCLUSIONS	63
5.1 General Discussion and Theoretical Implications	63
5.2 Limitations and Future Research	65
REFERENCES	67
APPENDICES	73
APPENDIX A : Time Series Characteristics of Promotion Depth and Diffusion Variables / Category Level Model	75
APPENDIX B : Time Series Plots of Variables Included in Category-Brand Level Model	77
APPENDIX C : ARDL Lag Order Specifications	81
APPENDIX D : Stability Tests and Residual Diagnostics for ARDL Models ..	83
APPENDIX E : Residual Diagnostics for ARDL Models.....	85
APPENDIX F : Estimated Parameters of Short-Run and Long-Run Models (Dynamic Variables)	87
APPENDIX G : Estimated Parameters of Short-Run and Long-Run Models (Strategy and Seasonal Dummy Variables	98
CURRICULUM VITAE	102

ABBREVIATIONS

AIC	: Akaike Information Criteria
ARDL	: Autoregressive Distributed Lag
ARIMA	: Autoregressive Integrated Moving Average
ADF	: Augmented Dickey Fuller
BLS	: Bureau of Labour Statistics
CLR	: Classical Linear Regression
CEC	: Conditional Error Correction
DLM	: Distributed Lag Models
ETS	: Econometric Time Series Models
ECM	: Error Correction Model
IRI	: Information Resources Inc
GARCH	: Generalized Auto-regressive Conditional Heteroskedasticity
GIS	: Geographic Information Systems
KPI	: Key Performance Indicators
KPSS	: Kwiatkowski–Phillips–Schmidt–Shin
LRD	: Long Run Dynamics
ML	: Machine Learning
SKU	: Stock Keeping Units
SSE	: Sum Square Error
UECM	: Unrestricted Error Correction Model
TPR	: Temporary Price Reduction



SYMBOLS

χ^2	: Chi-Square
λ	: Box-Cox Power Transformation Parameter
t	: Trend





LIST OF TABLES

	<u>Page</u>
Table 1.1 : Components of Marketing-Mix Program.	1
Table 3.1 : Alias used on behalf actual brand names.	34
Table 3.2 : Descriptive Statistics for Sales Quantity Variable.	37
Table 4.1 : Unit root test results for category level variables.	41
Table 4.2 : ARIMA(7,0,2) + IGARCH (1,1) in mean model estimated parameters.	45
Table 4.3 : Significance of models indicators.	50
Table 4.4 : Auto-Correlation tests on model residuals.	51
Table 4.5 : Unit root tests on residuals.	51
Table 4.6 : Bounds test results.	53
Table 4.7 : Correlation matrix for ARDL model Residuals.	54
Table 4.8 : Hausman test results.	55
Table 4.9 : Significance of CEC model diagnostics.	57
Table 4.10 : Significance of LRD model diagnostics.	57
Table G.1 : Promotional Strategy and Seasonal Dummy Variables.	98



LIST OF FIGURES

	<u>Page</u>
Figure 1.1 : Elements of promotional mix.	2
Figure 1.2 : Types of sales promotions (according to sources).....	3
Figure 1.3 : Sales promotion tools.....	4
Figure 1.4 : Theories of price promotions.....	6
Figure 1.5 : Theoretical rationales for price promotions.	9
Figure 2.1 : Recent research streams in price promotions domain.....	18
Figure 3.1 : Main hypotheses tested in the study.	23
Figure 3.2 : Annual brand sales liquid-powder detergents.	34
Figure 3.3 : Laundry detergents category - quantity sold in kgs (y-axis).	36
Figure 3.4 : 2014 - 2018 daily laundry detergents sales (monthly aggregated. ...	38
Figure 4.1 : Estimation workflow	54
Figure 4.2 : Functional decomposition of promotions effects.....	58
Figure A.1 : Correlogram of variables used in category level models	75
Figure A.2 : Correlogram of variables used in category level models	76
Figure B.1 : Quantity Sold Variables in Logarithms	77
Figure B.2 : Category/Brand Level Prices in Logarithms	78
Figure B.3 : Daily Change in Prices	78
Figure B.4 : Daily Promotion Depth Allocations	79
Figure D.1 : Recursive CUSUM Test Plots for ARDL Models	83
Figure E.1 : Residual Diagnostics for ARDL Models	85
Figure F.1 : Estimated Parameters of SUR System - Beta Powder Product Line .	87
Figure F.2 : Estimated Parameters of SUR System - Beta Liquid Product Line ..	88
Figure F.3 : Estimated Parameters of SUR System - Alpha Powder Product Line	89
Figure F.4 : Estimated Parameters of SUR System - Alpha Liquid Product Line	90
Figure F.5 : Estimated Parameters of SUR System - Gamma Powder Product Line.....	91
Figure F.6 : Estimated Parameters of SUR System - Gamma Liquid Product Line	92
Figure F.7 : Estimated Parameters of SUR System - Delta Powder Product Line	93
Figure F.8 : Estimated Parameters of SUR System - Delta Liquid Product Line .	94
Figure F.9 : Estimated Parameters of SUR System - Omega Powder Product Line	95
Figure F.10 : Estimated Parameters of SUR System - Omega Liquid Product Line	96
Figure F.11 : Estimated Parameters of SUR System - Omicron Liquid Product Line.....	97



ASSESSING THE IMPACT OF PROMOTIONS ON SALES: A QUANTITATIVE APPROACH FOR A LARGE-SCALE RETAILER'S SALES PERFORMANCE

SUMMARY

American Marketing Association defines marketing as *"a system and operational process which includes various interconnected subsystems, harmonising with co-contributor elements to reach maximum efficiency."* This thesis seeks to understand and explain the role of the promotional mix, one of the four Ps of the marketing-mix problem.

Although sales promotions were acknowledged as a dissolving stock activity by sales management literature until the late 1960s, with increasing competition in the retail sector, it has become a vital instrument to impulse sales both for the long term and short term. However, within three decades, especially after the introduction of the television and online media (proper mediums for transmitting instant offers), the sales promotion activities had become more sophisticated, and their frontiers had outstretched beyond the frontiers of a single chapter to a stand-alone book.

In the meantime, technological advances in data storage and computation areas enable scholars to create complex, multi-channel promotion analyses; the literature recognised promotions as an essential element in the marketing system. As a result, the sales promotion domain has become one of the significant divisions of marketing literature. In a modern sense, as a critical element of the marketing mix, the promotion has three main objectives, providing information to consumers and others, increasing demand, differentiating a product or category, stabilising sales, and accentuating a product's value. Therefore, most of the tools used by retailers from the sales promotion toolbox could be taxonomised in the price promotions domain.

Price promotions' concrete impulse and response mechanism ease the effort of tracking and understanding effects created by sales trends. However, To accomplish a price promotion task, a company needs a clear understanding of which kind of promotions are working and why? Although current business intelligence applications can reflect the flow of cash and stocks of a company, promotions have complex relationships with various Key Performance Indicators (KPIs) of a business system. This aspect makes distinguishing the next value-added from a promotion a complicated job. This thesis aims to portray a reliable quantitative model to decompose price promotion's effect on sales trends. Most studies in price promotions have only focused on single response mechanisms like category effect, cannibalism, cross-category effects or brand switching. This study aims to contain responses of all courses given above in a single inclusive system of equations. Formulating a complete model system for the pilot category would allow practitioners to replicate results to all product inventory and eases the decision-making process extensively.

Regarding the outcome of the studies, managerial relevance can be classified on the timing and nature of the impact created. In modern retailers' daily lives, promotions are critical to sustaining an increase in demand in the long term. On the other hand, retailers expect promotions to act as a balancer on lowering excess stocks in the short term. That promotes current actions and future strategies for sustaining long term increased demand. Therefore, a researcher studying in this field, especially in the business intelligence domain, should be aware that they should provide actionable, essential and meaningful insights for the practitioners. In order to achieve these kinds of outcomes, academic scholars should suggest a decision-making process in which retailers can observe the response of sales trends to their strategic moves, which are mainly classified as exogenous effects.

Developing a reliable base for assessing promotions' impact on sales is strongly related to formulating a correctly specified model. Therefore, market response models are beneficial, especially for researchers working on the company's secondary data compiled from the enterprise database. A response model exhibits how one variable depends on other variables. For example, dependent variables could be sales or other KPIs of interest to marketing practitioners. On the other hand, independent variables are assumed to affect the dependent variable. Together these variables constitute a market response model. A response model defined on time series or cross-sectional data as an empirical response model. Accordingly, if a researcher prefers to study the direct and secondary impacts of price promotions on the retail level, market response models extended with exogenous promotion policy variables would be a yielding alternative. On the other hand, it is possible that to solve the true nature of promotions (create academic knowledge) and create insightful managerial relevance (prescriptive analytics), quantitative methods, including econometric response models, are the most efficient way. In this dissertation, I aimed to provide this kind of dual knowledge discovery for academic research and the retail industry.

The research is based on three hypotheses which led me to construct two categories / multi-brand promotional effectiveness models. While the first section of the empirical study formulates the variables used in the next part of the study, including volatility modelling to promotion effectiveness has created an alternative approach. The second part of my empirical work was my playground to decompose and analyse net sales effects created by price promotion. The findings concluded that promotional strategy significantly affects the sales quantity of category/brand pairs both in the long and short term. As expected, I concluded that most of the sales bump created through promotions stems from the product's own promotional activity. On the other hand, results provided that promotions applied to competitor brands and categories also cause a significant change in sales trends.

This research provides a timely and necessary study of creating pioneering a central promotion effectiveness assessment system for practitioners. By utilising the models produced in this study, the retail executives could organise promotional strategies from a wide-angle.

PROMOSYONLARIN SATIŞLAR ÜZERİNDEKİ ETKİSİNİN DEĞERLENDİRİLMESİ: BÜYÜK ÖLÇEKLİ BİR PERAKENDECİNİN SATIŞ PERFORMANSINA İLİŞKİN KANTİTATİF BİR YAKLAŞIM

ÖZET

Amerikan Pazarlama Derneği pazarlama disiplini, *"...bir birine destek olan fonksiyonları, bağlantılı farklı alt sistemler şeklinde harmonize ederek etkinliği en üst seviyeye çıkaran bir süreç ve sistem"* olarak tanımlamaktadır. Bu tez çalışması pazarlama karışımının (marketing mix) dört P'sinden biri olan promosyon karışımının (promotion mix) tanımlanan sistem içerisinde rolünü anlamayı ve açıklamayı amaçlamaktadır.

Satış promosyonları 1960'ların sonlarına kadar genellikle stokların eritilmesi için yapılan faaliyetler olarak anlaşılmaktaydılar. Ancak perakende sektöründe artan rekabetin bir sonucu olarak, satış promosyonları kısa ve uzun vadede satışları etkilemek için önemli bir araç haline geldiler. Sadece otuz sene içerisinde özellikle televizyon ve çevirim içi ortamların da hayatımıza girmesiyle, satış promosyonları daha karmaşık hale geldi. Daha önce satış yönetimi kitaplarındaki küçük bir bölümden ibaret olan bu disiplin, ayrı bir kitaba konu olabilecek ana bir araştırma disiplini olarak ortaya çıktı.

Öte yandan, veri saklama ve işleme hızında yaşanan teknolojik gelişmeler araştırmacıların daha kapsamlı ve çok kanallı promosyon analizleri yapmalarına imkan verdi. Geçen zaman içerisinde promosyon araştırması disiplini pazarlama disiplinin ön plana çıkan parçalarından biri haline geldi.

Günümüzde, pazarlama karışımının kritik bir elemanı olan promosyonun üç ana amacı bulunmaktadır. Bunlar, Müşterilere ve diğer ajanlara bilgi sağlamak ve talebi arttırmak, ürün yada kategoriye yönelik talebi arttırmak ve ürün değerini arttırmak şeklinde özetlenebilir. Bu amaçları gerçekleştirmek için perakendecilerin satış promosyonları alet çantasından sıklıkla kullandıkları araçlar fiyat promosyonları grubu içerisinde sınıflanabilir.

Fiyat promosyonlarının anlaşılması kolay etki ve tepki mekanizması kullanımları sonrası satış trendlerinde ortaya çıkan değişikliklerin, pazarlama yöneticileri tarafından rahatça anlaşılmasını sağlamaktadır. Ancak, bir şirketin fiyat promosyonu görevini başarı ile tamamlayabilmesi için hangi promosyon tiplerinin çalıştığı ve neden başarılı oldukları konusunda net bir bilgiye sahip olması gerekir. Güncel iş zekası uygulamaları nakit ve stok akımını çok rahat yansıtabilmektedir. Ancak promosyonların ürettikleri değer in öngörülmesi, şirket bünyesinde takip edilen çeşitli performans göstergeleri ile aralarındaki çok boyutlu ilişki nedeniyle zor görev dir. Bu araştırma ortaya koyacağı güvenilir modelleme ile fiyat promosyonlarının satış üzerindeki etkisini ayırtırmayı hedeflemektedir. Fiyat promosyonları üzerine yapılan birçok çalışma sadece kategori etkileri, markalar arasında geçişler gibi tek bir tepki mekanizmasını açıklamaya

çalışırken, bu çalışma literatürde adı geçen bütün mekanizmaların aynı anda fiyat promosyonlarına tepkilerini tahmin etmeye çalışan bir veri madenciliği projesidir. Seçili kategoride, tüm ürünleri kapsayacak bir denklemler sistemi tahmini yapılarak, uygulamacıların aldıkları kararlarının etkilerini gerçeğe yakın bir yapıda birden fazla rakip firma ve markanın bir arada olduğu bir ortamda gözlemlemelerini sağlamaktadır. Çalışmada pilot kategori ve ürün grupları için kurulan sistem farklı kategori ve ürün grupları için uygulanabilir esnekliktedir.

Akademik çalışmaların sonuçlarının işletme açısından anlamı, yaratılan etkinin doğası ve zamanlamasına göre sınıflanabilir. Günümüzde perakendecilerinin günlük operasyonlarında talebi uzun dönemde arttırabilmenin yolu promosyonlardan geçmektedir. Bunun yanı sıra promosyonlar, kısa vadede stok fazlasının eritilmesi açısından da önemlidirler. Promosyonları hem kısa hem de uzun dönem etkilerinin perakendeciler için kritik değer taşıması, bu aracın hem günü yönetmede hem de gelecek stratejisini belirlemede önemli olduğunu gösterir. Bu nedenle iş analitiği alanında çalışan bir araştırmacı, sayısal modelleri kullanarak, pazarlama yetkililerine aksiyon alınabilir, önemli ve anlamlı iç görüler önerdiklerinden emin olmalıdırlar. Bu çeşit çıktılara ulaşmak için dışsal etkiler olarak sınıflanabilecek pazarlama stratejisine satış trendinin gösterdiği tepkinin bir karar alma süreci şeklinde sunulması gereklidir.

Promosyonların değerlendirilmesi için güvenilir bir yapı oluşturulması kurulan öğrenme modelinin doğru belirlenmiş olmasına bağlıdır. Bu nedenle özellikle şirket veri tabanlarından derlenen ikincil veri ile çalışan araştırmacılar için piyasa tepki (market response) modelleri yararlı araçlardır. Tepki modelleri kullanılan bir değişkenin diğer değişkenler üzerinde nasıl bir etki yaptığını gösteren araçlardır. Örnek olarak bağımlı değişken satışlar olarak alındığında bağımsız değişkenler ise bağımlı değişkenin değerlerine etki eden değişkenler olarak modele yerleştirilebilir.

Ampirik bir tepki modeli zaman serisi yada yatay kesit veri modeli üzerine kurulur. Eğer bir araştırmacı fiyat promosyonların birincil ve ikincil etkileri üzerinde çalışmak isterse bu modeller dışsal strateji modelleri ile zenginleştirilebilir. Ekonometrik zaman serisi modellerinin kullanılması promosyonların gerçek doğasının anlaşılmasını sağlarken (akademik çıkarım), aynı zamanda işletme için de öneri verici analitikler üretilmesini (işletme için çıkarım) sağlar. Bu tezde her iki bilginde üretilmesini sağlamaya çalıştım.

Araştırma için iki kategori ve birden fazla markadan oluşan bir sistem olarak bir promosyon verimliliği değerlendirme modeli üretilmiştir. Ampirik çalışmanın ilk aşamasında yer alan çalışma promosyon verimliliği ölçümü için kullanılacak değişkenlerin etkinliklerinin test edilmesini amaçlanmıştır. Bu değişkenlerin etkinliklerinin istatistik geçerliliği sorgulanırken aynı zamanda promosyonların satışların ortalama seviyesi ve oynaklık ölçümleri üzerinden etkili olup olmadıkları da sorgulanmıştır. Sonuçlar özellikle satışların ortalama seviyesini değiştirmek için promosyonların etkili bir yol olduğunu göstermektedir.

Çalışmanın ikinci aşamasında fiyat promosyonları kanalı ile üretilen etkinin ayrıştırılması ve analiz edilmesi için ilk aşamada etkinliği test edilen değişkenleri de içeren çok denklemlerli bir model kurulmuştur. Sonuçlar promosyonların hem uzun hem de uzun dönemde satışlar üzerinde etkisi olduğunu göstermektedir. Beklendiği üzere yaratılan satış büyümesinin büyük oranda birincil etkilerden kaynaklandığı

görülmektedir. Öte yandan seçilmiş markaların satışlarının rakip markalar için yapılan kampanyalardan etkilendiği de görülmüştür.

Bu araştırma günümüzde perakendecilerin ihtiyaç duymakta olduğu yenilikçi bir merkezi promosyon verimliliği değerlendirme sistemini önerisini ortaya koymaktadır. Çalışmada sunulan veri madenciliği modelini kullanarak perakende yöneticileri promosyonel stratejilerini geniş bir bakış açısı ile değerlendirme fırsatı bulacaktır.





1. INTRODUCTION

1.1 Sales Promotions

Long term sustainable growth in the sales trend of a company mainly depends on how marketing officials direct healthy demand. In this quest, [1] first introduced the marketing mix concept as a well-established framework for marketers. Borden reveals his marketing - mix concept based on the definition of [2], positioning the marketing executives as a mixer of ingredients. As a decider of craft, sometimes they use their recipe; sometimes, they tend to mix components immediately available while designing their marketing strategy. Using marketing-mix, companies try to optimise a combination of marketing procedures and policies to bring the desired behaviour of trade and consumer spending.

Promotion, one of the most significant features of four components of the marketing-mix model, aims to inform, persuade, and remind consumers to influence their opinion or elicit a response.

Table 1.1 : Components of Marketing-Mix Program.

	Definition	Concepts
Product	An item that satisfies the consumer's needs or wants	Product design, Product assortment, Branding, Returns
Price	The amount a customer pays for a product.	Price – Setting, Price tactics, Price Strategy
Place	Providing customer access	Market coverage, Franchising, Assortment
Promotion	Marketing communications	Promotional Mix, Message Strategy

In line with that definition, the promotion has four main objectives; providing information to consumers and others, increasing demand, differentiating a product or category, stabilising sales, and accentuating a product's value. These objectives can be achieved by a series of efforts and tactics entitled the promotional mix.

As a sub-model of the marketing – mix, the promotional mix includes advertising, public relations, sales promotions and personal selling elements, as seen in Figure 1.1 [3]. From the consumer goods perspective, Advertising and sales promotions have more importance than public relations and direct sales. Sales promotions include short-term, temporary incentives to consumers or wholesalers curated to stimulate sales and reinforce other marketing and promotion mix elements. While mass media advertising is designed to build a brand image over time, sales promotions are prominent and planned to generate sales trends.

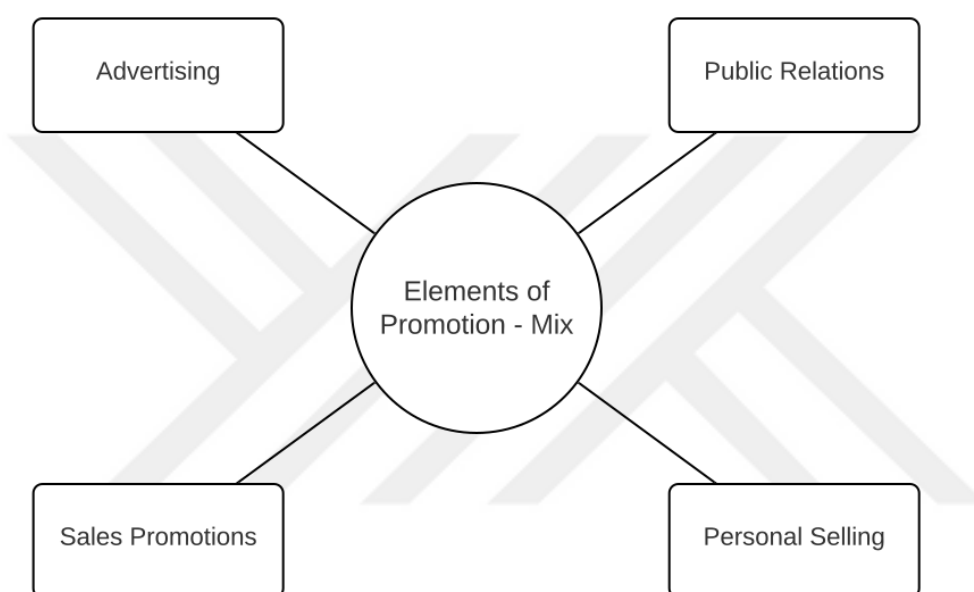


Figure 1.1 : Elements of promotional mix.

Purposes of sales promotions cover stimulating short-term demand, encouraging brand switching, inducing trial use, promoting price orientation, and obtaining immediate, often measurable results. Sales promotions are an essential tool in marketing-mix both for manufacturers and retailers. As mentioned earlier, retailers are using sales promotion constantly to increase the productiveness of other components of the promotional mix, particularly advertising and personal selling.

1.1.1 Types of sales promotions

1.1.1.1 Trade promotions / retailer promotions

Most of the promotions refer to collaborative decision-making processes among retailers and manufacturers and long-term planning for sustaining stable expanding sales trends. According to where the decision-making process takes place, sales promotions distinguish into two groups; the retail promotions, which include the price or non-price promotions that retailers offer to customers as a premium to make purchases and the trade promotions, that manufacturers offer retailers as an incentive to offer retail promotions (Figure 1.2).

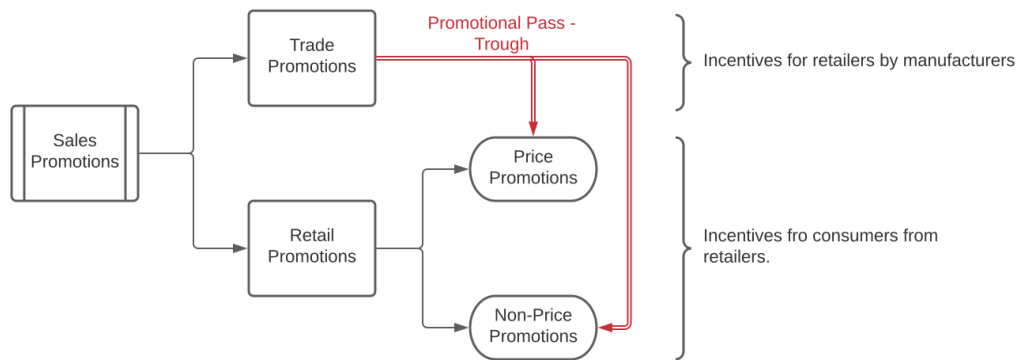


Figure 1.2 : Types of sales promotions (according to sources).

