Creation and application of a comparative financial index for the Australian fast-moving consumer goods (FMCG) industry

Submitted by

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Dedication

This thesis is proudly dedicated to………

My wife, Ana Maria, and my son, Samuel, for nursing me with affection and love. They have appreciated my efforts and always provided cheerful encouragement during the period of this study. After all, we are still a family.

All my beloved family; my mother Marina, my father Epaminondas and my brothers Harvey and Jose Luis.

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I gratefully acknowledge the support received from Western Sydney University and especially the School of Business. I would also like to thank every staff member for their continuous support throughout the whole period of my PhD study.

Statement of Authentication

The work presented in this thesis is, to the best of my knowledge and belief, original except as acknowledged in the text. I hereby declare that I have not submitted this material, either in full or in part, for a degree at this or any other institution.

[redacted]

Juan Carlos Franco Laverde

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List of Abbreviations

ANZSIC	New Zealand Standard Industrial Classification
ARCH	Autoregressive Conditional Heteroscedasticity
CAPM	Capital Asset Pricing Model
CPG	Consumer Packaged Goods
FIML	Full Information Maximum Likelihood
FMCG	Fast-Moving Consumer Goods
GARCH	Generalised Autoregressive Conditional Heteroscedasticity
GMM	Generalised Method of Moments
ISIC	International Standard Industrial Classification
MMM	Marketing Mix Modelling
SKU	Stock Keeping Unit

ABSTRACT

Fast-moving consumer goods (FMCGs) are food and non-food daily consumer items that are exhausted when used once and thus have short lifespans. Purchase of these items is typically a result of small-scale consumer decisions. Research in this thesis explores the similarities between value sales volatility in the FMCG industry and that of commodities traded on financial markets. The research is based on the imminent need and opportunity to identify and quantify the value sales volatility of brands traded in retail stores in Australia and aims to gain an increased understanding of brands' overall performance. Specifically, this thesis seeks to answer the question: *What are the antecedents of brands' sales volatility in the Australian retail sector and how do they influence brand performance overall?* To this end, a "Brands Index", analogous to financial market indices such as the S&P500 and All Ordinaries Indices, is created to test the conceptual framework. The importance of the creation of a Brands Index in the FMCG industry in Australia is absolute. The index itself represents an excellent contribution to the management and marketing disciplines as it allows any brand or set of brands to be compared against the overall market (represented by the Brands Index).

This thesis theorises a market index for the FMCG industry in Australia and measures and captures its observed volatility clustering by using ARCH-GARCH models and CAPM theory to calculate brand betas. Two competing methodologies will be advanced to calculate returns; namely, with and without the presence of an equivalent risk-free rate of return. From these two methodologies, only returns including the risk-free rate are shown to successfully pass the CAPM test.

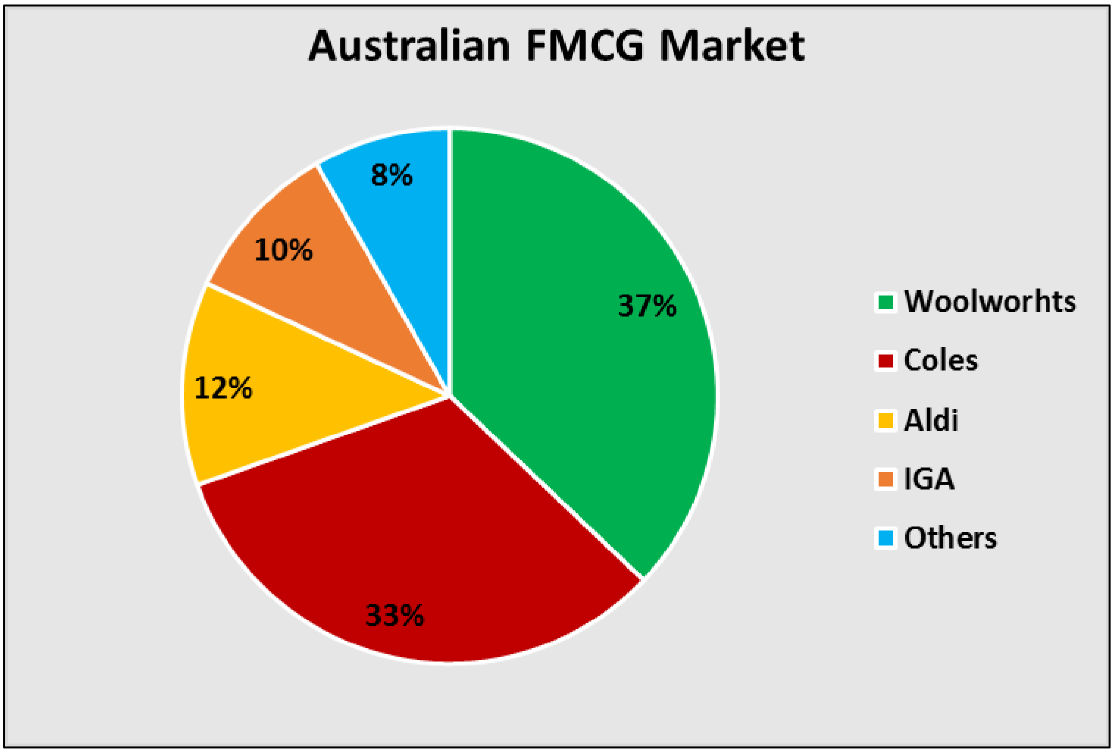
CHAPTER 1: INTRODUCTION

1.0 Overview

Fast-moving consumer goods (FMCGs), also known as consumer packaged goods (CPGs), can be defined as goods that are exhausted when used once (e.g., ice cream, packaged food), or that have a short lifespan (deodorants, household cleaning products). The main characteristics of FMCGs are their frequency of purchase, the little-to-no decision-making effort required by consumers to choose the items, and their generally low prices, high sales volumes, extensive distribution networks and high stock turnovers. As opined by Tariq et al. (2013), FMCGs differ from durable goods based on product shelf life. High demand among consumers makes FMCGs highly perishable. Low prices are another determining factor that gives FMCGs their distinctiveness. FMCGs are one of fastest-moving industries in terms of high product stock turnover (Aydin et al., 2007). Most FMCG goods are sold through retailers and pharmacies due to their quick shelf turnover (Franco-Laverde, 2012). Manufacturers such as Unilever, Nestle, Procter & Gamble and Johnson & Johnson, to name a few, are some examples of FMCG manufacturers.

Research in this thesis focuses on FMCG brands traded in Woolworths and Coles Group supermarkets in Australia. The two retailers represent about 70% of total dollar FMCG industry sales (Roy Morgan, Finding No. 7063, 2016). Thus, given the high level of concentration, it is considered that Woolworths and Coles are a good representation of overall FMCG industry operations in Australia. Relative market share amongst retailers in the FMCG industry is shown in Figure 1.1 below.

Figure 1.1 Prominent entities in the Australian FMCG market



(Source: www.roymorgan.com/findings/7063, 2016)

In the context of the whole retail trade industry, the FMCG industry belongs to the 'food retailing' subdivision and accounts for 41% of retail trade industry turnover (ABS release 8501.0, 2016). The retail trade industry, in turn, contributed to about 13% of all industries turnover in the financial year 2014/15 (ABS release 8155.0, 2016). Putting these figures in context, the FMCG industry drove around 5.4% of total retail trade turnover in the 2014/15 financial year. In terms of the variety of products available, there are 23 broad categories and 223 subcategories available through Woolworths supermarkets (www.woolworths.com.au, 2015) and 20 broad categories and 164 subcategories available through Coles (http://sustainability.wesfarmers.com.au/our-businesses/coles, 2016).

As FMCGs are purchased for daily usage, consumers do not typically need to spend a substantial amount of time choosing them. Low-involvement decision making is therefore one of the basic features of purchasing FMCGs. Although some FMCG products have a greater shelflife than others (for example alcohol, toiletries and cleaning products), their high turnover is another factor that distinguishing them as FMCGs (Aydin et al., 2007). Additionally, high product turnover typically occurs with a meagre profit margin (Franco-Laverde et al., 2012).

Despite marketing and economic theory having been credited with analysing and explaining brand performance, most analysis largely ignores patterns of weekly change in brand sales traded in-store (Franco-Laverde, 2012). Market volatility is one factor that motivates companies to change their business strategies regularly in response to changing market conditions. Francis (2009) has opined that in order to succeed in the FMCG market, major retailers try to increase the number of product variants they sell; thereby providing a wider range of options in order to attract and retain more customers. Companies with a specific specialisation in one sector or category may subsequently venture into another sector/category to increase sales. In the FMCG sector, stock keeping units (SKUs) define the amount of sales for a company—the more SKUs, the higher the growth trajectory (Aydin et al., 2007). As brands are made of various SKUs, the summation of SKU sales constitutes the total brand sales. Thus, a brand can be made of a single, large or small number of SKUs.

A common feature of FMCGs is that the majority of SKUs will, at some time or another, experience temporary reductions in price, multi-buy activations (e.g. “buy 3 get 1 free”), advertising, or other marketing activities aimed to drive demand. When initiated by one brand, competing brands in the same category will tend to do the same in order to maintain market share (Franco-Laverde, 2012). Consequently, these different activities generate noise, not only in the total weekly brand sales, but also in total category sales. This noise resembles what is known in finance as volatility (symbol σ), which is the degree of variation of a trading price series over time as measured by the standard deviation of logarithmic returns (Engle, 1982). For the purpose of research in this thesis, the noise in the weekly brand sales resulting from marketing activities designed to drive demand will be described in the context of volatility. Thus, the concept of volatility in this thesis is then understood as the degree of variation of a brand value sales series over a specific period of time. As opined by Satchell and Knight

(2011), market volatility can decide the success or failure of an organisation and, therefore, is the driving force behind brand performance. Volatility in financial markets refers to the variation in prevailing trading prices over a stipulated time scale. The Australian FMCG industry is highly volatile as both the numbers of market participants and their marketing activities (price promotions, advertising, new product launches, etc.) over any given period are high (Franco-Laverde, 2012).

Volatility in the FMCG context is therefore understood as the weekly variation of sales value at brand, category or total FMCG value sales. It is expected that periods of high marketing activity across different competing brands will create high volumes of volatility, while periods of low marketing activity will produce low levels of volatility. This phenomenon has been previously studied, mostly in the finance discipline, and is known as *volatility clustering* (Mandelbrot, 1963). Volatility clustering in finance can be defined as periods in which prices show wide fluctuations over an extended time period, with periods of relative calm following (Li & Hong, 2011). Based on the previous analogy, this research elaborates on the presence of volatility clustering in the FMCG industry. Given our understanding of the drivers of brand sales volatility (price promotions, advertising, new product development, competitors activities, etc.), in order to understand the performance of the FMCG industry as a whole and also the performance of individual brands against the market, this thesis proposes, first, the creation of a market index for the FMCG industry that is similar to those of stock markets (e.g. the Standards & Poors or All Ordinaries Indexes). Hence, this thesis discusses 1) the concept of volatility clustering and its measurement, 2) the creation of a market index and 3) the implementation of the capital asset pricing model (CAPM; Lintner, 1965; Sharpe, 1964) as a complementary technique to support brand performance and portfolio management. The introductory chapter of the thesis (Chapter 1) gives the background to the thesis, addressing aspects such as the research question, objective, scope, highlights of the framework, methodology and contributions of the study. It also outlines the thesis structure in brief.

1.1 Introduction

The term *fast moving*, as applied to goods, is in opposition to *consumer durables* or *hard goods*, which do not quickly wear out. More specifically, consumer durables yield services or utility over time, rather than being completely used up when used once (Majumdar, 2007).

Purchases of FMCGs account for a significant portion of consumers' budgets. Retail trade in these products, that is, their supply to households, has attracted considerable interest from consumers and policy-makers because a well-functioning retail sector is crucial for daily provision of these essential products at high quality and low cost (Aydin et al., 2007).

According to the ABS (release 8501.0, 2016), the FMCG industry belongs to the 'food retailing' subdivision and accounts for 41% of retail trade industry turnover. In turn, this contributed to about 13% of all industry turnover in financial year 2014/15. Thus, the FMCG industry accounted for around 5.4% of total retail trade turnover in the 2014/15 financial year.

The International Standard Industrial Classification (ISIC) is the principal classification code for different product activities. The code is especially helpful in collecting and analysing relevant data regarding different productive activities segregated according to economic perceptions and principles. An ISIC code comprises four different yet related categories: *section*, *division*, *group* and *class*. By way of example, a product with an ISIC code having a division number ranging between 41 and 43 would mean that the product is related to the construction industry. The ISIC code is immensely helpful in ensuring the continuous flow of information necessary for proper monitoring of the manufacturing and sales of products according to their divisions. In addition, the ISIC code is responsible for categorising products according to a universal product differentiation mechanism, allowing uniform data assessment on local and international bases. The data assessment model, therefore, provides parity to different research institutes for proper and authentic comparison. According to Çelen et al. (2005), the retail market for FMCGs includes businesses in the following seven categories of the

ISIC (Revision 3) 4-digit code: ISIC 5211 - retail sale in non-specialized stores; ISIC 5219 - other retail sale in non-specialized stores (department stores, etc.); ISIC 5220 - retail sale of beverages, food items, and tobacco in specialized stores; ISIC 5231 - retail sale of pharmaceutical and medical goods, cosmetic and toilet articles; ISIC 5251 - retail sale through mail order stores; ISIC 5252 - retail sale through arcades and open markets; and ISIC 5259 non-store retail sale.

In Australia, the New Zealand Department of Statistics together with the Australian Bureau of Statistics (ABS) has produced the Australian and New Zealand Standard Industrial Classification (ANZSIC) to be used in the process of statistics collection and publication in Australia and New Zealand. ANZSIC replaced the Australian Standard Industrial Classification (ASIC) and the New Zealand Standard Industrial Classification (NZSIC). The ANZSIC code comprises four categories that are slightly different to those of the ISIC code. These four categories are: *division*, *subdivision*, *group* and *class*. The ANZSIC code is therefore useful as a comparable record of information about related industries in Australia and New Zealand (www.abs.gov.au/ANZIC, 2013).

The retail sector for FMCGs in Australia is highly concentrated. Two companies, Woolworths and Coles, dominate the market with a combined share of about 70% of the total dollar sales of the industry. Consequently, these two major retailers have extremely high purchasing power. These two companies are major suppliers of FMCGs in the Australian market and sometimes act as facilitators that help FMCG manufacturers find relevant customers. The remaining 30% market share is made up of Franklins, Aldi, Metcash and independent or non-aligned convenience stores (Roy Morgan, Finding No. 7063, 2016).

Manufacturers within the FMCG industry support their premium brands mostly with a combination of advertising, marketing and pricing activities. Most advertising activities include advertisements on different media such as TV, radio, cinema, magazines, print and online, etc. In addition, marketing activities at points-of-sale are also performed (e.g. degustation, free samples, and others). By contrast, pricing activities include temporary price discounts (known as price promotions) which normally last for one, two or four weeks. Price is then an important consideration in the consumer decision-making process (Monroe, 2003). It shapes consumer perceptions of a brand, and changes in price can markedly change demand for the brand. The most widely used measure of consumer response to price changes is *price elasticity* (Schindler, 2012), which is the percentage change in demand for a one-percent change in price. Price elasticity is the numerical representation of consumer's price sensitivity towards a particular brand (or product; Wakefield & Inman, 2003).

Promotional tactics are often used in order to introduce a new product to the customers, along with informing consumers of the latest offers on the product. The reason behind such promotional tactics is that major retailers want to attract new customers whilst retaining existing ones. Factors that have been widely shown to correlate with larger price elasticities include: brands with smaller market shares (e.g. Bolton, 1989a; Guadagni & Little, 1983; Scriven & Ehrenberg, 2004); goods that can be stockpiled (e.g. Bell et al., 1999; Danaher & Brodie, 2000); and retailer support, such as in-store displays and feature advertising (e.g. Bemmaor & Mouchoux, 1991; Huber et al., 1986; Van Heerde et al., 2001).

"Every Day Low Prices" (EDLP), a type of discounting program, are also carried out and normally last for more than ten weeks. Multi-buys are commonly found in supermarkets as well (e.g., "buy two get one free" discounts). Such activities seek to ensure there is an improvement or maintenance of the positions held by specific brands in a retail outlet.

It should be noted that the research presented in this thesis is not about the execution of all the marketing and pricing activities of brands traded in supermarkets; rather, it is concerned with the historical weekly dollar sales patterns observed, in order to assess the brand performance and portfolio management of Woolworths, Coles and manufacturer groups in Australia. The present study is aimed at shedding more light on the volatility generated from the high sales turnover of brands in the Australian FMCGs retail trade industry. Market volatility is very important to manufacturers and brand suppliers (Woolworths and Coles), as manufacturers have to increase or decrease their overall production based on the prospects of the market. On the other hand, high volatility warrants that suppliers increase their activities. Accordingly, this research concentrates on this aspect to evaluate brand performance and portfolio management for manufacturers and for suppliers of goods such as Woolworths and Coles—two of the biggest retail companies in Australia.

1.2 Background to the Study

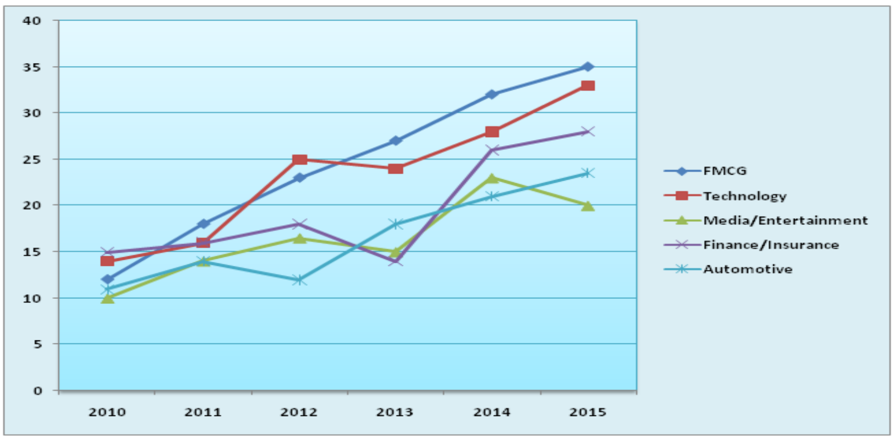
The business literature is replete with econometrics research on a wide range of topics pertaining to the performance of brands in the retail industry. Cook (1998) explains how econometric analysis can help identify the specific effects of advertising on retail performance. Three main reasons for such analysis are: 1) the need to simplify the detail obtained from scanning data; 2) the complexity of advertising strategies; 3) it provides information which can help in budget deployment. Schults and Meer (2001) discuss econometric modelling and its use in marketing. Use of econometric models in marketing has grown very rapidly in the last two decades with the advent of technology that makes it easy even for the inexperienced. The history of econometrics is described briefly. Four important lessons have been learnt: 1) that modelling most benefits companies that institutionalise its use (so that the data are always available, etc.); 2) that models must be transparent and intelligible to management; 3) that regression-based models are most sensitive to short-term and past activities, but may not be good at predicting future or long-term movements; 4) that models can never replace good judgement. The use of artificial neural networks (ANN) as an alternative approach to multiple regression has gained popularity in different fields, and some studies have demonstrated the superiority of ANN over multiple regression (Martensen & Gronholdt, 2005).

The review of the academic literature in Chapter 2 demonstrates a striking imbalance in research—little attention has been given to the observed value sales patterns generated from the high sales turnovers of brands trading in the FMCG industry. The observed value sales pattern is the past record of the activities of an organisation, reflecting its pattern of operations over a certain period. This is an identifiable set of data that may be very helpful in understanding the mood of consumers over a certain period. Marketing theory, focusing on brand performance according to pricing and marketing activities, stands out as the dominant field where most of the research has been conducted.

The FMCG industry, alternatively referred to as the consumer packaged goods (CPG) industry, thrives on those products that consumers purchase at regular intervals. Sanchez and Potter (2013) opine that the FMCG industry is basically attached to the storing and selling of products; and as such, efficient operations and supply chain management are also important considerations. Thus, these authors focused their research on the comparison of FMCG logistics operations to benchmark logistics practices.

One of the most important characteristics of the FMCG industry is the nature of the financial operations that take place. Although the products are not hugely profit-earning, the quantity of sales makes up for it (Franco-Laverde, 2012). In Australia, according to the ABS (release 8501.0, 2016), the FMCG industry accounted for around 5.4% of total retail trade turnover in the 2014/15 financial year. As shown in Figure 1.2 below, the FMCG industry has been one of the fastest-growing industries in Australia in the last few years.

Figure 1.2 Comparison of growth achieved by some of the prominent industries in Australia



(Source: Marketingmag.com.au, 2016)

Low operating costs and efficient distribution channels are some other characteristics of the FMCG industry. As the population of Australia grows, so does this sector. One of the foremost positive aspects of this industry is the number of employment opportunities it creates. For this reason, several well-established business organisations have chosen to venture into this arena. The Australian Government has been instrumental in facilitating the industry with large amounts of Foreign Direct Investment support. Poulis and Poulis (2011) have opined that the government has supported the industry tremendously and that the return bounties are helping the country in various ways. The growing popularity of the organised retail sector means that the suppliers, including Woolworths and Coles, can utilise the increasing per capita income of the urban population in better ways.

The “marketing mix” is a strategic technique referenced by various organisations as a way of presenting a product to customers. It is instrumental in assessing brand presence in the market amidst heightened market volatility and is central when making determinations of the offerings of a product or a brand. Historically, the marketing mix was comprised of four main aspects: *price*, *promotion*, *product* and *place* (McCarthy, 1960). More recently, three additional aspects have found mentioned in the mix: *people*, *physical environment* and *process* (Booms & Bitner, 1981). Lauterborn (1990) later introduced the four ‘C’s as a more customer-driven replacement for the four ‘P’s, these being *consumer*, *cost*, *communication* and *convenience*. In 2012, a new four ‘P’s theory was proposed to include *people*, *processes*, *programs* and *performance* (Kotler, 2012). The marketing mix is important for understanding the reasons for market volatility and the notable features that influence the market. However, Sharp (2010, 2016) suggests that exercises in segmentation, brand differentiation and personality are mostly wasted efforts because most purchasing decisions are made with the ‘emotional brain’. Mr. Sharp believes a marketer’s focus should be on simple and consistent brand assets that are easy to remember; and when seen, trigger instinctual responses.

Measuring and quantifying the effectiveness of marketing activities in consumer-packaged goods in particular has brought together economic science, the marketing discipline and econometricians to develop what today is known as marketing mix modelling (MMM; Franco-Laverde, 2012). Thomas (2006) asserts that despite the currency of this topic in the media, the concepts and tools of MMM date back at least 30 to 40 years. The topic is of growing interest partly because of the corporate world's interest in growing topline revenue. A second reason for the growing interest in MMM is the proliferation of new media (i.e., new ways to spend the marketing budget), including the internet, online communities, search engines, event marketing, sports marketing, viral marketing, cell phones and text messaging, etc.

Marketing mix modelling makes use of statistical analyses—such as multivariate regression—of sales and marketing time series data to estimate the effects of different marketing techniques on sales, and to then forecast their impact on other sales strategies in the future. In many cases, it is used to maximise the influence of advertising and promotional strategies on sales revenue and profit. The objective of MMM is to provide marketers with scales for the effectiveness of each marketing aspect in terms of sales-volume contribution. The market elements may refer to varied influencing factors such as the four and seven 'P's of marketing, comprising *price*, *product*, *place* and *physical environment*, among others. The sales volume generated in dollar terms is then divided by cost accordingly to create a range of return on investment (ROI) figures for each element of the marketing mix. Ideally, the learned knowledge is then assumed to streamline marketing strategies and tactics, maximise the marketing plan, forecast sales and still simulate different scenarios (Franco-Laverde, 2012).

Econometric techniques focus on the decomposition of product sales into *base sales* and *incremental volume*. Base sales denotes the long-run or trend element of a product time series that indicates the underlying customer taste. Conversely, incremental volume is the short-run trend that captures periodical sales variations as a result of temporary reductions in selling prices, multi-buy initiatives and above-the-line media activities. Conventional methods use static ordinary least squares (OLS) tactics that inflict a fixed or deterministic baseline. Such OLS methods do not only provide a virtual split of base sales and incremental volumes; by construction, they also preclude any analysis of the long-run effects of marketing activities (Dekimpe & Hanssens, 1999).

One alternative solution is to apply dynamic cointegrating vector autoregression (VAR) techniques, an estimation method often used in the econometrics literature to evaluate the long-term impacts of economic indicators. Application of VAR models in the marketing literature has been discussed in Dekimpe and Hanssens (1999). Practically, however, the method is often unfeasible in the context of fully-specified mix techniques. A preferred approach is to use a technique that will separate the two data features; that is, short and long run, and allow a complete analysis of these in separate stages.

The logic behind the use of time series regression analysis can be justified for two main reasons. First, each and every marketing mix model uses time-ordered data and is basically a time series equation with elements of the marketing mix. Second, the model gives a direct decomposition of a time-ordered data series into trend, seasonal and random error components. It is therefore an ordinary phase in decomposition of product sales into short-term marketing factors (incremental) and long-term base (trend). Such decomposition produces an evolving baseline, which can then be meaningfully analysed to quantify long-run ROI (Cain, 2014). The benefits of MMMs include the fact that business entities get absolute ideas about the process through new or existing products pitched to customers. Additionally, the business entities attain knowledge of various causes and effects of market volatility.

Researchers, including Dekimpe and Hanssens (1999), Ataman et al. (2010), Larsen (2011) and Cain (2014), have also begun to explore a more holistic view of all the players in the arena—such as by considering manufacturers and suppliers together—rather than focusing on separate demand patterns in isolation, as per the single-equation marketing mix models explored so far. Models that are resultant of direct consumer decision-making processes are termed *demand systems*. Demand systems are of two main forms: *continuous choice* and *discrete choice*. Continuous choice structures are based on classical utility maximisation ideas, where consumers choose the equilibrium quantities of all commodities at their disposal. Conversely, discrete choice forms are derived from 'characteristics' theories of utility maximisation (Lancaster, 1966), invoking a binary structure where the decision to choose a product is concurrent with a decision to *not* choose a competing substitute. The latter is more dominant in marketing theory, and facilitates assessment of the competitive performance of the brand marketing strategies of all players in the market (Cain, 2014).

In sum, no systematic effort has yet been made to research brands' value sales volatility generated from all supporting marketing mix activities. Rather, efforts have been devoted to isolating each aspect of the marketing mix. The following section outlines the research problem addressed by this thesis and the reasons why it will undertake a deep discussion of brand value volatility and its consequences. In this framework, *sales value risk* is defined as the deviation from the average weekly sales value within a specific time horizon, while *sales value volatility* will be used to quantify sales value risk (Thurner et al., 2012). This background information section has identified a clear research gap in the literature.