In addition to these two main groups, the business market promotions, a small but essential sub-group of sales promotions, are targeted to business markets. Although trade and retail promotions are mainly strategic tools for retailers, business market promotions are used in many sectors besides retailing. Business promotions primarily target creating a brand image, which could be counted as the main branch of sales promotion that oversees all markets rather than creating a pass-through between consumers, retailers, retailers, and manufacturers.

The trade promotions lead most of the retail price promotions offered to customers. It is rare for retailers to finance price reductions on products with their capital solely. [4] remarks trade spending represents the second largest cost category of Consumer Packaged Goods (CPG) after the cost of production. In addition, [5] claims that

up to 25% of manufacturer revenue from the products is spent on trade promotions. Like retailers, manufacturers also pump increasing quantities of money into sales promotions. However, this study focuses on Retail Sector Promotion Dynamics, which is why the sole examination of trade spending is neglected. However, I assessed the effect of trade spending on promotion success at the consumer level. Trade spent provided by manufacturers is accounted for in the total amount of promotion offered by the retailer. Researchers interested in the manufacturer side of promotion deals, namely trade promotions, mainly study forward-buying, pass-through created as a function of trade dealing, and net sales impact of incentives given to retailers.

Impacts of price promotions can be categorised as brand switching, store switching, category switching, stockpiling or increased consumption effect. Since the 1980s, while the gradual increase in consumer spending has flattened following post-war consumerism, most manufacturers treat sales promotions have a more significant and more immediate effect on sales than advertising has. In this context, marketers use various tools for promoting a brand or product in different market structures. [6] categorises the techniques used by retailers across different market dimensions. (Figure 1.3) Among these tools price-off deals that correspond to temporary price reductions, Coupons and Bundling are typical illustrations of price promotions applied in the Consumer market.

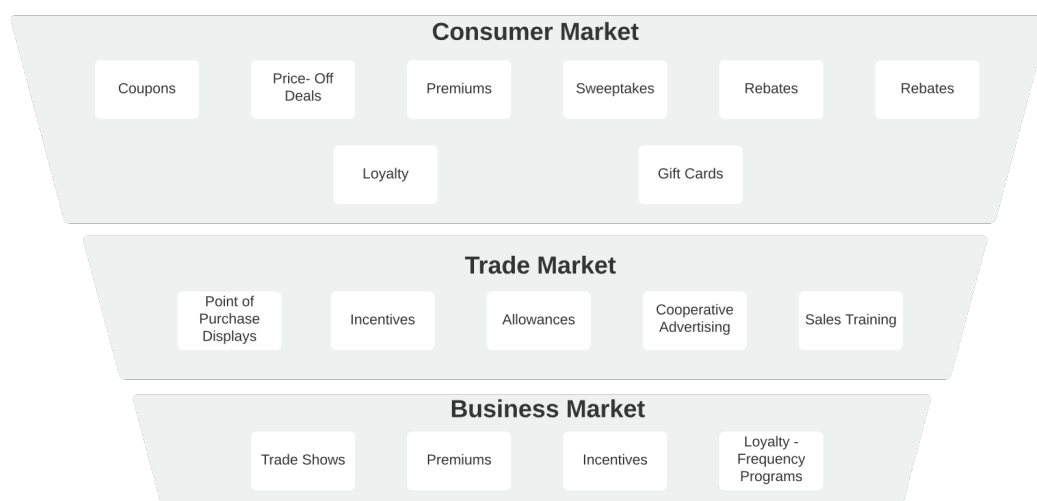


Figure 1.3 : Sales promotion tools.

The most common example of retail promotions is price promotions which contain Temporary Price Reductions (TPRs), coupons, and multi-product bundle promotions. On the other hand, a somewhat indirect type of sales promotion is non-price promotions which contain features, displays and advertisements and other point of sale materials. Most active areas in retail promotions research can be summarised as store trafficking, brand-switching, purchase acceleration and repeat purchasing as reference prices.

1.1.1.2 Price - non price promotions

Sales promotions cover temporary price changes to impulse sales trends of products. They mostly are recognised by scholars as an essential tool for creating short term sales stimuli. Although promotions were anticipated as short-term drivers until the 1980s, recently increasing competition in the retail sector turned promotions into a stimulant for sustaining long-term growth in sales trends. This conversion caused sales promotions to expand beyond temporary price reductions, and non-price promotion strategies have also begun to emerge in marketing.

Price promotions are generally designed with any monetary incentive given to consumers. Study of [7] describes types of sales promotions in two main groups that marketers name “pull” and “push” promotions. The push promotions are temporary price reductions primarily sourced by a trade deal between manufacturer and retailer. The manufacturer or wholesaler’s trade promotion margins are transmitted to consumers via a retailer. Therefore, push promotions could be regarded as a typical application of price promotions.

On the other hand, pull price promotions, which are non-price sales promotions, are rebates, price packs and cents-off deals offered by retailers mainly at the time of the purchase deal or after the transaction. Non-price promotions usually contain an extra product offer with the regular product, also known as premiums. It is a promotional program that allows the consumer the opportunity to use the product or service free [8]. For instance, providing free samples as testers is a form of non-price promotion.

1.1.2 Theories of price promotions

In their recent review on price promotions, [9] discusses theories of price promotions only from the retailer context and classifies them into three main streams; macro-economics, micro-economics and marketing areas. As retailer promotions are a consequence of trade promotions, the theorising of the trade promotion side would be a more complicated process that would cover bargaining literature from microeconomics.

Macroeconomics literature attempts to implement pricing patterns observed in the retail sector to their models of the economy. Much of the effort in this literature is on documenting consistency between observed prices and theoretical macro-economic models. To some extent, they generally test Keynesian sticky-price models.

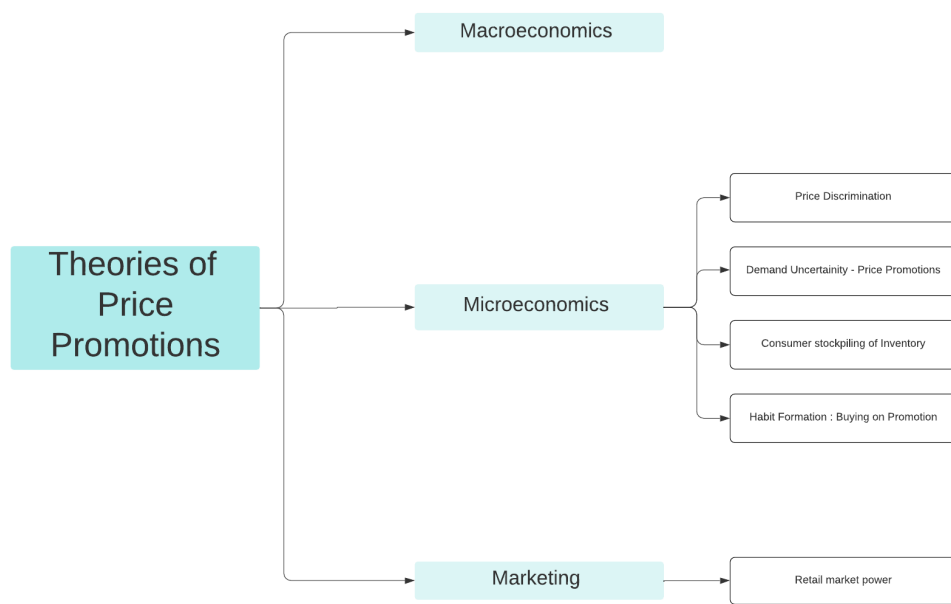


Figure 1.4 : Theories of price promotions.

A simplistic approach would treat price promotions as unilateral decisions by a seller to respond to immediate changes in supply and demand. [10] defines promotions as “*call options with unlimited quantities*”. Using Bureau of Labour Statistics (BLS) data used to construct the Consumer Price Index, they showed that the variance in price inflation mainly was created due to the size of price changes rather than the fraction of the

items with price changes. Their findings support the hypothesis suggesting that price promotions significantly affect inflation.

Price Discrimination

A widespread view in microeconomics literature claims that price promotions are utilised to discriminate among consumers. It is mostly accepted that Varian's [11] study on price discrimination serves as a theoretical base for price promotions. The heterogeneity in demand is the primary assumption behind the effect of price discrimination on sales. The null hypothesis implies that heterogeneity in demand is not attainable both in the short term and long term. However, even in the early stages of price promotion research, scholars have proven that Temporary Price Promotions (TPR) cause a substantial increase in sales [12]–[14].

The concept of price discrimination can be categorised in three ways;

a) Inter-Temporal

b) Inter-Store

c) Inter-Brand

Regarding inter-temporal price discrimination, many consumers choose to postpone their purchases until the price promotion. However, consumers having immediate necessities have to buy at the current price. In the case of Inter-temporal price discrimination, consumers are loyal to a specific brand and store and do not switch. By focusing on a single firm's pricing strategy seminal work of [11] first examined time-dependent price discrimination caused by promotions channel. His study motivated proceeding studies like [15,16].

Price competition in a retail duopoly is studied by [17], and he points out that retail promotions are not random at all. Price promotions reflect retailers' strategic decisions about regular and discounted prices. Mainly, these strategic plans aim to absorb new consumers to the store. Thanks to this mechanism, retail competition is also an essential aspect of price discrimination, leading to store switching. These studies conducted by marketing researchers noted that price promotions might lead to store

switching. That is why properties of inter-store price discrimination should also be included in a promotion study.

Finally, researchers also rationalised price promotions as a competitive tool for brands. Price promotions typically have short-term impact on brand switching [18], effectively stealing share from competitors. From the manufacturer's perspective, inter-brand price discrimination would be a way of stealing sales share from its competitors.

As stated in the introduction section, most of the analysis we will apply in this study purposes to clarify the effects of promotional decisions on shoppers' decision to buy the product from competitor brands. Besides passages between brands, I will also analyse if promotions are qualified to create category pass-through between substitute products. On the other hand, an essential aspect of theory connected with inter-store price discrimination, the store-switching mechanism of price promotions, will be neglected in this study.

Demand Uncertainty

Demand uncertainty provides another rationale for price promotions. Demand uncertainty is related to external and internal variables that cause sudden increases or decreases. Figure 1.5, taken from [19] provides a comprehensive taxonomy of these theories. When the information on demand is known and not time is driven, the retailer may offer promotions aiming to inform customers about the quality of the product (induce a trial). A retailer can also use promotions to speed up purchases. For example, if the price discount is deep enough, consumers may purchase and stockpile products such as olive oil for the next several months. However, research has shown that purchase acceleration boosts sales for the short-term, but its long-term effects are controversial [20].

In CPG, [18,21] found that purchase acceleration is slight in magnitude compared to brand switching. Price promotions may also encourage consumers to buy at weekends instead of weekdays or purchase on holidays. Finally, excess supply is a rationale for price promotions following demand probing or yield management. Purchase acceleration, demand build-up and induce trail theories related to demand uncertainty

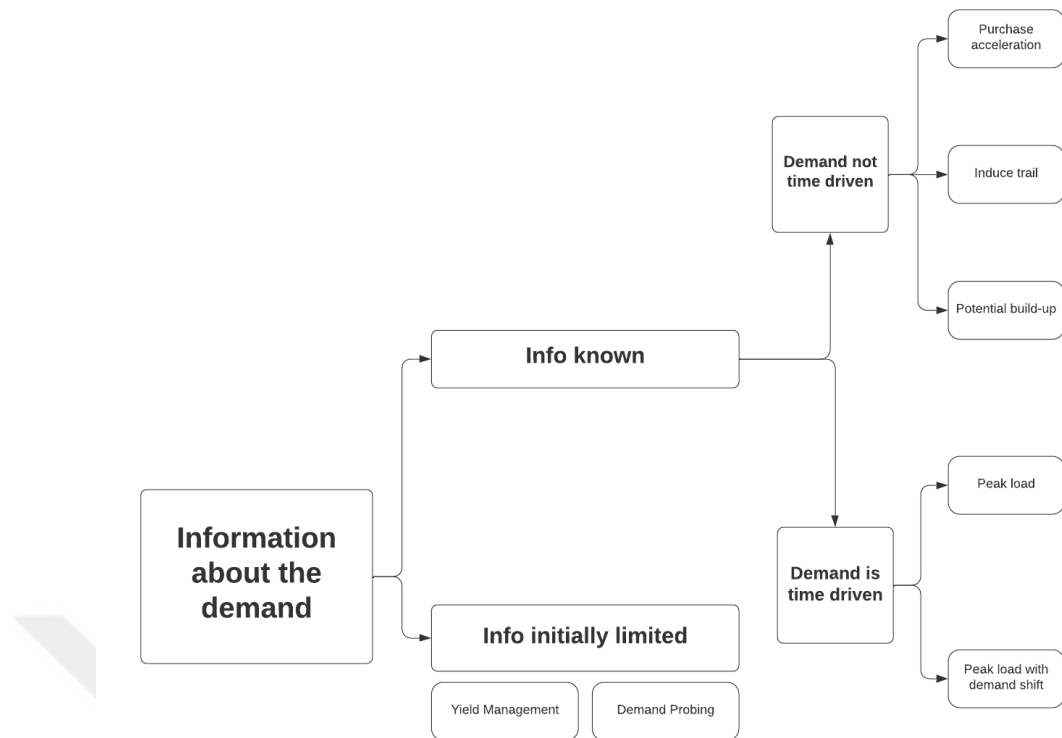


Figure 1.5 : Theoretical rationales for price promotions.

comprise the first part of this study which aims to understand price promotions' effect on sales volatility.

Consumer Stockpiling

Another likely explanation for price promotions is that they influence consumers' purchase timing and quantity, which is a specific form of inter-temporal price discrimination discussed previously. [12] 's seminal study proposed an inventory-theoretic model of retail pricing. They posited that promotions are the mechanism to shift inventory-carrying costs between retailer and customer. Their analysis shows that consumers should stockpile products when prices are discounted and that high-demand products should be discounted less deeply but more often.

Habit Formation

Once consumers are accustomed to buying on price promotions and shopping for regular deals, removing price promotions can be extremely difficult for manufacturers and retailers. Standard economic models assume that consumers only respond to

price promotions with the motivation of monetary savings. On the other hand, [22] developed a framework to reconcile much of this work. He suggested that consumers not only enjoy the practical benefits of price promotions but also sense hedonic pleasure along the shopping process. He also claims that it originated from price promotions.

Models of habit formation with price expectations typically require that price promotions have been offered in the past (and become a habit) or that consumers believe they will be offered in the future (And are expected).. Once consumers buy on a deal, it can be difficult or costly to change their behaviour and eliminate price promotions.

Retail Market Power

Another aspect of price promotions is that they result from retail market power. For example, if manufacturers cannot profitably sell directly to consumers, retailers in some market power because of their ability to efficiently reach those customers. Under this approach, trade funds can be viewed as a financial transfer from a manufacturer to a retailer to access the retailer's scarce resources – in other words, its customers.

There are many price promotion strategies, and no single theory can explain all empirical observations in the field. However, in their recent review on-field, [9] argues that a complete explanation should account following significant factors.

1.1.3 Research question and significance

Over the last 50 years, a significant research effort consumed on identifying the effects of sales promotions on sales. Through this research endeavour, criteria for measuring the results of promotions have been refined and developed. Substantive results compiled over time allow us to make a concrete generalisation on how sales promotions work and if they affect sales volumes or not. On the other hand, the decomposition of sales bumps and quantification of net sales value created through promotional activities is still an open research area.

Retail Price Promotions are the most widely investigated area during the five decades of research stream on the promotional mix. The last three decades have seen a growing

trend toward price promotions research; the introduction of scanner data collected from households by marketing research companies and widespread usage of transactional databases of retailers provided an excellent experiment stage for the researchers.

However, early quantitative studies primarily focused on household-level consumer scanner data initially distributed by Information Resources Inc (IRI). For more than a decade, IRI data was the leading observation unit to test the significance of promotional effect on sales. A growing body of published works using IRI data provides evidence in assessing the decomposition of sales bumps created through promotional activities (price elasticity of demand with the existence of price promotions) and the long-term effects of promotions on sales trends and product life cycle. A review on [23] first ten years of promotion research has conclusively shown that it is generally proved that promotions have a significant effect on sales, especially in the short term. On the other hand, few studies examined the existence of promotional effect on retailer level aggregated temporal data.

This study provides an overview of theories of price promotions. Based on previous literature, my research assesses the dynamic relationship between sales volume and price promotions by employing econometric time series models. While decomposing these linkages study formulates its hypothesis that Temporary Price Reductions (TPR) can have many direct and indirect sales effects. For instance, increases in sales would stem from brand switching, store switching, category switching, stockpiling or increased consumption. The study presented in this thesis is concerned with two consequent applications of price promotions. Firstly, a mean and volatility model proves the suggested promotion KPI variable and whether promotion depth is significant. Secondly, by utilising promotional depth and other promotion-related variables created at the category/brand level, the study breaks down the total promotional effect on sales to its sources given earlier in the text. Very few studies have attempted to quantify the impact of promotions on both the mean level and volatility of sales trends. In addition, there have been very few empirically published accounts of promotional elasticity decomposition both on category and brand level, which is regarding time series methods.



2. LITERATURE REVIEW

2.1 Early Studies on Sales Promotions

The formation of the Marketing Science Institute (MSI) boosted the number of attempts at quantitative applications of issues related to marketing science. MSI is a research institute which aims to fill the gap between academic research and industry needs, and 29 companies funded it at the time of establishment [24]. Interestingly, one of the first monographs published by the institute was [25] which investigates promotional effects on sales via mathematical models. Therefore we can say that promotion research is one of the original research streams in the marketing domain.

Before the IT revolutions of the 80s and 90s, ideal data for a quantitative researcher on sales promotions were limited to a few diary panel data sets; it was impossible to have large store or household-level scanner data in today's context. Although early pioneering works on sales promotions were based on mathematical models, also there were some objections to the use of quantitative methods in promotion research [26]. In his study, he considered unpredictable, immeasurable market conditions such as economic conditions and claimed that assessing the quantitative effects of promotion is impossible. On the other hand, seminal studies focusing on the sociology of consumption, such as [27,28] points out that contemporary macro data sources are inefficient in reflecting implications of economic conditions on consumption, and there is a strong need for a macro indicator to represent the consumption of society. These conceptual discussions led to the emergence of empirical applications of marketing response models by the second half of the 60s.

In his seminal work, [11] introduces price discrimination as a theoretical basis for price promotions. He names "price dispersion" as a pseudonym to describe the price discrimination phenomenon. The Literature categorizes the results of price discrimination may cause in three aspects;

Inter-temporal; shoppers may postpone their purchases until the price promotion is offered.

Inter-store; here, shoppers are willing to buy from whichever store advertises a lower price (retail competition).

Inter-brand; shopper has a strong preference to shop in a specific store, but they are also willing to switch brands if they encounter lower prices (manufacturer competition).

Despite its limitations arising from focusing on a single firm [11] motivated several demand-based assessments of price promotions [15,16,29]. Although much of the earlier works on sales promotions have focused on demand related analysis, in his frontier study [18] was the first scholar that employed current scanner data from IRI to decompose the effects of promotions on the coffee beans category group. Besides rationalising price promotions are competitive tools for brands, he also points to extra consumption created in the category and stockpiling effects. The researchers succeeding the Gupta within the price promotion research field generalised that price promotions have a short-term impact on brand switching. His work created instant interest in demand equation elasticities and cultivated a path to recent hot research areas in the promotions domain.

2.2 Price Promotions Research Stream and emerge of Quantitative Analysis in Price Promotion Research

As mentioned in the introduction section of the study scope of this study is limited to the price promotions sub-domain of the sales promotions domain. Therefore after delivering earlier periods of sales promotions literature, this thesis's literature review will mainly concentrate on price promotions research which occupies most of the promotions literature.

There are two well-settled review papers on price promotion research. One of them [23] describes empirical generalisations reached by scholars until 1995. In conclusion, their systematic review identifies empirical generalisations in the literature in 11 distinct areas.

1. Variations in consumer responsiveness to deals

2. Sources of deal volume
3. Cross-deal effects
4. General magnitude of deal and price effects
5. Impact of deal depth and frequency of deals
6. Merchandising advertising effects on promotion
7. Long-term effects of deals
8. Pass-through of trade deal funds
9. Troughs after deal
10. Store switching effects
11. Psychological pricing of deals

A more recent review by [9] classifies theories of price promotions into three major groups, macro-economics, micro-economics and marketing areas. While macroeconomics literature attempts to implement pricing patterns observed in the retail sector to their models of economy, marketing and microeconomics literature focuses on pricing and customer behavioural aspects of price promotions.

Among the given generalisation concepts, variations in consumer responsiveness to deals, the general magnitude of deal and price effects, impact of deal depth and long-term effects of deals are also in the scope of this thesis.

Empirical evidence has supported the claim that price promotions can create a significant magnitude of change in purchase behaviour. However, price promotions, especially temporary price reductions (TPR), can have many direct and indirect sales effects. For example, increases in sales would stem from brand switching, store switching, category switching, stockpiling or increased consumption. Therefore, any assessment to assess the real effects of promotions should include the decomposition concept on the spot. In his seminal work, Gupta [18] examined the sales bump during the promotion period. He aimed to identify the brand-switching, purchase acceleration, and stockpiling effects created throughout the promotion. Using IRI scanner data on coffee beans, he found out that more than 84% of the sales increase originated from

brand-switching. Among his findings, purchase acceleration was the second most contributing factor in sales bump with a 14% share. In their empirical review [30] summarise various studies done on sales promotions between 1988 and 2003. Based on household scanner-panel data, they report that most sales elasticity is attributable to secondary demand effects (brand switching). At the same time, the remainder attributed to primary demand effects (timing acceleration and quantity increases). Consequently, they decompose brand switching effect share at a lower level at 33%. Successor studies, such as [31,32] generalise Gupta's approach to many categories and products. The joint approach observed in these studies was to create inference on the increase in sales courtesy of the promotions by investigating price elasticity. Brand switching, stockpiling, inter-purchase durations, and in or ex – category expansion is the main determinants caused by sales at the end of the promotion process. [33] deals with micro-effects of promotions; she employs household-level scanner data to test if promotions create an increase in expenditures of individuals. A Study of [21] finds that most incremental sales (75 per cent on average), triggered by price promotions, result from brand switching. Consequently, [34] extend their study to the multi-category framework to assess the complementary and substitution effect caused by price promotions.

More recent studies decompose promotional effects by retaining advanced econometrics and machine learning methods. In their research [35] employ a joint Hierarchical Bayes, Vector Error Correction and Variance Autoregression approach and introduce five main influential effects (asymmetric price effect, neighbourhood price effect, asymmetric share effect, neighbourhood share effect and private label versus national brand asymmetry) based on thirty-three categories scattered along with five stores.

Despite lucid research climate in classic econometric applications of measuring the effects of sales promotions after 2010, studies related to machine learning and data mining have become widespread in this area. On the conceptual side, [36] marks the importance of the big data revolution in marketing modelling and describes a machine learning (ML) framework. On the other hand, when we look at applications related to ML area, in their seminal work [37,38] states as current economic conditions and recent development in logistics and communication areas lead to a more complex

environment of simultaneous and concurrent promotional activities. So, they suggest the implementation of machine learning algorithms to promotion effect research and benchmark four-well known machine-learning algorithms such as k-Nearest Neighbours, Regression Neural Networks, Multi-layer Perceptron, and Support Vector Machines.

Besides efforts on using ML algorithms in promotion elasticity research, the popularity of the issue, dealing with high dimensional store level transaction data also gains importance in the field. [39] uses LASSO (Least Absolute Shrinkage and Selection Operator) algorithm to reduce the extremity of multicollinearity problem while analysing interactions between promotions on 326 food products in 15 different categories. Moreover, [40] examines promotions for perishable products for the context in which the success of promotion does not depend on restrictions to stockpile.