1.3 Research Problem

In finance, *volatility* can be defined as the magnitude of variation in a price series over time, as measured by the standard deviation of returns (Thurner et al., 2012). However, volatility in the FMCG context is understood as the weekly variation of sales value at the brand, category or total FMCG levels (as mentioned in Section 1.0: Overview). On this understanding, we can explore the similarities that value sales volatility in the FMCG industry may have with that occurring in financial time series. The related phenomenon of *volatility clustering* in returns, that is, periods in which prices swing widely for an extended time period followed by a period of relative calm (Gujarati, 2003), was documented as early as 1963 by Mandelbrot (1963) and shortly after by Fama (1965). However, it was not until Engle (1982) and the advent of ARCH and GARCH models that financial econometricians began modelling the phenomenon seriously. Since then, the field has grown greatly and research has used these methodologies[1] (see, e.g., Nelson, 1991 and Engle, 2002).

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[1] Engle, R. (2002). New frontiers for ARCH models. *Journal of Applied Econometrics*, *17*(5), 425-446.
Francq, C., & Zakoian, J. M. (2011). *GARCH models: Structure, statistical inference and financial applications*. John Wiley & Sons.

Compared to the extensive research addressing the application of financial econometrics techniques to financial time series data, research on applying them in other fields is more limited. Most of the research has focused on brand portfolio management and brand investment. Studies argue that it is possible to create a product portfolio equivalent of an efficient frontier in a similar way to modern portfolio theory (MPT; Cardozo & Smith, 1983). Cardozo and Smith (1983) have, however, received criticism, as several problems were identified that were associated with the extension of financial portfolio theory to firms' product investments (Devinney et al., 1985). In reply, Cardozo and Smith (1985) pointed out that, unfortunately, there is no ambiguously defined "market or index against" which the performance of a particular business unit can be compared. The current thesis explicitly revisits this topic and formulates the steps required to create such an index.

Soon after, Granger and Lee (1989) conducted an investigation of production, sales and inventory relationships using multicointegration and non-symmetric error correction models. Ryals et al. (2007) performed a study on return maximisation and risk minimisation in marketing portfolios, and developed a model that calculates the efficient frontier, helping them select an optimal portfolio. One of the main outputs of Ryals et al. (2007) is that marketing portfolios differ from financial ones in the sense that the allocation of marketing funds affects the portfolio's returns. Proper allocation, together with judicial marketing portfolios, help to ensure that financial portfolios receive enough attention. However, not many studies have used a similar technique. More importantly, none of the theories or techniques related to volatility measurement in financial econometrics has been previously applied to FMCG brands in order to capture their value sales volatility over time.

The work by Cardozo and Smith (1985) clearly indicates the lack of a 'market or index against' which to compare the performance of a particular business unit. Therefore, the creation of a brand index that uses an approach similar to that of the All Ordinaries Index in Australia or the Standard & Poor's 500 Index in the United States seems to be the best way to analyse and compare individual brands' sales value volatility.

With respect to the research background outlined in Section 1.2, the problem of comprehending brands' sales volatility needs to be pursued and described in the specific context of brand performance in supermarket stores. Accordingly, financial econometrics may be very useful as a novel alternative for explaining sales patterns within the FMCG industry in Australia. The next section discusses the research questions and the key objectives of this thesis.

1.4 Research Question and Objectives

The central research question to be addressed in this study is: "*What are the antecedents of brands' sales volatility in the Australian retail sector and how do they influence brand performance overall?*"

To respond to the above research question, this thesis aims to create a detailed and theorised "Brands Index" that is able to measure the individual sales value movements of brands in the industry in order to better understand overall FMCG sales value behaviour. Particular attention will be paid to the phenomenon known as *volatility clustering*, based on relevant theories and current literature. The specific objective of the research is to design a modelling technique that is able to compare individual brand performance against the Brands Index. Using this index, each brand will be able to understand their exact position relative to other prominent market players.

This objective is conceptualised by testable hypotheses presented in Chapter 3 of the thesis. The proposed framework is presented in the following section to provide a summarised view of the research.

1.5 Conceptual Framework

From the earlier discussions, a lack of studies on the variability in weekly brand sales values (observed volatility) is clearly inferred. The creation of a Brands Index (based on techniques used by similar indices such as the All Ordinaries and Standard & Poor's) will facilitate the use of econometric techniques (that have never been applied to the FMCG industry) to devise model(s) of sales value volatility. One of the main advantages of forecasting volatility is that it allows the simulation of theoretical prices more accurately and reliably than older techniques such as historical, stochastic and local volatility models (Bollerslev & Mikkelsen, 1999).

The motivation for employing the ARCH class of models is the phenomenon commonly referred to as *volatility clustering* or *volatility pooling*—that is, where the level of volatility in the current period is positively associated with its level during the immediately preceding period(s). This was first documented by Mandelbrot (1963) and soon after by Fama (1965).

As previously discussed, brands in the FMCG industry react quickly when competing brands undertake initiatives such as a major investment in advertising, new product development or price promotional activity. An outcome of this is that the overall market will show higher levels of activity (noise) in the general sales pattern, because the competing brands will adopt similar marketing activities in order to maintain their market share and brand positioning. However, after a period of time, the market will tend to return to a lower (normal) level of sales noise. Hence, the assumption made in this research is that volatility clustering could be present in the proposed Brands Index as periods of high sales fluctuation are follow by periods of relative calm. Price promotions, and the types of promotional steps taken by companies, have extensive links between them in terms of overall market volatitlty (Leeflang & Parreño-Selva, 2012). Promotional strategies (e.g. discounted prices) are intended to increase demand and inform customers about the kinds of products that the company is going to launch sooner. As an outcome, promotional actions incur certain costs for companies and, ultimately, they must increase prices marginally to recover those cost. After a while, the market is expected to return to a more stable pattern until the next new initiative is made.

An extensive review of the literature (Chapter 2) demonstrates the need for a Brands Index that empirically verifies the existence of volatility and its implications for brand management. Consequently, the fundamental framework proposed above will aid in the adoption of financial econometrics models, which are proposed in Chapter 3. The next section explores the scope of the thesis.

1.6 Scope of the Thesis

This research proposes to 1) develop the necessary techniques and methodologies for devising an appropriate Brands Index, 2) identify the brand criteria to be included in the index, and 3) determine the number of brands that will be included in it. In addition, this research will determine the model that best predicts movement in the FMCG Brands Index; and the modelling options for comparing individual brands against it. A description of these methodologies and techniques is provided in Chapter 2. The approach is proposed to:

- create a Brands Index that measures the disparate sales movement of numerous brands in the FMCG industry. This will help understand overall FMCG sales behaviour, with particular attention paid to the presence of the phenomenon known as *volatility clustering*.
- Use financial econometrics techniques to verify the presence of volatility clustering in the Brands Index and investigate its relationship with individual brands.
- Develop a modelling technique able to compare individual brands' performance against the Brands Index.
- Enhance the understanding of the FMCG industry in Australia, thus strengthening the relationships between retailers and brand suppliers.

The research will highlight benefits for both retailers and manufacturers. Retailers will gain information to better allocate shelf space to different brands, and manufacturers will gain information to better elaborate their brand portfolios. Time series data has been collected for five categories (100+ brands) towards generalisations of the findings from January 2004 to December 2012.

1.7 Significance of the Thesis

The research presented in this thesis is significant in numerous ways. This section outlines the significance from theoretical and practical perspectives.

Within the framework of this thesis, *sales value risk* is understood as the deviation from the average weekly sales value within a specific time horizon. *Sales value volatility* will be used to quantify this sales value risk. Thus, this thesis will help retailers and manufacturers by introducing the concepts of *sales value risk* and *sales value volatility*, which will provide valuable information that supports brand investment in the Australian FMCG industry. Allender and Richards (2012) have opined that keeping prices constant in a changing market may backfire, as rival firms may reap benefits by decreasing their price marginally. The processes introduced and developed in this thesis will help explain sales and better predict its observed patterns. Furthermore, the research will draw on and contribute to the current literature in economics, business, finance and marketing, as financial econometrics has not been previously used to model the operations of the FMCG industry.

Over the last three decades, researchers and practitioners have used various techniques for predicting asset returns. These include the random walk hypothesis, analyses of the microstructure of securities markets, and testing of the capital asset pricing model and arbitrage pricing theory (Vollmer, 2014). They have also investigated the term structure of interest rates, dynamic models of economic equilibrium, and nonlinear financial models such as ARCH, GARCH and their various extensions. However, most of the previous developments and techniques have only been applied in the financial arena—a fact which represents an excellent opportunity to explore their applicability in other industries such as the FMCG industry in Australia.

The proposed approach will offer additional information to the FMCG industry in the form of the Brands Index, quantification of volatility, and use of the index for comparing a brand's performance against the overall market.

1.8 Research Methods and Analysis

In order to effectively conduct the proposed research and test the research framework, quantitative approaches will be used as discussed in Chapter 3 and Chapter 4. In brief, for quantitative testing of the model, primary data was extracted from the Aztec database. Aztec is a specialised firm that supplies weekly information for the entire FMCG industry, including baseline sales, incremental sales due to promotional activity, shelf prices, promotional prices, and many others metrics (see Appendix 1 for definitions). The Aztec database is immensely helpful in formulating effective strategies to understanding the way the FMCG industry is performing. The available weekly data used in this research is a time series of nine years' duration, with a total of 468 observations for each brand spanning the period January 2004 to December 2012.

To test the conceptual framework, I first created an index for a selected category where the presence of volatility is tested. Second, a set of regressions for individual brands' metrics against this category index is performed. Finally, a wider index including all available data from all five categories used is created in order to generalise the findings. Chapter 3 and Chapter 4 explore alternative financial econometrics time series approaches in order to improve the results, taking into account observed volatility and the relationship between individual brands and the Brands Index. Such an approach has not been previously studied in the FMCG industry.

1.9 The Thesis in Context

A review of the academic literature has revealed that thus far, no attempt has been made to explore volatility in the FMCG industry. Similarly, studies of marketing mixes and their individual contributions to sales have also largely overlooked volatility. The models introduced and developed in this thesis are important in context because marketers are becoming increasingly more data-driven in order to meet their sales targets. Marketing mix models (MMMs), for instance, are very important in clearly understanding the contributions of all elements of the marketing mix. While MMMs' focus is the individual contribution of all marketing mix sales drivers to overall brand performance, the research in this thesis looks at the overall influence of marketing activities on a brand's weekly sales value variation, which should somehow reflect the success or failure of their marketing mix. As such, this thesis makes a rational choice to create and incorporate a Brands Index, measure its volatility, and allow brands to compare their performance against it. This goes beyond investigation of the effects of individual marketing activities.

1.10 Major Areas of Contribution

The research in this thesis will contribute in a number of ways to the body of knowledge of three combined fields: economics, finance and marketing, as follows:

- from a theoretical perspective, the thesis examines economic theory using econometrics and what is known today as marketing mix modelling, to gain a better understanding of the individual contributions of each element of the marketing mix;
- it will provide a more holistic view across discrete choice forms from the 'characteristics' theories of utility maximisation (Lancaster, 1966), invoking a binary structure where the decision to choose a good is concurrent with a decision *not* to purchase a competing alternative;
- the conceptual schema proposed in the theoretical model will be validated by the construction of a Brands Index where volatility is found to be present.
- brand managers will be able to compare individual brands' performance against the Brands Index in addition to traditional marketing mix indicators;
- two new concepts will be created in marketing theory, namely, *sales value risk* and *sales value volatility*, which are explained in detail in Chapter 3;
- the research will adopt the concept of *beta* from modern financial theory to recreate a proxy for systematic risk, so that an alternative methodology for brand portfolio optimisation within the marketing arena can be provided; and
- finally, while this research will adapt some financial theories for use in marketing, an appropriate methodological process will be followed to test their reliability and validity, thus contributing a quantitative methodological approach to economic and marketing business research.

Further details of these contributions are discussed in Chapter 6 and Chapter 7.

The thesis additionally contributes to the understanding of various economical aspects through the assessment of marketing mixes. This understanding also makes the role of individual managers in setting prices relevant. The thesis discusses the marketing mix concept in intricate detail and enhances theories for employing financial as well as economic methods. With the help of the research in this thesis, brand managers will be able to use the 'brand beta' for the benefit of organisations' profitability. This thesis also contributes to the assessment of the concepts of sales value risk and sales value volatility. As a result of changing market dynamics, the thesis presents an alternative for optimising marketing strategies so as to maximise profitability. In order to evaluate a specific brand's performance, a proper methodology based on CAPM theory is also provided.

1.11 Limitations of the Thesis

It is noted that the research presented in this thesis does not use a strong theoretical background in marketing theory. This is due to the fact that there is no evidence of the existence of a FMCG market index. The creation of a Brands Index within the FMCG industry in Australia is therefore highly dependent on finance theory.

The information collected from the Aztec data sources is authentic; however, it is limited to five categories rather than representing the entire FMCG market (refer discussion in Chapter 4) and, therefore, the findings and implications are provided accordingly. Despite this, the methodologies for producing a more comprehensive index that includes all categories and brands and investigates its applicability will also be provided. The review of the literature suggests that the applicability of such an index is immense, but the lack of previous research in this field limits the opportunity for comparison of the results. To keep the thesis within manageable proportions for rigorous investigation and to maintain parsimony, only the ARCH, GARCH and some of their related models, including EGARCH and TGARCH, have been included. Extensive use of the CAPM and some alternatives will be explored in the analysis of brand performance and portfolio optimisation. Opportunities for further research to follow on from this study are discussed in detail in Chapter 7.

1.12 Thesis Outline

In sum, this chapter has provided a background and overview of the thesis. The background information explicitly identifies a research gap in the literature. The research problem, research question and objective, and the justification of the thesis clearly signify the importance of this research. This chapter also provided an outline of the investigation, including the research framework, methodological approach and areas of contribution. Given the framework of this thesis, the following chapter (Chapter 2) contains a comprehensive discussion of the relevant theories which were identified from a detailed review of the literature. These theories focus on the creation of an index, the measurement of volatility, and support for using the CAPM as a complementary technique to support brand performance and brand portfolio management.

The overall outline, as well as the organisation of this thesis, are discussed in this section. The thesis comprises seven chapters, each of which is introduced as follows.

Chapter 1: Introduction explores the concept of the Brands Index and sales value volatility, the background to the research problem, the research question, the objectives of the research, a framework based on background literature, the scope and significance of the thesis, a brief outline of its methodology, the research context, and the expected contributions and limitations of the thesis. The chapter introduces the research topic and establishes the problem statement, justifying the legibility of the research.

Chapter 2: Literature Review focuses on four major dimensions, which consolidate the review of relevant theories, focus on the creation of an Index and its applicability in different types of research, and review the identified antecedents. The chapter additionally discusses literature related to volatility from many different perspectives in order to adapt the concept for use in the FMCG industry. The chapter identifies all the relevant literary sources to offer a better understanding of the concepts essential to the research topic.

Chapter 3: Conceptual Framework develops a conceptual model with hypothesised relationships and a framework for the creation of the Brands Index following the techniques used by the most relevant similar indices (All Ordinaries and Standard & Poor's). The chapter further proposes the model(s) that best predict sales value volatility in the Brands Index, and sets the scene for the use of the CAPM to explain individual brand performance. The chapter presents a brief representation of the connection between the concepts and the formation of the research variables.

Chapter 4: Methodology, Data and Research Plan covers the data sources and their key statistics, and outlines the issues relevant issues to the quantitative research approaches used in this thesis. The chapter includes the rationale for the modelling approach, creation of the index, and using beta as a proxy for risk. Alternatives to the traditional ARCH and GARCH modelling techniques are also explored for capturing volatility in the Brands Index. The chapter also provides a section on results validation and initial findings. Additionally, the chapter brings into focus the specific set of methods chosen for investigating the research topic.

Chapter 5: Hypothesis Testing and Initial Discussions describes the best model for measuring volatility in the Brands Index. The findings of the model are discussed with respect to hypothesis testing and potential paths for future research. This chapter presents the two alternative methodologies for calculating returns that are relevant to the research question.

Chapter 6: Findings and Implications presents the main findings—with clear implications for both brand suppliers and brand managers—in relation to the interpretation of the results and their applicability for portfolio optimisation. The chapter brings into focus and analyses the data collected from primary sources.

Chapter 7: Summary and Conclusions consolidates the answers to the research question and objectives. The chapter synthesises the overall findings, which follows the research implications for researchers and practitioners. Detailed contributions to theory and the body of knowledge are also discussed. Based on the research findings and background, several future research directions are suggested. Finally, the limitations of this research are addressed. The chapter presents a summary of the entire dissertation and offers effective suggestions for solving the discussed problems.

CHAPTER 2: LITERATURE REVIEW

2.0 Overview

This chapter reviews the extant literature, explores the theoretical foundations underpinning stock market indices and the concepts of volatility and the capital asset pricing model (CAPM), and discusses their relevance in marketing and business research. This review also consolidates marketing mix modelling studies and the literature related to its application in marketing theory. As noted in Chapter 1, the extant literature in financial econometrics is replete with works pertaining to economics and finance fields, with limited research performed in the marketing discipline. In this chapter, all these topics are considered in the context of narrowing the research question. The aims of this chapter are to:

- review the relevant theories and consolidate their rational arguments into the theoretical paradigm (Section 2.1.1);
- review the relevant literature related to volatility measurement and development of the CAPM to facilitate their probable application in marketing theory (Section 2.1.1);
- review the supportive streams that provide more insights for this study, focusing on brand portfolio management and the concept of the marketing mix (Section 2.1.2);
- consolidate existing index methodologies which have potential for duplication in the FMCG context (Section 2.2); and
- synthesise the review to consolidate the antecedents of volatility, marketing mixes and the CAPM (Section 2.3).

2.1 Review of Fundamental Research Streams

The main purpose of this review is to develop a theoretical foundation for the research presented in this thesis and to identify antecedents of volatility in market indices and the CAPM. Initially, the review consolidates the literature pertinent to stock market indices and volatility measurement, before discussing the theories of portfolio management and marketing mix. Further, the review identifies some of the key studies that have combined finance, economics and business theory in the marketing discipline.

The following subsections review three fundamental research streams for this thesis, its theoretical foundation, a brief review of pertinent studies, and the plausibility of applying these theories to the FMCG industry in Australia.

2.1.1 Theoretical Foundation of the Study

Over the last three decades, financial markets have seen an extraordinary growth in the use of quantitative and statistical methods (Ataman et al., 2010). People involved with finance work, including investors and traders, are now routinely using sophisticated statistical and econometric techniques in portfolio management, proprietary trading, risk management, financial consulting and securities regulation. Researchers and practitioners of financial econometrics have used various techniques for predicting asset returns, testing the random walk hypothesis, analysing the microstructure of securities markets, testing the capital asset pricing model (Barberis et al., 2015) and arbitrage pricing theory (Wilhelm, 2012). Financial econometrics relates to learning more about the term structure of interest rates, dynamic models of economic equilibrium, and nonlinear financial models such as ARCH, GARCH and their various extensions (Money-zine.com, 2016).

Considering the use of quantitative and statistical methods, it is important to define what is meant by the term *financial econometrics*, as this is the core foundation of this research. According to Zapranis and Refenes (2012), this simple question does not have a simple answer. Broadly speaking, the term financial econometrics is understood as the application of statistical techniques to problems in finance (Chen et al., 2012). However, as the literal meaning of the word econometrics is “measurement in economics” it is important to recognise that the adaptation of statistical and time series methods, originally pioneered for economics, was later applied to finance. Thus, in general terms, the tools and techniques used in economics are basically the same as those used in financial applications. Nevertheless, it seems that the main difference relates to the data in terms of its availability, frequency, accuracy, timing and other properties. For instance, while macroeconomic data, such as budget deficit, population, employment, money supply and others, are measured on an annual, monthly or weekly basis, financial data are observed and available at daily, hourly or minute-by-minute frequencies. The result of these data differences is that more powerful techniques can often be applied to financial data than to economic data (Barndorff-Nielsen et al., 2012).

As the core foundation of this research, financial econometrics is defined herein as *the integrated use of economics, statistics and econometrics methods and applied mathematics*. All these methods have equally important roles to play. Financial activities generate many new problems, economics provides useful theoretical foundations and guidance, and quantitative methods such as statistics, probability and applied mathematics are essential tools for solving quantitative problems in finance (Fan, 2004). Risk management, portfolio allocation, capital asset pricing, hedging strategies and volatility in financial markets are all research areas that employ financial econometrics in their analyses. The use of financial data in empirical work has been widespread in recent years. By the same token, several books on financial econometrics are now available (see, e.g., Barndorff-Nielsen et al., 2012; Campbell et al., 1997; Gouri´eroux & Jasiak, 2001; Rupper, 2004). Thus, this thesis explores the use of financial econometrics techniques in business marketing and management disciplines; specifically, to deal with weekly sales patterns in the FMCG industry.

To understand the theoretical foundations of this thesis, it is important to note that until about 30 years ago, most empirical finance researchers relied on simplistic statistical and econometric analytical tools (Campbell et al., 1997). With rapid accelerations in computing power, the increased availability of high-quality data for a range of financial instruments, and the development and adaptation of more sophisticated econometric techniques, empirical finance has undergone dramatic changes in recent years. These advances can also be applied to business marketing and management analysis. Milestone developments in financial econometrics over the past two decades include time-varying volatility models in the form of ARCH and stochastic volatility formulations and robust methods-of-moments-based estimation procedures, such as the generalised method of moments (GMM). Both of these innovations have clearly influenced much of the subsequent work in the field (Stock et al., 2012).

The phenomenon of *volatility clustering*, that is, periods in which prices swing widely for an extended time period, followed by periods in which there is relative calm (Gujarati, 2003), was documented as early as the 1960s by Mandelbrot (1963) and soon after by Fama (1965). However, it was not until Engle (1982) and the advent of the ARCH and GARCH models that financial econometricians started to model volatility clustering seriously. Since then, this field of study has grown enormously and numerous papers have been written using ARCH and GARCH methods. Related models, including ARCH-M, IGARCH, EGARCH, FIGARCH, TGARCH and TARCH, to mention just a few, have also been proposed. All of these methodologies have been implemented extensively in derivatives trading and risk management.

The autoregressive conditionally heteroscedastic (ARCH) model is a variant of time scale that is often employed when researchers need to define volatile variances in time series data. Pederzoli (2006) opined that ARCH models are useful for describing increased variations in volatility over a brief period of time. However, the ARCH model is similarly useful in describing steadily increasing variance over time. The sudden increasing or decreasing nature of product stocks in an organisation and the invariable impact of such instances need clear description. For these reasons, ARCH models were developed. By way of example, ARCH models are useful for describing different variances when using an ARIMA model (Money-zine.com, 2016).

Generalised autoregressive conditional heteroscedasticity (GARCH) models are especially helpful in defining falls or surges in the prices of financial instruments under adverse economic scenarios. Hansen et al. (2014) opined that GARCH models help to understand the increased volatility during a financial crisis that a simple regression model may not be able to define. GARCH models are also especially helpful in evaluating sudden events such as ‘black swan’, which are usually difficult to predict and often deviate beyond the expected situation in financial markets. The two models (ARCH and GARCH) are therefore very helpful for the research presented in this thesis, as they help to understand market variance and the way the FMCG industry functions in the Australian market.

Data for some financial instruments is becoming available at intervals shorter than one day (high frequency or tick-by-tick data) and contains very useful information about market microstructures. Engle (2000) argues that many of the inference procedures routinely used in the literature for analysing daily or lower-frequency observations are ill-suited to the modelling of high-frequency data. An assumption underlying the ARCH and stochastic volatility models is that there are equally-distant, discretely-sampled observations. However, with high-frequency financial time series data, the intervals between observations may vary because at times when the market is very active, prices change very rapidly; while at other times, there may be large gaps between successive observations. In response to this observable fact, the autoregressive conditional duration (ACD) model was developed by Engle and Russell (1998) with the objective of modelling the times between high-frequency observations.

Long-memory dependence in the mean of asset returns is another topic that has been researched recently. However, Venezia et al. (2011) stated that empirical findings have, in turn, stimulated a renewed interest in the development and refinement of inference procedures for long-memory processes. Nonetheless, it is certainly possible that, from a pragmatic perspective, the assumption of long-memory will yield the most accurate empirical out-of-sample volatility forecasts according to Bollerslev et al. (2011). In addition, it is also found in the literature that volatility in financial markets is also affected by crime and political uncertainty in specific countries (Franco-Laverde & Varua, 2007).

From the perspective of marketing theory, consumer behaviour in regards to price promotions is one of the important aspects that defines the approach of the FMCG industry. As Allender and Richards (2012) have opined, price promotion tactics are aimed towards appeasing consumers and attracting them to purchase products. Han et al. (2012) reiterate a similar view, stating that price promotions often lead to a general price fall in the market as other brands also try to attract consumers by discounting product prices. However, Lam et al. (2010) have argued that price promotions often lead to negative brand identity, as most consumers perceive that prices are only slashed when an organisation is not performing at its desired level. In addition, companies often sell defective products at a throw-away price so that they can bring in a new product range. The FMCG industry is a high-turnover sector, as the amount of sales far surpasses that of other industries. Although the product life cycle is quite short, consumers' quick and unthinking purchasing behaviour means that sellers do not have to try hard to sell their products. However, increasing competition means that leading companies are producing products by mass production, hence nullifying the prospects of smaller entities. Suchard et al. (2012) have opined that indices can be used to measure the effects of price promotion tactics on the prospects of the overall market, and that the performance of brands can be measured accordingly.

2.1.2 General Review of Marketing Applications

Contrary to the substantial amount of research on the applications of financial econometrics techniques and methods in financial markets, research on applications in fields other than finance is more limited. Granger and Lee (1989) conducted an investigation of production, sales and inventory relationships using multicointegration and non-symmetric error-correction models. The empirical research addressed the important question of whether or not a firm's advertising expenditures and sales are related to each other in the long run. Baghestani (1991) used the Engle and Granger (1987) two-step approach to study the long-run equilibrium or cointegrating relationship between the advertising and sales of the Lydia Pinkham Company. Evidence of a systematic relationship between both variables, and significant error correction terms in both the advertising and sales equations, were found. Dekimpe (1993) applied the Johansen (1988) full information maximum likelihood (FIML) approach to the same dataset as that of Baghestani and showed that some of the substantive findings of his work were caused by small-sample biases. Not only was the FIML estimate of the cointegrating vector different from Baghestani's, Larsen (2011) also showed that sales do not respond to deviations from the long-run equilibrium, and that the identified cointegrating relationship was only caused by the company's policy of setting advertising funding as a fraction of current and past sales.

As reviewed in Dekimpe and Hanssens (2000), time-series (TS) techniques were initially used in marketing for the following reasons: 1) for forecasting purposes, 2) to determine the temporal ordering among variables through Granger-causality tests, or 3) to determine the impact of marketing variables over time (e.g. through transfer-function analysis). Recently, there has been a renewed interest in the use of TS techniques, not only to demonstrate the existence of certain substantive marketing phenomena, but also to derive empirical generalisations on their relative size and frequency of occurrence. Studies in the former tradition have, for example, shown that TS techniques can be used to quantify short-term, long-term and permanent effects (Dekimpe & Hanssens, 1995), momentum (Bronnenberg, Mahajan, & Vanhonacker, 2000), business-as-usual, hysteresis and escalation (Dekimpe & Hanssens, 1999), advertising copy and repetition wearout (Naik, Mantrala, & Sawyer, 1998), the half-life of advertisements (Naik, 1999), synergy (Naik & Raman, 2003), and strategic foresight (Naik, Raman, & Winer, 2005). Studies in the latter tradition include Nijs et al. (2001), Pauwels and Srinivasan (2004), and Srinivasan et al. (2004). A typical design in these studies is a two-stage approach where the same time-series technique is first applied to a multitude of brands and/or product categories, after which one tries to explain the observed variability in various summary statistics (e.g. short or long-run elasticity estimates) through a number of marketing-theory based hypotheses.