Another important aspect of price promotion research is the assessment of the long-term and short-term effects of price promotions. The previously mentioned 1995 review of [23] states conflicting evidence on the long-term effects of price promotions. Thanks to improvements in the collection and storage of transactional data, researchers of the second decade of 21st century had a chance to build more advanced and comprehensive models to calculate parameters for more complex interactions between categories and SKUs. In his study [41] exercised an Error Correction Hierarchical Bayes attraction model and found that while price promotions generally have a short-run impact, the feature promotions such as bundling have more substantial long-run effects. Unlike his study, [42] has argued that long-term cumulative effects are significant, although smaller in size than immediate effects. Finally, [43] claimed that trade promotion transfers were less effective drivers of long-term brand performance than other marketing investments of the manufacturers.

2.3 Recent Developments in Price Promotions Research

More recent attention in price promotions exclusively focuses on more industry related problems given in Figure 1.6.

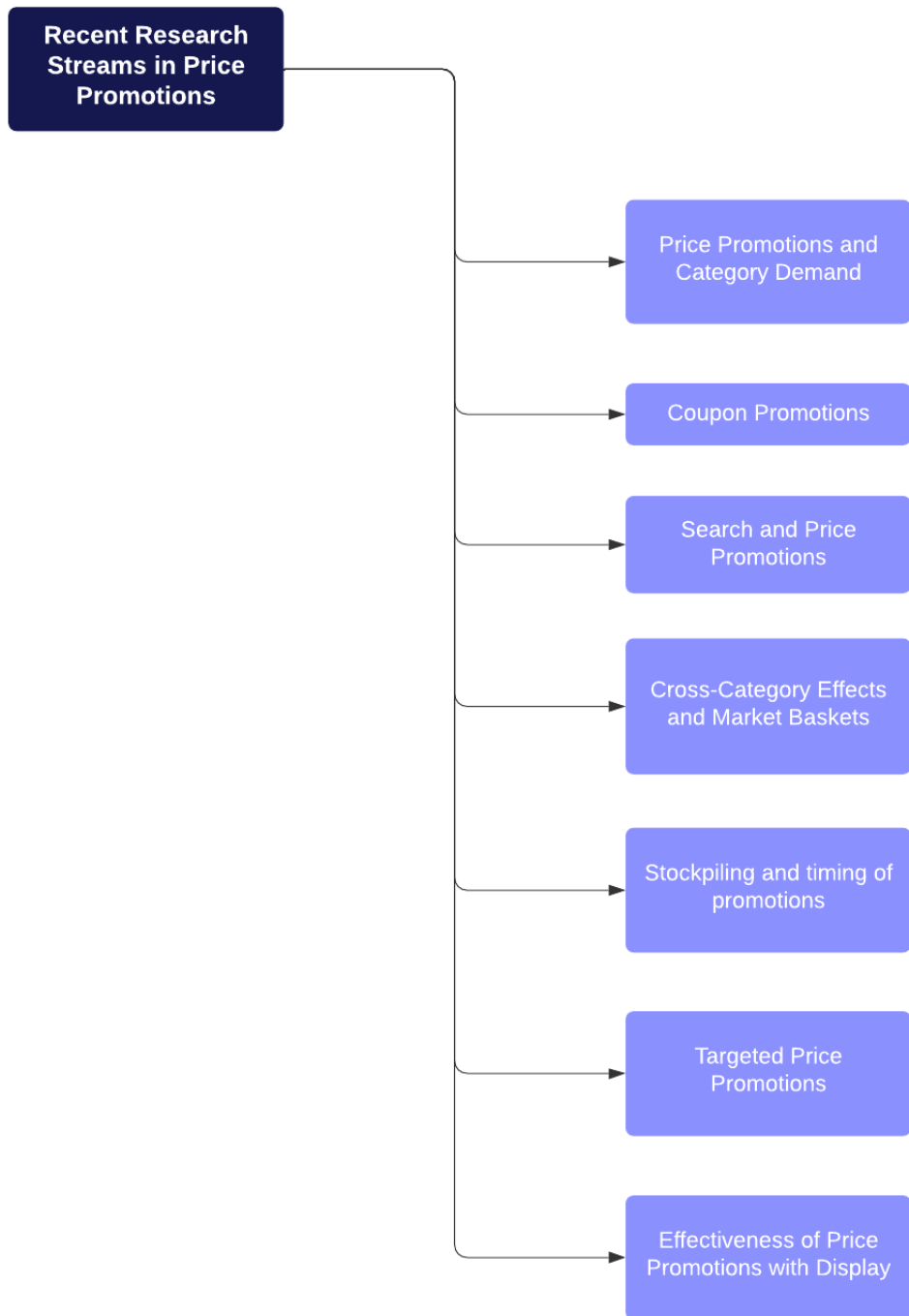


Figure 2.1 : Recent research streams in price promotions domain.

Although early price promotions research extensively focuses on the decomposition of promotion effects, the presence of time series econometrics studies trying to investigate the effects of price promotions on aggregated category levels increased significantly after the 2000s. In their detailed assessment [44] applies basic time series models on 560 categories for four years period and found that despite extensive promotional activity during the analysis period, category demand is stationary. On the other hand, they also found that short-term elasticities display a higher impact of price promotions. In their study, [45] borrowed the concept of the testing significance of variation caused in sales trends by promotions from [46] work and employed a GARCH model for the assessment. The multi-category framework has been revisited by [47], they pointed out that cross-price effects between categories are minor and cross-price effects are due to coincidence rather than complimentary.



3. METHODOLOGY

3.1 Empirical Context and Data

3.1.1 Empirical context

Over the last five decades, academic studies in the marketing field have increased significantly in number and quality. In the meantime, especially after the 1970s, quantitative methods for measuring the sales response to marketing decisions have undergone tremendous developments. Especially, an increase in the number of quantitative studies has received strong support from improvements in data collection processes. For example, while non-representative small sample data was the only way to test promotional responses in the 1950s and 60s, starting from the 80s, marketing research companies began to provide the first versions of larger scanner panels. Finally, from the beginning of the 90s, most retailers constructed enterprise-level databases for reporting purposes. Hence, the amount of data available for modelling studies has increased significantly.

In this thesis, data for quantitative applications have been provided from the data warehouse of one of Turkey's largest nationwide supermarket chains. The company mainly operates in urban areas of the country. Installed in the late 90s, the company's data warehouse is one of the oldest retail databases in Turkey. Regarding its market share, the company is a sound representative of the Turkish Retail Sector. On the other hand, with its 84 Million population with a median age of 31, Turkey offers a solid and dynamic customer base for assessment of promotions. In short, one of the most rigid constraints for this type of promotional efficiency study, the problem of "accessing reliable data on a generalisable scale", was granted at the beginning of the project.

Emergence of modern data collection technologies has led marketing science practitioners to implement tools from the econometrics discipline to assess the response of sales figures to the marketing mix components. Following these improvements in the

theoretical modelling side, researchers began to test the sales response to the impulses created via marketing – decision variables. A response model exhibits how one variable depends on other variables. Dependent variables could be sales or other Key Performance Indicators (KPIs) of interest to marketing practitioners. In addition, independent variables are assumed to affect the dependent variable. Together these variables make up a market response model. [48] defines a response model based on time series or cross-sectional data as an empirical response model.

This Research conceptualises its base response model on the Econometric Time Series Models (ETS) methodology. ETS can be used for appraising relations between promotional activity variables and category sales. This modelling technique catches relations between variables over time. The following definition from [49] expresses a complete description of the ETS method approach in marketing, "ETS analysis in marketing is building models of marketing systems that delineate relations between organisations and markets through flows of communication and exchange. These models, called response models, are useful for understanding the behaviour of markets and for predicting the impact of marketing actions". As seen from the definition, the properties of the ETS modelling approach are firmly in line with the objectives of prescriptive analytics.

Depending on the study's objective, ETS models employ theoretical econometric or time series models for the analysis. Analytic techniques can be divided into three main types: Descriptive analytics, which only aims to describe specific facts using reporting or data visualisation. Predictive Analytics deals with cross-sectional or temporal data to make predictions on unknown observations (forecasting from a time series perspective). Finally, Prescriptive Analytics, which corresponds to the aim of this study which is providing a decision support system for marketing executives, focuses on finding the best course of action given the available data. This thesis intends to assess sales response to the promotional activity; hence prescriptive analytics approach is preferred.

After specifying our perspective on the analytic modelling approach, what follows is a description of the main hypothesis tested in the quantitative application phase.

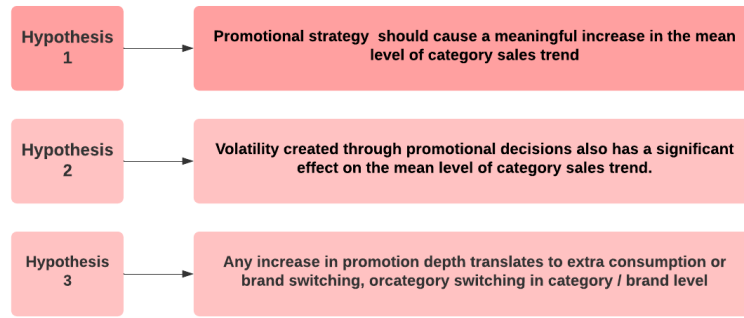


Figure 3.1 : Main hypotheses tested in the study.

The first hypothesis tested in this thesis states that promotional strategy decisions, especially changes in the number of products in promotions and the magnitude of promotions, should cause a significant change in the mean level of sales trend. After determining whether the first hypothesis is valid or not, the second hypothesis states that volatility created through promotional decisions also significantly affects the mean level of sales trend. Our second hypothesis deals with a relatively untouched area of quantitative marketing studies on promotion. Best of our knowledge, only the study pointing to promotions effects on sales variation is [46].

The final hypothesis deepens our investigation to the category/brand level. Any change in promotion depth would create a meaningful extra demand or causes category switching or brand switching of the available demand. A holistic approach is utilised in the third analysis stage, integrating brand and competitor material to establish more generalise outcomes.

In order to test the first two hypotheses, I borrowed a pair of high-frequency econometric analysis models, and their details will be provided in the Econometric Framework section. Furthermore, two exogenous policy variables, promotion depth and promotion diffusion, are added to time series models, and their significance in the system is tested. Finally, the conceptual model used for the testing procedure of the first two hypotheses is presented in (eq. 3.1).

$$\Delta^D y_t = \sum_{i=1}^p \phi_i \Delta^D y_{t-i} + \sum_{j=1}^q \phi_j \varepsilon_{t-j} + \beta_1 \text{Promo Depth}_t + \beta_2 \text{Promo Diffusion}_t + \varepsilon_t \quad (3.1)$$

Where $\hat{\beta}_1$ and/or $\hat{\beta}_2$ is significant, it is possible to infer that promotions affect the mean level of sales.

On the other hand, a more complex conceptual model is also needed to test the final hypothesis on category/brand level decomposition of promotion decisions. As stated in the introduction section of this thesis, I focused on the laundry detergents category. Let *pow* as an identifier for powder detergents sub-category and *liq* as identifier for liquid detergents category. In addition, promo terms represent vectors including various promotional strategy variables such as price per kgs/lit, promotion depth, the first day of the promotion, last day of the promotion, level dummy indicating days promotion in effect and other exogenous variables (seasonality related, special days, 1st wave of Covid 2019 Health Crisis.). These promo variables are designed at the category/brand level to ensure decomposition of promotional effects in *brand*, *switching*, *cannibalisations*, *category switch*, *own effect*.

$$\begin{aligned}
Q_{liqA_t} &= f_{A1}(prom_{liqA}, prom_{liqB}, prom_{liqC}, prom_{powA}, prom_{powB}, prom_{powC}, Z_{liqA}, \dots) \\
Q_{liqB_t} &= f_{B1}(prom_{liqB}, prom_{liqC}, prom_{liqA}, prom_{powB}, prom_{powA}, prom_{powC}, Z_{liqB}, \dots) \\
Q_{liqC_t} &= f_{C1}(prom_{liqC}, prom_{liqB}, prom_{liqA}, prom_{powC}, prom_{powB}, prom_{powA}, Z_{liqC}, \dots) \\
Q_{powA_t} &= f_{A1}(prom_{powA}, prom_{powB}, prom_{powC}, prom_{liqA}, prom_{liqB}, prom_{liqC}, Z_{powA}, \dots) \\
Q_{powB_t} &= f_{B1}(prom_{powB}, prom_{powC}, prom_{powA}, prom_{liqB}, prom_{liqA}, prom_{liqC}, Z_{powB}, \dots) \\
Q_{powC_t} &= f_{C1}(prom_{powC}, prom_{powB}, prom_{powA}, prom_{liqC}, prom_{liqB}, prom_{liqA}, Z_{powC}, \dots)
\end{aligned} \tag{3.2}$$

This conceptual model ultimately has the power to decompose the effects of promotional strategy on sales, as I stated in the theories of promotions section. Therefore, a more detailed account of the conceptual models mentioned in this section will be given in the following section.

3.1.2 Econometric framework

The current investigation utilises an array of econometric assessment techniques to test three hypotheses given in the previous section. All econometric methods described in this section are conducted using R Open Source Programming Language and STATA 17 SE software. Moreover, incorporating brand and category level assessment into modelling efforts caused a need for more reliable technology for data collecting and processes. Therefore, Big Data Environment and powerful servers containing 48 microchip cores to run estimation techniques are used in the analysis. The sponsor company provides all software and hardware facilities used in this thesis.

3.1.2.1 Univariate mean level and volatility modelling

Autoregressive Integrated Moving Average (ARIMA) procedure proposed by [50] assumes response variables are outcomes of a stationary process that is partly predictable from its own values is estimated. Then, the ARIMA method is extended with exogenous variables (ARIMAX- ARIMA with eXogenous variables). Exogenous variables contain promotional policy variables. Hence, the study will recommend a promotional policy for marketing professionals by creating inference from these parameters.

The standard form of an ARIMA(p,d,q) model is given (Eq 3.1). Here, y_t represents the logarithmic transformation of a stationary process, while x_t represents exogenous variables that significantly affect y_t process.

$$\Delta y_t = \mu + \phi_1 \Delta y_{t-1} + \dots + \phi_p \Delta y_{t-p} - \theta_1 \varepsilon_{t-1} - \dots - \theta_q \varepsilon_{t-q} + \gamma_i x_t + e_t \quad (3.3)$$

ARIMA methodology restricts the assumption that the dependent variable of the equation is stationary. Primarily stationarity concept refers to generating a function for the series that does not change through time [51]. This concept translates to dependent variable should not contain any identifiable trend change in mean and variance level over time. The stationary time series could still include short-term local changes in mean and variance levels, but these movements are constant around a certain level in the long term. In this Research, we tried to extract these short-term fluctuations and test whether they are statistically significant or not. Any exposition on the long-term effects of promotions on category sales is beyond the assessment of this hypothesis.

One great advantage of the Box-Jenkins approach we used is its principle of parsimony. Box-Jenkins method [50] deals with the over-parameterisation problem by autoregressive distributed lag parameters and targets to explain most of the realisations on the variables by employing endogenous effects. After determining a powerful method to explore sales volume, the next issue is to link short-term fluctuations in sales volume with promotion decisions.

As noted earlier, the first hypothesis was to test if promotions significantly impact the mean level of sales by using the ARIMA method. However, a variance modelling

framework is employed to test our second hypothesis, which assumes that "sales promotions significantly affect the category sales volatility".

One of the most common procedures for estimating variance is GARCH (Generalised Autoregressive Conditional Heteroscedasticity) methodology in the econometric time series context. GARCH family models were first proposed by [52]. Most of the Research using GARCH has been carried out in the financial econometrics domain. Especially for the sake of estimating volatility for option pricing. However, the most efficient way to characterise a time series is both identifying its mean level and volatility measure. So when one needs to assess the conditional variance of temporal data, the GARCH methodology is a reliable tool for variance estimation. In this study, we used this methodology to illustrate the volatility pattern of sales and added promotion variables to see if they had a significant effect on sales or not.

Simple identification of GARCH(p,q) is given in (Eq 3.2); the First component of a GARCH process is a mean level model (ARIMA) estimated in the previous section. The second equation of the system focuses on estimating the variance. Likewise, in the ARIMAX(p,d,q) model, again, x_i represents an exogenous variable that significantly affects the conditional variance of the series. Like the mean level model estimation, we also included exogenous promotion-related variables to monitor their effects on sales volume.

$$\begin{aligned}\Delta y_t &= \mu + v_t \\ \sigma_t^2 &= \omega + \alpha_i \varepsilon_{t-q}^2 + \dots + \alpha_q \varepsilon_{t-q}^2\end{aligned}\tag{3.4}$$

Finally, it is also the case that there would be a relationship between conditional variance and conditional mean, which was estimated previously. [53] introduced ARCH in mean (ARCH-M) method to contain these interactions. In ARCH-M models, the conditional mean is an explicit function of the conditional variance process (Eq 3.3). ARCH-M models can also be generalised to a GARCH process. A typical GARCH(p,q)-M system can be identified as follows:

$$\begin{aligned}\Delta y_t &= \mu + \psi_1 \sigma_t^2 + v_t \\ \sigma_t^2 &= \omega + \alpha_i \varepsilon_{t-q}^2 + \dots + \alpha_q \varepsilon_{t-q}^2\end{aligned}\tag{3.5}$$

Thanks to the GARCH-M extension, now it is possible to induce time-varying uncertainty in the mean level model. The estimated coefficient ψ provides information

on how the change in volatility would affect the mean level of sales volume. Consequently, v_t presents the error series for the mean model. Suppose the time-varying heteroscedasticity hypothesis for this term is rejected. In that case, that translates to the existence of a variance trend and the second equation of the system that estimates conditional variance should be estimated.

3.1.2.2 Autoregressive distributed lag models

This Research's primary objective is to test whether decomposed effects of price promotions significantly affect sales or not. Secondary aims contain to offer a prescriptive for marketing managers on how they will fine-tune their promotion strategy. An appropriately designed decision support system will sustain sufficient prescriptive inference on promotion–category sales interactions. For this reason, atheoretical ETS methodologies, which are primarily targeted to overcome forecasting problems or to test the significance of external factors, would be naive in assessing the third hypothesis, which requires a much more structured approach to modelling.

There exists a variety of dynamic specifications used in applied time series econometrics. The Autoregressive Distributed Lag (ARDL) modelling approach used in this Research is one of them. These models make up a class of regression models that include lags of the dependent variables and current and lagged values of explanatory variables. Consequently, a practitioner aiming to test long-run and short-run response parameters could estimate parameters with less effort than other cointegration and error correction-related methodologies.

The origin of ARDL models relies on the seminal work of [54] on Distributed Lag Models (DLMs). Although the original idea behind DLM models was investment portfolio optimisation, it has an advantage that lets the model contain both current carryover effects on the dependent variable. This property makes DLM approach a good application tool for advertising, energy, agricultural and epidemiology research [55]. Researchers can test both long and short-run effects on a dependent variable

using this tool. A general specification of DLM is

$$\begin{aligned} y_t &= \alpha + \beta_0 x_t + \beta_1 x_{t-1} + \dots + \beta_q x_{t-q} + u_t \\ &= \alpha + \beta(L)x_t + u_t \end{aligned} \quad (3.6)$$

where u_t is the error term and assumed serially uncorrelated.

However, this method is not valid for analysing dependent variables that are supposed to contain an autoregressive pattern. The autoregressive model specifies that the output variable depends linearly on its lagged values and an error term. Hence a researcher can contain both previous endogenous effects simultaneously with exogenous values. An ARDL model is employed to apply regression analysis between a dependent endogenous series and the k number of exogenous series. Exogenous series could also be in the form of deterministic trend components, seasonal effects or dummy variables containing special shopping days.

When there are only one dependent and one independent variable exists, an ARDL specification given as $ARDL(p,q)$ translates to regression consisting of p lag of exogenous and q lags of dependent series. Inclusion of lags of dependent series makes regression autoregressive. When the number of lags of i th independent series shown by $p_i, i = 1, \dots, k$ then general form of an $ARDL(p,q)$ model can be written as Eq. 3.5.

$$y_t = \alpha_0 + \alpha_1 t + \sum_{j=1}^k \sum_{l_j=0}^{p_j} \beta_{jl} x_{l-j} + \sum_{i=1}^q \gamma_i y_{t-i} + \varepsilon_t \quad (3.7)$$

ε_t represents innovations, α_0 is the constant term, and α_1 is the coefficients associated with the linear trend. Together with β_{ij} and γ_i are the features that stand for the effects of lagged values of dependent and independent variables.

Although the initial purpose of ARDL models was to implement autoregressive and exogenous factors simultaneously, recent advances in econometric research bundled these models as an ideal tool for examining long-run and short-run dynamics of time series. ARDL models ease estimation of Error Correction Models (Short-Term) and Co-integration vectors (long-Term). At the same time, it is possible to employ exogenous seasonality and special day dummies in the regression.

Theories imply that linear combinations of certain non-stationary time series variables should be stationary [56]. Variables satisfying this condition are Cointegrated variables

and share statistically similar stochastic trends, so they cannot drift too far apart. Cointegration variables also have error correction representation that responds to the deviations from long-run equilibrium. While cointegrating vectors represent long-run parameters, error correction representations can be examined.

ARDL Bounds test purposed by [57] is an efficient approach both for cointegration analysis and also for error correction mechanism estimation. The testing procedure employs (eq 3.5) for estimating dynamic inter-temporal relations. Using the ARDL model, they extract two equations: Post-Regression Derivation of Long-Run Dynamics (LRD) and Conditional Error Correction (CEC). Although traditional cointegration tests like [58,59] require all variables in the VAR to be $I(1)$. This condition requires the pre-testing of a unit root before estimation.

In contrast, the Bound Test approach purposes a robust test whether dependent or independent variables are $I(1)$ or $I(0)$ or mutually cointegrated. Moreover, the method requires testing the significance of the CEC model's cointegration relation. Notably, the test is a typical procedure of F or Wald test. Our study contains insights derived from LRD (Log-Run Dynamics) and CEC (Short-Run Dynamics) models in the presence of cointegration relation.

3.1.2.3 SUR estimation

Conceptual representation for brand/category level models was given in equation 3.1. In this study presence of two categories and six brands forces the examination of the third hypothesis stating that price promotions cause brand/category level differentiation in sales needs to be examined with a multi-equation system. In this setting, estimation of the entire parameter set representing own effects, cannibalisation, brand and category switching can be done with 11 distinct dynamic linear equations.

Pooled regression approach proposed by [60] for wage determination models in 38 different United Kingdom (UK) industries assumes all independent variables at the right side of the equations are the same; hence it is valid to consider all coefficients are identical. However multi equation system constructed in this study does not resemble the previous study. For example, every system's brand/category level equation includes

the same features related to promotion decisions, such as promotion depth, promotion end and start dates. However, each model requires different lagged var specifications to overcome autocorrelation and heteroskedasticity problems in error terms. Hence exploratory right-side blocks of equations are not identical to each other. Therefore it is impossible to use pooled regression method in this study.

However, even "poolability" is sustained in the system; still, some of the equations might be connected due to a significant correlation between their error terms. If the disturbances (error terms) are correlated across equations, then these kinds of equation systems are called simultaneous equations [61]. All the endogenous variables are random variables. Hence, any change in error term affects all endogenous variables.

This context refers to a violation of the assumption that the Classical Linear Model states that *observations on independent variables can be considered fixed in repeated samples*. This means that endogenous variables used as regressors are correlated. Consequently, Ordinary Least Square (OLS) estimator is biased and, even asymptotically, is not efficient.