Dekimpe and Hanssens (1999) applied unit root tests to sales, price, advertising and promotion support in order to define long-term elasticity. Larsen's (2011) findings reveal that only prices evolved over time, in terms of both absolute prices and the price differential relative to the competition; whereas sales, advertising and promotion support were stationary. Cain (2005) modelled and forecast brand share for a small segment of the toiletries category comprising four differentiated brands. Using over five years of quad-weekly TS data from 1995(5) to 2000(12) it was concluded that the model structure provides a convenient method of separating the short- and long-run behaviours of brands in the market, thereby allowing a formal analysis of their time-series properties. Cain also showed that the model avoids unit root testing and first differencing of the data—providing marketing variable parameters that are directly interpretable as short-run own and cross effects describing short-run substitution patterns between components brands and how the model's extracted trend component can be used to describe the pattern of long-run substitutability in the system. This, in conjunction with co-integration analysis, is widely used in the economics literature. It also provides a useful methodology for assessing the long-run effects of marketing mechanics.

Applied economists have utilised several econometric models or functional forms for estimating consumer demand, from the linear expenditure system (LES; Stone, 1954) and the trans-log model (Christensen et al., 1975) to more sophisticated models such as the almost ideal demand system (AIDS; Deaton & Muellbauer, 1980). The main objective of these models is derivation of the price elasticity of demand and quantification of the effectiveness of all marketing activities. Consumer demand in the consumer-packaged goods industry has brought together economic science, marketing disciplines and econometricians to develop what is known today as marketing mix modelling (MMM). MMM uses statistical analyses such as multivariate regression of sales and marketing time series data to estimate the impact of various marketing tactics (the marketing mix) on sales and then forecast the impact of future sets of tactics. It is often used to optimise the advertising mix and promotional tactics with respect to sales revenue or profit. The objective of MMM is to provide marketers with an assessment of the effectiveness of each marketing element in terms of its contribution to sales volume. The sales volume generated in dollar terms is divided then by cost accordingly to create a range of return on investment (ROI) figures for each element of the marketing mix. Ideally, this learning is then adopted to adjust marketing tactics and strategies, optimise the marketing plan and to forecast sales while simulating various scenarios (Franco-Laverde, 2012).

Criticism of the MMM approach usually centres on its use of static ordinary least squares (OLS) techniques that impose a fixed or deterministic baseline. Not only can this method give an artificial split into base and incremental volumes, by construction it precludes any analysis of the long-run impact of marketing activity. One solution is to apply the dynamic cointegrating vector autoregression (VAR) model—an estimation technique commonly used in the econometrics literature for evaluating the long-term effects of economic indicators. In practice, however, the technique is often impractical in the context of fully-specified mix models (Mintz and Currim, 2013). A preferable approach is to use a methodology that can directly separate both the short- and long-run features of the data, allowing a complete analysis of both in distinct stages. Time series regression analysis is a logical choice for two reasons. Firstly, all marketing mix models involve time-ordered data and are essentially time-series equations with additional marketing mix components. Secondly, the technique provides a direct decomposition of any time-ordered data series into trend, seasonal and random error components. It is then a natural step to decompose product sales into short-term marketing factors (incremental) and long-term base (trend). This generates an evolving baseline, which can then be meaningfully analysed to quantify long-run ROI (Cain, 2014).

Recently, researchers such as Dekimpe and Hanssens (1999), Larsen (2011), and Cain (2014) have begun to explore a more holistic view of all players together, including manufacturers and suppliers, rather than focusing on separate demand patterns in isolation as single-equation marketing mix models have. Approaches derived directly from the consumer decision-making process are known as *demand systems*. Demand systems are designed to take into account the demands of consumers along with existing market conditions to link the willingness of customers to purchase a product with the ready suppliers and traders. Market demand is therefore necessary to understand the general mood of the market as it is the assimilation of different individual buyers' perceptions (Hu & Chuang, 2012). Demand systems have two broad forms: *continuous* and *discrete choice*. Continuous choice structures are helpful for understanding consumer perceptions of product choice. For example, consumers may simultaneously choose products that are competitive in nature; for example, a consumer buys soaps from two different companies because of the individual choices of family members. Here, consumers are consciously choosing to purchase different products, knowing that their features may not be same. In such circumstances, rival companies stand to gain significantly. The demand in the market remains at the optimum level, benefiting all the competing entities.

However, Suchard et al. (2012) have opined that continuous-choice structures do not permit a monopolistic market—where a single business entity rules the market. Although the profit margin is not generally huge, the market scenario is self-sustaining. Therefore, Brown et al. (2012) pointed out that an ideal market would be one such as this and would attract transparent marketing activities, as the need to gain the upper hand in a highly-competitive market would not be there. However, once the number of entities increases, the situation becomes tougher for those entities due to heightened competition. Smaller entities, especially, will face tougher market conditions and due to their smaller potential reservoirs of resources, reaching potential customers can become a problem. Continuous choice structures are based on classical utility maximisation ideas where the consumer chooses equilibrium quantities of all goods in the choice set. Discrete choice forms, on the other hand, originate from 'characteristics' theories of utility maximisation (Lancaster, 1966) invoking a binary structure where the decision to choose one good is concurrent with a decision to not purchase any competing alternative. Therefore, the competition in the market becomes tough. Here, the members of a family would try to choose only a single product among several other brands.

Chan et al. (2012) have opined that this is the ideal type of market competition, where market players such as manufacturers and suppliers want to achieve competitive supremacy at any cost. Therefore, competition gradually rises. The firms operating in FMCG industry would obviously want to gain the upper hand by improving their manufacturing facilities and supply lines. However, Leonidou et al. (2013) have argued that this ideal competitive market-demand situation may be unfit for smaller organisations with limited choices due to economic constraints. In addition, this would give rise to non-transparent business activities to gain competitive advantage among competitors. Unethical business practices may follow, and business entities, especially smaller ones, will eventually face the risk of being wiped out from the market. The structure is necessary, however, to understand the present condition of a business entity in light of the position of its competitors. This structure is more prevalent in marketing theory and is ideally suited to quantifying the competitive performance of brand marketing strategies across all players in the market (Cain, 2014).

Table 2.1, below, presents an overview of the challenges and proposed approaches in marketing research that uses econometric techniques.

Table 2.1 Overview of marketing research approaches using econometrics

Challenges	Approaches	Selected Relevant Papers
1. Data Richness: *1.1 Aggregation* Over consumers Over time periods *1.2 Parameterisation* (Stores, SKUs) *1.3 Pruning*	 Segment-level response Optimal data interval Mixed data sampling Pooling parameters Dimension reduction Bias-reducing techniques	 Lim et al. (2004) Tellis & Franses (2004) Ghysels et al. (2003) Horváth et al. (2004) Pauwels, Naik & Mela (2004) Zanutto & Bradlow (2001) Andrews & Currim (2004)
2. Lucas Critique	Super-exogeneity tests Varying-parameter models Spectral analysis	Franses (2005) Naik & Raman (2003) Van Heerde et al. (2005) Naik et al. (1998) Bronnenberg et al. (2004)
3. Broadening Techniques & Marketing problems	Kalman filter Spectral band-pass analysis Bayesian error-correction Strategic foresight Marketing-finance interface Internet bid analysis	Naik et al. (1998) Deleersnyder et al .(2004) Fok et al. (2004) Naik, Raman, & Winer (2005) Mizik & Jacobson (2004b) Pauwels et al. (2004b) Joshi & Hanssens (2004) Naik & Jap (2004)
4. Asymmetric Response	Add error correction terms	Simon (1982) Hansens & Levien (1983)
5. Definition Consistency	Define long-run elasticity	Dekimpe & Hanssens (1999) Nijs et al. (2001) Pauwels et al. (2002) Wierenga & Horváth (2004)
6. Changing Dynamics	Structural breaks Dynamic IRFs Moving windows	Deleersnyder et al. (2002) Pauwels & Srinivasan (2004) Yoo (2004) Pauwels & Hanssens (2004)

The study of pre- and post-promotion dips in sales have been the subject of increased attention (Van Heerde, Leeflang, & Wittink, 2004). Pre- and post-promotion dips refer to two different situations. In the first instance, traders promote certain products to attract customers to choose their products over other similar ones. Promotional tactics may vary with the change of sellers, but the core idea remains same. The main idea behind expensive product promotion campaigns is to inform the customers about products. However, Buil et al. (2013) have opined that promotional strategies also try to incite immense shopping sprees by stating how much importance the product has in the lives of the targeted consumers. Prior to the promotion phase, an organisation may go through a bad sales period. Therefore, management of that organisation may decide to try and attract more customers. However, it has often been observed that even after the promotion phase, an entity may still face a dip in sales figures. A reason for this is that they are potential indicators of stockpiling acceleration and deceleration (Macé and Neslin, 2004).

Acceleration is understood as the effect that promotions have in inducing consumers to purchase earlier than they would otherwise; this is sometimes referred to as the "Pantry Effect" and refers to convincing consumers that a product is inseparable from their lives. Czinkota and Ronkainen (2013) have opined that this is a psychological urging of consumers to obtain an artificial need. Easy availability of a product is one of the reasons that companies try to use this method. Another reason is that some companies may want to run down stocks of their current SKUs prior to bringing in new and upgraded ones. Conversely, *deceleration* is the effect that price promotions have on deferring purchases until a new promotion is available (Buil et al., 2013). Prices may be varied to deter consumers from buying a product until such time as the company comes up with new features that complement the existing product range. Thus, products are priced in such a way that customers can be temporarily held back from purchasing them. Within this context, the calculation of price promotion profit goes beyond the incremental sales made during the promotion and adjusts for the promotional dynamics of post-promotion acceleration and pre-promotion deceleration.

In the FMCG industry, specifically, a price promotion has inherent risk (a promotion may not be effective or it may be very effective) and, as such, a concern of the marketer must be to minimise this risk. This analogy draws parallels with financial markets and, in particular, modern portfolio theory (MPT; Elton et al., 2009). MPT tries to assemble a portfolio of assets in order to maximise their potential return amidst heightened financial market activity. MPT states that the return on any individual asset relies on the entire portfolio's risk assessment. Beyhaghi and Hawley (2013) have opined that MPT preferences less-risky portfolios. That is to say, if an investor is provided with a choice between two portfolios, they would invariably choose the less risky one. However, Elton et al. (2009) have argued that investors can be pursuaded to take higher-risk portfolios when returns are also higher. Mitra (2011) has opined that different investors would have a different risk assessment strategy, and that the geographic location of the market is quite important in formulating its actual risk. For example, in European markets, the risk would be mostly apolitical. However, in Southeast Asian countries, the inherent risks factors are associated with political and social causes most of the time. Hence, the risk assessment factors also vary with the location of the market.

The way risk is defined is therefore different among different investors, as the willingness to earn more profit varies according to the individual. Therefore, understanding MPT is crucial in understanding how investors look at market risk from individual standpoints. MPT asserts that investors are risk-averse. The hypothesis is that investors would like to earn as much return as possible for any given level of risk. Investors construct portfolios to optimise or maximise their expected return, based on a given level of market risk (Markowitz, 1952). According to the theory, it is possible to construct an efficient frontier of optimal portfolios offering the maximum possible expected return for a given level of risk.

Whilst there is a substantial amount of research on the applications of MPT in financial markets (see, for example, Neslin & Van, 2008), research on applications in fields other than finance is more limited. Most research outside of finance, specifically in marketing, has focused on brand or product portfolio management and brand or product investment. Research in this thesis will consider the creation of a Brands Index and the applicability of the capital asset pricing model (CAPM; Lintner, 1965; Sharpe, 1964) as an alternative method for constructing brand portfolios in the FMCG industry. The methodology and respective modifications will be discussed in Chapter 3. Some studies argue that it is possible to create a product-portfolio equivalent of an efficient frontier in a similar way to MPT (Cardozo & Smith, 1983). Cardozo and Smith (1983), however, generated criticism (Devinney et al., 1985) and several problems were identified with their extension of financial portfolio theory to the product investment of firms. Specifically, Devinney et al. (1985) stated that Cardoso and Smith (1983) showed a theoretical misunderstanding in two ways. Firstly, the data was inappropriate for the empirical analysis used. Secondly, there was no *a priori* reason why the firm should be only limited to its current investment. In reply, Cardozo and Smith (1985) pointed out that, unfortunately, there exists no ambiguously defined “market or index against” which to compare the performance of a particular business unit. Wensley (1986) emphasised that financial approaches have developed from traditional budget methods to the CAPM and the use of discount rates related to the systematic risk of the project and its beta, while the marketing approach has relied on the classification of either products or business units into various boxes. Ryals et al. (2007) continued to further explore return maximisation and risk minimisation in marketing portfolios, calculating the efficient frontier and helping select optimal marketing portfolios; specifically, in relation to the portfolios of brands, markets, consumer segments and campaigns. One of the main outputs from previous studies is that marketing portfolios differ from financial ones in the sense that the allocation of marketing funds affects portfolio returns.

The rationale behind the CAPM is that it provides an intuitively simple and appealing model of the relationship between required rates of return and risk. The CAPM tries to define the fine-scale relationship between risk inherited through market activities and the expected return. The theory is, therefore, immensely helpful in measuring investment in risky portfolios based on prevailing market conditions. Zabarankin et al. (2014) have opined that CAPM strives to make the compensation process of investors in two ways: by measuring risk and by using the risk-free rate to compensate investors over a certain period. The CAPM formula is as follows:

Equation 2.1

$$E(R_i) = R_f + \beta_i[E(R_{Mkt}) - R_f]$$

where:

$E(R_i)$ is the expected return on security *i*

R_f is the risk free

β_i is the beta of the security

$[E(R_{Mkt}) - R_f]$ is the risk premium

The basic premise of the CAPM is that investors need to be compensated in two ways: *time value of money*, and *risk*. The time value of money is represented by the risk-free rate (*Rf*) in the formula, and compensates investors for placing money in an investment over a period of time. The second half of the CAPM formula represents the underlying risk, and calculates the amount of compensation the investor needs for taking on additional risk. This is calculated by taking a risk measure (beta) that compares the returns of the asset to the market over a period of time, and to the market premium (*Rf*), where *Rm* is the market return (Koop, 2006).

The CAPM asserts that investors should hold a portfolio that is some combination of risk-free assets and the market portfolio, and that the exact combination depends on each investor's taste. The risk of an asset that is borne by investors will be the component that contributes to the risk of the market, which is measured by its beta. Beta (*β*) is understood as a measure of the relative contribution of an asset to the risk of the market portfolio. It is also known as *aggregated risk* or *undiversifiable risk*. As the beta of the market portfolio is unity, all assets can be easily identified as being more or less risky than the market as whole. The following relationship for the beta unfolds: if $\beta >$ or < 1, the asset is more or less risky than the market, respectively.

Cao and Ward (2014) have opined that portfolio investment amounts to risk-free investment where investors try to reduce risk by segregating the total investible amount into several parts. The idea of total risk, as the modern idea states, is that an ideal portfolio will be comprised of diversified shares that are correlated with one another to reduce the market risk without reducing the expected return margin. Koop (2006) has opined that systematic risk will be balanced with total risk to make the investment portfolio safe and secure.

The Sharpe ratio is another method used to rank the performance of a portfolio. The Sharpe ratio is a measure of the excess return (or risk premium) per unit of risk in an investment asset or a trading strategy (Sharpe, 1994). I posit, therefore, that the ratio would be immensely helpful in forming a new index to assess the performance of the FMCG industry. The Sharpe ratio deals with the potential risk that business entities endure in adverse market situations, and the new index will try to work with new baseline sales figures to lessen the problem of market risk.

This research analyses the compensation of a brand due to the combination of all its marketing activities (spending on advertising and price promotions, just to mention a few). The Sharpe ratio is used to characterise how well the return of an asset compensates the investor for the risk taken. When comparing two brands, the brand with the higher Sharpe ratio gives a better performance with the same sales value risk. The main advantage of the Sharpe ratio in this context is that it is directly computable from any observed series of returns without the need for additional information on the source of profitability (in the context of this research, weekly variability in sales value is used).

In the FMCG context, beta will be used as an estimate of the sales value risk of the brand being considered, while volatility will be first examined by calculating the variance (or standard deviation) of the percentage changes in sales values over some historical period. This will then become the volatility forecast for all future periods. This historical volatility will be useful as a benchmark for comparing the forecasting volatility of more complex models such as the ARCH and GARCH family models.

The previous review reveals that no systematic attempt has been made in the literature to study brands' sales value volatility generated from all supporting marketing mix activities. The work by Cardozo and Smith (1985) clearly indicates the lack of a ‘market or index against’ which to compare the performance of a particular business unit. Wilhelm (2012) opined that comparisons are necessary to understand the relevant position of any two portfolios standing on the same ground. Research in this thesis explicitly retakes this topic and formulates the steps required to create such an index. Accordingly, the criticisms of systematic risk or market risk can then be revised. The next section explores the methodologies available for creating a Brands Index. The creation of the index will allow the use of the financial econometrics reviewed so far.

2.2 Index Background

In a financial context, an *index* is a statistical measure of change in an economy or a securities market. The index is itself is an imaginary portfolio of securities representing a particular market or a portion of it. Each index has its own calculation methodology and is usually expressed in terms of change from a base value. Thus, the percentage change is more important than the actual numeric value (Wilhelm, 2012). The main differences between various indices are the types of securities held and the weighting schemes used (Standards & Poor's, 2007). The information provided below has been taken and adapted from Standards and Poor's (indices.standardandpoors, 2016).

2.2.1 All Ordinaries Index Formula

The All Ordinaries Index (AOI) is market value-weighted index that includes all the ordinary shares listed on the Australian Stock Exchange. Each company’s influence on the AOI is directly proportional to its market value. The AOI summarises price movements by following changes in the aggregate market value (AMV) of the constituent stocks. The AMV is adjusted for capital changes and stock additions and deletions. The simplified calculation formula for the AOI is as follows:

Equation 2.2

$$\frac{\text{Current AMV}}{\text{Adjusted previous minute}'\text{sAMV}}\ X\ Previous\ minute's\ index = Current\ index$$

Formally, we have:

Equation 2.3

$$Today's\ closing\ index = Yesterday's\ closing\ index\ X \left[\frac{\sum(P_{ci} * q_{oi})}{\sum(P_{oi} * q_{oi})}\right]$$

where:

P_{oi} = the opening price of company *i*'s shares

P_{ci} = closing price of company *i*'s shares

q_{oi} = number of listed shares for company *i* at the opening of trading (this will be the same as at the close of trading the previous day)

By construction, the only reason why the numerator and the denominator of the ratio above can differ is that prices change over time.

In summary, the AOI is a weighted sum of price movements where the weights are the values of the shares listed for company *i* as a proportion of the total value of the listed shares of all companies included in the index.

2.2.2 The Standard & Poor's 500 Index formula

The Standard & Poor's 500 Index (S&P 500) is calculated using a base-weighted aggregate methodology; this means that the level of the index reflects the total market value of all 500 component stocks relative to a particular base period.

The formal formula used to calculate a cap-weighted index value such as the S&P 500 Index value, is:

Equation 2.4

Index Value = $\frac{1}{Divisor} X \sum[Price(i) X IndexShares(i)]$.

Herein, i ranges from 1—500, representing each stock in the S&P 500. The market value of the index is:

Equation 2.5

$$\sum[Price(i)XIndexShares(i)].$$

Thus, as above, the following relationship unfolds:

Equation 2.6

Index Value = Market Value / Divisor

Equations 2.2 – 2.6 above each have significant implications for this thesis. The AOI equations (2.2 and 2.3) are largely helpful in assessing the true value of an organisation. Aggregate market value can be used to summarise the gross changes incurred by respective brands in the market. On the other hand, the S&P 500 formulae (2.4 – 2.5) deal with all of the 500 components that reflect the baseline sales of the companies. Therefore, concerned entities can relate their individual performances to these indices to understand their present mode of operations.

There are many types of indexes, each trying to measure different groups of stocks. These are summarised as follows:

i. *Broad-based*

Small-cap, Mid-cap and Large-cap: The term "cap" herein refer to a stocks' market capitalisation. Market capitalisation describes the resources available to an organization (Bollerslev & Mikkelsen, 1999). In this context, *large-cap* refers to companies with a significant outstanding amount of market resources. The *mid-caps* are the smaller stocks and the *small-caps* are the smallest in this group. Although several FMCG companies do not trade in stock markets, the concept of market capitalisation can be related to the stock keeping units (SKUs) of those companies. The larger the number of SKUs a company holds, the greater its chances of capturing the market.

Value: The value of an asset is the potential price that the asset would fetch at the time of selling. Therefore, market specialisation is an important for a company in determining its real value. Therefore, for the FMCG industry, the profit gained after selling a product would decide future trends in the market.

Growth: Growth in the securities market may refer to the difference between the first public offering of a share and its latest price. Most business organisations try to maintain share prices at a nominal level to encourage more buyers to be part of the company (Barberis et al., 2015). Therefore, the growth of the companies depends on the overall function of the companies in the market itself.

Geographic region: The merit of an investment depends on the sensitivity of a region. Therefore, some investors will try to tap the entire market by having a global presence. On the other hand, most investors try to look specifically at certain markets for more concentrated activities (Wilhelm, 2012).

ii. Narrow

Economic Sector: The economic sector of a particular region or country depends on a great many factors and, therefore, investors try to adhere to those factors to gain sound knowledge (Jayaraman et al., 2012). An index related to an economic sector, therefore, looks to keep those factors in notice to provide investors the chance to invest cautiously. For example, political unrest in a country would automatically make its financial market risky for further investment. An economic sector-related index tries to categorise countries according to their present risk factors to create a safe environment for investment.

Industry: An industry-specific index tries to provide adequate information related to present activities across different sectors. Such an index is constituted of the activities of different industries over a specific period to try to inform investors about which sectors are under- and over-performing.

Alternatively, any combination of the above index types may be employed. The following groupings are usually based on simple financial ratios:

- Size (small, mid or large) is based on market capitalisation, which equals *price* multiplied by *shares outstanding*; and
- Style (value or growth) is often based on the book-to-price ratio, which is the company's common equity divided by its share price.

Index constituents can be either equal-weighted, price-weighted or cap-weighted. By way of example, if we wanted to form a new index comprised of five artificial assets (brands) we would have, for each of the above three weighting methods:

i. Equal-weighted

Equal weighting consists of giving each stock equal representation in the index. In this example, given five assets, each would have a weight of 20%. To design such an index, we would designate some investment amount (for example, $10,000) to be invested in each stock and then divide the investment amount by the current asset price to determine how many shares to buy.

Equation 2.7

$$r(t) = \frac{p(t)f(t) + d(t)}{p(t-1)} - 1$$

ii. Price-Weighted

Using a price-weighted index methodology, the higher the asset price, the greater the weight the asset has in the index. For example, Company 2 may have twice the weight of Company 1 on the basis of price, even though Company 1's market capitalisation is larger than Company 2's.

iii. *Cap-weighted*

Cap-weighting is weighting by market capitalisation, which equals *shares* times *price*. In this case, index shares (how much one needs to hold to match an index) are the same as shares outstanding (the number of shares a company has issued). The S&P 500 and AOI are cap-weighted indices.

Calculations for five artificial assets are given below in Table 2.3. Different weighting methods are useful in measuring the performance of different brands in the market. Table 2.3 show the results for different share prices from price (0) to price (3).

Table 2.2 Hypothetical outstanding shares and share price variation for five companies

Company	Sales	Shares	Share Price 0	Share Price 1	Share Price 2	Share Price 3
Company 1	$25,000.00	6,000	$57.00	$60.00	$61.00	$62.00
Company 2	$140,000.00	3,100	$84.00	$82.00	$81.00	$80.00
Company 3	$100,000.00	10,000	$53.00	$55.00	$60.00	$65.00
Company 4	$45,000.00	2,800	$125.00	$120.00	$110.00	$100.00
Company 5	$50,000.00	5,000	$62.00	$60.00	$70.00	$60.00

Table 2.3 Returns from equal-, price- and cap-weighted indices

Index Weightings	Price t=0	Price t=1	Price t=2	Price t=3	Return
Equal-weighted index	$50,000.00	$49,943.00	$51,755.69	$50,342.57	**0.69%**
Price-weighted index	$3,810,000.00	$3,770,000.00	$3,820,000.00	$3,670,000.00	**-3.67%**
Cap-weighted index	$1,792,400.00	$1,800,200.00	$1,875,100.00	$1,850,000.00	**3.21%**

It can be easily seen from the above tables that the way an index is weighted makes a big difference in terms of index returns. In this example, price weighting gives most of the weight to Company 4, so the index value goes down, while cap weighting gives most of the weight to Company 3, so the index value goes up, and equal weighting gives the same result as the average of the individual asset's returns.

2.2.3 The Divisor, Adjustments and Criteria to be included in the Brands Index

i. The Divisor

Index values for different indices—even those using the same weighting methodology—are typically hard to compare because they all start at different base values, i.e., the value when the index is first created. Indices generally start with a base value at date $t = 0$. Comparisons across indices can only be done if the objects are comparable by having similar features, including base date and value. To solve this issue, indices can be re-based by introducing what is called a *divisor*, so that the index can start at any given value. The initial divisor is the initial (time $t = 0$) price of the index divided by the base value of the index. In the cap-weighted example in Table 2.2 above, this is: 1,792,400.00 / 100 = 17,924.00.

Table 2.4 Various divisors

Divisor	Price t=0	Price t=1	Price t=2	Price t=3	Divisor
Equal-weighted index	100.00	99.89	103.51	100.69	**$500.00**
Price-weighted index	100.00	98.95	100.26	96.33	**$38,100.00**
Cap-weighted index	100.00	100.44	104.61	103.21	**$17,924.00**

From the above results, the next fundamental relationship holds:

Equation 2.8

Index Value = Market Value / Divisor

ii. Index Adjustments

It is important to note that if a company changes the number of outstanding shares, the divisor needs to be adjusted to reflect this fact. In the proposed Brands Index on any given week, its value is the quotient of the total available market value of the index's constituents and its divisor, as per the formula given above. Continuity in index values is maintained by adjusting the divisor for all big changes in the constituents' sales values after the base date. This includes brands' additions and deletions to the index. The divisor is adjusted such that the index value at an instant just prior to a change in sales value equals the index value at an instant immediately following that change. An example of this methodology is shown in Chapter 3, when a new category is brought in.

In general terms, when a category/brand is replaced by another category/brand, the index divisor is adjusted so that the change in the index value that results from the addition or deletion does not change the index level.

iii. Criteria for a brand to be included in the Brands Index

This is a set of different criteria that can be used to reference the Brands Index and its subindices in the FMCG industry. The four criteria are: *domicile*, *eligible brands*, *market value* and *sector classifications*. Only brands currently selling products in retail supermarkets will be considered for inclusion in the FMCG Brands Index and sectarian indices.

Domicile: The index draws from the entire universe of brands sold in the retail supermarkets in Australia.

Eligible Brands: All brands sold through retail supermarkets. However, brands with less than 52 weeks of available data will be ineligible for index inclusion.

Market Value: The Brands Index only includes brands that are considered to be saleable, and *market value* (which is the weekly dollar sales) is a key criterion for brand selection. The market value criterion for a brand's inclusion is based upon the weekly average market sales of the brand over the last 52 weeks.

Sector Classification: Brands are classified by the same classification as that given on the data source by the data's owner (oral care, laxatives, grooming, ice cream, deodorants, hair care, skin care, toiletries, etc.)

2.2.4 Analogy with All Ordinaries and Standard & Poor's Australian Indices

For the creation of the Brands Index, this research follows the techniques used in equity indices such as the AOI and S&P500, whose underlying variables are stocks. For the purpose of this research, the fundamental variables are brands. Thus, the proposed Brands Index will focus on the relative weekly change of defined brands that will frame the newly-created index. The Brands Index will be a weighted average index rather than a simple index. Therefore, the brand with the largest market value will have the largest weight and impact on the overall index. Chapter 3 deals with the creation of the Brands Index.

2.3 Synthesis

A number of conclusions can be drawn from the above discussion with regards to the need for the creation of a Brands Index and its applications in the FMCG industry. First, the current literature (discussed in Section 2.1.1) in finance and more specifically in financial econometrics can be adapted for use with the created Brands Index to test for volatility. However, some adjustments (explained in Chapter 3) will need to take place in order to be able to adapt the financial methodologies studied in this chapter. Second, despite modern portfolio theory drawing attention in several studies in marketing research, the literature review revealed that it has not taken volatility into account, most likely due to the lack of existence of such an index. Third, while most of the studies in marketing research rely on marketing mix modelling (MMM) techniques, with the main difference being the nature of the model, i.e., static (fixed base, focusing on the short term) or dynamic (changing base, introducing the long term component), the key aim has been to isolate the effects of each element of the marketing mix. The object is to work out an ROI metric for media investment across different media channels. Fourth, the researchers conceptualised the concept of the capital asset pricing model (CAPM) as a development from traditional budget methods and the use of discount rates related to the systematic risk of the project, its beta, while the marketing approach has relied on the classification of either products or business units into various boxes (Wensley, 1986). To their criticism on systematic risk or market risk, Cardozo and Smith (1985) clearly pointed out that, unfortunately, there exists no ambiguously defined 'market or index against' which to compare the performance of a particular business unit. Therefore, further study is required to fill this gap and provide empirical assessment that will contribute to a better understanding of the brands acting within the Australian FMCG framework. Accordingly, the next chapter of this study proposes a comprehensive research framework incorporating the creation of a Brands Index, the measurement of volatility and the application of the CAPM with particular modifications, along with hypothesised path relationships.

CHAPTER 3: CONCEPTUAL FRAMEWORK

3.0 Introduction

This chapter presents the conceptual framework of the thesis and the hypothesised application of financial theory. In finance, *volatility* is understood as the degree of variation of a trading price series over time, and is measured by the standard deviation of returns (Basu & Forbes, 2014). Financial volatility is something that is omnipresent and therefore cannot be avoided altogether. Satchell and Knight (2011) have opined that financial volatility may occur due to several reasons. Variance and standard deviation are two of the most effective parameters used to understand the difference between an investment and the accumulated outcome (Basu & Drew, 2010). Market volatility warrants that the underlying asset fluctuates as per the present condition of the market. Thus, investors have to be wary about that. In addition, daily trading in the financial market gives rise to market volatility, which can cause future catastrophes (Satchell & Knight, 2011). This chapter thus aims to form an analogy between financial volatility and the present operations of the FMCG industry.

Although market volatility has a deep influence over the ways that business entities work presently, i.e. in the short-term, Barberis et al. (2015) opined that the long-term effect of volatility is also immense. Commercial activities that are conducted on a daily basis are inherently uncertain owing to unpredictable market conditions. Lower levels of volatility provide the chance to spread an investment among several subsectors to earn the desired result. Authentic portfolio management strategies warrant that investors study the market in order to understand the principal influencing factors affecting it (Macé & Neslin, 2004). Afonso and Furceri (2010) have opined that volatility clustering has other prominent effects. *Kurtosis*, which is a measure of whether the distribution of asset returns over time is light-tailed or heavy-tailed in relation to a normal distribution, is one of those effects. According to Aghion et al. (2010), volatility has a direct link with past actions in the market. Thus, companies must keenly monitor factors that influence their market in order to determine the best way to respond to volatility. In the FMCG context, therefore, brand managers will need to have a strong knowledge of market variants in order to eliminate anomalies in their portfolio.

A significant amount of financial research in the last three decades has been devoted to the phenomenon known as volatility clustering; first noted by Mandelbrot (1963) as "*large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes.*" Although Mandelbrot was in fact defining long-term dependence, the notion of volatility clustering found its reference in this quote.

The presence of volatility clustering in financial time series has led to the introduction and extensive use of ARCH-GARCH models in financial forecasting and derivative pricing. Autoregressive conditional heteroscedasticity (ARCH; Engle, 1982) and generalized autoregressive conditional heteroscedasticity (GARCH; Bollerslev, 1986) models are designed to deal specifically with volatility clustering. Most the applications in this area have been dedicated to the measurement of volatility clustering illustrated in most financial indices such as the S&P 500, AOI, NASDAQ and Dow Jones (see, for example, Barberis et al., 2015). In order to derive the actual outcome from an investment in the presence of volatility clustering, investors can use GARCH models to make authentic forecasts for participating companies (Francq & Zakoian, 2011). Ali (2011) opined that modern arbitrage pricing tactics are based solely on the ARCH model, and that the model is helpful in assessing volatility clustering in a clear and understandable manner.

This chapter discusses the creation of a Brands Index, the definition and measurement of volatility within the FMCG context and the adaptability of the CAPM (as discussed in Chapter 2) as an alternative method to create brand portfolios. The aims of this chapter are to:

- propose a conceptual framework to create an index for brands traded in the FMCG industry (Section 3.1);
- propose a quantitative framework for measuring volatility clustering in the Brands Index (Section 3.2); and
- validate the use of the CAPM as a competing model to add to the literature on brand portfolio management (Section 3.3).

The objective of the research presented in this thesis is the creation of a Brands Index for the FMCG industry in Australia. The Index aims to measure the performance of the brands, not just at a particular point in time, but over long periods, in order to mitigate the negative side of market superficiality (Yamamoto, 2010). A significant contribution of the Brands Index is in meeting companies' need to have a quantitative framework that enhances their power to improve calculations related to the margin of profit. The FMCG industry is inherently uncertain (i.e. risky). Individual brands do not know what competing brands are planning to do in terms of price promotions or media investments, and this increases market risk and volatility. Thus, participating companies have to be cautious to avert any avoidable risk (Barberis et al., 2015). FMCG products are produced ready-for-purchase and, therefore, can require extensive marketing to promote their sale. Another characteristic of FMCG products is that consumers do not spend significant amounts of time deciding to purchase them. Their shelf life being low, these products provide a relatively low profit margin, but their quantity of sales mean that the profit of the company is more than compensated for.

In order to understand and create an appropriate portfolio of FMCG products, there is a need to examine the CAPM and the ways it may be used to help brand managers. A *portfolio* in this context refers to a group of different brands available in the market. Brand managers will try to put different brands into different brackets in order to reduce the risk of loss in any one of the brands (Cao & Ward, 2014). The aim of the chapter is to consolidate the antecedents of volatility, the marketing mix, and the CAPM as a strategy to help brand managers make informed decisions on marketing strategies that increase sales and maximise returns.

3.1 Proposed Index Creation

The conceptual framework for the creation of a Brands Index follows the techniques used in construction of equity indices such as the AOI and the S&P500 (presented in Chapter 2), wherein indices are cap-weighted and the fundamental underlying variables are stocks. For the purpose of this research, the fundamental underlying variables are brands. The methodology of the creation of the Brands Index is discussed in Chapter 4. The aim of the creation of the Index is hypothesised in the presence of volatility clustering, as evidenced in the discussion in Chapter 2. As opined by Hu and Chuang (2012), volatility clustering is practically a normal financial phenomenon. Volatility clustering reveals that when returns are interlinked, absolute potential returns may exhibit a significant autocorrelation function. Of the different types of indices available in financial theory, the Brands Index will be a cap-weighted average index rather than a simple index, as discussed in Chapter 2. Cap-weighted is most suited for this thesis, since it will assist in investigating the theoretical concept of the volatility clustering path drawn from the literature and test this through hypotheses, as stated in Chapter 2. Therefore, the brand with the largest market value will have the largest weight and impact on the overall index, following the same formula as that of financial markets but adapted as follows:

Equation 3.1

$$Current\ period's\ closing\ index = Last\ period's\ closing\ index \times \left[\frac{\sum(\tilde{P}_{ci} * q_{ci})}{\sum(P_{oi} * q_{oi})}\right]$$

where:

P_{oi} = the opening price of brand *i* units

P_{ci} = closing price of brand *i* units

q_{ci} = number of total units for brand *i* at the close of the period

q_{oi} = number of total units for brand *i* at the opening of the period

$\sum(P_{ci} * q_{ci}) = AMV_{(t-1)}$ = Aggregated market value in the previous period

$\sum(P_{oi} * q_{oi}) = AMV_{(t)}$ = Aggregated market value in the current period

For any given brand, its price (P_i) multiplied by its quantity of units sold (q_i) gives the total dollar value figure at any point in time. However, the prices and quantities change week-by-week due to specific marketing-mix activities having taken place over time (price promotions, advertising, etc.). Thus, relative to Equation 2.3 for a financial index, the variable (q_{oi})—i.e. the number of listed shares for company *i* at the opening of trading—is replaced by the variable (q_{ci}) in Equation 3.1. Due to the changing nature of price and quantity variation week-on-week, the variable (q_{ci})—i.e. the number of total units for brand *i* at the closing week—is introduced to overcome the issue of price and quantity variation.

Although there is a clear difference in the proposed index's formula (Equation 3.1) where the quantity component q_i becomes dynamic rather than static, the final objective is still the same: to analyse and draw conclusions from changes in the value of the index over a given period of time. The Brands Index will be based on change in the aggregated market value (*AMV*) of the brands represented in it. The formula for calculating the index is as follows:

Equation 3.2

$$Index(t) = Index(t-1) \times \frac{AMV(End\_of\_t-1)}{AMV(Start\_of\_t)}$$

As previously discussed in Chapter 2 and earlier in the current section, an index is a single descriptive statistic that summarises the relative change in an underlying group of variables. In an equity index such as the AOI and S&P500, the fundamental variables are stocks. For the purpose of this research, the fundamental variables are brands. So, the proposed index will focus on the relative weekly *AMV* change of the brands that consitute the Brands Index.

A second distinction from financial market indices is also emphasised in this research. The main variable that changes in financial markets is the share price of a given company. Share prices effectively go up and down and there is no maximum or minimum imposed on them when traded in the stock market.[2]

In the FMCG industry, brands clearly show a separation of product sales into *base sales* and *incremental volume sales*. Base sales represent the long-run or trend component of the product time series, driven by factors ranging from regular shelf price and selling distribution to underlying consumer brand preferences. Incremental volume sales, on the other hand, are essentially short run in nature, capturing the period-to-period sales variation driven by temporary selling price discounts, multi-buy promotions and off- and online media activity (Cain, 2014). The proportions of base and incremental sales vary depending on whether or not the brand is heavily or lightly promoted. Base sales range from 60% to 90% of total sales whereas incremental sales represent the remainder—some 10% to 40% of total sales (Franco-Laverde, 2012). The part of the sales figure that resembles the previous sales figure of the same financial period is called the base sale. On the other hand, the incremental volume sale refers to any portion added to the main sales figure over a specific period, albeit a short one. Therefore, the base value may have similarity with the previous period's figure, but the incremental value always looks different.

The financial success of a company is caused by the volume of incremental sales. Thus, the main variation of a brand's sales value come from the brand's short-term activities starting from the base value, rather than from a free value. This is in opposition to financial indices where no minimum is imposed on share prices. The implication of this is that a minimum range of values needs to be created for every brand within the Brands Index according to each brand's base value. Only then can companies understand the level to which prices of product units can fluctuate. Czinkota and Ronkainen (2013) opined that having a clear and prolific range value provides the management of the company a chance to improve its performance by improving its operational values and styles. In most cases, the weekly sales will never reach a value below the base amount. The reason being that the company has to perform exceedingly badly in order for this

[2] The exchange can halt/suspend trade in a stock if its price falls too far in a short time.

to occur. In addition, market conditions also have to be so adverse that the company becomes unable to continue its daily commercial activities. Temporary variations in weekly sales will always tend to return to the long-term trend (the base) unless the company performs exceedingly well and increases base sales permanently. By way of an example, if a company has products selling in the market at a baseline sale of 100 units per week in the previous year, the company must perform exceedingly well to increase baseline sales to 120 units per week. This hypothetical increase can be permanent or part of an upward trajectory if the company is using efficient marketing strategies such as price promotions and media messages that aim to fulfil customer preferences.

A negative return will not be taken into account if it represents a return to base levels, as it does mean bad performance, just a movement back to the long-term trend. The product prices of a company often go up and down through the year based on the performance of the entity itself. Therefore, while the fortune of the company fluctuates over a financial year, it is their annual report that shows the ultimate state of affairs. Therefore, if a negative turn ends at the base level after soaring high, the negative turn will not be taken into account. Chapter 4 deals with the suggested adjustments accordingly. Thus, based on the arguments supporting the creation of a Brands Index following a similar methodology to those of financial markets with the respective adjustments, it is hypothesised that:

> *Hypothesis 1: The variation in the weekly sales of the proposed Brands Index follows a volatility-clustering pattern similar to that of financial market indices.*

A volatility clustering pattern may be a normal financial state of affairs, and large changes would only lead to larger changes over time. Market volatility is therefore related to the bigger changes that may take place in the market, since the influencing factors are numerous, such as advertisement and promotion strategies. For example, if a small regulatory change is induced to regulate the market, the consequences would also likely be smaller. On the other hand, if bigger steps are taken by regulatory authorities or by the companies themselves, the changes are bound to be larger. An example of small regulatory change would be to increase the shelf price by 3%, for instance, which would result in smaller consequences as losing some weekly sales. On the contrary, decreasing the price temporarily (for one or two weeks) by 20% would represent large changes in sales (the price elasticity figure will determine the magnitude of this change). Therefore, the index created should be able to reflect these changes in price and also be capable of capturing the magnitude of the noise in overall sales.

3.2 ARCH-GARCH and Alternative Models – A Framework for Conceptual Insight

In regards to measuring volatility, the standard econometric tools have become the ARCH and GARCH models. The main focus of ARCH/GARCH models is on the assumption of the least squares model—that the expected value of the error term, when squared, is the same at any given point. Thus, instead of considering this as a problem to be corrected, ARCH/GARCH models treat heteroscedasticity as a variance to be modelled. As a result, not only are the deficiencies of least squares corrected, but a prediction is computed for the variance of each error term (Engle, 2001).

The motivation for ARCH-class models is the phenomenon known as *volatility clustering* or *volatility pooling*, wherein the current level of volatility tends to be positively correlated with its level during the immediately preceding periods. Following this rationale, this thesis assumes that volatility clustering arises in the FMCG sector when some brands react after another brand has taken initiatives such as a major investment in advertising, new product development, or simply more price promotional activity. Such activities make the market more 'noisy' (i.e. volatile) as the other brands tend to follow. After a while, the market should return to a slower pattern until the next initiative is made.

The primary descriptive tool for capturing volatility has been the calculation of the standard deviation over a fixed number of recent observations. Following Engle's approach, an ARCH model is defined as follows:

Equation 3.3

$$Y_t = \beta_1 + \beta_2 x_{2t} + \beta_3 x_{3t} + \beta_4 x_{4t} + u_t$$

where:

$$u_t \sim N(0, \sigma_t^2)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2$$

$\alpha_0 > 0$ and $\alpha_1 \geq 0$

Using the ARCH specification in Equation 3.3, the conditional mean (which describes how the dependent variable Y_t varies over time) can take almost any form. This model can easily be extended to the general case where the error variance depends on q lags of squared errors, which would be known as an ARCH (q) model as follows:

Equation 3.4

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_1 u_{t-2}^2 + \ldots\ldots.. + \alpha_q u_{t-q}^2$$

To test for ARCH effects, the coefficients in the Equations 3.3 and/or 3.4 need to be statistically significant. If statistically significant, the conclusion reached is that the error variances are correlated. Depending on the significant lagged coefficients, the model is defined as an ARCH (q).

The GARCH model introduced by Bollerslev (1986) is also a weighted average of past squared residuals, but it has declining weights that do not go to zero. In order to work out a GARCH model, the conditional variance σ_t^2 will be called h_t, so the model would be written as:

Equation 3.5

$$Y_t = \beta_1 + \beta_2 x_{2t} + \beta_3 x_{3t} + \beta_4 x_{4t} + u_t$$, with variance h_t

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_1 u_{t-2}^2 + ...+ \alpha_q u_{t-q}^2$$

In the context of the GARCH specification, another way of expressing an ARCH (1) model, for instance, is:

Equation 3.6

$$y_t = \beta_1 + \beta_2 x_{2t} + \beta_3 x_{3t} + \beta_4 x_{4t} + u_t$$

$$u_t = v_t \sigma_t \qquad v_t \sim N(0,1)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2$$

The GARCH model allows the conditional variance to be dependent upon previous own lags, so the simplest case of a GARCH (p,q) would be:

Equation 3.7

$$h_t = w + \sum_{i=1}^{q} \alpha_i y_{t-i}^2 + \sum_{j=1}^{p} \gamma_j h_{t-j}$$

or

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2$$

Note that the above relation only holds if $\alpha + \beta < 1$ and is logically correct if the weights are positive, such that $\alpha > 0, \beta > 0, w > 0$.

Using GARCH models, it is possible to interpret the current fitted variance h_t as a weighted function of a long-term average value (dependent on α_0), information about volatility during the previous period $(\alpha_1 u_{t-1}^2)$ and the fitted variance from the model during the previous period $(\beta\sigma_{t-1}^2)$ (Rupper, 2004).

GARCH models can also be generalised in the form GARCH (*p*,*q*) to allow for more lags in volatility in the previous periods (u_{t-p}^2) and in the fitted variance during the preceding periods (σ_{t-q}^2), as follows:

Equation 3.8

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-p}^2 + \beta\sigma_{t-q}^2$$

In addition to the ARCH/GARCH models, other models are explored herein to better capture volatility clustering in the Brands Index. These include the EGARCH, TGARCH and ACD as alternative means of capturing positive returns, which are explained in detail in Chapter 4, Section 4.3.

The integrated generalised autoregressive conditional heteroscedasticity (IGARCH) model is a restricted version of the GARCH model, where the persistent parameters sum to one, and a unit root is incorporated in the GARCH process. The condition for this is given as:

Equation 3.9

$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-p}^2 + \beta\sigma_{t-q}^2$; where:

$$\sum_{i=1}^{p} \beta i + \sum_{i=1}^{p} \alpha i = 1$$

The exponential generalised autoregressive conditional heteroskedastic model (EGARCH) by Nelson (1991) is another form of GARCH model. Formally, an EGARCH (*p*,*q*) can be expressed as:

Equation 3.10

$$\log \sigma_t^2 = \omega + \sum_{k=1}^{q} \beta_k \, g(Z_{t-k}) + \sum_{k=1}^{p} \alpha_k \, log\sigma_{t-k}^2$$

where:

$g(Z_t) = \theta Z_t + \lambda\big(|Z_t| - E(|Z_t|)\big), \sigma_t^2$ is the conditional variance

$\omega, \beta, \alpha, \theta$ and λ are coefficients.

The parameter Z_t in Equation 3.10 may be a standard normal variable or come from a generalised error distribution. The formulation for $g(Z_t)$ allows the sign and the magnitude of Z_t to have separate effects on the volatility. Since $\log \sigma_t^2$ may be negative, there are no (fewer) restrictions on the parameters.

The threshold GARCH (TGARCH) model (Zakoian, 1994) is similar to, though not the same as, the GJR model (Glosten, Jagannathan, & Runkle, 1991). The model is an extension of GARCH with an additional term added to account for possible asymmetries, with the conditional variance defined as follows:

Equation 3.11

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1}$$

where:

$I_{t-1} = 1$ if $U_{t-1} < 0$; $= 0$ otherwise

The condition of non-negativity is $\alpha_0 > 0$, $\alpha_1 > 0$, $\beta \geq 0$, and $\alpha_1 + y \geq 0$. It means that the model is still admissible, even if $y < 0$, provided that $\alpha_1 + y \geq 0$.

The autoregressive conditional duration (ACD) model was proposed by Engle and Russell (1998) to model irregularly-spaced financial transaction data. *Duration*, in this instance, is defined as the time interval between consecutive events. Since duration is necessarily non-negative, the ACD model has been used to model time series that consist of positive observations. In addition, the error distribution of ACD models moves closer to an exponential, which is consistent with duration homogeneity (Dungey et al., 2014). An ACD (p,q) model with an exponential distribution is given as:

Equation 3.12

$$x_i = t_{i-}t_{i-1}, i = 1,2, \ldots.,$$

For simplicity, this research assumes that $x_i > 0$ for all i. The ACD model postulates that $x_i = \varphi_i \epsilon_i$, where $\{\epsilon_i\}$ is a sequence of independent and identical distributed (i.i.d.) random variables with $E(\epsilon_i) = 1$ and positive support, and φ_i satisfies

Equation 3.13

$$\varphi_i = \alpha_0 + \sum_{j=1}^{p} \alpha_j \, x_{i-j} + \sum_{v=1}^{q} \beta_v \, \varphi_{i-v},$$

where p and q are non-negative integers and α_j and β_v are constant coefficients. Since ϵ_i has a positive support, it may assume the standard exponential distribution. The exponential ACD model, EACD (1,1) is defined as:

Equation 3.14

$$x_i = \varphi_i \epsilon_i, \quad \varphi_i = \alpha_0 + \alpha_1 x_{i-1} + \beta_1 \varphi_{i-1}.$$

Under the weak stationary assumption, $E(x_i) = E(x_{i-1})$, so that:

Equation 3.15

$$E(x_i) = E(\varphi_{i-1}) = \frac{\alpha_0}{1-\alpha_1-\beta_1}.$$

Subsequently, $0 \leq \alpha_1 + \beta_1 < 1$ for a weakly-stationary process $\{x_i\}$.

The class of model that better predicts the change in sales for the created Brands Index is given in Chapter 5. As a result of the previous revision of existing financial theory methodologies for capturing volatility, the following causal relationship can be proposed in the present context to test the hypotheses:

> *Hypothesis 2: Volatility in the created Brands Index can be forecast using ARCH/GARCH models or any of their extensions.*
>
> *Hypothesis 3: Changes in weekly sales in the created Brands Index can be simulated using the volatility forecast.*

3.3 The Proposed CAPM-FMCG Competing Model

It was argued in Chapter 2 that the lack of a market index disallows the use of the CAPM in marketing research. Previous studies intending to use the CAPM for analysing portfolio indices, such as Cardozo and Smith (1985), failed due to the lack of such an index. This thesis revisits this topic by creating a comparative Brands Index in such a way that the CAPM can be used. As a result, portfolio theory related to the use of the CAPM will bring new insights to marketing research.

With a market index for the FMCG industry (the Brands Index; Section 3.1), the CAPM (Sharpe, 1964; Lintner, 1965) formula can be applied to evaluate risk for a brand or a set of brands. Two return calculation methodologies derived from the CAPM formula are given as follows, starting with the CAPM formula:

Equation 3.16

$$\tilde{r}_{it} - \tilde{r}_{ft} = \beta_i(\tilde{r}_{mt} - \tilde{r}_{ft}) + \tilde{\varepsilon}_{it}$$

$$\tilde{r}_{it} = \tilde{r}_{ft} + \beta_i(\tilde{r}_{mt} - \tilde{r}_{ft}) + \tilde{\varepsilon}_{it}$$

The table below highlights how this research will adapt the CAPM methodology in the context of the Brands Index, and introduce the CAPM-FMCG model.

Table 3.1 Specification 1: CAPM in the FMCG context, including risk-free

Term	Sharpe/Lintner CAPM	Term	CAPM-FMCG
$\tilde{r}_{it}$	the asset's return for period *t.*	$\tilde{r}_{it}$	the percentage change in value sales of a specific brand$_{(i)}$ at period *t*,
$\tilde{r}_{ft}$	the risk-free return for period *t.*	$\tilde{r}_{Bft}$	brand risk-free is equal to a brand base sales at period *t*
		$\tilde{r}_{Mft}$	market risk-free equal to the market base sales at period *t*
$\tilde{r}_{mt}$	the return on the market for period *t*	$\tilde{r}_{mt}$	the percentage change in value sales for the market at period t
β_i	the slope (beta) value	β_i	same
$\tilde{\varepsilon}_{it}$	the error term	$\tilde{\varepsilon}_{it}$	same

In order to satisfy the above conditions, the CAPM formula for the FMCG industry becomes:

Equation 3.17

$$\tilde{r}_{it} - \tilde{r}_{Bft} = \alpha_i + \beta_i(\tilde{r}_{mt} - \tilde{r}_{Mft}) + \tilde{\varepsilon}_{it}$$

Note that the risk-free component for a given brand $\tilde{r}_{Bft}$ in Equation 3.17 is different to that of the market $\tilde{r}_{Mft}$, as their respective base sales values are different. This is the main difference between Equation 3.16 (original fomula) and Equation 3.17 (modified formula for FMCG). Table 3.2 shows the analogy if the risk-free component is not considered and, thus, Equation 3.17 is reduced to:

Equation 3.18

$$\tilde{r}_{it} = \alpha_i + \beta_i(\tilde{r}_{mt}) + \tilde{\varepsilon}_{it}$$

Table 3.2 Specification 2: CAPM in the FMCG context, excluding risk-free

Sharpe/Lintner CAPM	CAPM-FMCG
$\tilde{r}_{it}$ is the asset's return for period *t*	$\tilde{r}_{it}$ is the percentage change in value sales of a specific brand for period *t*
$\tilde{r}_{ft}$ is the risk-free return for period *t*	there is no free-risk asset in this context.
$\tilde{r}_{mt}$ is the return on the market for period *t*	$\tilde{r}_{mt}$ is the percentage change in sales value of the Brands Index for period *t*
$\alpha_i and \beta_i$ are the intercept (alpha) and slope (beta) values	same
$\tilde{\varepsilon}_{it}$ is the error term with N(0,1)	same

The concept of a risk-free rate of return, within the context of this research, is expanded next. In the FMCG industry, total sales are made up of base sales (long-term sales) and incremental sales (short-term sales) coming from temporary price reductions and other factors as stated previously in this chapter. In Specification 1 from Table 3.1, the volatility that this research elaborates on is the volatility generated by the difference between total sales and base sales (known as incremental sales). Thus, this study focuses on the volatility originating from incremental sales (refer to Appendix 1 for the definition of base and incremental sales) and elaborates on both return calculation methodologies in Chapters 4 and 5. Therefore, the risk-free component within the FMCG context refers to base sales, because if no additional marketing-mix activities are conducted, then the brand's sales are simply its base sales. This concept is not far from that in finance, wherein a risk-free asset is understood as the theoretical rate of return of an investment with no risk of financial loss (Engle & Russell, 1998). Chapter 4 deals with the required adjustments to the CAPM formula in order to adapt it within the FMCG context. Chapter 4 shows the calculations for Specification 1 (substracting base sales from total sales) where the changes in sales do not consider the previous week's sales, but a base sales figure from the same period. As total sales are greater than or equal to base sales, then the returns from Specification 1 will always be positive. Specification 2, in contrast, shows positive and negative returns as the calculations consider the previous week's sales.