In this case, [62] recommends estimating these equations as a set. Employing a single giant regression would increase the efficiency of parameters. This technique proposed by [63] is called Seemingly Unrelated Regression (SUR) Estimation.

Let there are N equations $Y_i = X_i\beta_i + \varepsilon_i$. By stacking the sets of observation, these equations can be written in the form of equation 3.8.

$$\begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{bmatrix} = \begin{bmatrix} X_1 & 0 & 0 & 0 \\ 0 & X_2 & 0 & 0 \\ \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & X_N \end{bmatrix} \begin{pmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_M \end{pmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_3 \end{bmatrix} \quad (3.8)$$

or $Y^* = X^*\beta^* + \varepsilon^*$ Where $M \times 1$ vector of error terms is,

$$\varepsilon = [\varepsilon'_1, \varepsilon'_2, \dots, \varepsilon'_3]$$

and strict exogeneity of X_i is assumed,

$$E[\varepsilon|X_1, X_2, \dots, X_M] = 0$$

and homoskedasticity and no autocorrelation within each equation

$$E[\varepsilon_m, \varepsilon'_m|X_1, X_2, \dots, X_M]$$

Now, if we assume a correlation between error terms across equations, the variance-covariance matrix of ε^* will not be diagonal.

The most practical methodology to check violation of exogeneity assumption is to check if the correlation matrix of disturbances is an identity (unit) matrix or not. For example, the test of sphericity proposed by Bartlett [64], which states the null hypothesis that the correlation matrix of residuals is an identity matrix and there is no relation between error terms of individual models. However, recently, the Bartlett test has been highly criticised for its inclination to reject the no-relation hypothesis. Moreover, its Chi-Square based test statistics formula forces the rejection of the null hypothesis even in a large sample context.

So a more robust specification procedure should be used to decide using a generalised form of simultaneous equation system instead of estimating individual OLS regression.

If we fail to prove any significant correlation between error terms of equations, then it is expected that OLS and SUR parameter estimates are equal. However, suppose the difference between parameter vectors estimated with OLS and SUR is significant. In that case, It can be said that to reach efficient parameters for the last models, one should use SUR estimations. Therefore, study borrow the Hausman Specification test, popular in panel data model applications, to test parameter vector equality.

3.1.3 Data

As mentioned in the introduction section, this thesis examines three hypotheses to test if price promotions significantly affect sales. In addition to the proof of concept objective, this study also intends to decompose incremental sales added to its sources. Accordingly, the study involves two different research designs for analysis.

First, two hypotheses primarily aim to provide evidence on the category level significance of promotions on sales trends' mean level and volatility. The secondary objective of the model used to assess these hypotheses is to check whether two KPIs created for this analysis, the promotion depth and diffusion, are significant at the category level or not.

Finally, the third hypothesis of the study is connected to testing the brand-category level linkages. While earlier analysis focuses on the short-term effects of promotion, this experiment is dedicated to creating inference both for the short and long term. Although both analyses work on the laundry detergents category sales, the modelling design differs according to their objective. Data design for both analyses will be shared in the following two sections.

3.1.3.1 Data and feature creation

As the introduction section mentions, this thesis examines three hypotheses to test if price promotions significantly affect sales. In addition to the proof of concept objective, this study also intends to decompose incremental sales added to its sources. Accordingly, the study involves two different research designs for analysis.

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3.1.3.2 Feature creation

Hypotheses 1&2 Univariate Mean Level Analysis:

The study-related data with the first two hypotheses come from the company level daily category sales database. Sales data contain the daily quantity of sales in kilograms and are aggregated by daily frequency from 02.01.2014 to 31.12.2018, which translates to

1825 observations. In order to minimise the effects of persistent inflation in Turkey, sales quantities are used instead of sales revenues.

In addition to sales figures, the number of SKUs (Stock Keeping Units) in promotion for the detergent category and daily discounts and sales in Turkish Liras are also queried from the companies' databases. However, these two promotion-related raw variables hardly deliver properties of a key performance indicator (KPI) for promotion efficiency. Therefore two actionable features are derived for the study.

Promotion Depth: This feature is created to contain the magnitude of discounts in the model. Only category level values per day are calculated and included in the model. Depth is a ratio type variable, assessing the share of discounts on the category to the expected revenue. The derivation method can be represented as (Equation 3.9)

$$PromotionDepth_{t,b} = \frac{TDoP_{t,b}}{TDoP_{t,b} + Sales_{t,b}} \quad (3.9)$$

Where, TDoP = Total Discounts on Products

Promotion Diffusion: This variable represent the intensity of promotions over the category. Diffusion is a ratio variable, which can be calculated as,

$$PromotionDiffusion_{t,c} = \frac{NumberofproductsonPromotion_t}{NumberofallSKUsSoldt,c} \quad (3.10)$$

Prices: All prices used in the models are in terms of the prices per kgs or litres. To our knowledge, liquid soap, a comparable product with liquid detergents, has a density of around 1.01 kg/ml; it is practical to use the price per kgs and litres together in an analysis.

Hypothesis 3 Category/Brand-Level Model:

Category/Brand Level Model is an extended version of the category level model. Nevertheless, it distinguishes itself from the earlier model in the depth of the analysis. While the category level model assesses promotional decisions' effect on aggregated category level data, the latter models determine promotional elasticities at the brand/category level. In assessing category/brand level models, data collected between 01.01.2017 and 31.03.2021 is employed to estimate ARDL models and SUR estimation. Data were aggregated in brand category / brand level, and sub-categories included in the analysis were powder and liquid detergents groups. Although

transaction data gathered contains information on more than 20 brands, most of them do not have a continuous demand for our five year observation period. The analysis contains six leading brands for the powder detergent category and five leading brands for the liquid detergent category. Regarding five-yearly averages, the presence of selected brands constitutes over 75 percent of sales revenue in their categories (Figure 3.2). In the course of time from 2017 to 2022 main brand - category lines changed minimally. The share of outsider brands to the analysis never account for more than quarter of all sales. However in powder detergent side there is a sudden increase in share of excluded brand, this phenomenon caused by entrance of a new player to the market. However, because we are not able to assess full five year sales data for this product line it's not included into the analysis.

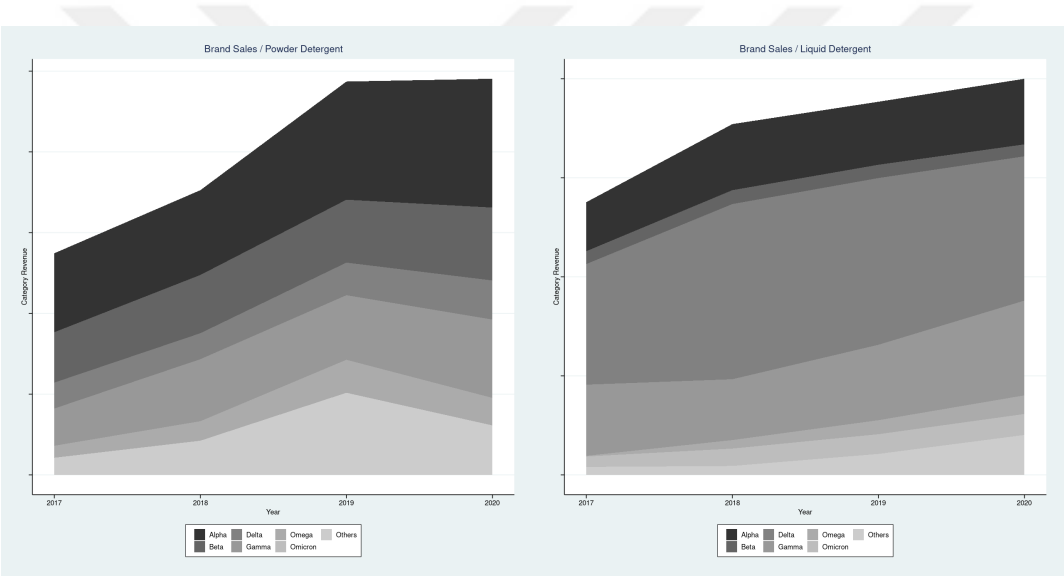


Figure 3.2 : Annual brand sales liquid-powder detergents.

Due to the privacy rights of third parties, brand names are anonymised in the text. Alias used for brands can be seen in Table 3.1.

Table 3.1 : Alias used on behalf actual brand names.

Liquid Detergents	Powder Detergents
Alpha	Alpha
Beta	Beta
Gamma	Gamma
Delta	Delta
Omega	Omega
Omicron	

However, tools that could be employed to estimate response models are similar for both research designs.

Promotion Depth and Price variables calculated for category level model are also prepared for brand level models. On the other hand *Promotion Diffusion* variable was not included in the second stage of modelling. As the number of SKUs offered by the retail lowers when one moves from category level to brand/category level, the precision of these variables diminishes.

In the final stage of data collection, promotion depth and price variables affect the model dynamically, and some static exogenous promotion strategy related variables are included in the models. These variables are used to add the effect of the first/last day and duration length of the promotions. They can be listed as follows;

$$\begin{aligned} \text{Promotion Start Dummy}_t &= \begin{cases} 1, & \text{if the first day of the promotion} \\ 0, & \text{otherwise} \end{cases} \\ \text{Promotion End Dummy}_t &= \begin{cases} 1, & \text{if the last day of the promotion} \\ 0, & \text{otherwise} \end{cases} \\ \text{Promotion Duration Dummy}_t &= \begin{cases} 1, & \text{if there is promotion on the corresponding date} \\ 0, & \text{otherwise} \end{cases} \end{aligned} \quad (3.11)$$

3.1.3.3 Data preprocessing

Data pre-processing refers to manipulating or dropping data before it is used to ensure or enhance performance and is an essential step in the data mining / modelling process. Data collection phases are often loosely monitored, resulting in out-of-range values (e.g. Sales= -100) or missing values.

Because data contributed to the study was collected from Companies' transactions databases, the problems highlighted above were not expected to occur in the dataset. The retailer has extensive data quality process to facilitate the data cleaning phase. However, the inclusion of the early days of the Covid-19 health crisis caused a missing value problem for a brief period. Turkish Government enforced a two-day full-curfew between 24th and 25th May in 2020. Unlike other curfews applied during the pandemic, short trips for grocery shopping were also prohibited. Although the category-level

model does not include the pandemic era, the brand-level model has suffered from this problem. Linear imputation is done on sales quantity, price and promotion depth variables of brand sales series for these two days.

In addition to data cleaning operations, data transformation applications are also an important application area in modelling. This research's econometric time series methodologies fit variables to a linear estimation. While this requirement does not mean that variables should be linear, a linear model is the best way to reach independent, trend-free, and normally distributed error terms. Generally, outliers and influential observations are the most common issues causing the violation of linearity assumption. For example, figure 3.3 reveals that category sales contain frequent daily quick leaps from the average level of sales series.

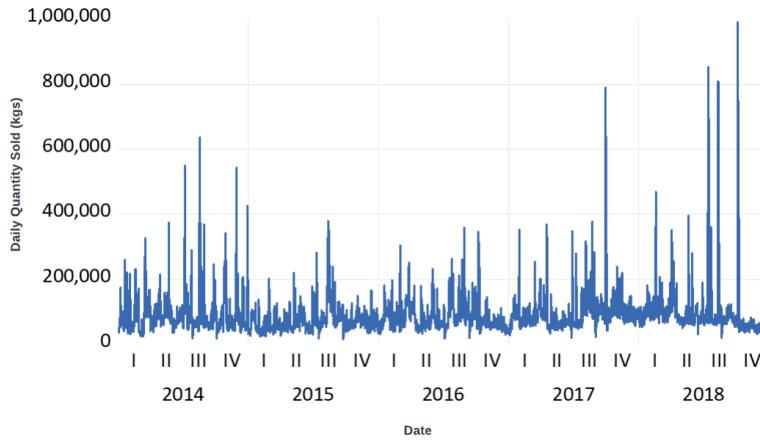


Figure 3.3 : Laundry detergents category - quantity sold in kgs (y-axis).

The quantity sold peaks on the promotion days; in some cases, three or four times of increase from daily averages can be observed. It is challenging to assess other underlying time series components in this setting visually.

Descriptive statistics for sales data Table 3.1 shows a considerable difference between the median and mean level of the series. Excess skewness and kurtosis figures indicate influential outliers. In order to smooth the appearance of these outliers, the methodology proposed by [65] is applied to sales quantity data. Although, calculated λ value -0.55 corresponds to $1/\sqrt{x}$ transformation, but since the estimated coefficient is so close to the lower bound of this transformation $-0.5 \leq \lambda \leq 0$, logarithmic transformation which corresponds to $\lambda=0$ level applied to the sales

Table 3.2 : Descriptive Statistics for Sales Quantity Variable.

	Quantity	Log-Transformed Quantity
Mean	93616.5	11.3
Median	72205.7	11.2
Maximum	990813.8	13.8
Minimum	15844.14	9.67
Std. Dev.	75639.5	0.53
Skewness	4.93	0.80
Kurtosis	40.12	4.76

variable. After transformation, the series smoothed considerably. This analysis proves that logarithmic transformation polishes the effect of outliers in the series, as can be seen in Figures 3.3 and 3.4. Brand/category level sales figures also present the same pattern.

Consequently, in addition to sales quantity and price values of category level models, their brand/category level models equivalents are also applied to logarithmic transformation. Because *Promotion Depth* and *Promotion Diffusion* variables are in ratio scale and they are bounded between 0 and 1, generally they are not expected to cause violation of linearity of residuals problem. Despite when no promotion days are excluded *promotion depth*'s distribution converges to normal distribution (Figure A.1), there are significant outliers in *promotion diffusion* variable. However as all outlier observation corresponds to 1, which means nearly all products are on promotion on given day. These are the all category special discounts days organized once or twice a year. Their presence is limited with less than 10 days in our 1545 days of data and distribution of *promotion depth* variables converges to normal distribution when these observations are excluded (Figure A.2).

In line with the data exploration given in previous paragraph, *promotion depth and diffusion* variables in both analyses are left with their non-transformed values. Their graphics explaining their time series properties can be find in Appendix A.

Despite transformation applications, the continuing presence of outliers in the log-transformed data is still observable. Nevertheless, to contain problems arising from these outliers, dummy variables presenting extraordinary sales activity days (e.g. mother's day, women's day, Covid-19 first wave etc...) will be added to the model

the estimation process of the mean level modelling. On the other hand, deterministic
11 seasonal dummies were added to the analysis in the brand/category level models.





4. EMPIRICAL FINDINGS

4.1 Price Promotions Effects on Mean Level and volatility of Sales Trend

This thesis set out to assess the effectiveness of price promotions in a retailer's sales performance. The first question in this study sought to determine if a change in the magnitude of price promotions affects the mean level and volatility of sales trends or not. Next, a mean and variance estimation modelling methodology is applied to data to determine if hypotheses one and two hold.

The ARIMA modelling procedure, the primary response model for this research, requires the dependent variable to be stationary. In order to test this condition, all numeric variables contained in the model are tested on the existence of the unit root. Sales Quantity, price, promotion depth and promotion diffusion variables are examined by using the Augmented Dickey-Fuller (ADF) methodology proposed by [66,67]. ADF) Unit Root Test statistics presented in Table 4.1 reject the presence of the unit root in sales quantity, price, and promotion diffusion variables.

Table 4.1 : Unit root test results for category level variables.

Variable	Equation Type	Statistics
<i>Unit Root Tests-ADF</i>		
Promotion Depth	<i>Linear, Constant</i>	-8.99
Promotion Diffusion ¹	<i>Constant</i>	-13.89
Quantity Sales	<i>Linear, Constant</i>	-7.38
Price	<i>Linear, Constant</i>	-5.05
<i>Stationarity Test-KPSS</i>		
Promotion Depth	<i>Linear, Constant</i>	0.19
Promotion Diffusion	<i>Constant</i>	0.42
Quantity Sales	<i>Linear, Constant</i>	0.14
Price	<i>Linear, Constant</i>	0.14
Philips-Perron Unit Root test is used ¹		

Regarding promotion diffusion series, due to frequent outliers caused by all-category level promotions held 3 or 4 times a year, we chose to use [68] extension of the ADF

approach. This extension proposes a non-parametric alternative method for controlling the presence of serial correlation and heterogeneity when estimating the equation used for unit root testing. This alternative approach is a robust way of dealing with series, including excess heterogeneity caused by outliers.

Although unit root test results are conclusive for all series at $P > 0.95$ confidence level, I double-checked the results by plotting lagged correlograms of variables. In addition to this analysis, the stationarity hypothesis test [69] is also applied to the series. Apart from the unit root testing test examining a series to find evidence for a unit root in the series, stationarity tests place the condition of stationarity on zero hypotheses. In that way, I will be able to check results from an opposite vantage point.

The KPSS procedure does not contradict ADF findings regarding the promotion diffusion series. However, KPSS test statistics for the Sales Quantity variable remained at the critical level threshold. In the meantime, autocorrelation and partial autocorrelation function parameters of logarithmic transformed sales quantity exhibit a quickly decaying Autocorrelation function graph accompanying Partial Autocorrelation function graph is damping instantly (Figure A.3). Consequently, we accepted the results of the ADF analysis and determined that the sales quantity variable is stationary.

On the other hand, contradictory outputs from different (KPSS and ADF) approaches are obtained regarding the promotion depth variable. One can add Δ Promotion Depth variable to the model or use Promotion Depth in its original state. Although KPSS stationarity test statistics of promotion depth is slightly above the threshold and unable to reach 0 levels in 12 lags, the correlogram shows a steady decrease in autocorrelation over time (Figure A.3). In order to not lose information with over differencing, I chose to include promotion depth to the model as a stationary variable. In summary, findings suggest that only the price variable shows a clear view of the existence of the unit root.

After determining possible unit root presence in series, the mean and variance level model used for testing hypotheses 1 and 2 can be estimated. Representation of the

system used for analysis is given in Equations 4.1 and 4.2

$$\begin{aligned}
y_t = & \alpha_0 + \sigma_t^2 + \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \alpha_3 y_{t-3} + \alpha_4 y_{t-4} + \\
& \alpha_5 y_{t-5} + \alpha_6 y_{t-6} + \alpha_7 y_{t-7} + \\
& \beta_1 \varepsilon_{t-1} + \beta_2 \varepsilon_{t-2} + \psi_1 \text{promo} - \text{diff}_t + \lambda_1 \text{promodepth}_t + \\
& \theta_1 \Delta \text{price}_t + \tau_1 \text{pf} - \text{dumm}_t + \delta_1 \text{target}_t + \gamma_1 \text{feast1}_t + \gamma_2 \text{feast2}_t + v_t \\
\sigma_t^2 = & \alpha_6 + \alpha_7 \sigma_{t-1}^2 + \beta_3 a_{t-1}^2 + \psi_2 \text{promodiff}_t + \lambda_2 \text{promodepth}_t + \theta_2 \Delta \text{price}_t \\
& \text{for, } \alpha_7 + \beta_3 = 1 \quad (4.2)
\end{aligned}$$

In this system, σ_t^2 , incorporates the presence of volatility term to the mean model while ψ_1 and λ_1 translate the effect of promotion variables to the sales level. Beside, ψ_2 and λ_2 presents effect of promotional variables to variance equations. In addition to promotion effects, a signal for category-wide promotion is contained in the model with *pf - dumm*. Target campaigns, the type of promotions which motivates the customer to increase their purchases to a certain limit to be eligible for a considerable amount of discount on the basket, appeared as *target* variable. Two feast dummies presenting the effect of the first days of two major religious holidays are added to the model with *feast1* and *feast2* dummies.

Finally, to assume the model has correctly specified the error term of the mean level model (Equation 4.1), v_t should be an iid (Independent and identically distributed) series. In order to test if this assumption holds ARCH-LM testing procedure is applied on v_t , the error term of the mean level equation. The ARCH-LM testing procedure proposed by [70] identifies particular volatility clusters in the data. If these clusters differ significantly by time, the model's error term includes auto-regressive conditional variance. In this case, assumptions of classical linear regression are violated. ARCH-LM test applied on v_t of the system given in Equation 4.1 leads to an LM stat equal to 79.12 because a testing regression with seven lags is employed in modelling, and the critical value for the test is $\chi_{0.05,7}^2 = 16$, this translates to rejection of constant variance hypothesis. This result points to the need to include a volatility equation (GARCH) in the system. After the variance model is included, the LM test value retreats to 1.13, which indicates constant variance in disturbances. Including variance equation and estimated conditional variance on the mean equation transforms

model to a simultaneous estimation procedure, specification details for the GARCH model will be outlined below.

According to the procedure in the first step, the standard GARCH procedure proposed by [52] is estimated. However, the estimated reaction parameter value in the GARCH model was positive as the sum of the reaction and persistence parameters exceeded 1; the IGARCH model eases restrictions of GARCH on parameters with $\alpha_7 + \beta_3 = 1$ condition is employed in the final model.

Finally, to test the IID condition of the model's ultimate error term, both KPSS and ADF type stationarity/unit root tests were applied to the error term of the final mean level equation. Results point out that disturbances are $I(0)$ with a 0.99 per cent level of confidence.

The approach I took in this study, which concerns the mean level and variance model simultaneously, adds a different perspective to previous generalisations in the literature on promotional effects on category sales. Unlike previous studies focusing on exogenous promotion decisions on total category sales, this study used a quantitative technique generally used by forecasting and financial econometrics discipline to assess promotional decisions' effects on the mean level while considering variability in sales created through promotions.

So, the assessment of analysis results consists of two stages. First, testing the hypothesis that promotional decisions have a statistically significant effect on the mean level of sales in the short term. Second, the transfer mechanism created through uncertainty created by promotional decisions indirectly affects the mean level of sales.

Parameter estimates of the precipitated model are summarised in Table 4.2. Because their parameters have no interpretable effect on sales values, AR, MA, ARCH, and GARCH parameters are neglected in the table. Nevertheless, parameter estimates show that both promotion diffusion and promotion depth variables are statistically significant and positively affect mean sales levels.

On the other hand, the volatility term in the mean level equation (ARCH-m parameter) adversely impacts sales quantity. Regarding two promotion elasticity variables in our model, any one percentage point increase in promotion diffusion and depth creates

Table 4.2 : ARIMA(7,0,2) + IGARCH (1,1) in mean model estimated parameters.

Variable	Coefficient	Z Stat
<i>Mean Model</i>		
σ^2	-0.35	-5.11
Promotion Diffusion	1.53	12.87
Promotion Depth	1.14	5.25
Δ Price	-0.98	-12.99
pf-dumm	-0.60	-3.99
feast-1	-0.88	-11.57
feast-2	-1.08	-13.30
<i>Volatility Model</i>		
Promotion Diffusion	0.06	1.69
Promotion Depth	0.06	1.33
Δ Price	0.01	2.63

1.5% and 1.1% impulse sales. As expected, the average unit price level of the category hurts category sales. Every 1% increase in price level translates to a 1% decrease in sales quantity.

Outcomes on promotional strategy variables suggest that the presence ratio of the number of products in the promotion to category (promotion diffusion) is more effective than the magnitude of discount offered to customers (promotion depth). However, our findings can be cautiously compared with the results of earlier studies employing the role of TPRs on sales. Although research designs of previous studies differ in category, time interval and design of promotional decision variables aspects, they were able to report that TPRs are practical tools that work in favour of positive sales quantity trends.

Among previous studies, [44] study was the most comparable study with the presented research design. Instead of univariate mean and volatility model specification, they used a Vector Autoregression Model with Exogenous variables approach, which can be defined as a multivariate extension of our study and found that promotion depth's mean promotion elasticity among assessed categories is at 2.21.