Both return calculation specifications from the CAPM formula, including and excluding the risk-free component, are analysed in Chapter 4 and tested in Chapter 5. Technically, when excluding the risk-free component from the CAPM formula, it is reduced to a single-index model (Benninga, 2001). The reduced formula is as follows:

Equation 3.19

$$\tilde{r}_{it} = \alpha_i + \beta_i(\tilde{r}_{mt}) + \tilde{\varepsilon}_{it}$$

The single-index model (SIM) was developed as an attempt to simplify some of the computational complexities of calculating variance-covariance matrices (Sharpe, 1963). The simple assumption in SIM is that the return of each asset can be linearly regressed on a market index.

The concept of *risk* in the FMCG industry, specifically on the topic of price promotions, has been studied by Franco-Laverde et al. (2012). In Chapter 2 it was stressed that a price promotion has inherent risk, and that the marketer's objective is to minimise this risk. This analogy allowed Franco-Laverde (2012) to draw parallels with financial markets and, in particular, modern portfolio theory (MPT). The most important point in portfolio theory is that investors should diversify. Brand managers, according to finance theory, should hold a portfolio of assets; accordingly, the risk they bear is the risk of the portfolio. The risk of a portfolio is less than the weighted sum of the risks of individual assets. The main conclusion from this statement is that the risk of an individual asset (understood as its variance or standard deviation) will be composed of two parts; a part that contributes to the risk of the portfolio, and a part that is diversified away (Bishop et al., 2000). This research deals with the adaptation of these concepts to brands in the FMCG industry. Thus, manufacturers offering a diverse number of brands to retailers across different categories should be able to apply these techniques in order to minimise their brands' risks. Chapter 4 deals with this operation in the FMCG industry.

The CAPM asserts that investors should hold a portfolio that is some combination of risk-free assets and the market portfolio, according to the investor's preference for risk. Thus, the risk of every asset that is borne by investors will be the component that contributes to the risk of the market, which is measured by its *beta* (β). Beta, in this context, is understood as a measure of the relative contribution of an asset to the risk of the market portfolio. It is also known as *aggregated risk* or *undiversifiable risk*. As the beta of the market portfolio is unity, all assets can be easily identified as being more or less risky than the market as whole. It then unfolds that if β > or < 1, then asset returns are more ($\beta > 1$) or less ($\beta < 1$) risky than market returns.

In the FMCG context, the creation of a Brands Index as a proxy for a market index allows this thesis to create a series of betas for each brand within the FMCG industry. These betas generated for FMCG brands are a close measure of the volatility, or systematic risk, of a brand's portfolio in comparison to the market as a whole (measured by the Brands Index). Chapter 4 deals with this operation in the FMCG industry.

The main critique to the CAPM is twofold; firstly, it is a model of expected returns but it can only be tested on ex-post realised returns. Secondly, the market portfolio used in testing the model should contain all risky assets, and no such portfolio is observable. Most indices of listed shares do not contain all risky assets. Further, these indices usually contain only a sample of listed shares (Roll, 1977). A key insight of Roll's critique is that the only legitimate test of the CAPM is whether the proxy for the market portfolio being used in empirical tests is, in fact, the market portfolio.

In finance, the variable of interest is asset returns, which are normally calculated as the natural log of the current share price divided by the share price in the previous period:

Equation 3.20

$ln\ (P(_t)/P(_{t-1}))$

Instead of having a return figure, this thesis utilises the relative change in sales values calculated using the same formula as in finance; that is:

Equation 3.21

$ln\ (Value\ Sales\ (_t)/Value\ Sales(_{t-1}))$

which is simply the natural logarithm of sales values in period *t* divided by sales values in period *t* - 1. Thus, the previous formula can be then applied with or without the inclusion of the risk-free component (i.e., base sales). Chapter 4 shows how the formula works so that both approaches can be tested and conclusions drawn on the best one.

Beta will be an estimate of the sales value risk of the brand being considered, while volatility will be first examined by calculating the variance (or standard deviation) of the percentage changes in sales values over some historical period. This will then become the volatility forecast for all future periods. This historical volatility will be useful as a benchmark for comparing the forecasting volatility of more complex models such as the ARCH- and GARCH-family models specified previously. Both return calculation methodologies—with and without risk-free components—will be developed in Chapter 4 and tested in Chapter 5.

Modern finance theory suggests that in order to test the SML, the following is required (Kürschner, 2008):

1. For each of the assets in question, determine the asset beta. This can be achieved by regressing each asset's return against the market index returns. This is often denoted as the *first-pass regression*.
2. Regress the mean returns of the assets on their respective betas; this is the *second-pass regression*.

If the CAPM in this descriptive format holds, then the second-pass regression should be the security market line (SML).

In the context of this research, the CAPM test is adapted to first regress the weekly changes in sales values for a set of brands against the Brands Index to obtain the first-pass regression. Second, the mean returns of the brands are also regressed again with the newly-obtained betas for each brand (or set of brands) to get the second-pass regression. If the model holds, then the SML should depict a statistically significant positive slope.

A full illustration of this methodology, in combination with their respective adjustments to the FMCG industry, will be considered in Chapter 4.

The theories studied so far have provided extensive and significant support for implementing the CAPM in the FMCG industry. All the manufacturers, suppliers and consumers are in place; a Brands Index as a proxy for a market index, brands as a proxy for assets, and the beta calculation as a proxy of volatility or systematic risk. Therefore, having recourse to the above supporting evidence, it is hypothesised:

> *Hypothesis 4: The calculation of beta (as a measure of volatility or systematic risk) allows a brand or set of brands to be compared with the market as a whole.*

Hypothesis 5: The computation of the second-pass regression (the mean returns of brands on their respective betas) should be the security market line (SML-FMCG).

The proposed conceptual framework and proposed competing models are tested in Chapter 5 using empirical information.

3.4 Synthesis

This chapter has described the creation of a Brands Index that will help measure the performance of the FMCG sector. The cap-weighted average method is most suitable and for that reason, AMV has found special mention here. The chapter has also defined brands' base sales and a suitable Brands Index to measure these. Base and incremental values are the two most important measures of the sales performance of retail brands in the FMCG industry. While *base value* refers to baseline sales, *incremental value* deals with additional sales resulting from managerial initiatives such as discounting and promotions.

The ARCH and GARCH models have served the purpose of measuring volatility clustering in the created Brands Index. However, volatility in financial markets is highly unpredictable and, sometimes, even these models fail (Mandelbrot 1963). Therefore, inception of a new model is important. This chapter has tried to present that proposed model by using the concept of volatility clustering. Volatility clustering correlates in a positive manner with the previous periods. Price promotional tactics are one of the important parts of volatility clustering, and the technique tries to make a positive splash among consumers. Favourable commodity prices increase customers' incentives to consume more.

The proposed model is specifically formulated in order to measure the performance of FMCG brands by taking the CAPM approach. Therefore, portfolio theory also can be used to gain insights into marketing research. The theory therefore allows us to measure the performance of one or more brands relative to the entire market.

CHAPTER 4: METHODOLOGY, DATA AND RESEARCH PLAN

4.0 Overview

This chapter provides justification for the methodology used in this thesis. The research design and analytical path of any research program should have a specific methodological direction based on its research objective and framework. The proposed framework describes the creation of a Brands Index for the FMCG industry in Australia. It uses a cap-weighted methodology similar to that of the Standards & Poor's (S&P500) and All Ordinaries (AOI) Indices, as discussed in Chapter 2. The framework then proposes a scientific investigation to quantify the observed volatility in the created Brands Index and, finally, proposes a modified CAPM to calculate individual brand for comparison with the overall FMCG market.

The calculation of each brand's beta provides an additional framework with which to build brand portfolios in marketing research. It goes beyond traditional approaches that were unable to achieve this due to the lack of a comparative index. Accordingly, this research sets up a methodology for the creation of a Brands Index, assesses and quantifies its volatility and, furthermore, strives to explore the use of brand betas through the application and modification of the CAPM. The aims of this chapter are to:

- present an overview of the data at hand, illustrating some key statistics and justifying the creation of a Brands Index that follows the S&P500 and AOI market index methods, within a research approach that validates the concept of volatility clustering (Section 4.1);
- propose a cap-weighted average indexing methodology to create a Brands Index for the Australian FMCG industry (Section 4.2);
- provide a rationalisation for the use of the ARCH/GARCH family of models to measure the observed volatility in the Brands Index (Section 4.3);
- explore the CAPM as an alternative technique to work out systematic risk and brand portfolios in the FMCG industry (Section 4.4); and

4.1 Data Availability and Key Statistics

The data for this research were taken from the Aztec dataset. Aztec is a provider of scan data for the FMCG industry. The database includes data on the Woolworths and Coles Group companies, and grocery stores in general. It also provides data for the pharmacy sector. The datasets are not available to the public, as brand owners must pay for it. However, the same data is also available for competitors that pay for it. Thus, it is available to a segment of the public which include other brands when they pay for this data. For the purposes of this research, the data I am permitted to use (with the condition to be de-branded and de-categorised) is real scan data recorded at a weekly frequency for five categories, which have been renamed and classified as follows:

1. *Category A* – comprising 91 brands, of which only 29 satisfied the condition for inclusion in the Brands Index. Share in the Brands Index is 31% from Year 6.
2. *Category B* – made of 41 brands where only 26 brands passed the condition to be included in the Brands Index. Share in the Brands Index is 13% from Year 6.
3. *Category C* - made of 116 brands where only 66 brands passed the condition to be included in the Brands Index. Share in the Brands Index is 16% from Year 6.
4. *Category D* - made of 20 brands where only 14 brands passed the condition to be included in the Brands Index. Share in the Brands Index is 2% from Year 6.
5. *Category E* - made of 28 brands where only 21 brands passed the condition to be included in the Brands Index. Share in the Brands Index is 38% from Year 6.

It will be recalled from the discussion in Chapter 2 that only brands currently selling products in retail supermarkets are considered for inclusion in the FMCG Brands Index and sectarian indices, and that brands with less than 52 weeks of available data are ineligible. A total of 296 brands were analysed, of which 156 satisfied the condition for inclusion. Category E was introduced in Year 6 with the intention of reworking the index divisor. For illustrative intentions, Table 4.1 shows the key statistics for the Brands Index and the five brands (one per category) with the highest value share for each category. Calculations for the top-10 brands in each category are shown in Appendix 6.

Table 4.1 Summary statistics for five brands and the Brands Index

Date	Brands Index	A-Brand1 Value	B-Brand1 Value	C-Brand1 Value	D-Brand1 Value	E-Brand1 Value
4/01/2004	**1,000.00**	$1,131	$470	$775	$128	$0
11/01/2004	**1,067.27**	$1,229	$486	$768	$140	$0
18/01/2004	**1,069.54**	$1,190	$514	$784	$144	$0
25/01/2004	**1,085.64**	$2,140	$590	$738	$154	$0
1/02/2004	**1,062.77**	$1,293	$489	$782	$145	$0
8/02/2004	**1,127.80**	$2,547	$587	$767	$161	$0
15/02/2004	**1,030.93**	$1,122	$521	$774	$149	$0
22/02/2004	**1,055.63**	$1,182	$505	$755	$174	$0
…	**…**	…	…	…	…	…
28/12/2008	**1,076.99**	$1,039	$591	$634	$237	$0
4/01/2009	**1,184.69**	**$1,170**	**$681**	**$687**	**$250**	**$3,741**
11/01/2009	**1,242.47**	$980	$670	$691	$343	$3,919
18/01/2009	**1,229.40**	$1,567	$796	$683	$278	$3,731
25/01/2009	**1,178.54**	$920	$696	$670	$262	$3,643
…	**…**	…	…	…	…	…
2/12/2012	**1,243.64**	$752	$722	$535	$289	$4,046
9/12/2012	**1,273.71**	$728	$695	$558	$293	$3,780
16/12/2012	**1,342.17**	$855	$672	$579	$425	$3,662
23/12/2012	**1,385.24**	$1,475	$1,196	$608	$333	$3,722
30/12/2012	**1,107.61**	$732	$840	$478	$280	$3,210
Key Statistics	**Brands Index**	**A-Brand1 Value**	**B-Brand1 Value**	**C-Brand1 Value**	**D-Brand1 Value**	**E-Brand1 Value**
Mean	**1,272.59**	$1,165	$826	$614	$309	$3,785
Std. Dev.	**61.98**	$527	$203	$50	$33	$302
Minimum	**1,079.93**	$563	$513	$478	$246	$3,062
Maximum	**1,458.26**	$4,084	$1,499	$753	$425	$5,450

The summary statistics in Table 4.1 are taken from week 262 in order to include Category E Brand1 figures. It can be seen that brand E-Brand1 has the highest share of the Brands Index. Tables 4.2 and 4.3 present the returns for the data provided. Both results are shown next: returns from the previous period and positive returns.

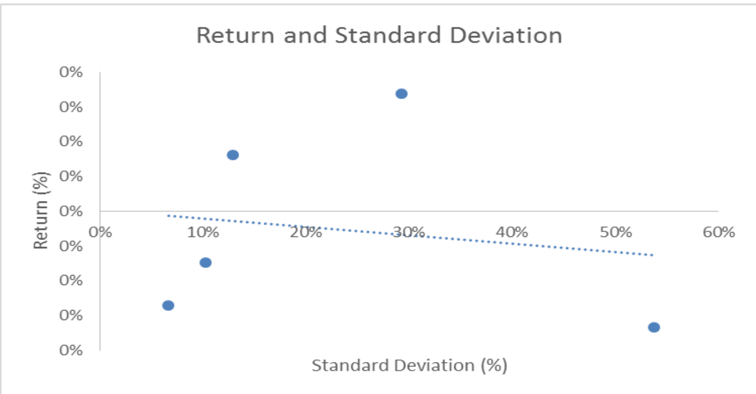
Table 4.2 Returns summary statistics for five brands and the Brands Index

Date	Brands Index	A-Brand1 Return	B-Brand1 Value	C-Brand1 Return	D-Brand1 Return	E-Brand1 Return

4/01/2004						
11/01/2004	**6.5%**	8.2%	3.5%	-0.8%	9.0%	
18/01/2004	**0.2%**	-3.2%	5.5%	2.0%	2.9%	
25/01/2004	**1.5%**	58.7%	13.9%	-6.0%	6.8%	
1/02/2004	**-2.1%**	-50.4%	-18.9%	5.7%	-6.1%	
8/02/2004	**5.9%**	67.8%	18.4%	-2.0%	10.4%	
15/02/2004	**-9.0%**	-82.0%	-12.0%	0.9%	-7.9%	
22/02/2004	**2.4%**	5.3%	-3.2%	-2.5%	15.8%	
…	**…**	…	…	…	…	
28/12/2008	**-27.5%**	-39.9%	-36.1%	-22.8%	-24.1%	
4/01/2009	**9.5%**	11.9%	14.3%	8.0%	5.6%	
11/01/2009	**4.8%**	-17.8%	-1.7%	0.6%	31.5%	4.6%
18/01/2009	**-1.1%**	46.9%	17.3%	-1.1%	-21.0%	-4.9%
25/01/2009	**-4.2%**	-53.2%	-13.4%	-2.0%	-6.2%	-2.4%
…	**…**	…	…	…	…	…
2/12/2012	**-5.4%**	-64.2%	9.7%	-2.2%	-9.6%	-15.8%
9/12/2012	**2.4%**	-3.2%	-3.8%	4.3%	1.2%	-6.8%
16/12/2012	**5.2%**	16.0%	-3.4%	3.6%	37.3%	-3.2%
23/12/2012	**3.2%**	54.5%	57.6%	4.9%	-24.5%	1.6%
30/12/2012	**-22.4%**	-70.0%	-35.3%	-24.1%	-17.2%	-14.8%
Key Statistics	**Brands Index**	**A-Brand1 Return**	**B-Brand1 Value**	**C-Brand1 Return**	**D-Brand1 Return**	**E-Brand1 Return**
Mean	**0.0001**	-0.0017	0.0017	-0.0014	0.0008	-0.0007
Std. Dev.	**0.0654**	0.5373	0.2928	0.0668	0.1294	0.1031
Minimum	**-0.2237**	-1.5761	-0.8242	-0.2405	-0.4186	-0.3755
Maximum	**0.2361**	1.4901	0.8243	0.2776	0.4034	0.4419

Table 4.2 presents some key statistics. From the weekly standard deviation, we see that A-Brand1 is the most volatile, followed by B-Brand1, D-Brand1, E-Brand1 and C-Brand1. All means are quite low, with only B-Brand1 and D-Brand1 being positive. A plot of the five brands' returns and their respective standard deviations is presented in Figure 4.1.

Figure 4.1 Relationship between returns and standard deviations for the five category-leading brands



Although the result is not conclusive as it is based on few observations, Figure 4.1 suggests a negative relationship between average returns and their respective standard deviations. This is inconsistent with theory, as it is expected that the most volatile brands should have higher returns. Returns calculated in a positive fashion (total sales in period *t* minus base sales in period *t*) are shown in Table 4.3, below.

Table 4.3 Returns (*Rf*) and Brands Index summary statistics for the five category-leading brands

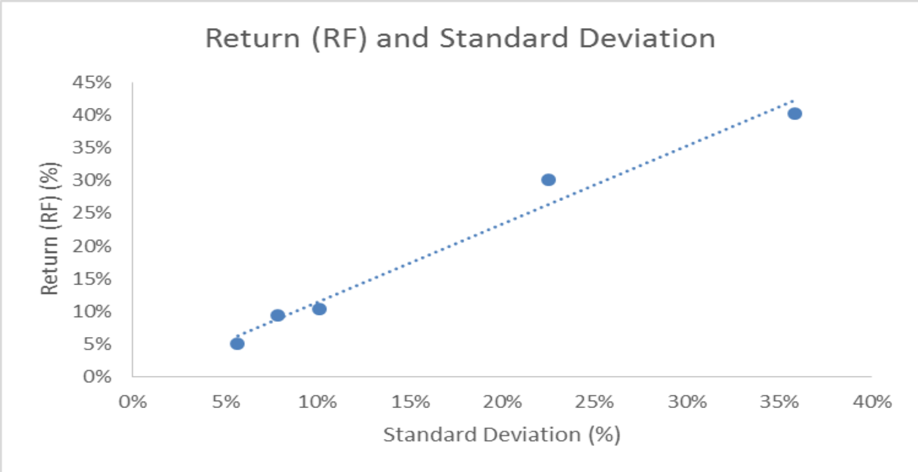
Date	**Brands Index (*Rf*)**	**A-Brand1 Return (*Rf*)**	**B-Brand1 Return (*Rf*)**	**C-Brand1 Return (*Rf*)**	**D-Brand1 Return (*Rf*)**	**E-Brand1 Return (*Rf*)**
4/01/2004	**0.0%**	0.0%	0.0%	0.0%	0.0%	
11/01/2004	**3.0%**	8.7%	0.0%	0.0%	0.0%	
18/01/2004	**3.2%**	5.5%	5.0%	0.0%	0.0%	
25/01/2004	**4.7%**	64.2%	18.9%	0.0%	6.8%	
1/02/2004	**2.5%**	13.8%	0.0%	0.0%	0.0%	
8/02/2004	**8.5%**	81.6%	18.4%	0.0%	11.1%	
15/02/2004	**0.0%**	0.0%	6.4%	0.0%	0.0%	
22/02/2004	**1.9%**	0.0%	0.0%	0.0%	18.9%	
…	**…**	…	…	…	…	
28/12/2008	**0.0%**	26.9%	0.0%	0.0%	0.0%	
4/01/2009	**0.0%**	40.8%	16.6%	7.3%	0.0%	5.5%
11/01/2009	**4.4%**	23.0%	14.9%	8.0%	31.5%	10.2%
18/01/2009	**3.4%**	69.9%	32.2%	6.8%	10.6%	5.3%
25/01/2009	**0.0%**	16.7%	18.7%	0.0%	0.0%	0.0%
…	**…**	…	…	…	…	…
2/12/2012	**0.0%**	11.3%	18.6%	0.0%	0.0%	18.7%
9/12/2012	**2.3%**	8.2%	14.8%	0.0%	0.0%	11.9%
16/12/2012	**7.6%**	24.2%	11.4%	5.6%	39.0%	8.7%
23/12/2012	**10.7%**	78.7%	69.0%	10.5%	14.5%	10.3%
30/12/2012	**0.0%**	8.7%	33.7%	0.0%	0.0%	0.0%

Table 4.3 (cont.)

Key Statistics	**Brands Index (*Rf*)**	**A-Brand1 Return (*Rf*)**	**B-Brand1 Return (*Rf*)**	**C-Brand1 Return (*Rf*)**	**D-Brand1 Return (*Rf*)**	**E-Brand1 Return (*Rf*)**
Mean	**0.0482**	0.4027	0.3010	0.0506	0.1034	0.0946
Std. Dev.	**0.0389**	0.3582	0.2251	0.0567	0.1009	0.0788
Minimum	**0.0000**	0.0000	0.0000	0.0000	0.0000	0.0000
Maximum	**0.1821**	1.6575	0.9546	0.2794	0.5252	0.4847

The term *Rf* in Table 4.3 indicates that the risk-free component has been taken into account while calculating the returns. Results in Table 4.2 show that the standard deviation follows the same pattern as Table 4.3 but at a lower scale. Importantly, the means are highly correlated with the returns.

Figure 4.2 Relationship between returns (*Rf*) and standard deviation for the five category-leading brands



The volatility of the Brands Index will be tested using ARCH-GARCH techniques, with special attention given to the E-GARCH model as it deals with positive returns. Traditional forecasting methods will also be evaluated on the Brands Index and compared with the predictions of the ARCH-GARCH models. Then, the CAPM model will be tested through the use of first-pass and second-pass regression. If the CAPM model in this descriptive format holds, then the second-pass regression should be equivalent to the security market line (SML). Therefore, the proposed models are tested in Chapter 5 and interpreted in Chapter 6.

4.2 Brands Index Methodological Approach

As stated in the conceptual framework in Chapter 3, this thesis proposes a cap-weighted average index methodology to create a Brands Index for the Australian FMCG industry. This is done in order to investigate the theoretical concept of volatility clustering drawn from the literature and tested according to the hypotheses stated in Chapter 2. The index methodology helps to measure the change in a brand's market return index expressed in terms of change from a base value. The conceptual framework seeks to quantify the observed volatility from the aggregated brand sales value data that frame this index. The approach for this investigation is explanatory and comprises the techniques used by the most relevant indices—the S&P500 and the AOI. However, for further conceptual validation, adjustments to the description of volatility are also presented.

Therefore, a definition of *volatility* within the FMCG context is specified. Accordingly, the proposed research incorporates, for first time in marketing research, the concept of *volatility clustering*—and provides empirical evidence for its presence.

As discussed in Chapter 2, financial index calculation methods are conventionally based on market capitalisation—i.e. outstanding shares multiplied by price. An example of the market capitalisation method is given in Table 4.4, below, for five artificial stocks. This can be easily extended for any asset portfolio. In Table 4.4, the outstanding shares for five companies, together with their return calculations, are provided. A total of three share prices are given as well as the percentage return. In this sense, no company maintains dominance over others, as share prices for the companies keep changing.

Table 4.4 Hypothetical outstanding shares for five companies and return calculation

Company	Shares	Share Price 0	Total (0)	Share Price 1	Total (1)	Share Price 2	Total (2)	Share Price 3	Total (3)	Return
Company1	6,000	$57.00	$342,000	$60.00	$360,000	$61.00	$366,000	$62.00	$372,000	
Company2	3,100	$84.00	$260,400	$82.00	$254,200	$81.00	$251,100	$80.00	$248,000	
Company3	10,000	$53.00	$530,000	$55.00	$550,000	$60.00	$600,000	$65.00	$650,000	
Company4	2,800	$125.00	$350,000	$120.00	$336,000	$110.00	$308,000	$100.00	$280,000	
Company5	5,000	$62.00	$310,000	$60.00	$300,000	$70.00	$350,000	$60.00	$300,000	
Index Value			**$1,792,400**		**$1,800,200**		**$1,875,100**		**$1,850,000**	**3.21%**

It can be seen that the cap-weighted index (last row) is weighted by market capitalisation, so its value for each period is the summation of that of all five companies. The index return is calculated as the index value in Period (3) divided by the index value in Period (0) minus one, and is expressed as a percentage. The previous calculation has used the discrete compounded return method for illustrative purposes. The alternative return calculation is based on continuously compounded returns, which are worked out as the natural log of the index value in Period (3) divided by the index value in Period (0), so the return is 3.16%. The continuously-compounded return will always be smaller than the discretely-compound return. However, the reason to choose the continuously-compound return over the discrete one is given below.

Equation 4.1

$P_t = P_{t-1}e^{rt}$

Using the continuously-compounded return assumes that $P_t = P_{t-1}e^{rt}$, where r_t is the rate of return during the period $(t$ - 1, $t)$. Suppose that r_1, $r2, \ldots r_{12}$ are the returns for 12 periods, then price of the stock at the end of the 12 periods will be $P_{12} = P_o e^{r1+r2+\ldots+r12}$. This representation of prices and returns allows us to assume that the average periodic return is $r = (r1+r2+\ldots +r_{12})/12$. Since we wish to assume that the return data for the 12 periods represents the distribution of returns for the coming period, it follows that the continuously-compounded return is the appropriate return measure, and not the discretely-compound return (Benninga, 2008).

As described in Chapter 3, the formula used to calculate the proposed Brands Index needs to be adjusted, as both *units sold* and *price per unit* across all brands in the index change from period to period. This is in opposition to financial indices where the outstanding shares remain fairly constant for long periods of time. Lower prices in the FMCG industry are aimed at driving demand so that the number of units sold increases in response to lower prices. Brand managers therefore expect to gain more sales due to the presence of a higher number of units sold at a lower price and profit margin. As presented above in the results of the five artificial stocks example, Table 4.5 depicts the results for different units and prices from Period *(0)* to Period *(2)* for five brands, in order to estimate the Brands Index return.

Table 4.5 Hypothetical brand sales values and returns for five brands

Column 1	**Column 2**	**Column 3**	**Column 4**	**Column 5**	**Column 6**	**Column 7**	**Column 8**	**Column 9**	**Column 10**	**Column 11**
Company	**Units 0**	**Price 0**	**Total (0)**	**Units 1**	**Price 1**	**Total (1)**	**Units 2**	**Price 2**	**Total (2)**	**Return**
Brand1	5,000	$20	$100,000	10,000	$14	$140,000	5,200	$20	$104,000	
Brand2	4,500	$23	$103,500	4,600	$22	$101,200	16,000	$11	$176,000	
Brand3	2,500	$24	$60,000	2,700	$23	$62,100	4,900	$12	$58,800	
Brand4	1,200	$21	$25,200	3,600	$9	$32,400	1,150	$21	$24,150	
Brand5	12,500	$12	$150,000	5,500	$22	$121,000	5,600	$22	$123,200	
Index Value			**$438,700**			**$456,700**			**$486,150**	**10.27%**

The columns named ‘Units 1’ and ‘Units 2’ in Table 4.5 above have been added to the table, as units are not constant in the Brands Index computation. Following the cap-weighted methodology in Chapter 2, the index value (last row) is worked out as the weighting of total brand sales value for each period. Accordingly, the Brands Index value for each period is the summation of all five brands index values. The index return is calculated following the continuously-compounded formula.