Regarding the second hypothesis of the study, which suggests variation stemming from promotion strategy variables affect volatility and mean level of sales, ARCH in mean parameter which can be considered as the effect of volatility on mean level sales reports that every one unit increase in variance level of sales translates to 0.35% decrease in

the mean level of sales. An interesting side finding was that promotion diffusion, and promotion depth variables have limited indirect effect on the estimated conditional volatility of sales figures. Contrary to expectations, they are not significant under 95% level of confidence level. If confidence level eased to 75% it's possible to say that one percentage point increase in promotion diffusion and promotion depth variables create only 0.12 per cent increase in volatility level. As stated previously their effect on the mean level is indirect through variance equation. Findings show that most of the volatility in the system stems from sales' own autoregressive processes. Also, the necessity of the IGARCH modelling approach confirms this finding.

4.2 Price Promotions' Effects on Brand/Category Level

This section aims to incorporate competitor category and brand dimensions into the analysis. However, the previous category level model could explain the category growth effects of price promotions on sales. In addition, researchers can measure increased consumption rate because of the promotions and reference price elasticities for the category. From the long-term perspective, it is possible to assess purchase-event feedback through this analysis. However, analysis at the category level does not have the complete flexibility to decompose the specific basis of any sales bump created through promotional activities. Thus, to test the actual value created through promotions, we need to conceptualise a more detailed model that will assess the effects of promotions on brand, category, and store level.

Cannibalisation: The consumer switches from SKU j^* of brand b to SKU j of brand b

Brand Switching: The consumer switches from brand b^* to b

Category Switching: The consumer switches from a product from another category to brand b

Store Switching: The consumer switches from another store s^* to store s to buy brand b .

In this stage of the study, as a third hypothesis, brand level longitudinal data will be used to explore brand level sales effects of promotions in a two competitor category setting. The brand level model will provide the impact of distinct campaigns, frequency

and duration of promotions to the study. Moreover, the sales bump created through the beginning and at the end of the promotion will also be observable.

Regarding competition measures, brand-own and competitor brand promotion flags will also be added to the model. Besides the brand level promotion indicator, we will also be able to assess the expensiveness and bulkiness of the target brand and competitor within brand sales equations.

As mentioned previously, for decomposing promotional effects on all brands and sub-categories in laundry detergents category 11 ARDL models for category/brand pairs are estimated. Equation 4.1 exhibits a general form of an individual level model.

$$\begin{aligned}
y_a = & \alpha_a + \sum_{i=1}^n \beta_{a,i} y_{a,t-i} + \sum_{n=a}^p \sum_{i=0}^n \zeta_{n,i} X_{n,t-i} \\
& + \sum_{i=0}^n \gamma_{a,i} \text{PromoDepth}_{a,t-i} + \sum_{i=0}^n \sum_{n=a}^p \gamma'_{n,i} \text{PromoDepth}_{n,t-i} \\
& + \sum_{i=0}^n \eta_i \text{CategoryClassAveragePrice}_{t-i} \\
& + \delta_{a,1} \text{BrandPromo}_{a_t} + \sum_{n=0}^p \delta_{n,1}^* \text{BrandPromo}_{n_t} \\
& + \delta_{a,2} \text{BrandPromoStart}_{a_t} \\
& + \sum_{n=b}^p \delta_{n,2}^* \text{BrandPromoStart}_{n_t} + \delta_{a,3} \text{BrandPromoEnd}_{a_t} \\
& + \sum_{n=b}^p \delta_{n,3}^* \text{BrandPromoEnd}_{n_t} + \sum_{p=0}^v \lambda_p Z_p + \varepsilon_t
\end{aligned} \tag{4.3}$$

The economic theory proposes that if there is a long-term relationship between variables under consideration, their variances and means are constant and do not depend on time. However, most empirical studies have shown that this is not the case. Suppose the variables included in the equation have a common trend. Then, regardless of whether they have unit roots (time-varying mean and variance), it is possible to employ them in the econometric time series model.

The existence of this common trend is called co-integration, and estimation techniques based on this theory resolve the violation of CLR assumptions. In this thesis, ARDL co-integration technique and bounds co-integration testing procedure will be used for estimation.

ARDL Co-integration technique requires variables used in estimation to be stationary or can be stationary when first differences are taken. Thus all variables included in modelling should be $I(0)$ or $I(1)$ integration level. Most of the quantitative studies skip unit root assessment before estimating ARDL models regarding this property. However, the technique will collapse in the presence of an integrated stochastic trend of $I(2)$. Therefore although it is not a necessary condition, but it is advised to test for unit roots before estimation. Augmented Dickey-Fuller (ADF) Unit Root test and KPSS Stationarity tests are preferred in favour of assessing variables stochastic trend integration level. While the first procedure aims to prove the existence of unit root on the H_0 hypothesis, the latter places the stationarity state to H_0 . Test results for 66 dynamic variables show that all series has stochastic integration level at $I(0)$ or $I(1)$.

In the light of unit root test results, we can move to ARDL modelling phase. Models for all brand/category pairs are estimated using a big data machine provided by the sponsoring company and the ARDL package in the R programming language. There are two different sub-categories under laundry detergents' main group, namely liquid and powder detergents. As noted in the methodology section, six equations are estimated for the liquid detergent category, while five models are estimated for the powder detergent category.

4.2.1 Diagnostic tests

Looking back to the early days of econometric research, econometricians generally assumed that models well represent the mechanism generating the data. However, the low performance of econometric models in the wake of the 70s oil shock has changed this paradigm forever. It is now generally accepted that econometric models are generally false and fragile for unexpected structural changes. Hence new paradigm among the econometricians is that achieving a perfectly specified model is an impossible endeavour. In that sense, a functional model is not the one that is "realistic" but also one "plausible" and "informative". This view can be echoed by remarks attributed to George Box, *"All models are wrong but some are useful."* and Henri Theil, *"Models are to be used but not to be believed"*.

The following section discusses how useful are the 11 models contained in this study. In this context, being useful corresponds to "*correctly specified model*". This section aims to discuss potential issues that would mean violation of assumptions of the Classical Linear Regression model prelude to model estimation.

Firstly, the lag structure specification is the critical point in ARDL estimation. Correct specification of lagged values of dependent and independent variables mostly secures the correct specification of a model. However, a complete assessment of all five assumptions of CLR would require the practice of several model diagnostics test procedures. Although main diagnostic testing procedures are applied in this study, it is a fact that reaching a specified general model that would pass all diagnostic tests is improbable. So I borrow [62] proposal as an easy definition of a well-specified model, which corresponds to models whose residual series are mutually uncorrelated with zero mean and have the same Gaussian probability distribution. In other words, residuals should not be significantly different from white noise. Validation of this condition is strict enough to reach a proper model because it rules out genuine autocorrelation and heteroskedasticity.

Regarding on definition of the specification problem given above, I used five different specification tests in the post-estimation assessment of ARDL models;

- Lung-Box Autocorrelation test on residuals
- Specification of lag structure on R-Square and AIC values
- F- Test for assessing the overall significance of the model
- Unit Root test on residuals of the models

Although it is controversial whether deciding a necessary number of lagged values variables is a specification test or not, one should secure an optimal combination of lag structure to rule out possible contamination of time-varying trends (auto-correlation and heteroscedasticity) to error terms of models. Therefore, an iterative algorithm which tries different combinations of dependent and independent continuous variables is run on data. Every time the loop is triggered computer program estimates models

with different numbers of lagged variables and records AIC (Akaike Information Criteria) out-put of every model. Among these models, the one with the lowest AIC is selected as well, the specified model.

On the other hand, Exogenous dummy variables presenting the first day, end day and duration of the promotions and seasonal dummies are also included in the model with their current values on the corresponding date. However, because this research contains 11 different category/brand pairs and every set has three different continuous variables, at that point, in order to accomplish the lag specification job, the need for a powerful computer with enough CPU cores arises.

As mentioned previously, I used my data sponsor retailer's big data machines to overcome this challenge. The search algorithm trialled a large number of different estimation results to reach the minimum AIC value through this endeavour. As a result, minimum AIC values accompanied with Sum Square Errors (SSE) of brand/category level models are given in Table 4.3. Order specifications of the models can be found in Appendix C.

Moreover, for all brand / category pairs F-test and r-squared statistics show that all estimated models are significant (Table 4.3) under 0.95 confidence interval.

Table 4.3 : Significance of models indicators.

	R-square	F-Test Stat	AIC	SSE
Alpha Powder	0.85	49.80	843	0.30
Alpha Liquid	0.87	78.50	529	0.28
Beta Powder	0.68	26.70	2355	0.50
Beta Liquid	0.83	38.40	457	0.27
Gamma Powder	0.80	50.20	1424	0.37
Gamma Liquid	0.78	39.40	785	0.30
Omega Powder	0.90	83.20	800	0.30
Omega Liquid	0.96	190.00	1744	0.40
Delta Powder	0.87	84.40	1140	0.34
Delta Liquid	0.69	25.10	2332	0.49
Omicron Liquid	0.82	41.90	204	0.25

The third specification test traces the remaining autocorrelation in residuals of the models. Ljung-Box Autocorrelation Test applied on estimated models' residual series.

Results of the tests show that all of the error terms are free from auto-correlation at $\alpha_{0.05}$ level (Table 4.4).

Table 4.4 : Auto-Correlation tests on model residuals.

	Q-Stat	Lag Length	$\chi^2_{(\alpha=0.05,p)}$
Alpha Powder	2	1	3.84
Alpha Liquid	12	6	12.59
Beta Powder	14	7	14.07
Beta Liquid	7	4	11.14
Gamma Powder	6	7	14.07
Gamma Liquid	3	5	12.83
Omega Powder	4	4	11.14
Omega Liquid	16	10	18.31
Delta Powder	6	1	3.84
Delta Liquid	9	7	14.07
Omicron Liquid	7	7	14

The following diagnostic test applied to model residuals would indicate the existence of omitted variables. Time series plots of 11 residuals represent a pattern with zero means, and fluctuations that can be classified as outliers are rare. However, the residual series includes an interim shock in the early days of the Covid-2019 health crisis (Figure D.1). Although every 11 models include a special dummy variable for the first month of the pandemic, the effect of the health crisis is still contained in the residuals.

Table 4.5 : Unit root tests on residuals.

	Unit Root Test		Stationarity Test
	ADF	DF-GLS	KPSS
Alpha Powder	-26	-4	0.061
Alpha Liquid	-26	-17	0.036
Beta Powder	-27	-5.9	0.083
Beta Liquid	-27	-11	0.027
Gamma Powder	-27	-15	0.03
Gamma Liquid	-27	-8.2	0.021
Omega Powder	-26	-14	0.047
Omega Liquid	-28	-8.4	0.028
Delta Powder	-26	-10	0.042
Delta Liquid	-28	-2.8	0.028
Omicron Liquid	-27	-14	0.039
Critical Values ($n \rightarrow \infty$)	$\tau_{0.05} = 1.9$	$\mu_{0.05} = 0.46$	$\tau_{0.05} = 1.94$

Assessment of residual series based on plots should be backed with unit root testing methodology. However, the presence of excessive leaps in the data may exercise

hinter power of the ADF test, so the DF-GLS type unit root test purposed by [71] is added to the assessment procedure. DF-GLS is an extension of ADF methodology extensively used for series with auto-regressive solid characteristics. DF-GLS uses a slightly adjusted variant of ADF critical values in the decision-making process. Results of all three Unit root test approaches do not contradict each other and point out that all residual series are $I(0)$ and do not include un-explained trends (Table 4.5). Consequently, we can rule out the existence of omitted variables assumption.

In the final stage of diagnostic testing, the CUSUM test traces a possible structural change is applied to ARDL models to see if parameters are constant or not. Recursive CUSUM test results indicate that (Figure D.1), only *Omega Liquid* and *Alpha Liquid* models show temporal diversion from parameter stability. Because these structural changes are interim, I assume all models have parameter stability.

4.2.2 Post estimation analysis

ARDL models used in this study include autoregressive terms of sales quantity, promotion depth and price with changing lag lengths. In addition, every model includes exogenous promotion-related dummy variables and deterministic seasonality dummies. This vast arsenal is employed for a detailed decomposition of promotion effects. Unfortunately, this complexity makes the interpretation of the model parameters even harder. In order to overcome this issue, it is possible to estimate long-run and short-run error correction mechanisms to assess long and short term effects.

As noted in Chapter 3, Bounds Test Methodology purposed by [57] is an efficient way of testing cointegration. Bounds Test methodology estimates an unrestricted error correction model (UECM) to observe long and short-run drivers of the series together. After UECM estimation, an F-test (Wald) is applied to the parameters of the variables in the error correction model. If the parameters are significant, there is at least one cointegration vector between variables. Pesaran et al. [57] define five different cases according to the form of intercept and trend terms included in models. The methodology section gave a time series plot for 11 brand/category level sales figures (Figure 3.3 and 3.4). All of them contain a mean level over periods significantly

different from 0. However, the existence of a linear trend is not evident for each model, but I choose to include it in the error correction model since all y_{t-1} includes a trend. So, the test equation used in the analysis included unrestricted intercept and trend.

Table 4.6 : Bounds test results.

<i>Null Hypothesis : No levels relationships</i>		
	F (Wald Test)	P-value
Alpha Powder	5	(1.00E-06)
Alpha Liquid	18	(1.00E-06)
Beta Powder	23	(1.00E-06)
Beta Liquid	11	(1.00E-06)
Gamma Powder	21	(1.00E-06)
Gamma Liquid	20	(1.00E-06)
Omega Powder	16	(1.00E-06)
Omega Liquid	4	(8.00E-4)
Delta Powder	18	(1.00E-06)
Delta Liquid	24	(1.00E-06)
Omicron Liquid	18	(1.00E-06)
k=22, T>1000		

Bounds test results for 11 ARDL models show that every model constructed for this study is eligible for long-run and short-run analysis and includes at least one cointegration vector.

When Bounds Test results are derived, a typical ARDL estimations procedure is expected to be completed. However, most scholars neglect that ARDL models consist of the same variables, and it's most likely that their residuals are correlated. This concept was discussed in Chapter 3. As a relatively untouched area of ARDL applications, there is no widely accepted standard testing workflow on this issue among the econometricians. This study purposes the workflow presented in Figure 4.1 to test a possible violation of the CLR assumption that dictates that observations on independent variables can be considered exogenous in repeated samples. If the residuals are not independent of each other, it is apparent that this assumption does not hold.

Table 4.7 exhibits a cross-correlations matrix derived from residuals of 11 ARDL models estimated separately. All correlation coefficients are statistically significant under a 0.95 confidence interval. However, it is not an excellent way to determine

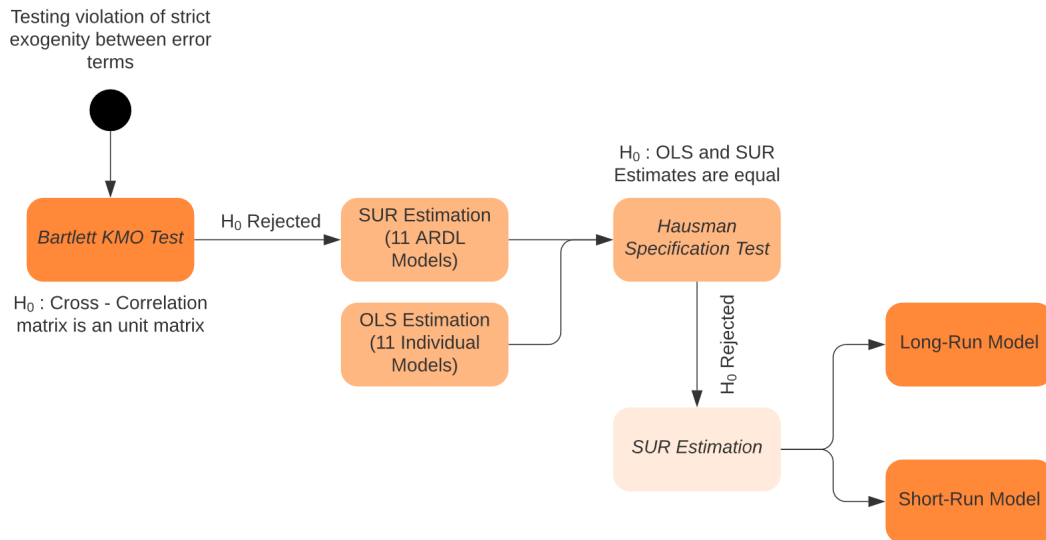


Figure 4.1 : Estimation procedure in the presence of violation of strict exogeneity between residuals.

the suspected violation by using the results of 66 different t-test values, which belong to all correlation coefficients. The Bartlett's Test of Sphericity [64] is widely used for assessing the equality of any correlation matrix to an identity matrix and can be applied as a joint hypothesis test on the correlation matrix presented in Table 4.7.

Table 4.7 : Correlation matrix for ARDL model residuals.

Correlation t-Statistic Probability	RESID A	RESID A	RESID B	RESID B	RESID D	RESID D	RESID	RESID	RESID	RESID T	RESID T
RESID ALPHA LIQ	1.000000										

RESID ALPHA POW	0.545249 25.43386 0.0000	1.000000									
	----	----									
RESID BETA LIQUID	0.562758 26.62061 0.0000	0.716953 40.21485 0.0000	1.000000								
	----	----	----								
RESID BETA POWDER	0.466441 20.61947 0.0000	0.449877 19.69710 0.0000	0.447826 19.58469 0.0000	1.000000							
	----	----	----	----							
RESID DELTA LIQUID	0.448931 19.64521 0.0000	0.409235 17.53791 0.0000	0.458908 20.19670 0.0000	0.364347 15.29841 0.0000	1.000000						
	----	----	----	----	----						
RESID DELTA POWDER	0.365569 15.35764 0.0000	0.423915 18.30197 0.0000	0.414301 17.79964 0.0000	0.257937 10.43923 0.0000	0.290122 11.85432 0.0000	1.000000					
	----	----	----	----	----	----					
RESID GAMMA LIQUID	0.474039 21.05168 0.0000	0.648062 33.27362 0.0000	0.650846 33.52125 0.0000	0.401969 17.16585 0.0000	0.375692 15.85167 0.0000	0.354619 14.83028 0.0000	1.000000				
	----	----	----	----	----	----	----				
RESID GAMMA POWD	0.479366 21.35830 0.0000	0.589722 28.55297 0.0000	0.606377 29.81828 0.0000	0.393748 16.74954 0.0000	0.384825 16.30308 0.0000	0.305362 12.53934 0.0000	0.605724 29.76757 0.0000	1.000000			
	----	----	----	----	----	----	----	----			
RESID OMICRON LIQU	0.457554 20.12126 0.0000	0.615750 30.55727 0.0000	0.706621 39.04878 0.0000	0.370465 15.59578 0.0000	0.398532 16.99124 0.0000	0.373174 15.72817 0.0000	0.586774 28.33498 0.0000	0.502567 22.73073 0.0000	1.000000		
	----	----	----	----	----	----	----	----	----		
RESID TURSIL LIQUID	0.140777 5.560107 0.0000	0.205980 8.230801 0.0000	0.142254 5.619613 0.0000	0.160546 6.360225 0.0000	0.139055 5.490738 0.0000	0.153336 6.067553 0.0000	0.172918 6.864927 0.0000	0.134127 5.292521 0.0000	0.132538 5.228672 0.0000	1.000000	
	----	----	----	----	----	----	----	----	----	----	
RESID TURSIL POWDE	0.544905 25.41104 0.0000	0.635541 32.18789 0.0000	0.670641 35.35229 0.0000	0.433597 18.81539 0.0000	0.423490 18.27961 0.0000	0.431642 18.71107 0.0000	0.567744 26.96796 0.0000	0.557262 26.24274 0.0000	0.566438 26.87654 0.0000	0.139228 5.497690 0.0000	1.000000
	----	----	----	----	----	----	----	----	----	----	----

The testing procedure proposed by Bartlett states the null hypothesis that the correlation matrix of residuals is an identity matrix, which leads to no significant relation between error terms of individual models. Regarding the correlation between 11 different residuals, Bartlett's test of sphericity is significant at a confidence level of 0.95 (χ^2_{55} , $prob < 0.001$).

However, recently, the Bartlett test has been highly criticised for its inclination to reject the no-relation hypothesis. Therefore, before reaching the final decision, a more robust specification procedure should be used to decide on using a generalised form of simultaneous equation system instead of estimating individual OLS regression.

The Hausman Specification test, which is very popular in panel data model applications to test parameter vector equality, is used in the study as a reliable indicator of contamination among residuals. In short, a particular test on if there is a significant difference between the parameters estimated separately and simultaneously as a system is applied to ARDL model parameters. Only 1 out of 11 models report that OLS and SUR estimations are identical (Table 4.8).

Table 4.8 : Haussman test results.

<i>Null Hypothesis : Parmeters are identical</i>		
	F (Wald Test)	P-value
Alpha Powder	318.00	(1.00E-06)
Alpha Liquid	253.54	(1.00E-06)
Beta Powder	120.26	(0.4247)
Beta Liquid	382.42	(1.00E-06)
Gamma Powder	183.15	(1.00E-06)
Gamma Liquid	268.6	(1.00E-06)
Omega Powder	309.81	(1.00E-06)
Omega Liquid	216.1	(0.04)
Delta Powder	247.14	(1.00E-06)
Delta Liquid	165.77	(0.03)
Omicron Liquid	489.72	(1.00E-06)
k=22, T>1000		

According to the estimation workflow proposed in Figure 4.1 11, ARDL models estimated at the Brand/Category level are a simultaneous system. In a system of simultaneous equations, all endogenous variables are random variables; a change in disturbance term changes all endogenous variables as they are determined

simultaneously. It is necessary to clarify that that kind of relationship means a possible violation of the CLR assumption that all independent variables are fixed. Estimation related problem that arises from this violation was discussed in detail in the methodology section.

What follows is a brief outline of the estimation of 11 ARDL Brand / Category level equations as a system. Seemingly Unrelated Regression estimation is a method used when the residuals of an equation system in which all equations are estimated separately are correlated.

As previously stated, when the existence of a cointegrating vector is proved for models, it's possible to employ a long-run cointegrating vector (LRD), and unrestricted conditional error correction model (CEC) derived from main ARDL models. While the CEC model explains short-term promotion dynamics affecting quantity sold between category/brand pairs, the LRD model contains information from cointegrating relations.

This part of the thesis discusses the findings from SUR estimation of CEC and LRD equations derived from 11 ARDL models. First, CEC and LRD equations are derived from ARDL models estimated with OLS. Then regarding previous procedures state that a system estimation is needed, derived CEC and LRD equations are estimated once more using SUR estimation. Finally, performance indicators on the significance of each equation estimated through SUR methodology are given in Table 4.9 and Table 4.10. They indicate that all models have significance in explaining Daily Quantity Sold (Long Term) and Δ Quantity Sold (Short Term).

Having defined the estimation procedure of long-term and short-term models, I will now move on to discuss findings decomposition of sales effects of promotions. Parameter estimates derived on a brand/category basis will be used for the reporting. To ease effort, instead of equations explanation, I will present results in four functional perspectives presented in Figure 4.4.

All analysis completed in this section was to assess the third hypothesis introduced in the methodology section. This hypothesis suggests that when the promotional effect is decomposed to brand/category level linkages, any change in promotional strategy

Table 4.9 : Significance of CEC model diagnostics.

	Number of Parameters	RMSE	χ^2	$P > \chi^2_{p,\alpha=0.05}$
Alpha Powder	161	0.3027	4984.21	0.000
Alpha Liquid	121	0.2801	3645.26	0.000
Beta Powder	116	0.4854	2601.21	0.000
Beta Liquid	171	0.2749	4487.27	0.000
Gamma Powder	114	0.3681	3125.31	0.000
Gamma Liquid	135	0.3010	2513.31	0.000
Omega Powder	137	0.3042	4974.95	0.000
Omega Liquid	182	0.3907	2314.08	0.000
Delta Powder	113	0.3326	7625.01	0.000
Delta Liquid	125	0.4804	2880.18	0.000
Omicron Liquid	150	0.2689	2667.43	0.000

Table 4.10 : Significance of LRD model diagnostics.

	Number of Parameters	RMSE	χ^2	$P > \chi^2_{23,\alpha=0.05}$
Alpha Powder	23	0.5126	1935.46	0.000
Alpha Liquid	23	0.4269	3055.30	0.000
Beta Powder	23	0.6516	1135.77	0.000
Beta Liquid	23	0.3901	2219.61	0.000
Gamma Powder	23	0.5034	2314.78	0.000
Gamma Liquid	23	0.4323	1594.65	0.000
Omega Powder	23	0.4992	3312.5	0.000
Omega Liquid	23	0.8870	5830.89	0.000
Delta Powder	23	0.4990	3526.11	0.000
Delta Liquid	23	0.7851	289.36	0.000
Omicron Liquid	23	0.3708	1933.95	0.000



Figure 4.2 : Functional decomposition of promotions effects.

variables would trigger a significant extra demand or causes category switching or brand switching of the existing demand. SUR method is used to estimate parameters that will illustrate the existence of that kind of relationship. Estimated parameters for *short-run* and *long-run* dynamic relations can be find in Appendix F. On the other hand, parameter estimation set concerning static promotion-related strategic decision for ie.. dummy indicating first and last day of promotions and duration of promotions are reported in Appendix G. Seasonal effects on week and month basis can also be seen from the outputs given in Appendix G.

4.2.2.1 Category - brand own effects

The first set of experiments concerning hypothesis 3 aims to expose category/brand level promotion's effect on its own sales. Therefore, in addition to *promotion depth* and *price* variables, the brand's previous sales in the corresponding category will also be assessed in this section.

Figure F.1 to F.11 reveals the primary effects defined in the previous paragraph. Strong evidence of negative price elasticity is found for all category/brand pairs, whether it's in liquid or powder. Price elasticities of both long-term and short-term equations are significant even at a $p > 0.99$ confidence level. While average (due to outlier values, median type averages are preferred) long-term price elasticity parameters values for powder detergents is -4.21 , the same value for the liquid production line is -0.68 . Findings on short-term price elasticity values are also in-line with long-term assessment. On the other hand, the lag length for daily price indicator changes variables spans from $t = 0$ to 6. Interestingly short-term own price change variables are significant for more prolonged lag levels compared to the powder detergent side.

Regarding estimated *promotion depth* parameters, which introduces the magnitude of promotions to the system, all short term and long term own effects are significant at $P > 0.95$ confidence level. Interestingly, the long-term *promotion depth* parameter of the Beta-Powder product line is a distinction. This product line's parameter is significant at $p > 0.91$ confidence level with the lowest elasticity value among other long-term effects with 1.3. On the other hand, median levels of long-term parameters of powder-liquid groups are 2.99 and 3.56, respectively.

Unlike short-term *price* effects, short-term effects of promotion depth do not span a long time range. In most of the equations, lag length for change in *Promotion Depth* parameter remains low at one or no lags. In this manner, the Gamma Liquid line is only the group as an exception. The short-term median effect of *Promotion Depth* variables of the product lines are 1.03 and 2.89 for powder and liquid detergents, respectively.

The promotion duration variable, which covers days category/brand group is in promotion for the corresponding days, is significant for all products at $p > 0.95$ confidence level. However, the parameter of this variable is only negative for the most expensive product line, the Omicron Liquid. Interestingly all other products' promotion duration variable is only significant for Omicron Liquid product.

4.2.2.2 Category switching effects

In order to investigate the category switching effects, I employed competitor categories and brands' price and promotion depth variables. In the long term, both Beta Powder, Gamma Powder and Omega Powder sales are affected negatively by Omicron Liquid's *Promotion Depth*. On the other hand, Alpha Powder, Gamma Powder and Delta Powder show significant responses to change in promotion depth in the short term. Among these short term effects Alpha Powder and Delta Powder point -1.70 and -1.60 sales retreat when the magnitude of Omicron Liquid promotions is increased. Long-term effects suggest that Omega and Delta Powder groups are affected by four different competitor product/category groups. While the promotion depth of Omicron and Delta Liquid are increased, both product lines lose sales. Because Omicron Liquid product line has the highest price level among 11 category/product groups, it is interesting that they steal extra purchases from the relatively cheaper powder detergent group.

Delta Powder suffers extensively from competitor category/brand promotions in the short term. For example, any one percentage point increase in Omicron Liquid and Gamma Liquid promotion depths affects Delta Powder sales by 4 and 1 per cent, respectively. On the other hand, in some cases increase in the promotion depth of certain products accompanies sales of competitor product/categories. For instance, any one percentage point increase in Omicron Liquid sales reflects Gamma Powder

sales by a 0.8 per cent increase. In addition, one percentage point increase in Omega Liquid products hikes Delta Powder sales by 1.49 per cent.

4.2.2.3 Within category effects

Indeed within category effect group contains brand change effects caused by price promotions. Any increase in *price* or *promotion depth* of certain category/brand pair affects sales of competitor products in the same category. Turning now to the experimental evidence on the brand preference effect of price promotions, in the long term, any one percentage point increase in Gamma Powder's promotion depth invokes 29 per cent increase in Delta Powder. However, it is impossible to refer to the same effect on the other side. However, as Gamma has a higher market share than the Delta product line, that would be the cause of the asymmetric relationship between the two brands. Here Delta Powder group can be regarded as an accompanier group to a larger product line. Surprisingly another minority product line with a lower market share indicates a similar accompanying effect. The Omega Powder detergent line is effected by four different product lines' promotion strategies. Moreover, any increase in *promotion depth* of Beta, Alpha, Gamma and Delta lines affects sales of the Omega Powder group positively. Even any one percentage point increase in promotion depth of Beta and Gamma Powder reflects with 3.03 and 6.06 per cent increase in long term sales of Omega Powder group. The remaining three powder detergent groups are also affected positively by other powder groups' promotional depth. However, the magnitude of affection is lower for the remaining products.

On the other hand, liquid detergents groups within category effects present a completely different scene. All product groups are affected negatively by other brands' promotion depth in the same category for all liquid detergent pairs other than Alpha and Delta.

4.2.2.4 Seasonal effects

Seasonal effects represent in this study are not interaction effects with the promotion depth variables of category/brand pairs. This thesis measured the net sales effect of seasonal terms and shopping-related important days after price and promotion effects are sterilised. When yearly effects are analysed, most product lines are positively affected if the corresponding months are August or September. However, Alpha Powder is only the product that showed no significant increase in sales during late summer. Looking into day of week effects, all product lines other than Beta Powder (brand with highest market share) and Omicron Liquid (brand with lowest market share) introduce higher sales volume on the weekends. Interestingly Omicron Liquid group reflects higher sales figures only when it is Monday.

Regarding religious holidays all product lines point to significant falls in their sales. However, the cause of this effect is entirely distant from our research. Most of the analysed market chain outlets are closed on the first day of religious holidays.

5. CONCLUSIONS

5.1 General Discussion and Theoretical Implications

This study aimed to assess if price promotions affect sales. Therefore, the study set out to objectively measure and assess the effect of price promotions both at the category and brand level. In the course of the research, I first identified measurable and efficient KPIs as a tool to measure promotion elasticities.

While, utilising three hypotheses, the analysis conceptualised examining the impact of price promotions on category/brand sales. The first two empirical sections focus on estimating the mean level and volatility of product sales in the existence of promotional strategy as an exogenous effect. Although there is a long history in the promotion research domain employing ETS in quantitative research, such as [41], this study approached the problem with borrowing methods frequently used by financial econometrics. The main idea behind this adaptation was to use the concept of financial econometrics to measure the effectiveness of exogenous market indicators on the price of financial instruments. This study first facilitates *promotion depth* and *promotion diffusion* as an exogenous factor and estimates sales with its endogenous process both by modelling mean and variance. Then I tested the effect of significant promotional strategy variables on the mean level and variance equations. My findings provided solid empirical confirmation of the hypothesis, suggesting that promotional variables significantly affect the mean level of sales. Finally, incorporating the endogenous process of price promotion together with exogenous promotional strategy variables and volatility model extended the model design in [72] and price promotions endogenous impact on consumption of categories once more validated.

The third empirical application initially set out a two category - multi-brand environment to test and decompose promotions' effects on sales quantities. Flexibility sustained with this elaborative equation system ensures practical, prescriptive outputs

for the professionals and scholars working in the sales promotions domain. The estimation method, which completes unbiased but not efficient ARDL estimations using SUR, is a contribution of this thesis to applied marketing research. This study showed that inter-brand / category relations should be considered in multivariate time series modelling studies in the marketing area.

In their review [23] noted on long-term effects of price promotions as "jury is still out". However, this research showed that after filtering *price elasticity* effects, long-run effects of *promotion depth* on 11 different product/category pairs is still significant, and higher than brand and category switching effects. This study contributes to the literature by identifying the magnitude of price promotions that significantly affect sales in the long term. Like long-term effects, short-term change in the product's own promotion magnitude variable is also significant for short-term models.

In terms of brand level cannibalisation, this study test significance and sign of *promotion depth* of the same brand's competitor category. This variable was significant for nine out of eleven models. Among them, only Alpha and Gamma brands reported a positive impact in the short and long term from the same brand's competitor-category promotion depth variable. Hence it can be said that the cannibalisation effect does not exist for these brands. On the other hand, Delta and Omega brands could not point to a significant cannibalisation effect in the long term. At the same time, there was an evident negative impact from cross-category- same brand promotion depth variable in the short-term. Therefore, the cannibalism effect is only valid in the short term for Delta and Omega brands. Finally, as noted previously, the remaining brands failed to report significant estimates for the variable facilitated to measure the cannibalisation effect.

In addition to inferences to be made on *promotion depth* variables, my model was also capable of assessing price elasticities when all promotional effects were included in equations. Results showed that both long-run and short-run own price effects are strongly significant and adversely affect quantity sales. Moreover, for all 11 category/brand pairs, it can be said that short-term price elasticity is higher than long-term.

It worth discussing results on the most expensive brand/category pair, the Omicron Liquid. This product line has the lowest own *promotion depth* elasticity among others, both for the long and short-term. Moreover, cross-category and within category brand switching effects are milder for this category. This refers to the Omicron brand having loyal customers and has a sales trend free from its own and competitors' promotional strategy.

5.2 Limitations and Future Research

This research has only examined product groups belonging to two competitor categories of a main category only for one retailer aggregated daily data. Hence, The current study is limited by the absence of store-level competition. Moreover, the results cover only the laundry detergents category, so it is impossible to generalise my findings to other main categories. However, the hypothesis testing procedure proposed in this research exhibits ends to end methodology both for long and short term relations. Therefore, this methodology can be traced to the assessment of other categories.

Further research might explore multiple retailers and various category setting using the proposed methodology for a more generalised inference. Apart from these main limitations, some minor extensions can be made to this research system. For example, a future study investigating the interaction effects of day of week and month of year variables and promotional strategy variables (eg. *promotion depth and price*) would construct a bridge between seasonality and price promotions.

Moreover, comparing price promotion effects for different customer segments would be interesting. The system purposed in this study can be repeated for different value and lifestyle segments of the customers. Studies comparing the reaction of various customer segments to sales promotions are less frequent in literature.



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APPENDICES

APPENDIX A : Time Series Characteristics of Promotion Depth and Diffusion Variables (Category Level Model)

APPENDIX B : Time Series Plots of Variables Included in Category-Brand Level Model

APPENDIX C : ARDL Lag Order Specifications

APPENDIX D : Stability Tests for ARDL Models

APPENDIX E : Residual Diagnostics for ARDL Models

APPENDIX F : Estimated Parameters of Short-Run and Long-Run Models (Dynamic Variables)

APPENDIX G : Estimated Parameters of Short-Run and Long-Run Models (Strategy and Seasonal Dummy Variables)



APPENDIX A : Time Series Characteristics of Promotion Depth and Diffusion Variables / Category Level Model

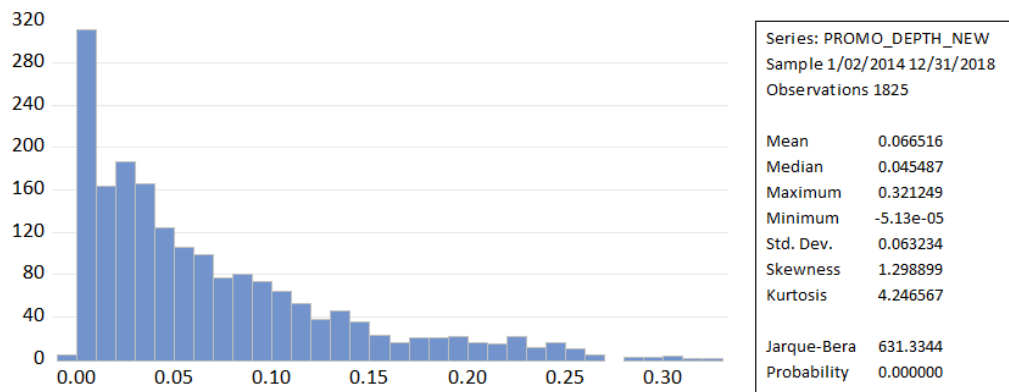


Figure A.1 : Histogram and Stats for Promotion Depth Variable.

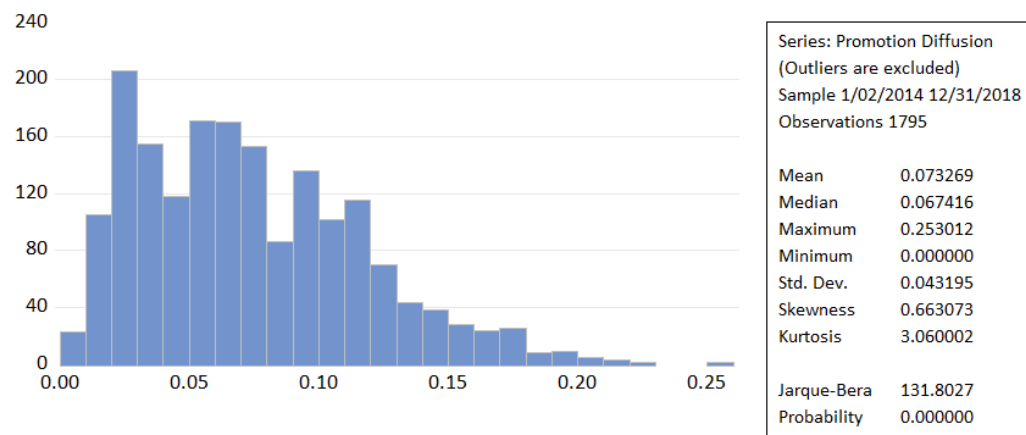
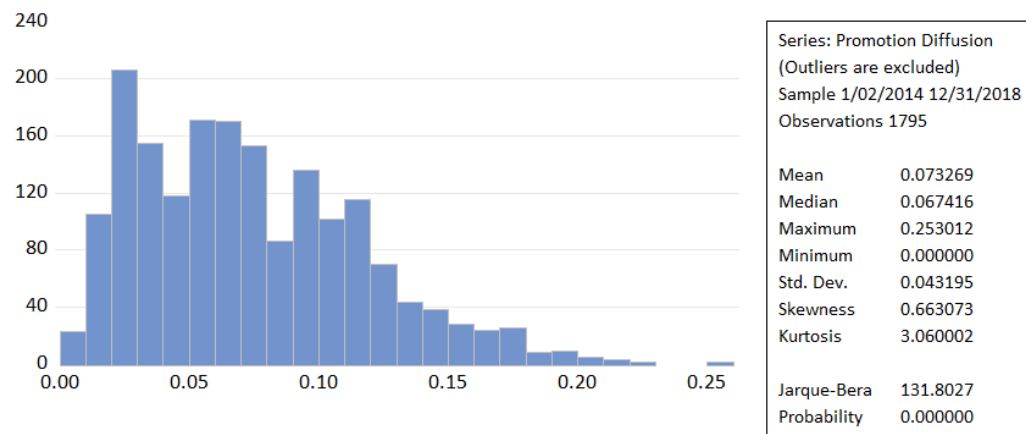
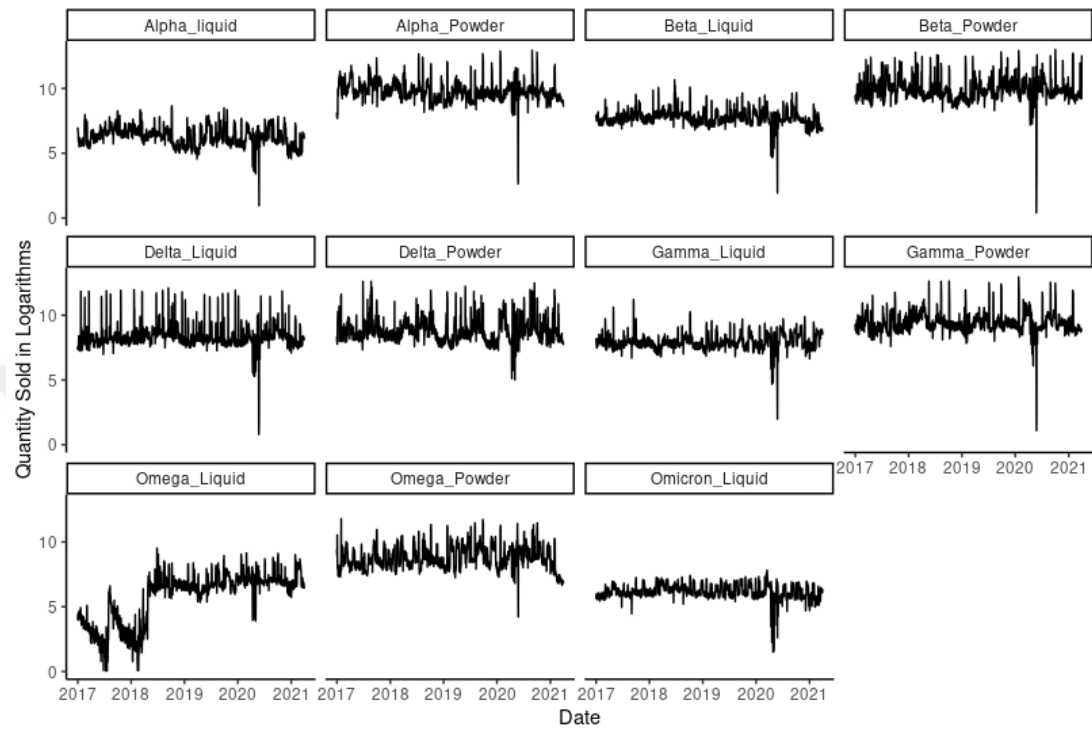


Figure A.2 : Histogram for Promotion Diffusion Variable (incl./excl. outliers).

APPENDIX B : Time Series Plots of Variables Included in Category-Brand Level Model



Source: Company DB

Figure B.1 : Quantity Sold in Logarithms.

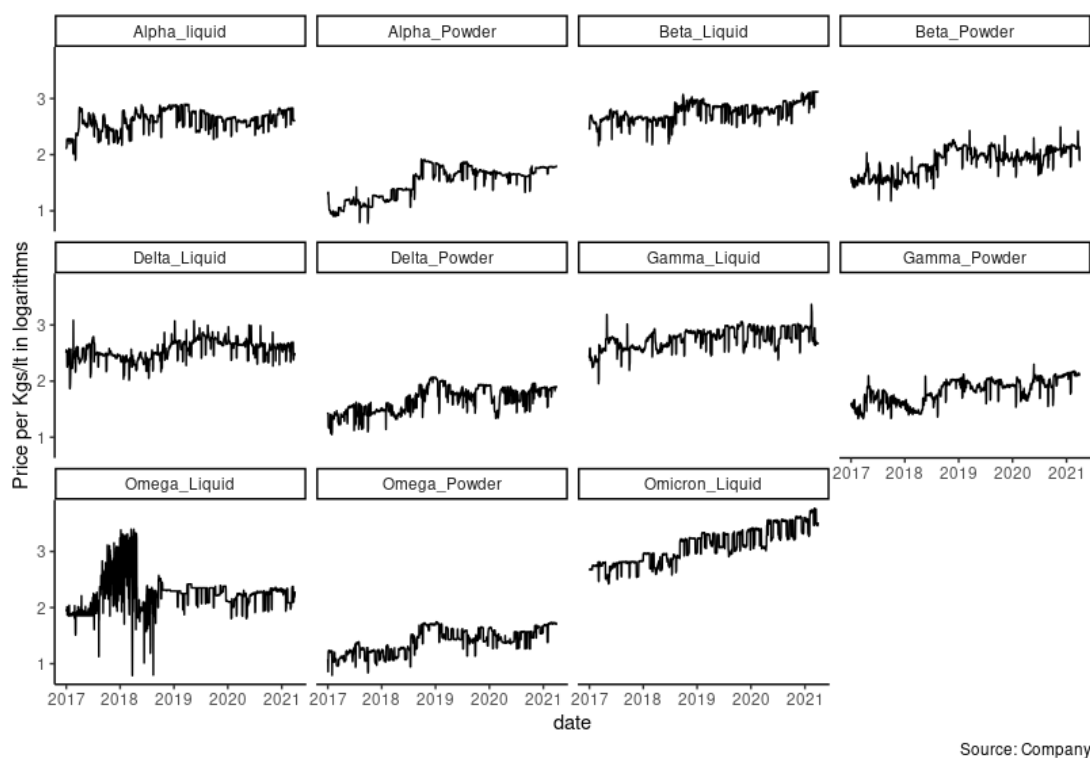


Figure B.2 : Category/Brand Level Prices in Logarithms.