Note that the above calculations do not take into account the risk-free component, as no subtraction has been made from Brands Index returns. Section 4.4 – CAPM within the FMCG context— shows the calculations required to obtain the Brands Index returns when the risk-free component (i.e. base sales) is taken into account. This research is interested in the volatility resulting from incremental sales as previously explained in Chapter 3. For optimal marketing volatility, there is a need for increased trade-off sales to counter the incremental effect. Thus, incremental sales will be the main driver of the observed volatility when looking at the positive returns option. An in-depth evaluation of the total value sales volatility will help the brand mangers make informed decisions regarding their FMCG products. This thesis is concerned with the change in total sales values of FMCG products sold at two major retailers in Australia: Woolworths and Coles.

As a starting point for creating the Brands Index, Table 4.6 shows the aggregated data from five FMCG categories operating within the FMCG industry at Woolworths and Coles. Section 4.1 provides details for each category that makes up the Brands Index, with key statistics for the Brands Index and selected brands. Volatility measurement is then rationalised in Section 4.3 with the application of ARCH-GARCH models. It also shows the difference in the Brands Index, with and without the risk-free component (base sales), to begin drawing findings.

i. Brands Index Value (BIV)

Brands Index Value is a figure measuring the perceptions of different brands and the real-time image of their products in the market as well as those from other competitors. The data is available on an instant-access platform (Aztec database) where manufacturers, suppliers and consumers can track any changes in brand perception by comparing results from different retail outlets in Australia. It is an important tool that can help producers and retailers improve on their marketing strategies to attract more customers by analysing the brand sales from different consumers across the Australian FMCG market. The data in Table 4.6 is from the Aztec database. Notes and clarifying figures for Table 4.6 are as follows:

1. Of the five categories, Category E was introduced in January 2009 with the intention of demonstrating the index adjustment concept introduced in Chapter 2, Section 2.2.1. From Table 4.6, the Brands Index value (BIV) is the summation of categories A, B, C and D up to December 2008. After the introduction of category E in January 2009, the BIV shows a clear step change that requires adjustment (see Figures 4.3 to 4.7 below).

2. The column named 'Index Value – Divisor' in Table 4.6 reworks the Brands Index starting from 1,000 and using it as a divisor for the first observation in week 1 ($12,457).

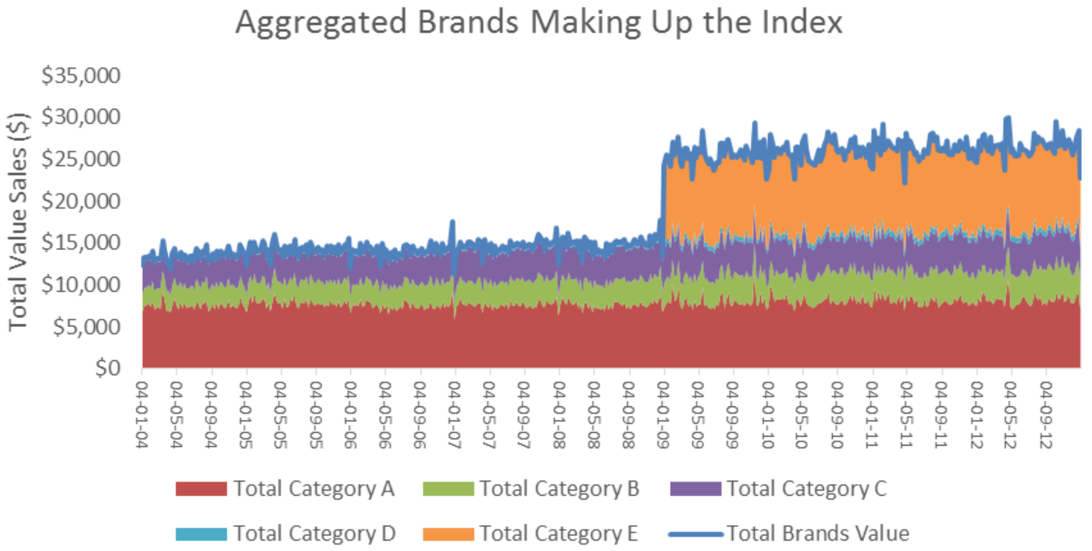
3. The Brands Index is then adjusted from week 262 to avoid a step change in the data (jumping from 1,076 in week 261 to close to 2,000 in week 262) due to the introduction of a new Category. Thus, a new divisor was introduced ($24,359).

4. The final Brands Index is placed in the column named "Index Adjustment" and the returns are calculated in the last column as the natural logarithm of the BIV at period (t), $BIV(t)$ divided by the BIV at period ($t-1$), $BIV(t-1)$.

Table 4.6 Brands Index Value (BIV)

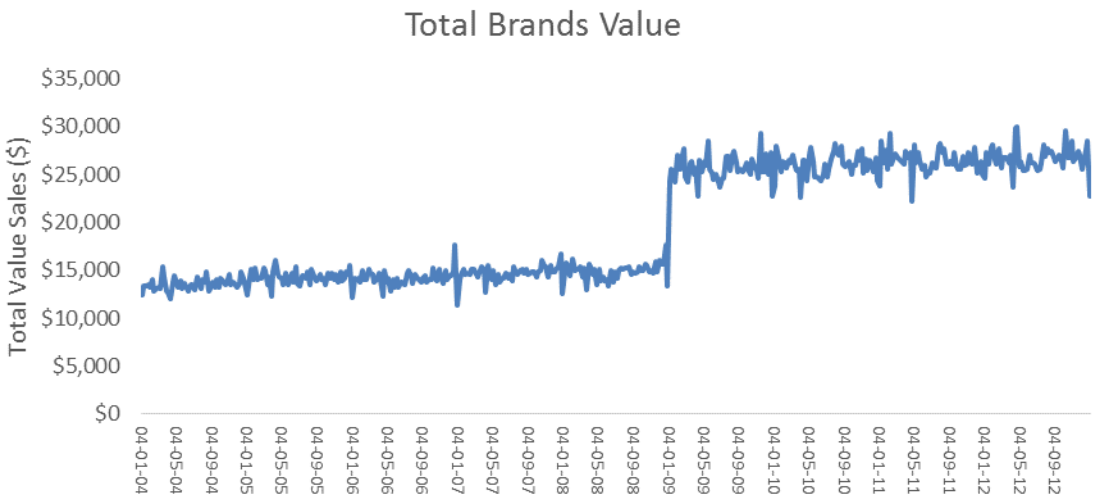
Date	Brands Index Value	Total Category A	Total Category B	Total Category C	Total Category D	Total Category E	Index Value - Divisor	Index Adjustment	Index Return= $\ln(BI_{(t)}/BI_{(t-1)})$
4/01/2004	**$12,457**	$6,863	$1,979	$3,280	$335	**$0**	1,000.00	1,000.00	
11/01/2004	**$13,295**	$7,603	$2,103	$3,232	$357	**$0**	1,067.27	1,067.27	6.51%
18/01/2004	**$13,323**	$7,584	$2,117	$3,260	$362	**$0**	1,069.54	1,069.54	0.21%
25/01/2004	**$13,523**	$7,922	$2,138	$3,100	$364	**$0**	1,085.64	1,085.64	1.49%
1/02/2004	**$13,239**	$7,415	$2,183	$3,282	$358	**$0**	1,062.77	1,062.77	-2.13%
8/02/2004	**$14,049**	$8,163	$2,360	$3,157	$367	**$0**	1,127.80	1,127.80	5.94%
15/02/2004	**$12,842**	$7,093	$2,159	$3,227	$363	**$0**	1,030.93	1,030.93	-8.98%
22/02/2004	**$13,150**	$7,278	$2,292	$3,200	$380	**$0**	1,055.63	1,055.63	2.37%
29/02/2004	**$13,202**	$7,446	$2,215	$3,188	$353	**$0**	1,059.82	1,059.82	0.40%
7/03/2004	**$13,138**	$7,137	$2,428	$3,196	$377	**$0**	1,054.65	1,054.65	-0.49%
…	**…**	…	…	…	…	**…**	…	…	…
28/12/2008	**$13,416**	$6,791	$2,396	$3,767	$462	**$0**	1,076.99	1,076.99	-27.55%
4/01/2009	**$24,359**	**$7,412**	**$2,909**	**$4,040**	**$511**	**$9,487**	**1,955.48**	**1,184.69**	**9.53%**
11/01/2009	**$25,547**	$7,836	$2,997	$4,133	$618	$9,964	2,050.85	1,242.47	4.76%
18/01/2009	**$25,278**	$8,141	$2,877	$4,106	$539	$9,616	2,029.28	1,229.40	-1.06%
25/01/2009	**$24,232**	$7,757	$2,655	$3,971	$531	$9,318	1,945.33	1,178.54	-4.22%
1/02/2009	**$27,039**	$10,283	$2,827	$4,053	$532	$9,344	2,170.62	1,315.02	10.96%
8/02/2009	**$25,578**	$8,153	$2,875	$4,100	$608	$9,843	2,053.38	1,244.00	-5.55%
15/02/2009	**$26,526**	$8,242	$2,899	$4,333	$546	$10,506	2,129.49	1,290.11	3.64%
…	**…**	…	…	…	…	…	…	…	…
18/11/2012	**$27,373**	$8,894	$3,935	$4,146	$599	$9,799	2,197.43	1,331.27	2.51%
25/11/2012	**$26,991**	$7,959	$3,673	$4,171	$619	$10,569	2,166.82	1,312.72	-1.40%
2/12/2012	**$25,571**	$7,839	$3,213	$4,149	$579	$9,790	2,052.78	1,243.64	-5.41%
9/12/2012	**$26,189**	$7,958	$3,458	$4,121	$595	$10,057	2,102.42	1,273.71	2.39%
16/12/2012	**$27,597**	$8,992	$3,428	$4,249	$722	$10,206	2,215.43	1,342.17	5.24%
23/12/2012	**$28,482**	$8,880	$4,061	$4,681	$615	$10,245	2,286.51	1,385.24	3.16%
30/12/2012	**$22,774**	$7,089	$3,118	$3,819	$536	$8,212	1,828.26	1,107.61	-22.37%

Figure 4.3 Total Brands Value made of five unadjusted categories



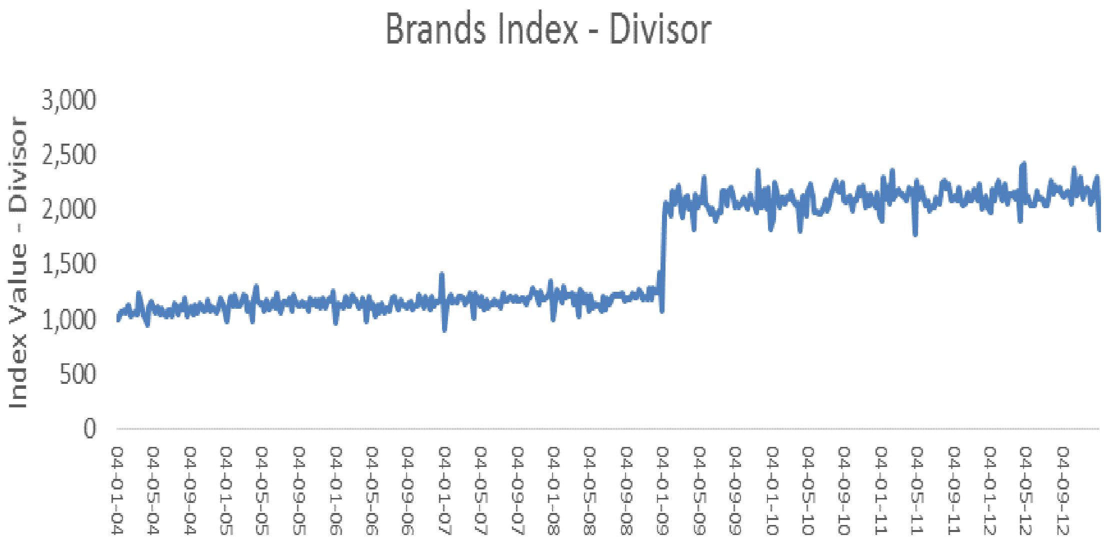
Of the five categories, Category E was introduced in January 2009 with the intention of demonstrating the Index adjustment concept introduced in Chapter 2, Section 2.2.1. From Table 4.6, the BIV is the summation of data for Categories A, B, C and D up to December 2008. After the introduction of Category E in January 2009, the BIV shows a clear step-change that requires adjustment to avoid the observed step-change below in Figure 4.4.

Figure 4.4 Total Brands Value



The column named ‘Index Value – Divisor’ in Table 4.6 reworks the Brands Index starting from 1,000 and using it as a divisor for the first observation in week 1 ($12,457). See Figure 4.5, below.

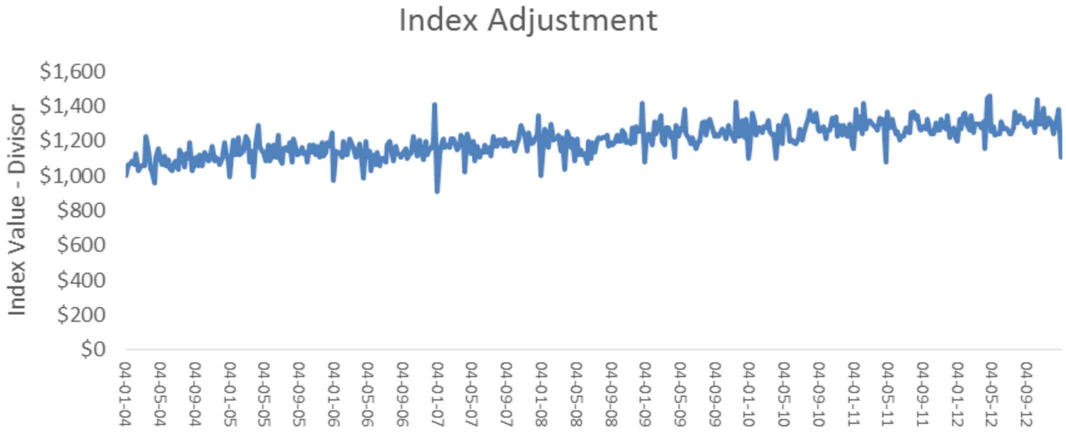
Figure 4.5 Brands Index before using the divisor methodology



Due to the introduction of a new category (Category E), the Brands Index is then adjusted from week 262 to avoid a step-change (jumping from 1,076 in week 261 to close to 2,000 in week 262) as seen in Figure 4.5, above. Thus, a new divisor was introduced ($24,359) from this point onwards.

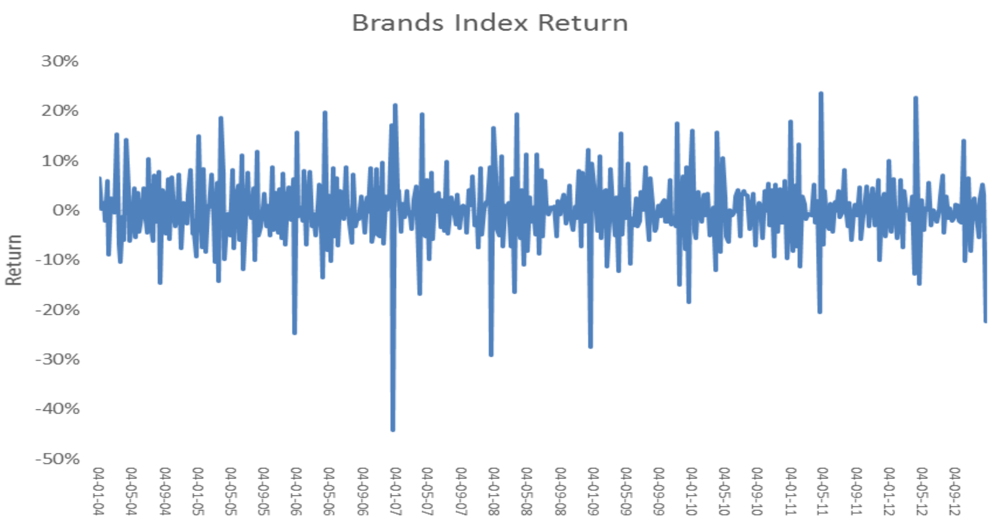
The final Brands Index is placed in the column named “Index Adjustment”. Figure 4.6 shows that due to the introduction of the new divisor from week 262, the step-change has disappeared. The index adjustment concept and formula was introduced in Chapter 2, Section 2.2.1.

Figure 4.6 Index adjustment.



In Table 4.6, the column named "Index Adjustment" and the returns are calculated in the last column as the natural logarithm of the BIV at period (*t*), *BIV(t)* divided by the BIV at period (*t-1*), *BIV(t-1)*. Figure 4.7, below, shows the adjusted Brands Index returns with positive and negative values.

Figure 4.7 Adjusted Brands Index Return



The above discussion presents evidence of similar positive and negative fluctuations in product returns volatility at different periods in their retail life. It implies that total sales value volatility affects the sales of products, as huge changes will result in huge return values. The following section explores the ARCH/GARCH techniques that deal with the topic of volatility clustering, as it can be seen from Figure 4.5 that the amplitude of the returns varies over time. Thus, the goal of these models is to provide a volatility measure like a standard deviation that can be used in marketing decisions concerning risk analysis and portfolio selection.

4.3 Rationalisation for the use of ARCH/GARCH and their extended modelling techniques.

As discussed in Chapter 3, the motivation for employing the ARCH class of models is the phenomenon known as *volatility clustering*, whereby the current level of volatility tends to be positively correlated with its level during the immediately preceding periods. Following this rationale and observing Figure 4.5, it seems that volatility clustering is present in the returns of the Brands Index. There is evidence of volatility clustering due to the presence of similar positive and negative fluctuations in the returns of the volatility of the products at different lags of the product. The main focus of this research is on the volatility that arises from incremental sales rather than from the total change in sales, as shown in Figure 4.5. Incremental sales generate volatility as some brands react after a brand has taken initiatives such as major investment in advertising, new product development or price promotions. Such volatility makes the market relatively more ‘noisy’, as the other brands tend to follow suit. After a while, the market should return to a more stable pattern until the next initiative is made.

The mathematical formulation for the ARCH-GARCH class of models has been given in Chapter 3, in addition to those of the TGARCH and EGARCH models. These four theoretical models will be used to quantify volatility. The EViews software will be the main tool used for this purpose. The five hypotheses presented in Chapter 3 will be validated in Chapter 5. However, as Brands Index returns is the key variable in this research—not only for measuring volatility but also for applying the CAPM to FMCG industry data—the rest of this section is devoted to the calculation of Brands Index returns, taking into account base sales.

As previously discussed in Chapter 3, the risk-free rate of return in finance is understood as the theoretical rate of return of an investment with no risk of financial loss in a given period of time. Government bonds are normally the best proxy for the risk-free rate of return (Bishop et al., 2000). The risk-free rate in this sense slightly varies from time to time. In the CAPM formula, $\tilde{r}_{ft}$ is placed in both sides of the equation and it takes the same value, as follows:

Equation 4.2

$$\tilde{r}_{it} - \tilde{r}_{ft} = \alpha_i + \beta_i(\tilde{r}_{mt} - \tilde{r}_{ft}) + \tilde{\varepsilon}_{it}$$

In the absence of the risk-free component (i.e. base sales in the current context) the returns in the FMCG context should simply be calculated as *ln(BIV(t)/BIV(t*-1*))* as discussed in Section 4.2 where *ln* is the natural logarithm and *BIV* is the Brands Index value at periods (*t*) and (*t*-1), respectively. However, as this thesis has also highlighted the fact that the volatility of interest originates from incremental sales, the next two fundamental equations unfold:

Equation 4.3

BIV - Total Sales = BIV - Base Sales + BIV - Incremental Sales

where:

Equation 4.4

BIV - Base Sales = BIV - Total Sales - BIV - Incremental Sales

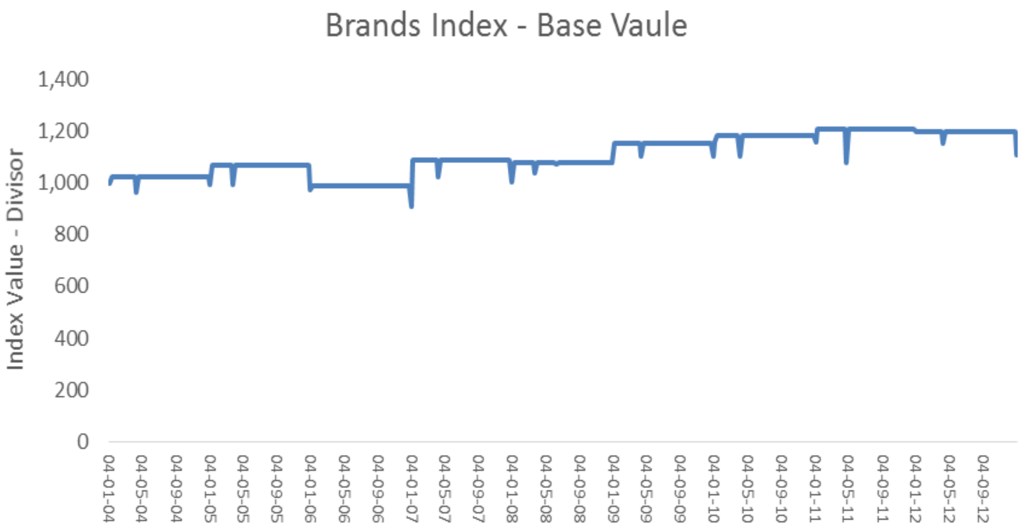
From Equations 4.3 and 4.4 above, it is clear that all we have is total sales and we need then to calculate the Brands Index base values in order to solve for incremental sales.

Brands Index base sales (discussed earlier in this chapter) are understood as the sales that would have been made if the brands making up the Brands Index were not conducting price promotion or any other marketing activities aimed to increase short-term sales. The same definition applies for each individual brand within the Brands Index. Thus, base sales should be the lowest value that the Brands Index takes in a given period of time, disregarding natural peaks or dips due to holidays or seasonality (as in the case of very seasonal categories such as ice cream, instant soup, soft drinks). This is obtained by sorting the data to remove outliers before analysis. Finally, the base estimate also requires an upper and lower threshold to capture the small weekly variations that are not pure incremental sales.

Although the Brands Index base, theoretically, should be the sum of the base sales of all brands making up the index, this research works with a proxy base, as explained next.

The calculation of base sales can be achieved by disregarding those specific outliers where sales naturally decrease due to holidays such as Easter or Christmas when the main retailers close for a few days (less than a week) or increase due to marketing activities (price promoitons, advertising, etc.) . This research considers a data point to be an outlier if the natural logarithm of the sales value in period *t* divided by the sales value in period *t*-1 is larger than 3% in absolute terms. The formula used is equal to ln(sales value(t)/sales value (t-1)). The data is sorted and filtered to remove these outliers, which are likely to distort the expected findings. The base computation also needs to make sure that in any given week, total sales are always greater than or at least equal to the calculated base sales. In addition, if the Brands Index exhibits a growing or declining trend, then the base sales should vary accordingly for a specified period of time. For the purposes of this research, the Brands Index and the individual brands under analysis vary their base sales every 52 weeks. Thus, having nine years of weekly data, nine different base sales figures need to be calculated. However, there is nothing to prevent us recalculating the base sales value over a shorter frequency (e.g. quarters). The decision must be made case-by-case using sales figures with the intention of capturing any upward or downward trend. Brands selling seasonal products such as ice cream, soft drinks or instant soup will, for instance, require more frequent base sale calculations in order to describe seasonal patterns in sales. If no clear trends are depicted in sales, then the baseline value becomes a straight line. This depends on the set base period when the analysis should commence. Observations for longer periods give a better representation of volatility clustering due to repeated patterns at similar periods in the calendar.

Figure 4.8 Base value of the Brands Index



It can be seen from Figure 4.8, above, that nine clear values have been calculated for each year of available data. In addition, outliers related to specific holidays have also been taken care of. Figure 4.9 provides a combined chart showing both total sales and base sales for the Brands Index. The calculation of base sales is important, as it represent the sales that would have happened if no marketing activities, such as price promotions, had taken place. The base sales are the point where sales return to after a price promotion, so the incremental sales can be calculated as total sales minus base sales. Figure 4.10 shows the result for incremental sales.

Figure 4.9 Brands Index – total value and base value

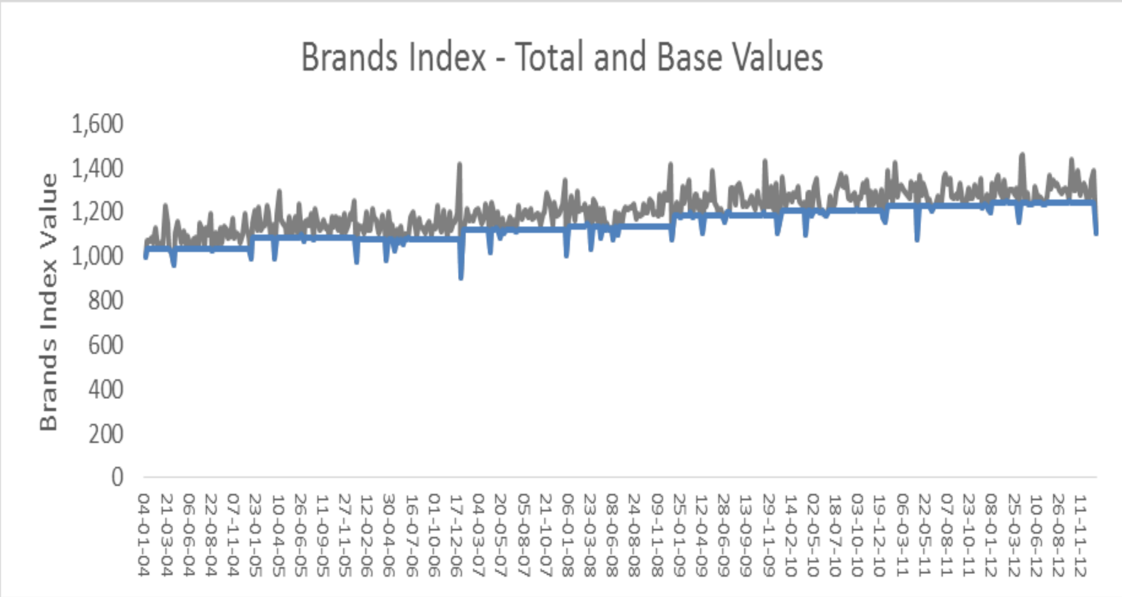
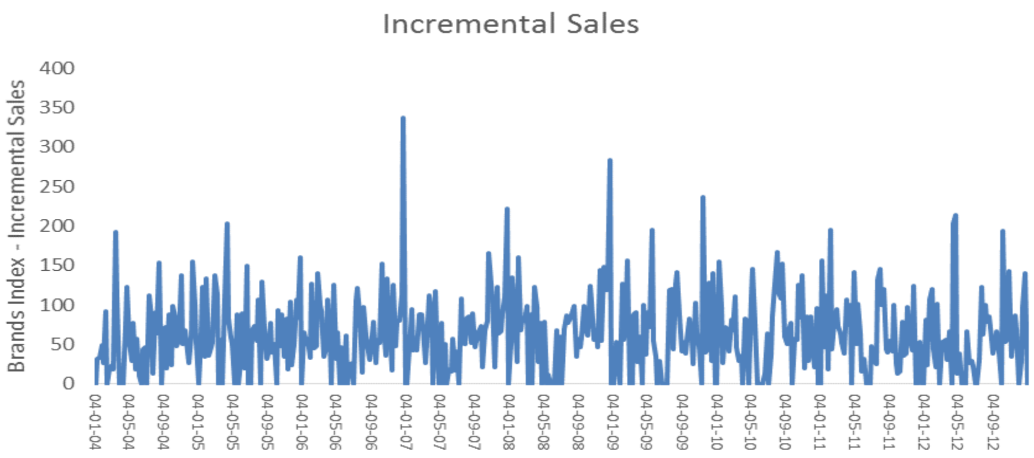


Table 4.7, below, shows the nine different values used to obtain the base values in Figure 4.9, so that incremental sales values can then be calculated as the difference between total sales values and base sales values. It is quite important to get the base calculation right to avoid corrupting the expected results, as the incremental sales volatility is the one that this study focuses on when dealing with the risk-free rate of return.