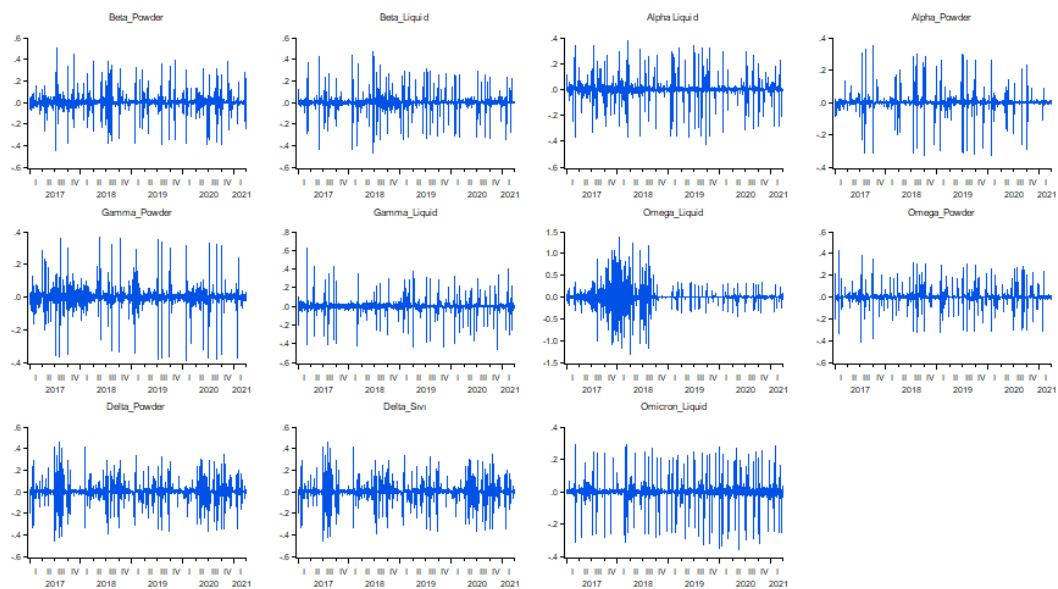
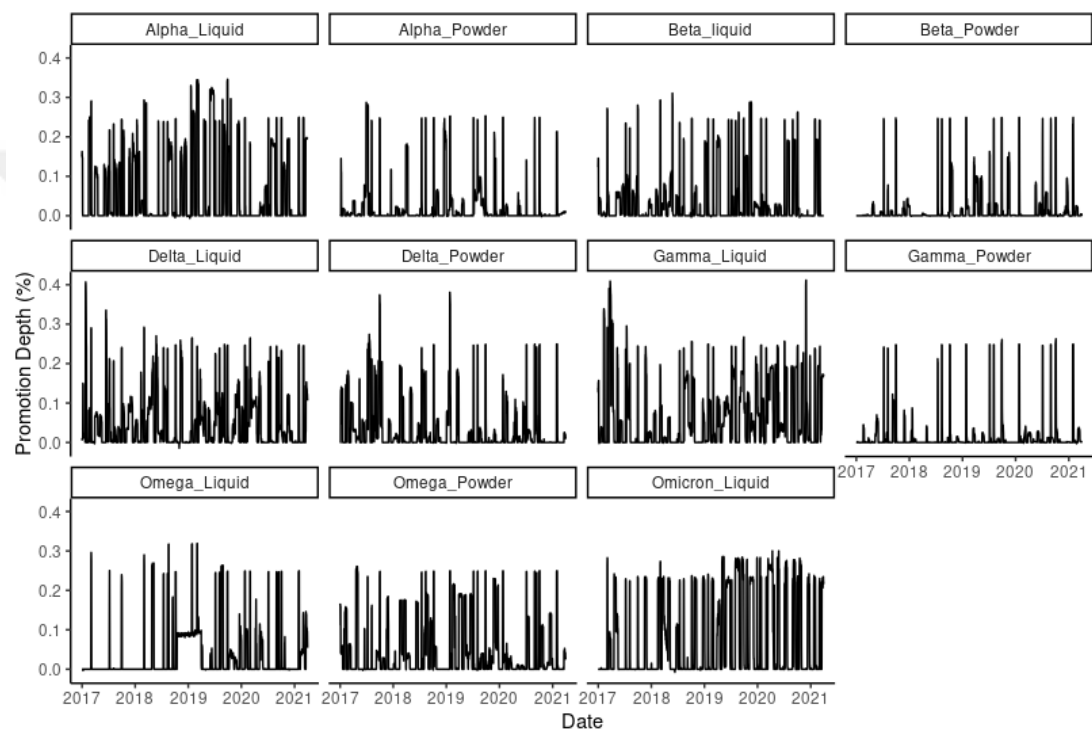


Figure B.3 : Daily Change in Prices.



Source: Company

Figure B.4 : Daily Promotion Depth Allocations.



APPENDIX C : ARDL Lag Order Specifications

- Alpha Powder Model : 6 6 7 0 4 7 2 7 7 1 1 3 4 6 1 1 2 5 0 0 2 7 6
- Alpha Liquid Model : 3 4 0 1 3 0 0 2 2 0 3 0 0 4 1 0 1 3 3 2 2 2 3
- Beta Powder Model : 3 3 3 4 0 2 0 0 3 0 1 3 0 0 3 0 2 3 0 0 3 1 3
- Beta Liquid Model : 6 7 7 7 6 6 0 2 6 3 3 6 0 0 3 1 1 3 7 4 7 5 6
- Gamma Powder Model : 3 3 0 1 1 2 0 7 3 0 1 0 1 0 0 1 1 3 1 1 1 2 2
- Gamma Liquid Model : 4 3 0 1 3 0 0 2 2 0 3 0 0 0 1 7 7 3 3 1 2 3 3
- Delta Liquid Model : 4 3 4 0 3 4 0 1 4 0 3 4 1 2 3 1 3 3 1 1 1 1 1
- Delta Powder Model : 3 0 3 1 2 0 0 1 0 0 0 7 1 0 1 0 1 4 0 0 1 2 2
- Delta Liquid Model : 4 3 4 0 3 4 0 1 4 0 3 4 1 2 3 1 3 3 1 1 1 1 1
- Omega Powder Model : 4 3 3 4 1 0 4 2 2 7 2 0 4 0 3 0 4 3 7 1 1 2 3
- Omega Liquid Model : 6 7 0 7 3 5 5 2 7 3 3 6 6 6 6 2 4 5 0 7 7 2 2
- Omicron Liquid Model: 6 7 7 1 3 0 0 7 7 0 0 3 2 6 0 0 3 3 1 0 7 7 5



APPENDIX D : Stability Tests and Residual Diagnostics for ARDL Models

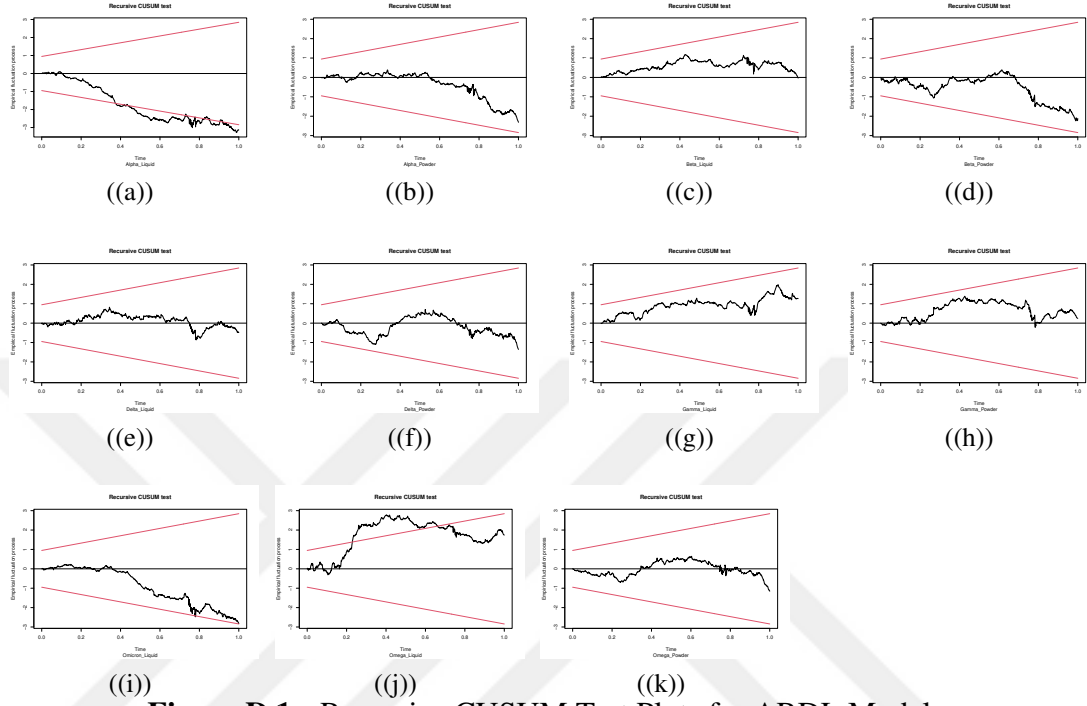


Figure D.1 : Recursive CUSUM Test Plots for ARDL Models.



APPENDIX E : Residual Diagnostics for ARDL Models

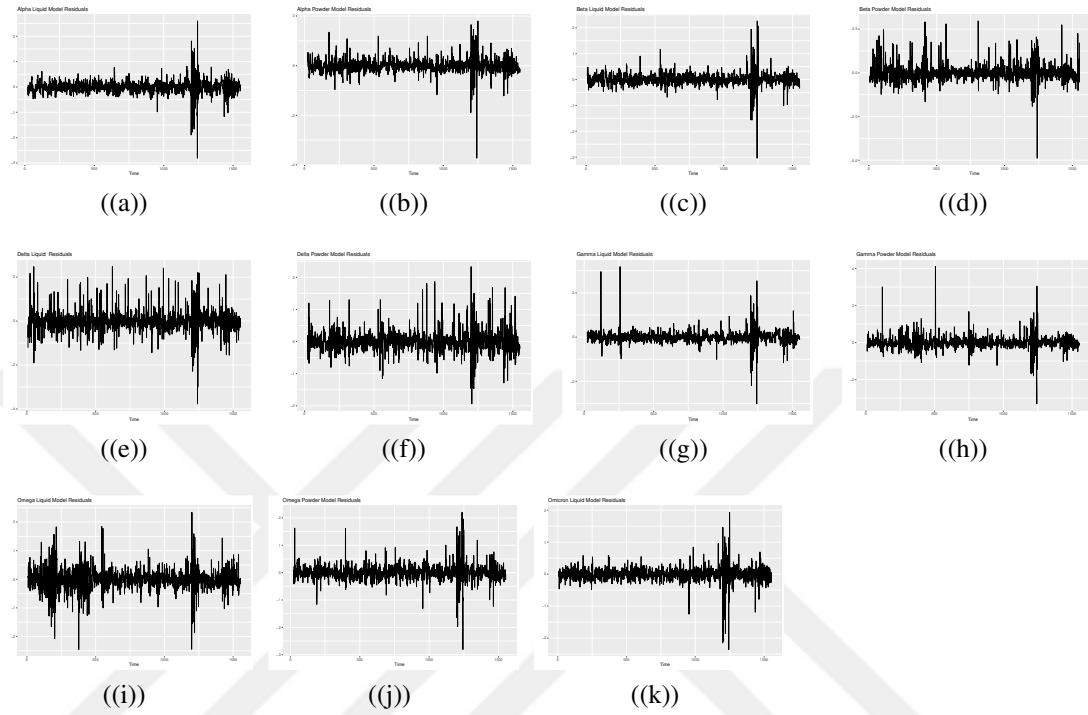


Figure E.1 : Recursive CUSUM Test Plots for ARDL Models.



APPENDIX F : Estimated Parameters of Short-Run and Long-Run Models (Dynamic Variables)

Long Run and Short Run Elasticities for Beta-Powder Dtergent Product Line									
Dynamic Effects									
Long Run Effects					Short Term Effects				
Coint Eq		Coef	z-stat	P> Z	EC Eq		Coef	z-stat	P> Z
Loyalty					0.03				
Brand Level Analysis	Own Effects	Price Beta Powder	-3.68	-19.78	0.000	Δ Price Beta Powder	-3.73	-17.15	0
		PD Beta Powder	1.13	1.69	0.091	Δ Price Beta Powder _{t-1}	1.04	4.33	0
						Δ PD Beta Powder	-3.76	-4.58	0
						Δ PD Beta Powder _{t-1}	2.73	3.42	0.001
						Δ PD Beta Powder _{t-2}	3.19	4.14	0
	Canibalization	Price Beta Liquid	-0.85	-3.72	0	Δ Price Beta Liquid t-1	0.49	2.12	0.034
						Δ Price Beta Liquid t-2	0.37	1.79	0.073
	Category Effects	Price Alpha Powder	0.41	2.17	0.03	Δ Price Alpha Powder t-1	-1.15	-3.51	0
		Price Omega Powder	1.44	6.38	0				
		PD Omega Powder	1.57	4.66	0	Δ Price Omega Powder t-2	-0.75	4.48	0
						Δ PD Gamma Powder	2.85	2.77	0.006
						Δ PD Gamma Powder t-1	-2.01	-2.34	0.019
					Δ PD Gamma Powder t-2	-3.91	-4.88	0	
	Cross - Category Effects	PD Omega Powder	1.57	4.66	0	Δ PD Gamma Liquid t	-1.63	-3.98	0
		PD Alpha Liquid	1.04	4.31	0	Δ PD Gamma Liquid t-1	0.65	2.08	0.037
		Price Omicron Liquid	-0.7	-2.57	0	Δ PD Omega Liquid t-1	-0.85	-2.13	0.033
		Price Alpha Liquid	0.58	3.75	0	Δ PD Omicron Liquid t	-1.82	-2.4	0.016

Figure F.1 : Estimated Parameters of SUR System - Beta Powder Product Line.

Long Run and Short Run Elasticities for Beta-Liquid Dtergent Product Line									
Dynamic Effects									
Long Run Effects					Short Term Effects				
Coint Eq		Coef	z-stat	P> Z	EC Eq	Coef	z-stat	P> Z	
Brand Level Analysis	Loyalty				Δ Quantity Beta Liquid t-2	-0.06	-3.45	0.001	
					Δ Quantity Beta Liquid t-3	-0.029	-1.72	0.085	
	Own Effects				Δ Price Beta Liquid t	-3.54	-27.05	0	
					Δ Price Beta Liquid t-1	-0.268	-2.15	0.032	
		Price Beta Liquid	-2.71	-19.63	0	Δ Price Beta Liquid t - 2	-0.51	-4.26	0
		PD Beta Liquid	2.06	8.83	0	Δ Price Beta Liquid t - 3	-0.32	-2.8	0.005
					Δ Price Beta Liquid t - 4	-0.38	-3.41	0.001	
					Δ Price Beta Liquid t - 5	-0.17	-1.63	0.103	
					Δ Price Beta Liquid t - 6	-0.26	-3.06	0.002	
					Δ PD Beta Liquid	0.54	2.54	0.011	
	Canibalization	Price Beta Powder	-0.2	-1.85	0.06	Δ Price Beta Powder t-2	-0.166	-1.71	0.086
		PD Beta Powder	-1.93	-4.8	0	Δ PD Beta Powder	-0.61	-1.78	0.075
	Category Effects								
		Price Alpha Liquid	0.26	2.85	0				
		Price Gamma Liquid	0.17	4.56	0	Δ Price Delta Liquid t-2	-0.19	-2.6	0.009
		Price Delta Liquid	-0.18	-1.95	0.05				
		Price Omega Liquid	0.17	4.34	0				
		Price Omicron Liquid	-1.46	-8.98	0				
		PD Alpha Liquid	0.66	4.56	0	Δ PD Alpha Liquid t	0.64	3.22	0.001
		PD Gamma Liquid	-0.21	-1.58	0.09	Δ PD Alpha Liquid t-2	-0.24	-2.3	0.02
		PD Delta Liquid	-0.74	-4.01	0	Δ PD Gamma Liquid t	-0.64	3.22	0.001
		PD Omega Liquid	0.68	3.04	0	Δ PD Delta Liquid t-2	-0.4	-2.8	0.005
	PD Omicron Liquid	-1.8	-7.99	0	Δ PD Omega Liquid t	0.83	2.73	0.006	
	Cross - Category Effects				0	Δ PD Omega Liquid t-1	-0.33	-1.77	0.077
					0	Δ PD Omicron Liquid t	-1.11	-3.57	0
		Price Alpha Powder	0.35	3.12	0	Δ Price Alpha Powder t	1.39	2.54	0.011
		Price Omega Powder	0.99	7.3	0	Δ Price Aplha Powder t-1	0.22	1.75	0.081
		Price Delta Powder	-0.46	-5.12	0	Δ Price Gamma Powder t	0.43	2.89	0.004
					0	Δ Price Gamma Powder t-1	-0.39	-2.89	0.004
					0	Δ Price Omega Powder t	0.49	1.76	0.079
		PD Gamma Powder	2.78	6.08	0	Δ Price Omega Powder t-2	-0.25	-2.18	0.029
		PD Omega Powder	1.12	5.55	0	Δ Price Delta Powder t	-0.17	-2.04	0.042
		PD Delta Powder	-0.36	-1.72	0.086	Δ PD Omega Powder t	0.49	1.76	0.079
					0	Δ PD Omega Powder t-2	-0.46	-2.43	0.015
					0	Δ PD Gamma Powder t	1.39	2.54	0.011
			0	Δ PD Gamma Powder t-5	0.69	2.35	0.019		

Figure F.2 : Estimated Parameters of SUR System - Beta Liquid Product Line.

Long Run and Short Run Elasticities for Alpha-Powder Detergent Product Line								
Dynamic Effects								
Long Run Effects				Short Term Effects				
Long Term Elasticity				Short Term Elasticity				
Coint Eq	Coef	z-stat	P> Z	EC Eq	Coef	z-stat	P> Z	
Brand Level Analysis	Loyalty			Δ Quantity Beta Powder t-2				
					-0.08	-4.12	0.000	
	Own Effects			Δ Price Alpha Powder t				
	Price Alpha Powder	-2.94	-19.57	0.000	Δ Price Alpha Powder t-1	-1.65	-7.15	0.000
	PD Alpha Powder	2.99	8.86	0.000	Δ Price Alpha Powder t-2	-1.52	-6.87	0.000
				Δ Price Alpha Powder t-6	-0.66	-3.57	0.000	
				Δ PD Alpha Powder t	1.03	2.72	0.007	
	Canibalization			Δ Price Alpha Liquid t				
	Price Alpha Liquid	0.69	5.72	0.000	Δ PD Alpha Liquid t	0.66	2.03	0.042
	PD Alpha Liquid	0.69	4.79	0.000				0.015
	Category Effects			Δ Price Beta Powder				
	Price Gamma Powder	-0.32	-2.43	0.015		-0.52	-4.3	0.000
	Price Omega Powder	1.44	6.38	0.000	Δ Price Beta Powder t-1	-0.24	-1.82	0.068
	Price Delta Powder	1.57	4.66	0.000	Δ Price Gamma Powder	-0.85	-4.98	0.000
	Price Omega Powder	0.95	5.34	0.000	Δ Price Delta Powder	-0.3	-2.96	0.003
	Price Delta Powder	0.32	2.77	0.006	Δ PD Gamma Powder t-1	-2.5	-4.6	0.000
				Δ PD Gamma Powder t-2	-0.98	-1.83	0.067	
	PD Gamma Powder	2.13	3.54	0.000	Δ PD Gamma Powder t-4	-0.85	-1.8	0.072
				Δ PD Omega Powder t	0.344	1.9	0.058	
				Δ PD Delta Powder t	-0.56	-2.44	0.015	
	Cross - Category Effects			Δ PD Gamma Liquid t				
	Price Omega Liquid	1.92	0.055	0.000		-0.83	-3.34	0.000
	PD Gamma Liquid	0.5	2.87	0.004	Δ PD Omicron Liquid t	-1.29	-2.89	0.004
	PD Delta Liquid	0.44	1.81	0.070	Δ PD Omicron Liquid t-1	-0.865	-2.04	0.041
				Δ PD Omega Liquid t	0.841	2.42	0.015	

Figure F.3 : Estimated Parameters of SUR System - Alpha Powder Product Line.

Long Run and Short Run Elasticities for Alpha-Liquid Dtergent Product Line									
Dynamic Effects									
Long Run Effects					Short Term Effects				
Coint Eq		Coef	z-stat	P> Z	EC Eq	Coef	z-stat	P> Z	
Brand Level Analysis	Loyalty				Δ Quantity Alpha Liquid t-1	-0.04	-2.95	0.003	
	Own Effects	Price Alpha Liquid	-0.41	-4.13	0.000	Δ Price Alpha Liquid t	-1.25	-8.28	0.000
		PD Alpha Liquid	4.93	31	0.000	Δ Price Alpha Liquid t -1	-0.42	-4.1	0.000
						Δ PD Alpha Liquid	3.46	13.88	0.000
	Canibalization								
	Category Effects	Price Alpha Liquid	-0.81	-5.36	0.000	Δ Price Delta Liquid t-2	-0.19	-2.6	0.009
		Price Gamma Liquid	0.21	2.19	0.028	Δ Price Omega Liquid t-1	-0.08	-3.38	0.001
		Price Omega Liquid	0.22	5.19	0.000				
		Price Omicron Liquid	-1.8	-10.08	0.000				
		PD Alpha Liquid	-0.68	-2.69	0.000	Δ PD Gamma Liquid t	-0.92	-4.09	0.000
		PD Gamma Liquid	-0.25	-1.58	0.090	Δ PD Delta Liquid t-2			
		PD Omega Liquid	-0.51	-2.09	0.000	Δ PD Omega Liquid t	0.62	1.96	0.050
		PD Omicron Liquid	-1.67	-7.99	0.000	Δ PD Omega Liquid t-1	-0.54	-2.85	0.004
	Cross - Category Effects	Price Beta Powder	-0.3	-2.5	0.012	Δ Price Alpha Powder t-1	0.17	2.54	0.011
		Price Delta Powder	-0.33	-3.34	0.001	Δ Price Aplha Powder t-1			
						Δ Price Gamma Powder t			
						Δ Price Gamma Powder t-1			
						Δ Price Omega Powder t			
		PD Beta Powder	-1.15	-2.62	0.000	Δ Price Omega Powder t-2			
						Δ Price Delta Powder t			
		PD Omerga Powder	-0.55	-2.53	0.012	Δ PD Omega Powder t-2	-0.41	-2.47	0.014
						Δ PD Omega Powder t-2			
						Δ PD Gamma Powder t			
					Δ PD Gamma Powder t-5	0.69	2.35	0.019	

Figure F.4 : Estimated Parameters of SUR System - Alpha Liquid Product Line.

Long Run and Short Run Elasticities for Gamma-Powder Detergent Product Line								
Dynamic Effects								
Long Run Effects				Short Term Effects				
Long Term Elasticity				Short Term Elasticity				
Coint Eq	Coef	z-stat	P> Z	EC Eq	Coef	z-stat	P> Z	
Brand Level Analysis	Loyalty			Quantity Gamma Powder t-2				
					-0.06	-3.64	0.0000	
	Own Effects			Δ Price Gamma Powder t				
	Price Gamma Powder	-3.81	-28.77	0.000		-3.55	-15.79	0.0000
	PD Gamma Powder	4.89	8.27	0.000	Δ Price Gamma Powder t-1	-0.58	-2.43	0.0150
				Δ Price Gamma Powder t-2	-0.84	-3.93	0.0000	
				Δ Price Gamma Powder t-3	-0.69	-4.21	0.0000	
				Δ PD Gamma Powder t	2.19	2.75	0.0060	
	Canibalization							
	Category Effects							
Brand Level Analysis	Price Beta Powder	0.3122	2.17	0.03				
	Price Alpha Powder	0.436	2.95	0.003				
	Price Omega Powder	1.13	6.48	0				
	Price Delta Powder	-0.38	-3.3	0.001				
	PD Omega Powder	1.37	5.25	0	PD Omega Powder	0.92	2.21	0.027
	Cross - Category Effects							
	Price Alpha Liquid	0.38	3.24	0.001	Δ Price Gamma Liquid t	0.38	2.45	0.014
	Price Omicron Liquid	-0.65	-3.11	0.002				
	PD Alpha Liquid	1.072	5.72	0	Δ PD Omicron Liquid t	0.8	1.86	0.062
	PD Omega Liquid	-0.79	-2.71	0.007				
	PD Omicron Liquid	-0.64	-2.21	0.027				

Figure F.5 : Estimated Parameters of SUR System - Gamma Powder Product Line.