Table 4.7 Minimum Brands Index values

Year	Brands Index - Minimum Value
Year 1	1036.1
Year 2	1087.2
Year 3	1075.0
Year 4	1122.2
Year 5	1135.1
Year 6	1188.5
Year 7	1205.5
Year 8	1226.3
Year 9	1244.5

Figure 4.10 Brands Index – Incremental Sales



The following three conditions need to be met before the returns results are determined.

1. Total sales value must always be greater or equal to the base sales value, to make sure that returns are always positive. This condition is necessary when computing the index returns based on incremental sales, which are positive in nature, as shown in Equation 4.5.
2. The minimum base value must be chosen after accounting for holidays or any sort of outliers. Thus, it is not the lowest value observed.
3. An upper and lower boundary for the base is essential to avoid returns that are not considered as incremental sales.

The calculation of the incremental sales returns in Equation 4.5 follows from Equation 4.4.

Equation 4.5

$$BIV Incremental = BIV Total\ Sales - BIV Base\ Sales$$

By dividing both sides of Equation 4.5 by $BIV_{\text{Base Sales}}$, it is possible to achieve the incremental returns ratio, which is simply the discrete compounded return, as follows:

Equation 4.6

$$\frac{BIVIncremental}{BIVBase\ Sales} = \frac{BIVTotal\ Sales - BIVBase\ Sales}{BIVBaseSales}$$

so the incremental sales returns becomes:

Equation 4.7

$$IncrementalReturn = \frac{BIVTotal\ Sales}{BIVBase\ Sales} - 1$$

Once the risk-free component (*Base Sales*) is subtracted from the *Total Sales*, a return for incremental sales is then obtained. Following from modern financial theory, this research is also interested in the continuously-compounded returns—the natural logarithm of *Total Sales* divided by *Base Sales*, as per Equation 4.8 below:

Equation 4.8

$$IncrementalReturn = ln\left[\frac{BIVTotal\ Sales_t}{BIVBase\ Sales_t}\right]$$

Two main modifications from the original formula of the CAPM including a risk-free component have been elaborated for the calculation of incremental returns in the FMCG industry. First, the denominator in the case of the FMCG industry is not the previous period sales (*t*-1*)*. The denominator in the FMCG instance is the *Base Sales* figure in period (*t*). Second, in the CAPM, the risk-free rate is the same value on both sides of the equation whereas in the FMCG industry, the risk-free component (*Base Sales*) on the left side is the corresponding base sales for any given brand under analysis, while the risk-free component on the right side of the equation is always the base sales of the overall Brands Index.

Note that depending on how flat or how seasonal a brand trend is, the base needs to be adjusted to avoid misleading returns coming from a lower/higher base that is not related with the incremental response. Thus, base sales will need to be adjusted to capture these patterns.

Table 4.8 below shows the output of calculations done to estimate the incremental returns for the Brands Index based on the base sales values calculated previously (Figure 4.10).

Table 4.8 Summary of Brands Index returns with and without risk-free rate of return

Date	Brands Index Value	Brands Index - Base Value	Brands Index - Incremental Value	Index Return Without Risk-Free	Index Return With Risk-Free
4/01/2004	1,000.00	1,000.00	0.00		0.00%
11/01/2004	1,067.27	1,036.08	31.19	6.51%	2.97%
18/01/2004	1,069.54	1,036.08	33.46	0.21%	3.18%
25/01/2004	1,085.64	1,036.08	49.55	1.49%	4.67%
1/02/2004	**1,062.77**	**1,036.08**	**26.69**	**-2.13%**	**2.54%**
8/02/2004	1,127.80	1,036.08	91.72	5.94%	8.48%
15/02/2004	1,030.93	1,030.93	0.00	-8.98%	0.00%
22/02/2004	1,055.63	1,036.08	19.55	2.37%	1.87%
29/02/2004	1,059.82	1,036.08	23.74	0.40%	2.27%
7/03/2004	1,054.65	1,036.08	18.57	-0.49%	1.78%
14/03/2004	1,229.24	1,036.08	193.16	15.32%	17.09%
…	…	…	…	…	…
21/10/2012	**1,300.24**	**1,244.52**	**55.72**	**0.17%**	**4.38%**
28/10/2012	1,387.67	1,244.52	143.15	6.51%	10.89%
4/11/2012	1,278.94	1,244.52	34.41	-8.16%	2.73%
11/11/2012	1,298.27	1,244.52	53.74	1.50%	4.23%
18/11/2012	1,331.27	1,244.52	86.75	2.51%	6.74%
25/11/2012	1,312.72	1,244.52	68.20	-1.40%	5.33%
2/12/2012	1,243.64	1,243.64	0.00	-5.41%	0.00%
9/12/2012	1,273.71	1,244.52	29.19	2.39%	2.32%
16/12/2012	1,342.17	1,244.52	97.65	5.24%	7.55%
23/12/2012	1,385.24	1,244.52	140.71	3.16%	10.71%
30/12/2012	1,107.61	1,107.61	0.00	-22.37%	0.00%

Table 4.8 above shows the resulting data after applying all calculations discussed earlier in this section. Both returns—with and without the risk-free component—have been calculated using the continuously-compounded return formula to show their effect on volatility clustering. The index return without the risk-free component uses the previous

data point to get the return (t-1) so one observation is lost, while the index return including the risk-free component utilises the data during the same period, and all returns are positive. The rationale behind displaying both returns becomes more evident in Chapter 5, as volatility forecasts from returns with and without the risk-free component are more accurate than when the risk is included.

By way of an example, in week 5, the return without the risk-free component is -2.13% [*ln(1,062.77/1,085.64)]* whereas the return with the risk-free component of 2.54% in the same week [*ln(1,062.77/1,036.08)*]. It is important to notice that both indices move in the same direction but the magnitude of the return is what makes the difference. Figure 4.11 below shows the positive returns (with the risk-free component) and Figure 4.12 following provides a comparison of both return calculation methodologies.

Figure 4.11 Brands Index with risk-free rate

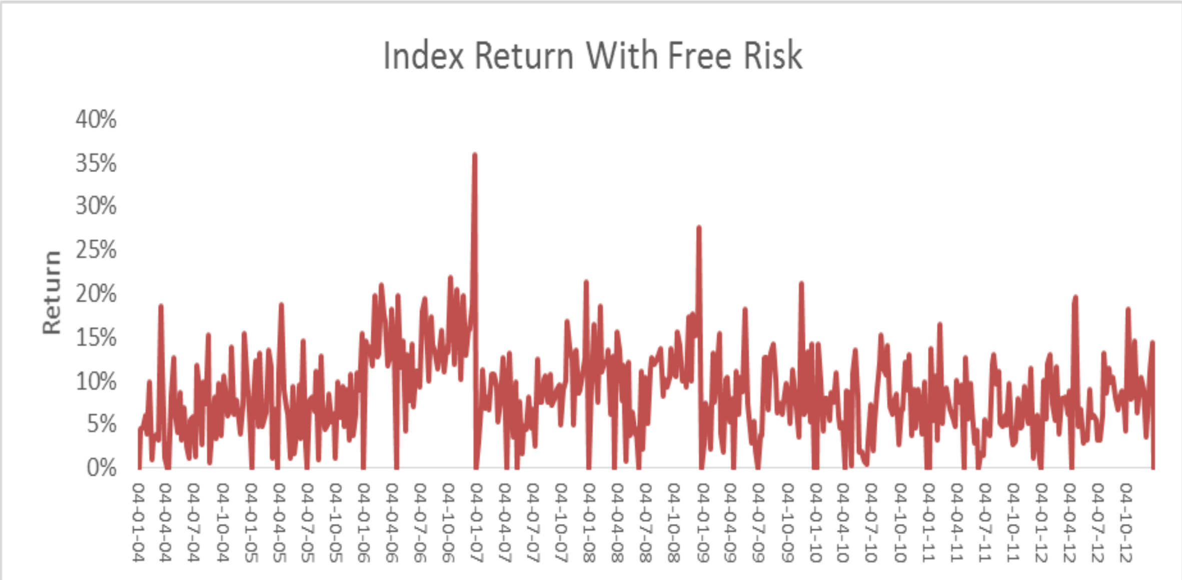
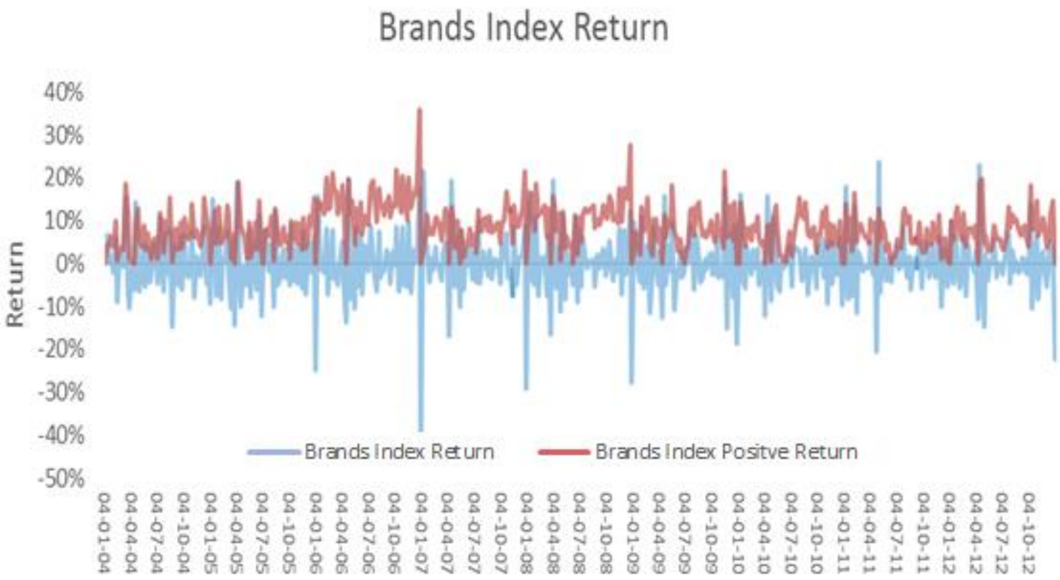


Figure 4.12 Index Comparison with and without risk-free rate



As discussed in Chapter 2, the autoregressive conditional duration (ACD) model was proposed by Engle and Russell (1998) to model irregularly-spaced financial transaction data, as seen in risk-free rate returns. Within this framework, duration is commonly defined as the time interval between consecutive events. Thus, a cluster of short durations corresponds to active trading and, hence, an indication of the existence of new information (Tsay, 2005). Since duration is necessarily non-negative, the ACD model has also been used to model time series that consist of positive observations. An example is the daily range of the log price of an asset. The range of an asset price during a trading day can be used to measure its price volatility. Therefore, studying ranges can serve as an alternative approach to volatility modelling (Parkinson, 1980). In addition, the error distribution of ACD models moves closer to being exponential, which is consistent with duration homogeneity (Dungey et al., 2014).

Although the fundamental objective of this research is not on ACD models, Chapter 5 show the results of its application on the created Brands Index (FMCGBR_RF), which depicts only positive returns. It can be also anticipated that the EGARCH model by Nelson (1991) will be the most suitable for capturing Brands Index volatility. The reason for this is that since the $log\ (\sigma_t^2)$ is modelled, then even if the parameters are negative, $\sigma_t^2 t$ will be positive. There is thus no need to artificially impose non-negativity. Furthermore, asymmetries are allowed for under the EGARCH formulation, since if the relationship between volatility and returns is negative, then y will also be negative (Brooks, 2008).

Equation 4.9

$$\ln(\sigma_t^2) = w + \beta \ln(\sigma_{t-1}^2) + \mathrm{y}\frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right]$$

Section 4.4 following focuses on the left-hand side of the CAPM and deals with the required changes to create brand *i*'s base sales and calculate the returns accordingly, as was done in this section for the Brands Index.

4.4 CAPM as a Proxy for Systematic Risk in the FMCG Industry

The discussion in the previous section explored two return calculation methodologies for index returns; the first dealt with the continuously-compounded returns computation based on previous observations, which allows for negative returns; and the second alternative created only positive returns by looking at total value changes from a starting point—the base sales. Thus, the concept of the risk-free component in the FMCG context has been understood as base sales, and it is subtracted from total sales to generate incremental sales as per Equation 4.5. The same methodology as that of Section 4.2 will be used to calculate returns with and without the risk-free component but at the brand level. In Section 4.1, it was shown that the index is the sum of all categories in it (in this research, a total of five categories). However, as we are moving one level down, at category level we need to look at the brands that make up a category. Table 4.6 is an example for brands in Category A at FMCG retail outlets.

Table 4.9 Brands making up Category A

Date	Category A	A-Brand1	A-Brand2	A-Brand3	…	A-Brand91
4/01/2004	**$6,863**	$1,131	$337	$461		$13
11/01/2004	**$7,603**	$1,229	$371	$365		$12
18/01/2004	**$7,584**	$1,190	$386	$424		$12
25/01/2004	**$7,922**	$2,140	$444	$368		$12
1/02/2004	**$7,415**	$1,293	$412	$338		$11
8/02/2004	**$8,163**	$2,547	$390	$323		$11
15/02/2004	**$7,093**	$1,122	$387	$373		$11
22/02/2004	**$7,278**	$1,182	$377	$371		$11
29/02/2004	**$7,446**	$1,254	$408	$346		$10
7/03/2004	**$7,137**	$1,127	$445	$550		$9
14/03/2004	**$9,383**	$3,309	$395	$309		$9
21/03/2004	**$8,301**	$2,769	$393	$448		$9
28/03/2004	**$6,972**	$1,126	$517	$316		$10
4/043/2004	**$6,927**	$1,216	$378	$428		$9
…	…	…	…	…		…
28/10/2012	**$9,405**	**$2,634**	**$621**	**$487**		$0
4/11/2012	**$7,954**	$787	$725	$505		$0
11/11/2012	**$8,229**	$574	$697	$304		$0
18/11/2012	**$8,894**	$804	$611	$286		$0
25/11/2012	**$7,959**	$1,429	$590	$426		$0
2/12/2012	**$7,839**	$752	$578	$373		$0
9/12/2012	**$7,958**	$728	$709	$284		$0
16/12/2012	**$8,992**	$855	$562	$552		$0
23/12/2012	**$8,880**	$1,475	$589	$658		$0
30/12/2012	**$7,089**	$732	$513	$593		$0

From Table 4.9, it can be seen that this Category is made up of 91 brands. However, from the previous discussion in this chapter, and based on the criteria provided in Chapter 2, it was found that only 29 brands had usable data. The reason for this is that some brands had no data at all, or less than 52 observations at the end of the period, and hence failed to satisfy the criteria for inclusion in the category and, therefore, to be part of the Brands Index.

Table 4.10 Final brands making up Category A

Date	Category A	A-Brand1	A-Brand2	A-Brand3	…	A-Brand29
4/01/2004	**$6,795**	$1,131	$337	$461		$144
11/01/2004	**$7,527**	$1,229	$371	$365		$145
18/01/2004	**$7,508**	$1,190	$386	$424		$148
25/01/2004	**$7,843**	$2,140	$444	$368		$163
1/02/2004	**$7,341**	$1,293	$412	$338		$165
8/02/2004	**$8,082**	$2,547	$390	$323		$148
15/02/2004	**$7,023**	$1,122	$387	$373		$163
22/02/2004	**$7,205**	$1,182	$377	$371		$161
29/02/2004	**$7,372**	$1,254	$408	$346		$151
7/03/2004	**$7,066**	$1,127	$445	$550		$142
14/03/2004	**$9,289**	$3,309	$395	$309		$150
21/03/2004	**$8,218**	$2,769	$393	$448		$149
28/03/2004	**$6,903**	$1,126	$517	$316		$148
4/043/2004	**$6,858**	$1,216	$378	$428		$146
…	…	…	…	…		…
28/10/2012	**$9,029**	**$2,634**	**$621**	**$487**		**$232**
4/11/2012	**$7,636**	$787	$725	$505		$269
11/11/2012	**$7,900**	$574	$697	$304		$285
18/11/2012	**$8,538**	$804	$611	$286		$279
25/11/2012	**$7,641**	$1,429	$590	$426		$282
2/12/2012	**$7,526**	$752	$578	$373		$281
9/12/2012	**$7,640**	$728	$709	$284		$289
16/12/2012	**$8,632**	$855	$562	$552		$280
23/12/2012	**$8,525**	$1,475	$589	$658		$309
30/12/2012	**$6,806**	$732	$513	$593		$257

Table 4.10, above, shows that slight differences for total Category A values resulted from reducing the number of brands from 91 to 29. The next level down would be to look at the SKUs (stock keeping units) of a brand. As previously identified in Chapter 1, a SKU is a machine-readable code used in tracking unique products in the store/inventory. Brands can be made of a single SKU or several SKUs depending on the variety of different individual products available. The summation of SKU sales equals the total brand sales; however, this research does not go into that level of detail. Some data cleaning (sorting and filtering to remove outliers) has been performed for the other four Categories (B to E) so the Brands Index satisfies the conditions discussed in Chapter 2.

Using the same calculations as discussed in Section 4.3, two brands' trends are shown below; for A-Brand1 and A-Brand2. The same process applies for every brand. First, plot the total sales trend. Second, work out a proxy for base sales. Third, compute returns for brand *i* using the continuously-compounded formula with and without the risk-free component (i.e., base sales for brand *i*).

Figure 4.13 A-Brand1 weekly sales

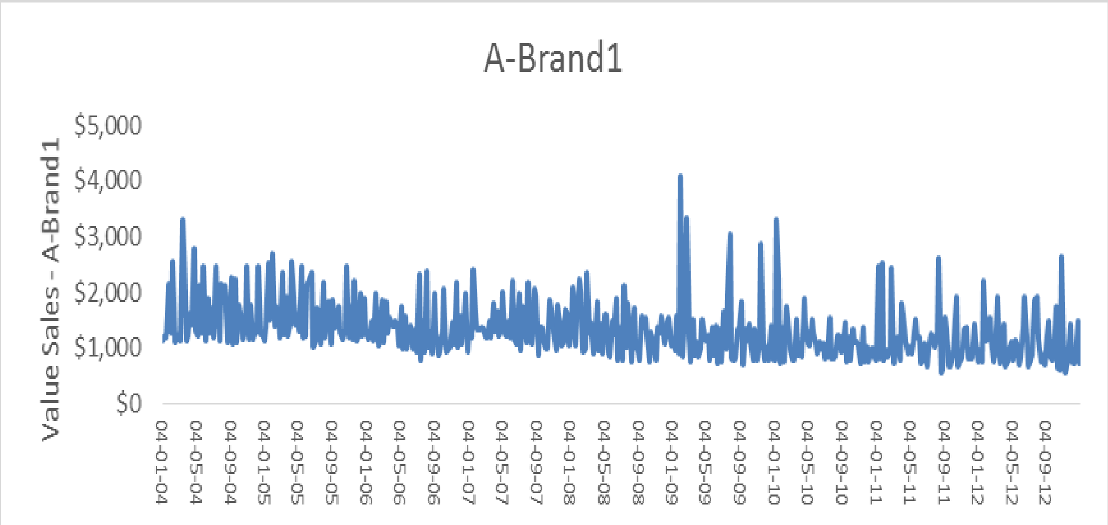
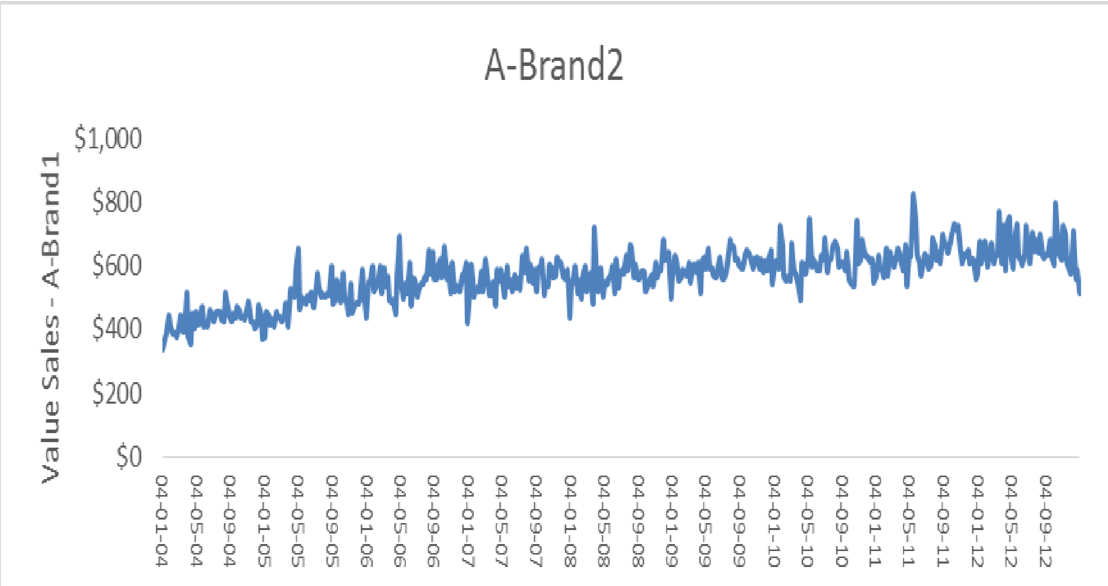


Figure 4.14 A-Brand2 weekly sales



The first thing to notice from Figures 4.13 and 4.14 is that A-Brand1 shows a declining trend with higher spikes, while A-Brand2 depicts the opposite pattern; an upward trend with shorter spikes. The impact of these differences should be reflected in the beta figures once they are calculated, as the most volatile brand should have a higher beta value. The base sales are shown below.

Figure 4.15 A-Brand1 weekly sales with a base worked out

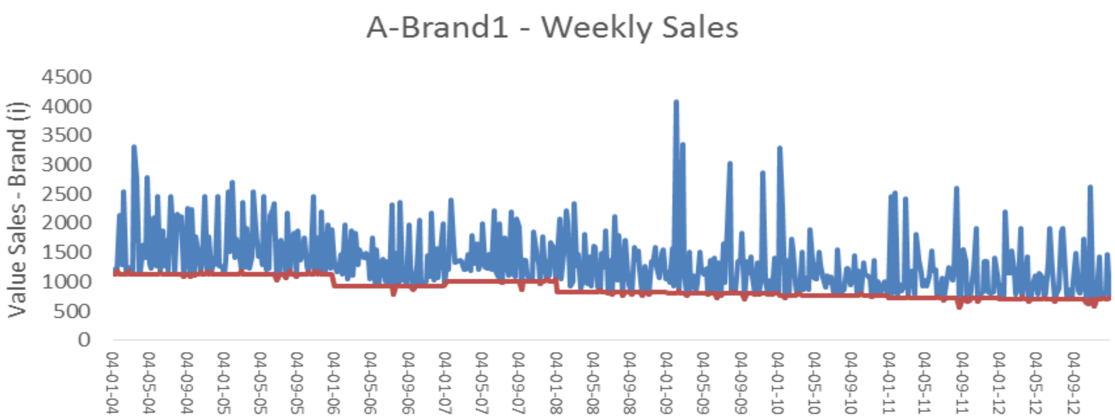
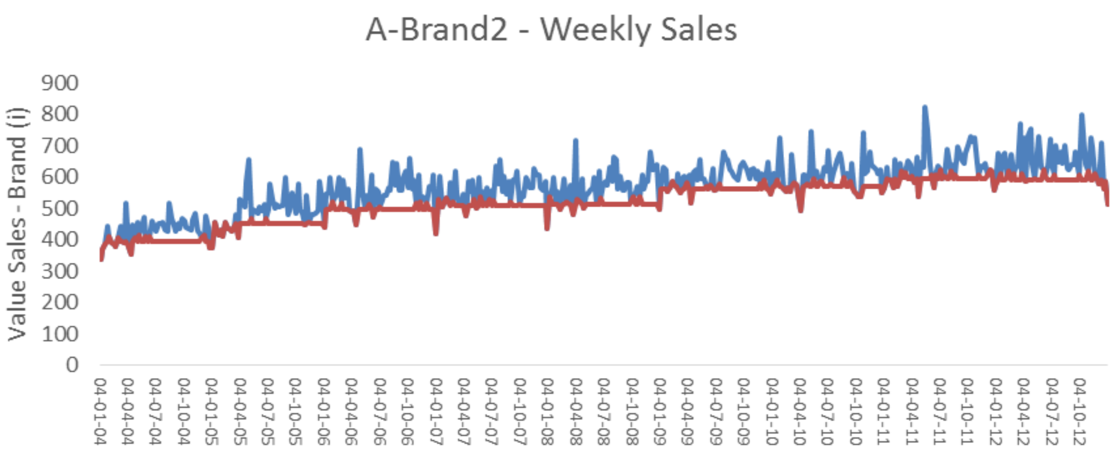


Figure 4.16 A-Brand2 weekly sales with a base worked out



In the previous section, the minimum value for each brand changes every 52 weeks in order to capture yearly base sales trends. Brand managers should examine their brand's base value occasionally to ensure that they meet the set goals. The managers should embrace appropriate marketing strategies to ensure profitability and an increased market share of the FMCG products in Australia. There is a need to keep varying the base values of brands so that the yearly base values for the FMCG industry maintain a clear trend in sales. This need for the base to vary throughout time becomes more evident when a clear upward or downward trend is seen. The minimum values used for A-Brand1 and A-Brand 2 are shown in Table 4.11, below.