Long Run and Short Run Elasticities for Gamma-Liquid Detergent Product Line											
Dynamic Effects											
Long Run Effects					Long Term Elasticity		Short Term Effects		Short Term Elasticity		
Coint Eq					Coef	z-stat	P> Z	EC Eq	Coef	z-stat	P> Z
Brand Level Analysis	Loyalty							Δ Quantity Gamma Liquid t-1	0.04	2.25	0.024
								Δ Quantity Gamma Liquid t-2	-0.06	-3.93	0.000
	Own Effects							Δ Price Gamma Liquid t-2	-0.42	-3.79	0.000
								Δ Price Gamma Liquid t-4	-0.24	-2.37	0.018
								Δ Price Gamma Liquid t-5	-0.23	-2.38	0.017
								Δ PD Gamma Liquid t	1.86	7.41	0.000
								Δ PD Gamma Liquid t-1	0.56	3.23	0.000
								Δ PD Gamma Liquid t-2	0.43	2055	0.018
								Δ PD Gamma Liquid t-3	0.49	3.05	0.002
	Canibalization							Δ Price Gamma Powder t-1	-0.41	-2.47	0.019
								Δ PD Gamma Powder t	2.28	3.53	0.000
	Category Effects										
								Δ PD Beta Liquid t	0.65	2.12	0.034
								Δ PD Omega Liquid t	1.08	3.13	0.002
	Cross - Category Effects										

Figure F.6 : Estimated Parameters of SUR System - Gamma Liquid Product Line.

Long Run and Short Run Elasticities for Delta-Powder Detergent Product Line								
Dynamic Effects								
Long Run Effects				Short Term Effects				
Long Term Elasticity				Short Term Elasticity				
Coint Eq	Coef	z-stat	P> Z	EC Eq	Coef	z-stat	P> Z	
Brand Level Analysis	Loyalty			Δ Quantiy Delta Powder t-1	-0.04	-1.99	0.047	
				Δ Quantiy Delta Powder t-2	-0.065	-3.21	0.0010	
	Own Effects			ΔPrice Delta Powder t	-7.36	-57.83	0.000	
	Price Delta Powder	-5.26	-45.49	0.000	ΔPrice Delta Powder t-1	-1.4	-6.3	0.000
	PD Delta Powder	1.3	4.81	0.000	ΔPrice Delta Powder t-2	-1.6	-7.67	0.000
				ΔPrice Delta Powder t-3	-0.759	-4.71	0.000	
				ΔPrice Delta Powder t-4	-0.822	-5.26	0.000	
				ΔPrice Delta Powder t-5	-0.858	-5.34	0.000	
				ΔPrice Delta Powder t-6	-0.873	-5.57	0.000	
				PD Persil Powder	-1.72	-4.8	0.000	
	Canibalization			ΔPrice Delta Liquid t-2	0.24	2.14	0.030	
Brand Level Analysis	Category Effects							
	Price Beta Powder	1.104	7.73	0.0000				
	Price Alpha Powder	0.62	4.29	0.0000				
	Price Gamma Powder	0.78	6	0.0000				
	Price Omega Powder	1.63	9.39	0.0000				
	PD Alpha Powder	0.85	2.61	0.0090				
	PD Gamma Powder	3.41	5.83	0.0000				
	PD Omega Powder	0.72	2.81	0.0050				
	Cross - Category Effects			Δ Price Omicron Liquid t	-0.83	-1.96	0.050	
	Price Beta Liquid	-0.3	-1.71	0.0870				
	Price Alpha Liquid	0.25	2.18	0.0290				
	Price Gamma Liquid	0.22	1.92	0.0550				
	Price Delta Liquid	-0.27	-2.33	0.0200	Δ PD Omega Liquid t	1.49	3.9	0.000
	Price Omega Liquid	0.09	2	0.0450		-1.6	-2.99	0.003
	Price Omicron Liquid	-0.93	-4.47	0.0000	Δ PD Omicron Liquid t-1	-1.03	-2.03	0.042
					Δ PD Gamma Liquid t	-0.47	-1.72	0.086
	PD Alpha Liquid	0.7	3.81	0.0000				
	PD Delta Liquid	-0.68	-2.92	0.0040				
	PD Omega Liquid	0.89	3.1	0.0020				
	PD Omicron Liquid	-1.21	-4.2	0.0000				

Figure F.7 : Estimated Parameters of SUR System - Delta Powder Product Line.

Long Run and Short Run Elasticities for Delta-Liquid Detergent Product Line													
Dynamic Effects													
Long Run Effects					Short Term Effects								
Coint Eq		Coef	z-stat	P> Z	EC Eq	Coef	z-stat	P> Z					
Brand Level Analysis	Loyalty				Δ Quantity Delta Liquid t	0.18	8.66	0.000					
					Δ Quantity Delta Liquid t-1	-0.06	-3.6	0.000					
					Δ Quantity Delta Liquid t-2	0.08	4.78	0.000					
	Own Effects				Δ Price Delta Liquid t	-1.12	-6.1	0.000					
					Δ Price Delta Liquid t-1	0.45	2.65	0.006					
					Δ Price Delta Liquid t-2	-0.75	-4.65	0.008					
					Δ PD Delta Liquid t	-2.19	-5.32	0.000					
	Canibalization	Price Delta Powder	-0.43	-2.33	0.017	Δ Price Delta Powder t-2	-0.46	-2.49	0.013				
						Δ Price Delta Powder t	-0.36	-1.95	0.052				
	Category Effects												
					Price Beta Liquid	-0.88	-3.2	0.001					
					Price Alpha Liquid	0.6	3.25	0.001					
					Price Omicron Liquid	-0.88	-2.68	0.007					
					PD Alpha Liquid	1.33	4.58	0.000	Δ PD Alpha Liquid t	0.75	1.83	0.067	
					PD Omicron Liquid	-1.02	-2.24	0.025	Δ PD Gamma Liquid t	-1.28	-3.14	0.002	
									Δ PD Gamma Liquid t-1	0.84	2.72	0.006	
									Δ PD Gamma Liquid t-2	0.78	2.64	0.008	
	Δ PD Omega Liquid t	1.23	2.13	0.033									
	Cross - Category Effects												
					Price Alpha Powder								
					Price Omega Powder	1.29	4.73	0.000	Δ Price Alpha Powder t-1	-0.84	-2.47	0.001	
					PD Beta Powder	-1.41	-1.74	0.080					
					PD Gamma Powder	3.19	3.46	0.001	Δ PD Omega Powder t-2	-1.12	-2.78	0.005	
PD Omega Powder	1.6	3.94	0.000	Δ PD Gamma Powder t	1.94	1.81	0.070						

Figure F.8 : Estimated Parameters of SUR System - Delta Liquid Product Line.

Long Run and Short Run Elasticities for Omega-Powder Detergent Product Line														
Dynamic Effects														
Long Run Effects		Long Term Elasticity			Short Term Effects		Short Term Elasticity							
Coint Eq		Coef	z-stat	P> Z	EC Eq	Coef	z-stat	P> Z						
Brand Level Analysis	Loyalty				Δ Quantity Omega Powder t-1					-0.15	-7.93	0.0000		
					Δ Quantity Omega Powder t-2					-0.08	-5.12	0		
					Δ Quantity Omega Powder t-3					-0.044	-2.83	0.005		
	Price Omega Powder				-4.21	-24.26	0.000	Δ Price Omega Powder t		-5.4	-31.57	0.0000		
	PD Omega Powder				3.83	14.83	0.000	Δ Price Omega Powder t-1		-1.31	-6.59	0.0000		
							Δ Price Omega Powder t-2		-1.33	-7.39	0.0000			
							Δ Price Omega Powder t-3		-1.02	-6.07	0.0000			
							Δ Price Omega Powder t-4		-0.77	-5.7	0.0000			
							Δ Price Omega Powder t-5		-0.48	-3.57	0.0000			
							Δ Price Omega Powder t-6		-0.65	-4.98	0.0000			
							Δ PD Omega Powder t		1.05	3.06	0.0002			
							Δ PD Omega Powder t-1		0.85	3.26	0.0010			
	Canibalization													
	Price Omega Liquid				0.11	2.38	0.017							
	PD Omega Liquid				-0.50	-1.74	0.082							
	Category Effects				Price Beta Powder		0.54	3.82	0.0000	Δ Price Alpha Powder t		0.62	2.03	0.0420
					Price Delta Powder		0.77	6.66	0.0000	Δ Price Gamma Powder t-1				
					Price Alpha Powder		1.9	12.95	0.0000					
					Price Gamma Powder		0.23	1.79	0.0730					
					PD Beta Powder		1.42	2.75	0.0060	Δ PD Delta Powder t		0.5	1.79	0.0730
					PD Alpha Powder		1.00	3.04	0.0020					
					PD Gamma Powder		1.95	3.33	0.0010					
					PD Delta Powder		0.57	2.11	0.0350					
Cross - Category Effects				Price Alpha Liquid		-0.23	-1.98	0.0480	Δ Price Omega Liquid t		0.59	1.72	0.086	
				Price Omega Liquid		0.11	2.38	0.0170	Δ Price Omicron Liquid t		-1.71	-4.19	0	
				Price Omicron Liquid		0.58	2.78	0.0050	Δ Price Omicron Liquid t -1					
				PD Alpha Liquid		0.44	2.38	0.0170	Δ PD Delta Powder t		0.5	1.79	0.079	
				PD Delta Liquid		-0.44	-1.89	0.0590	Δ PD Gamma Liquid t		-0.58	-2.37	0.018	
				PD Omega Liquid		-0.5	-1.74	0.0820						
				PD Omicron Liquid		0.72	2.51	0.0010						

Figure F.9 : Estimated Parameters of SUR System - Omega Powder Product Line.

Long Run and Short Run Elasticities for Omega-Liquid Detergent Product Line																	
Dynamic Effects																	
Long Run Effects					Long Term Elasticity		Short Term Effects		Short Term Elasticity								
Coint Eq					Coef	z-stat	P> Z	EC Eq		Coef	z-stat	P> Z					
Brand Level Analysis	Loyalty					Δ Quantity Omega Liquid t-1		-0.25	-9.78	0							
						Δ Quantity Omega Liquid t-2		-0.18	-7.44	0							
						Δ Quantity Omega Liquid t-3		-0.08	-3.66	0							
						Δ Quantity Omega Liquid t-4		-0.068	-3.13	0.002							
	Own Effects					Δ Price Omega Liquid t		-1.23	-21.92	0							
						Δ Price Omega Liquid t-1		-0.43	-5.17	0							
						Δ Price Omega Liquid t-2		-0.31	-3.91	0							
						Δ Price Omega Liquid t-3		-0.2	-2.68	0.007							
						Δ Price Omega Liquid t-4		-0.17	-2.34	0.019							
						Δ PD Omega Liquid		3.41	7.05	0							
						Δ PD Omega Liquid t-1		1.82	4.31	0							
						Δ PD Omega Liquid t-2		1.4	3.34	0							
						Canibalization					Δ Price Omega Powder t-1		-0.57	-1.95	0.051		
											Δ Price Omega Powder t-2		-0.54	-1.9	0.057		
	Δ PD Omega Powder t-2		-0.87	-2.04	0												
	Category Effects					Price Beta Liquid		-2.88	-9.18	0							
						Price Alpha Liquid		-0.64	-3.07	0.002							
						Price Gamma Liquid		-1.26	-6.18	0							
						Price Omicron Liquid		-2.76	-7.45	0							
						PD Beta Liquid		-3.1	-5.83	0							
						PD Gamma Liquid		-0.74	-2.46	0.014							
						PD Omicron Liquid		-3.64	-7.07	0							
						Δ PD Omicron Liquid t-1		-1.43	-2.26	0.024							
						Cross - Category Effects					Price Beta Powder		1.31	5.18	0		
											Price Alpha Powder		2.75	10.56	0		
	Price Gamma Powder		0.45	1.95	0.051												
	Δ Price Alpha Powder t-1																
	Δ PD Omega Powder t-2																
	Δ PD Gamma Powder t																
	PD Alpha Powder		-1.77	-3.03	0.002												
	PD Gamma Powder		7.17	6.88	0												
	PD Delta Powder		-0.84	-1.75	0.079												

Figure F.10 : Estimated Parameters of SUR System - Omega Liquid Product Line.

Long Run and Short Run Elasticities for Omicron-Liquid Detergent Product Line								
Dynamic Effects								
Long Run Effects					Short Term Effects			
Coint Eq					EC Eq			
	Coef	z-stat	P> Z			Coef	z-stat	P> Z
Brand Level Analysis	Loyalty				Δ Quantity Omicron Liquid t-2	-0.07	-3.19	0.000
					Δ Quantity Omicron Liquid t-4	-0.039	-2.32	0.020
					Δ Quantity Omicron Liquid t-5	-0.03	-2.26	0.024
					Δ Price Omicron Liquid t	-2.44	-14.33	0.000
					Δ Price Omicron Liquid t-1	-0.34	-2.42	0.000
					Δ Price Omicron Liquid t-2	-0.65	-5.56	0.000
					Δ Price Omicron Liquid t-3	-0.38	-3.72	0.000
					Δ Price Omicron Liquid t-4	-0.49	-4.86	0.000
					Δ PD Omicron Powder t-3	0.96	2.11	0.031
					Δ PD Omicron Powder t-4	1.09	2.47	0.010
	Own Effects							
	Price Omicron Liquid	-1.99	-12.86	0.000				
	PD Omicron Liquid	1.03	4.8	0.000				
	Category Effects							
	Price Delta Liquid	-0.18	-2.09	0.036	Δ Price Beta Liquid t	0.23	1.82	0.069
	Price Alpha Liquid	0.49	-2.58	0.010				
	Price Omega Liquid	0.09	2.64	0.080				
	PD Alpha Liquid	0.77	5.6	0.000				
	Cross - Category Effects							
	Price Alpha Powder	0.25	2.3	0.021	Δ Price Beta Powder t	0.21	2.03	0.043
	Price Gamma Powder	-0.21	-2.16	0.030				
	Price Omega Powder	1.01	7.83	0.000				
	Price Delta Powder	-0.41	-4.78	0.000				
	PD Gamma Powder	0.85	1.96	0.050	Δ PD Gamma Powder t	0.57	2.32	0.020
	PD Omega Powder	1.16	5.81	0.000				
	PD Delta Powder	-0.73	-3.66	0.000				

Figure F.11 : Estimated Parameters of SUR System - Omicron Liquid Product Line.

APPENDIX G : Estimated Parameters of Short-Run and Long-Run Models (Strategy and Seasonal Dummy Variables)

Table G.1 : Promotional Strategy and Seasonal Dummy Variables.

	Beta Powder			Beta Liquid			Alpha Powder			Alpha Liquid			Gamma Powder			Gamma Liquid		
	Coef	z	P> z	Coef	z	P> z	Coef	z	P> z	Coef	z	P> z	Coef	z	P> z	Coef	z	P> z
Promotion Strategy Indicators (Signal and Level Dummies)																		
promo_Beta_powder	0.17	4.64	0.00															
Beta_powder_start	0.91	11.24	0.00															
Beta_powder_end				0.06	2.62	0.01												
promo_Beta_liquid				0.09	1.83	0.07												
Beta_liquid_start				-0.14	-2.97	0.00												
Beta_liquid_end							0.12	5.54	0.00	0.04	2.17	0.03						
promo_Alpha_powder													-0.14	-2.16	0.03			
Alpha_powder_start																		
Alpha_powder_end				-0.06	-1.97	0.05				0.05	1.78	0.08						
promo_Alpha_liquid										0.15	2.57	0.01						
Alpha_liquid_start																		
Alpha_liquid_end				0.11	2.19	0.03												
promo_Delta_powder																		
Delta_powder_start				-0.09	-1.79	0.07				-0.10	-1.89	0.06						
Delta_powder_end										-0.07	-1.81	0.07						
promo_Delta_liquid																		
Delta_liquid_start	-0.13	-1.97	0.05															
Delta_liquid_end	-0.14	-2.13	0.03										0.11	3.55	0.00			
promo_Gamma_Powder													0.39	5.01	0.00			
Gamma_Powder_start																		
Gamma_Powder_end																0.08	3.36	0.00
promo_Gamma_liquid	0.07	1.87	0.06													0.34	5.76	0.00
Gamma_liquid_start																		
Gamma_liquid_end																		
promo_Omega_liquid	-0.13	-2.44	0.02				-0.08	-2.46	0.01							-0.08	-2.37	0.02
Omega_liquid_start																		
Omega_liquid_end				0.24	3.20	0.00	0.16	1.89	0.06	0.32	4.11	0.00				0.19	2.31	0.02
promo_Omega_powder																		
Omega_powder_start																-0.12	-2.05	0.04
Omega_powder_end	0.22	2.48	0.01	0.10	2.12	0.03	0.12	2.22	0.03	0.09	1.93	0.05				0.09	1.65	0.10
promo_Omicron_liquid	0.18	3.69	0.00				0.07	2.45	0.01									
Omicron_liquid_end																		
Omicron_liquid_start																		
Holidays and Extraordinary Shopping Activity Days																		
kurban_arife																		
Religious Holiday 2	-0.83	-3.30	0.00	-0.89	-6.71	0.00	-1.07	-7.00	0.00	-0.93	-6.68	0.00	-0.91	-4.85	0.00	-0.94	-6.25	0.00
Religious Holiday 1	-1.63	-6.55	0.00	-1.40	-10.77	0.00	-1.64	-10.77	0.00	-1.20	-8.81	0.00	-1.98	-10.77	0.00	-1.51	-10.27	0.00
Beginning of Fasting Season	-1.59	-6.43	0.00	-0.32	-2.46	0.01	-1.20	-7.91	0.00				-0.56	-3.05	0.00	-0.37	-2.49	0.01
New Years Eve																		
First Day of the Year																		
Womens Day																-0.12	-1.93	0.05
Day of Week																		
sunday				0.08	3.26	0.00	0.17	5.61	0.00	0.16	5.99	0.00	0.12	3.21	0.00	0.12	4.22	0.00
saturday				0.10	3.83	0.00	0.16	5.35	0.00	0.18	6.77	0.00	0.10	2.65	0.01	0.12	4.21	0.00
friday							0.11	3.67	0.00	0.08	3.13	0.00	0.08	2.09	0.04			
thursday	-0.21	-3.90	0.00	-0.05	-1.85	0.06												
wednesday							0.05	1.65	0.10	0.07	2.49	0.01						
tuesday	-0.12	-2.41	0.02	-0.06	-2.41	0.02												
Month of Year																		
january							-0.08	-1.74	0.08									
february							-0.16	-3.50	0.00									
march				0.07	1.74	0.08	-0.08	-1.67	0.10									
may							-0.08	-1.70	0.09	0.08	1.94	0.05	-0.12	-2.05	0.04			
june				0.12	2.85	0.00				0.14	3.21	0.00				0.13	2.66	0.01
july							-0.13	-2.71	0.01	0.11	2.36	0.02				0.08	1.66	0.10
august	0.16	1.99	0.05	0.12	2.72	0.01				0.11	2.32	0.02				0.08	1.65	0.10
september	0.15	2.00	0.05	0.15	3.67	0.00				0.14	3.26	0.00	0.12	2.04	0.04	0.12	2.61	0.01
october				0.08	1.85	0.06										0.11	2.15	0.03
november																0.08	1.66	0.10
december																		
Covid Out-Break (First Shock)													0.21	2.18	0.03			

Table G.1 (continued) : Promotional Strategy and Seasonal Dummy Variables.

	Delta Powder			Delta Liquid			Omega Liquid			Omega Powder			Omicron Liquid		
	Coef	z	P> z	Coef	z	P> z	Coef	z	P> z	Coef	z	P> z	Coef	z	P> z
Promotion Strategy Indicators (Signal and Level Dummies)															
promo_Beta_powder															
Beta_powder_start													0.07	1.75	0.08
Beta_powder_end															
promo_Beta_liquid				0.17	3.61	0.00				0.06	2.15	0.03	0.06	2.29	0.02
Beta_liquid_start															
Beta_liquid_end															
promo_Alpha_powder	0.05	2.14	0.03	0.10	2.75	0.01							0.04	1.95	0.05
Alpha_powder_start	-0.14	-2.23	0.03	-0.24	-2.65	0.01									
Alpha_powder_end				-0.16	-1.83	0.07				0.10	1.86	0.06			
promo_Alpha_liquid															
Alpha_liquid_start															
Alpha_liquid_end										0.13	2.22	0.03	0.09	1.81	0.07
promo_Delta_powder	0.09	2.81	0.01												
Delta_powder_start				-0.43	-4.48	0.00									
Delta_powder_end				-0.30	-3.08	0.00				-0.10	-1.68	0.09			
promo_Delta_liquid				0.13	3.64	0.00									
Delta_liquid_start				1.50	22.11	0.00	-0.10	0.05	0.07						
Delta_liquid_end				0.32	4.46	0.00				-0.09	-2.32	0.02			
promo_Gamma_Powder	-0.06	-2.06	0.04				-0.10	0.04	0.01						
Gamma_Powder_start				-0.23	-2.24	0.03									
Gamma_Powder_end															
promo_Gamma_liquid										0.04	1.78	0.08	0.04	2.13	0.03
Gamma_liquid_start	0.15	2.31	0.02	0.18	1.84	0.07									
Gamma_liquid_end							0.15	0.05	0.00						
promo_Omega_liquid															
Omega_liquid_start	0.31	3.00	0.00							0.19	2.25	0.02	0.16	2.13	0.03
Omega_liquid_end				0.35	2.49	0.01									
promo_Omega_powder				-0.08	-1.71	0.09									
Omega_powder_start				-0.18	-1.80	0.07				0.10	1.68	0.09			
Omega_powder_end															
promo_Omicron_liquid	0.13	3.93	0.00				0.10	0.04	0.01				0.05	1.77	0.08
Omicron_liquid_end	-0.10	-1.67	0.09				-0.15	0.08	0.08	-0.10	-1.91	0.06	-0.08	-1.71	0.09
Omicron_liquid_start				-0.26	-2.57	0.01				0.14	2.23	0.03			
Holidays and Extraordinary Shopping Activity Days															
kurban_aile															
Religious Holiday 2	-0.80	-4.67	0.00	-0.61	-2.45	0.01	-0.83	0.20	0.00	-1.10	-7.26	0.00	-0.94	-7.14	0.00
Religious Holiday 1	-0.60	-3.62	0.00	-1.22	-4.96	0.00	-1.03	0.20	0.00	-1.44	-9.72	0.00	-1.33	-10.26	0.00
Beginning of Fasting Season				-1.29	-5.24	0.00				-0.34	-2.29	0.02	-0.27	-2.06	0.04
New Years Eve													-0.28	-2.17	0.03
First Day of the Year															
Womens Day															
Day of Week															
sunday	0.10	2.94	0.00	0.13	2.64	0.01	0.12	0.04	0.00	0.20	6.77	0.00	-0.14	-5.27	0.00
saturday	0.12	3.65	0.00	0.11	2.35	0.02	0.20	0.04	0.00	0.18	6.24	0.00	-0.15	-5.84	0.00
friday							0.08	0.04	0.05	0.14	4.92	0.00	-0.17	-6.43	0.00
thursday				-0.17	-3.06	0.00							-0.22	-7.71	0.00
wednesday										0.10	3.26	0.00	-0.12	-4.58	0.00
tuesday				-0.21	-4.38	0.00							-0.22	-8.43	0.00
Month of Year															
january													0.09	2.23	0.03
february													0.09	2.27	0.02
march													0.12	3.12	0.00
may															
june	0.18	3.45	0.00	0.33	4.23	0.00				0.13	2.71	0.01	0.12	3.03	0.00
july				0.21	2.70	0.01									
august	0.17	2.90	0.00	0.32	3.85	0.00	0.13	0.07	0.07	0.15	3.05	0.00			
september				0.35	4.65	0.00				0.17	3.65	0.00	0.13	3.15	0.00
october	0.20	3.68	0.00	0.33	4.12	0.00				0.12	2.40	0.02	0.11	2.61	0.01
november				0.13	1.67	0.10				0.10	2.01	0.04	0.08	1.97	0.05
december				0.16	2.03	0.04				0.10	2.05	0.04	0.10	2.32	0.02
Covid Out-Break (First Shock)										0.13	1.62	0.11	-0.15	-2.24	0.03



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