Table 4.11 Minimum A-Brand1 and A-Brand2 values

Year	A-Brand1 - Minimum Value	A-Brand2 - Minimum Value
Year1	1132.1	395.7
Year2	1135.9	450.8
Year3	927.9	498.3
Year4	1011.0	510.3
Year5	834.1	515.3
Year6	807.7	561.5
Year7	773.4	568.9
Year8	720.0	596.0
Year9	704.9	592.1

From Table 4.11 above, it is apparent that the minimum value for the A-Brand1 trend declines over time while the minimum value for A-Brand2 increases due to their respective overall movements. The last step in this process is to use the continuously-compounded return formula using the same formulas as in the previous section. Figures 4.17 and 4.18 show the resulting returns for A-Brand1 and A-Brand2, respectively.

Figure 4.17 A-Brand1 weekly return with and without risk-free

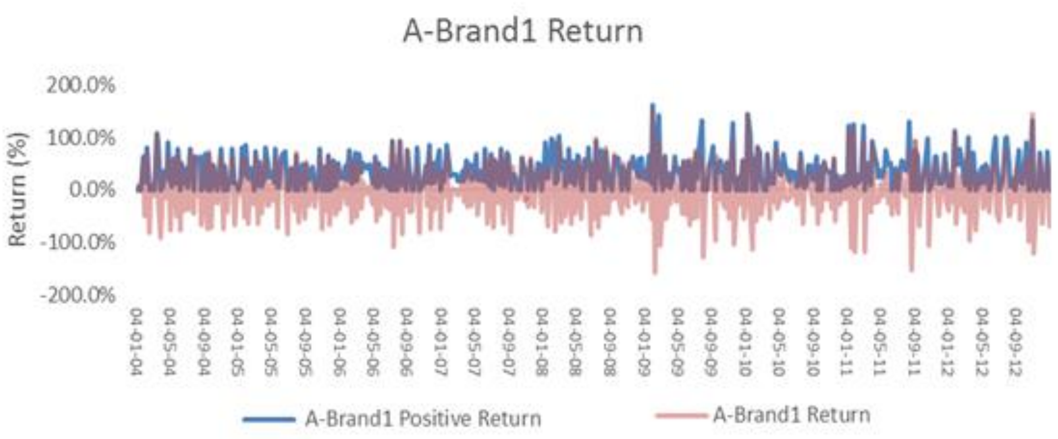
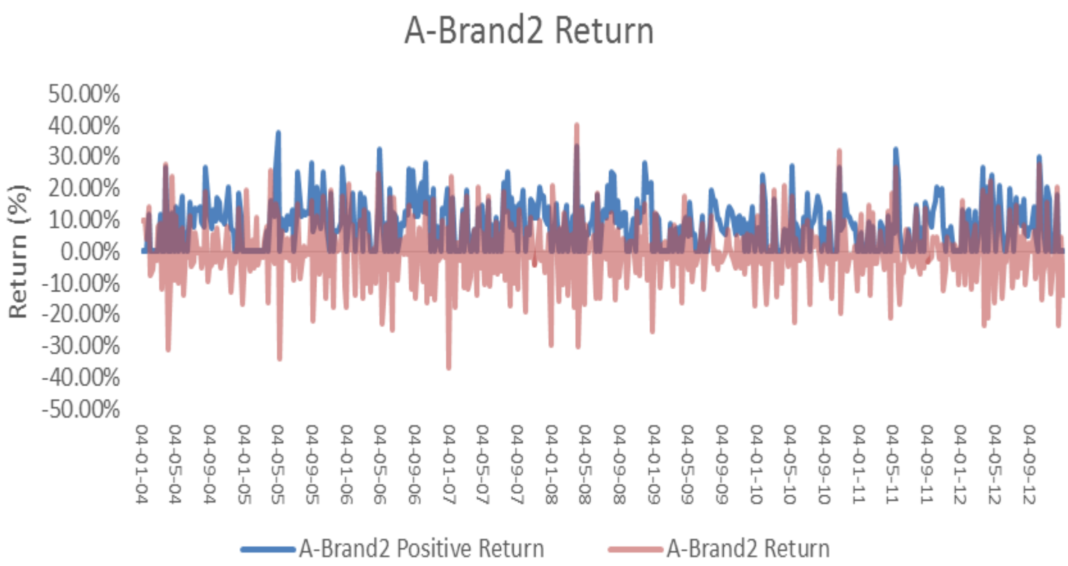


Figure 4.18 A-Brand2 weekly return with and without risk-free



The same process as for calculating returns can be then generalised to any brand and any number of brands. It is clear then that a process to work out brands' returns within the CAPM context has been developed for the FMCG industry, to identify the effects of total sales volatility. Now we have returns on both sides of Equation 4.2; on the left side we have brands, and in the right side we have the market, which is simply the Brands Index. To continue with the two-brands or more example, the next obvious step is to calculate the betas using the methodologies explained so far. Results of these calculations are provided in Chapter 5, wherein we test the theory.

In this thesis, the extra cost that a brand incurs in order to generate incremental sales has not yet been considered, but it has been assumed that a return that comes from incremental sales is divided by base sale values. However, if access to this confidential information is granted (such as gross profit for base sales and the cost of causing incremental sales) then a more realistic return could be worked out for each brand. An adaptation from Franco-Laverde et al. (2012) based on the formulas given by Neslin and Van Heerde (2008) is provided below, with the following terms and definitions:

π_o = Brand profit without incremental sales

π_p = Brand profit with incremental sales

M_o = Normal profit margin for a brand

δ = Trade deal offered by a brand

S_o = Normal (base sales) per week

Δ= Increase in sales per week

$\pi_p - \pi_p$ = Change in profit due to incremental sales

Following these terms and definitions, we have

Equation 4.10

$$\pi_o = S_o * M_o$$
$$\pi_p = (S_o + \Delta)(M_o - \delta)$$
$$\pi_p - \pi_o = \Delta(M_o - \delta) - S_o\delta$$

Equation 4.10 above is broken down in two parts; the first term is the increase in profits due to selling more (S_0 + Δ) during the incremental sales period, albeit at the reduced margin of $(M_o - \delta)$. The second term reflects lost contributions from base sales during the incremental sales week, i.e., the brand has sacrificed δ on those sales.

The term π_p will always generate a static profit disregarding the variation in Δ, and for the purposes of this research, a dynamic metric rather than a static one is needed. Thus, an additional calculation needs to take place in order to account for the incremental sales linked to the trade deal discounts offered by the brand (δ). Then, Equation 4.11 unfolds:

Equation 4.11

$$\frac{\pi_p - \pi_o}{\delta} = \frac{\Delta(M_o - \delta) - S_o\delta}{\delta} = \frac{\Delta\pi}{\delta}$$

Equation 4.11 is simply a dynamic ratio between the *change in profit* to the *trade deal discount*, which varies with Δ and δ accordingly. It can also be understood as the ratio of incr*emental profit* to *promotional spend. Profit* and *cost per unit* information is considered confidential by manufacturers or brand owners, and is not publicly available. However, if that information is available, the return formula for the ratio of incremental sales to base sales can be then modified to accomplish a more realistic result.

In order to maximise returns, this study relies on modern portfolio theory (MPT), which asserts that investors are risk-averse. The hypothesis is that investors would like to earn as much return as possible for any given level of risk. Investors construct portfolios to optimise or maximise the expected return, based on a given level of market risk (Markowitz, 1952). In the context of this research, MPT attempts to construct an efficient frontier of optimal portfolios offering the maximum possible expected return for a given level of risk. Risk will be first examined as the brand's standard deviation, to then be compared with the results of the beta calculations. Hence, the portfolio's expected return and variance are defined as:

Equation 4.12

$$E(r_p) = \sum_{i=1}^{n} \omega_i \, \mu_i$$

Equation 4.13

$$\sigma_p^2 = \sum_{i=1}^{n} \omega_i^2 \, \sigma_i^2 + \sum_{i=1}^{n} \sum_{j=1}^{n} \omega_i \, \omega_j \sigma_i \sigma_j \rho_{ij}$$

$i \neq j$

where:

n = Number of brands within the portfolio

$E(r_p)$ = Expected portfolio return

ω_i = Proportion invested in each brand

μ_i = Expected return of each brand

σ_p^2 = Variance of portfolio return

σ_i^2 = Variance of brand *i* return

σ_j^2 = Variance of brand *j* return

ρ_{ij}= Correlation between the returns of brands *i* and *j*

The expected return of the portfolio $E(r_p)$ is then a function of the proportion of the investment in each brand, ω_i, and the expected return of that brand, μ_i, while the portfolio's variance depends on the variance of product returns for individual brands *i* and j (σ_i^2, σ_i^2), the proportion of investments on brands i and j (ω_i, ω_j), and the correlation between the returns of brands *i* and *j* (ρ_{ij}). The covariance between return *i* and return *j* is defined as $\sigma_{ij} = \sigma_i \sigma_j \rho_{ij}$. Thus, the portfolio variance can be re-written as follows:

Equation 4.14

$$\sigma_p^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} \omega_i \ \omega_j \sigma_{ij}$$

The efficient frontier is the portfolio of brands that give the lowest variance of return of all portfolios with the same expected return or simply an efficient portfolio has the highest expected return of all portfolios having the same variance.

The objective is to minimise σ_p^2 subject to constraints:

Equation 4.15

$\sum_{i=1}^{n} \omega_i \, \mu_i = E(r_p)$ at a desired value, k

$$\sum_{i=1}^{n} \omega_i = 1$$

σ_p^2 and $E(r_p)$ in matrix notation are written as:

Equation 4.16

$$\sigma_p^2 = w' \Omega \, w,$$

$$E(r_p) = w'R;$$

Where:

W' = (1*n) row vector of weights

R = (n*1) column vector of expected returns

Ω = (n*n) covariance matrix

The matrix representation of these constrains is:

Equation 4.17

B*w = b

$$\begin{bmatrix} 1 & \ldots & 1 \\ R_1 & \ldots & R_n \end{bmatrix} \begin{bmatrix} w_1 \\ \ldots \\ w_n \end{bmatrix} = \begin{bmatrix} 1 \\ k \end{bmatrix}$$

where B is a (2 * n) matrix of 1's and asset returns, R and b is a (2 × 1) column vector with elements 1 and the desired minimum variance return, k.

Minimising σ_p^2 subject to B*w = b provides the solution:

Equation 4.18

$$w_k = \Omega^{-1}B'(B\Omega^{-1}B')^{-1}b$$

The global minimum variance portfolio (MVP) has the solution:

Equation 4.19

$$w^* = (\Omega^{-1}i)/(i'^{\Omega^{-1}}i),$$

where i is a (n * 1) column vector with probabilities = 1.

The return and risk of the global MVP are, respectively:

Equation 4.20

$$E\left(r_p^* = w'^*R\right)$$
$$\sigma_p^{2*} = (i'\Omega^{-1}i')^{-1}$$

Finally, the principal of diversification for manufacturers with more than one brand within the FMCG industry will be explained by using the Sharpe ratio to rank portfolios (Sharpe, 1966). The Sharpe ratio works with calculations regarding risk returns. The Sharpe ratio therefore refers to the average return on the risk-free rate over a certain period. Market volatility plays an important part, as the potential return will increase or decrease based on the market condition. Cao and Ward (2014) have identified that portfolio investment refers to risk-free investment, where brand managers try to reduce risk by segregating the total investible amount into several parts. The Sharpe ratio is simply the ratio of a portfolio's expected return minus the risk-free rate of return divided by the portfolio's standard deviation:

Equation 4.21

$$\left(S = \frac{E(r_p) - Rf}{\sigma_p}\right)$$

In summary, due to the commercial confidentiality of brands' profit and costing information, this investigation sticks with the available information. Manufacturers in the FMCG industry in Australia are not willing to offer brands' profit returns in case they reveal vital information to competitors that could adversely affect their business operations. Nevertheless, formulas have been provided to calculate the returns accordingly. Chapter 5 shows an example of the results with some hypothetical profit and cost data, in order to clarify the concept and to provide managerial implications. Some insights based on the Sharpe ratio will also be provided. The next section summarises the data at hand and present some key statistics. Then, I will test the hypotheses from Chapter 3 in the results and testing sections of Chapter 5.

4.5 Chapter Summary

Data extracted from the Aztec datasets was organised and presented in this chapter. Chapter 5 will validate the five hypotheses proposed in Chapter 3. The volatility of the created Brands Index will be tested using ARCH-GARCH-type modelling techniques. The EGARCH and TGARCH class of models are also presented to test for asymmetry in the returns. Traditional forecasting methods will be evaluated with the created Brands Index and compared with the predictions of the ARCH-GARCH models. Then, the CAPM will be tested through the use of first-pass and second-pass regression. If the CAPM in this descriptive format holds, then the second-pass regression should be equivalent to the security market line (SML). The proposed models will be tested and interpreted in Chapter 5. The framework then proposes a scientific investigation to quantify the observed volatility in the created Brands Index and, finally, proposes a modified CAPM to calculate individual brand betas that will allow comparison with the overall FMCG market.

Changes in weekly value sales for FMCG products in Australia have exhibited a number of robust characteristics that many researchers call “stylised facts”. Localised outbursts of volatility can be observed for most FMCG due to volatility clustering—a characteristic of fluctuations in the time series data (Bouchaud, 2002). The calculation of each brands’ beta value provides an additional framework with which to build brand portfolios in marketing research beyond traditional approaches that were not able to do so due to the lack of such index. Accordingly, this research set up a methodology for the creation of a Brands Index, assesses and quantifies the Brand Index’s volatility, and explores the use of brands betas through the application and modification of the CAPM.

CHAPTER 5: HYPOTHESIS TESTING AND INITIAL DISCUSSION

5.0 Overview

In Chapter 4, the calculation of volatility in the Brands Index and the use of CAPM to support brand performance were discussed in detail. Brands Index returns, along with their observed volatility, are tested in this chapter. The comparison of the results of the two alternative returns calculation methodologies provided in the previous chapter provides much clearer theory-driven results when validating the CAPM results in regards to the second-pass regression test. Thus, the five hypotheses proposed in Chapter 3 are validated in this chapter. Further, in Chapter 6, two clear implications from the hypothesis testing results are discussed for brand suppliers (retailers) and manufacturers (brand managers).

The aims of this chapter are to:

- Provide an overview of the results from the two alternative returns calculation methodologies for the FMCG Brands Index (Section 5.1);
- Test, report and discuss the results of the proposed hypothesis tests in Chapter 3 (Section 5.2); and
- Summarise the results of the hypothesis tests and discuss them in regards to their validation (Section 5.3).

5.1 Overview of Results from the Two Alternative Returns Calculation Methodologies

Chapter 4 created the FMCG Brands Index as a cap-weighted average index. It adapts the methodology used to construct the Standards and Poor's 500 (S&P500) and All Ordinaries (AOI) Indices. The Brands Index represents the sum of the total weekly sales in five categories of products sold by Woolworths and Coles retailers. This thesis proposed two clear methodologies for calculating the returns of individual brands and the Brands Index. Figure 4.7 in Chapter 4 charted the weekly returns for a nine-year period, computed as the natural logarithm of the sales value in period *t* divided by the sales value in period *t*-1. Figure 4.11 similarly charted the weekly returns for the same period of time, calculated as the natural logarithm of the sales value in period *t* divided by the base sales value in period *t*. Although both return calculation methodologies move in the same direction, differences in the magnitude of the returns calculated are notable and critical. Taking the risk-free component to be base sales, when there are no marketing activities to drive additional demand, then the resulting sales are base sales and the mean return is, hence, always greater than or equal to zero.

5.1.1 RESULTS FROM BOTH RETURNS CALCULATIONS

In this context, if there are no marketing activities aiming to drive additional demand, then the output always represents base sales only, and no significant volatility should be present. Significant volatility in the context of this discussion refers to deviations in the total sales value from that of base sales. If there are a low number of activities undertaken, then volatility tends to be lower. Conversely, volatility increases as the number of activities increase. *Activities*, in this research, refers to pricing activities, advertising activities, new product launches, in-store activation and promotional strategies. It will be recalled from Chapter 3 that Hypothesis 1 proposes that *the variation in the weekly sales of the proposed Brands Index follows a volatility-clustering pattern similar to that of financial market indices.*

Table 5.1 compares the key statistics for the two alternative return calculation methodologies. Henceforth, FMCGBR denotes FMCG brand returns without a risk-free component and FMCGBR_RF denotes FMCG brand returns including the risk-free component. The results in Table 5.1 show that the mean return without the risk-free component (FMCGBR) is close to zero, and when including the risk-free component (FMCGBR_RF), it is 8.4%. The reason for this difference in the mean returns is that FMCGBR comprises positive and negative return values representing changes in sales without reference to the base sales value, whereas mean returns including the risk-free component (i.e. base sales) are never less than zero. Although the means for both options are quite different, their standard deviations are not. The FMCGBR standard deviation is 0.0725, while that of FMCGBR_RF is 0.0505. The standard deviation figure can be understood as a proxy for volatility as it measures how far the returns move away from the average. Thus, based on the standard deviation figures, FMCGBR is much volatile than FMCGBR_RF. Not including a risk-free component therefore yields results more consistent with Hypothesis 1 than when the risk-free component is included.

Table 5.1 Brands Index and Brands Index (RF) key statistics

	FMCGBR	FMCGBR_RF
Mean	0.000218	0.084056
Median	0.000599	0.079513
Maximum	0.236116	0.359210
Minimum	-0.442790	0.000000
Std. Dev.	0.072546	0.050481
Skewness	-0.495425	0.671895
Kurtosis	7.248507	4.527322
Jarque-Bera	371.9091	80.87285
Probability	0.000000	0.000000
Sum	0.102209	39.42242
Sum Sq. Dev.	2.463024	1.192615
Observations	469	469

Next, I test for the presence of ARCH effects in FMCG Brands Index returns using both return calculation methodologies. The motivation for using ARCH-class models is the phenomenon known as *volatility clustering*. The assumption is that volatility clustering could be present in the Brands Index, because when a brand undertakes marketing initiatives or price promotional activities, other brands tend to react similarly, which generates noise in the market returns series. Reduced prices and offers of after-sale service to customers may not be the best way to promote sales. As such, there is a need to analyse sales volatility to aid in identifying alternative methods of increasing sales and profitability.

Following the process recommended in the literature, which was discussed in Chapter 3, the first step is to run an ordinary least squares (OLS) regression of FMCG Brands Index returns against its mean. Then, the residuals from the previous regression are squared and a regression against its own squared lags is carried out. The null and alternative hypothesis for the FMCG Brands Index returns, H0 and H1, respectively, are as follows:

H0: there is no presence of autocorrelation in the squared residuals

H1: there is presence of autocorrelation in the squared residuals

Test results are presented in Tables 5.2 and Table 5.3 below.

Table 5.2 ARCH test – FMCG Brands Index returns (FMCGBR)

Heteroscedasticity Test: ARCH

F-statistic	9.722738	Prob. *F*(5,458)	0.0000
Obs**R*-squared	44.52456	Prob. Chi-square(5)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Sample (adjusted): 2/15/2004 12/30/2012
Included observations: 464 after adjustments

Variable	Coefficient	Std. Error	*t*-statistic	Prob.
C	0.004275	0.000737	5.804100	0.0000
RESID^2(-1)	0.324234	0.047411	6.838853	0.0000
RESID^2(-2)	-0.107378	0.049868	-2.153243	0.0318
RESID^2(-3)	-0.012621	0.050124	-0.251797	0.8013
RESID^2(-4)	-0.023154	0.049866	-0.464326	0.6426
RESID^2(-5)	0.014511	0.047406	0.306107	0.7597

R-squared	0.095958	Mean dependent var	0.005290
Adjusted *R*-squared	0.086089	S.D. dependent var	0.013206
S.E. of regression	0.012625	Akaike info criterion	-5.893504
Sum squared resid	0.072995	Schwarz criterion	-5.839971
Log likelihood	1373.293	Hannan-Quinn criter.	-5.872431
F-statistic	9.722738	Durbin-Watson stat	1.970375
Prob(*F*-statistic)	0.000000		

Based on the *t*-statistic and the *p*-values, the results in Table 5.2 for the FMCGBR returns series suggest that autocorrelation in the squared residuals is present at least up to three lags at the 0.05 confidence level. Thus, the null hypothesis of no presence of autocorrelation in the squared residuals is rejected. The results in Table 5.3 likewise shows that the null hypothesis of no presence of autocorrelation in the squared residuals for the FMCG_BR is also rejected, though up to two lags and at the 0.01 confidence level.

Table 5.3 ARCH test – FMCG Brands Index returns (FMCGBR RF)

Heteroscedasticity Test: ARCH

F-statistic	4.191542	Prob. *F*(5,459)	0.0010
Obs*R*-squared	20.30457	Prob. Chi-square(5)	0.0011

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Sample (adjusted): 2/08/2004 12/30/2012
Included observations: 465 after adjustments

Variable	Coefficient	Std. Error	*t*-statistic	Prob.
C	0.001760	0.000309	5.686983	0.0000
RESID^2(-1)	0.163809	0.046500	3.522793	0.0005
RESID^2(-2)	0.022987	0.047085	0.488193	0.6256
RESID^2(-3)	0.063720	0.047009	1.355483	0.1759
RESID^2(-4)	-0.036002	0.047095	-0.764452	0.4450
7RESID^2(-5)	0.097320	0.046454	2.094964	0.0367

R-squared	0.043666	Mean dependent var	0.002553
Adjusted *R*-squared	0.033248	S.D. dependent var	0.004807
S.E. of regression	0.004726	Akaike info criterion	-7.858670
Sum squared resid	0.010252	Schwarz criterion	-7.805224
Log likelihood	1833.141	Hannan-Quinn criter.	-7.837633
F-statistic	4.191542	Durbin-Watson stat	1.991209
Prob(*F*-statistic)	0.000981		

In both Tables 5.2 and 5.3, the *F*-test and the LM-statistic are highly significant at the 0.01 level of confidence, suggesting the presence of autocorrelation in the squared residuals for the FMCGBR and FMCGBR_RF returns series. The conclusion reached is that the null hypothesis *H0* is then rejected for both alternative returns methodologies. The autocorrelation coefficients for the squared residuals corresponding to the two return calculation methodologies – FMCGBR and FMCGBR_RF – are provided in Tables 5.4a and 5.4b below.

Table 5.4a Brands Index returns correlogram of squared residuals (FMCGBR)

Sample: 1/04/2004 12/30/2012
Included observations: 469

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.287	0.287	38.752	0.000
		2	-0.015	-0.106	38.855	0.000
		3	-0.054	-0.022	40.260	0.000
		4	-0.037	-0.017	40.924	0.000
		5	0.001	0.014	40.925	0.000
		6	-0.008	-0.020	40.959	0.000
		7	-0.038	-0.035	41.657	0.000
		8	-0.058	-0.041	43.284	0.000
		9	-0.052	-0.029	44.580	0.000
		10	-0.053	-0.041	45.910	0.000
		11	-0.010	0.009	45.956	0.000
		12	0.043	0.037	46.835	0.000
		13	0.004	-0.028	46.844	0.000
		14	0.038	0.050	47.549	0.000
		15	0.095	0.076	51.899	0.000

Table 5.4b Brands Index returns correlogram of squared residuals (FMCGBR RF)

Sample: 1/04/2004 12/30/2012
Included observations: 470

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.169	0.169	13.507	0.000
		2	0.066	0.039	15.590	0.000
		3	0.078	0.063	18.482	0.000
		4	0.006	-0.020	18.498	0.001
		5	0.098	0.097	23.083	0.000
		6	0.006	-0.030	23.101	0.001
		7	0.002	-0.000	23.102	0.002
		8	0.082	0.073	26.324	0.001
		9	-0.014	-0.036	26.423	0.002
		10	0.020	0.014	26.624	0.003
		11	0.090	0.083	30.555	0.001
		12	0.002	-0.022	30.557	0.002
		13	0.009	-0.012	30.599	0.004
		14	-0.041	-0.044	31.412	0.005
		15	0.028	0.047	31.798	0.007

Examining the results in Tables 5.4a and 5.4b, which correspond to the two return calculation methodologies, the Ljung-Box test statistic (Box & Pierce, 1970) validates the conclusion for the ARCH test in Tables 5.2 and 5.3; namely, rejection of the null hypothesis of no autocorrelation at the 0.01 level of confidence for all lags considered. The first-order autocorrelation gradually declines from 0.287 in Table 5.4a and 0.169 in Table 5.4b. These autocorrelations are not large, but they are very significant. It means that the marketing strategies adopted by FMCG retailers will affect sales value volatility.

Based in the ARCH test carried out in Tables 5.2 and 5.3, and the Ljung-Box test specified in Tables 5.4a and 5.4b, the evidence suggests that autocorrelation is present in the squared residuals for both the two return calculation methodologies (FMCGBR and FMCGBR_RF). The next step is to consider GARCH-class models to further examine the matter. The results obtained after analysing the GARCH model will be used in predicting Brands Index returns, as well as for learning more about the term structure of Brands Index returns, and dynamic models of calculating brand betas for the FMCG industry in Australia.

The first step in the GARCH methodology is to define the mean and variance equations. Two competing models are employed. The mean equation in the first model only takes into account the intercept, while the mean equation in the second model comprises an autoregressive moving average (ARMA; Whittle, 1951). In the statistical analysis of time series data, ARMA models provide a parsimonious description of a weakly stationary stochastic process in terms of two polynomials; one for the autoregressive component and a second for the moving average component. Given a weakly stationary stochastic process, the variance and mean of the time series should not change over time (Koop, 2006). This specification is referred to as an ARMA(p,q) model, where p is the order of the autoregressive component and q is the order of the moving average component.

The results for a GARCH(1,1) and the final selected model are presented in Tables 5.5—5.10b for the FMCGBR returns series and in Tables 5.11—5.15b for the FMCGBR_RF returns series. The outputs for the rest of the combinations of the ARMA models, up to an ARMA(2,2) and up to GARCH(2,2), are presented in Appendix 2.

Table 5.5 GARCH(1,1) Brands Index returns (FMCGBR)

Dependent Variable: FMCGBR
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Sample (adjusted): 1/11/2004 12/30/2012
Included observations: 469 after adjustments
Convergence achieved after 24 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	*z*-Statistic	Prob.
C	-0.001044	0.002270	-0.459687	0.6457
		Variance Equation		
C	0.002625	0.000285	9.215425	0.0000
RESID(-1)^2	0.519217	0.078340	6.627783	0.0000
GARCH(-1)	0.041262	0.050429	0.818228	0.4132

R-squared	-0.000303	Mean dependent var.	0.000218
Adjusted *R*-squared	-0.000303	S.D. dependent var.	0.072546
S.E. of regression	0.072557	Akaike info criterion	-2.572491
Sum squared resid	2.463771	Schwarz criterion	-2.537091
Log likelihood	607.2492	Hannan-Quinn criter.	-2.558563
Durbin-Watson stat.	3.023078		

Table 5.6 GARCH(1,1) Brands Index returns – ARMA structure (FMCGBR)

Dependent Variable: FMCGBR
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Sample (adjusted): 1/18/2004 12/30/2012
Included observations: 468 after adjustments
Convergence achieved after 36 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 1/11/2004
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	*z*-Statistic	Prob.
C	0.000371	7.38E-05	5.024942	0.0000
AR(1)	-0.005960	0.053673	-0.111044	0.9116
MA(1)	-0.972169	0.010978	-88.55500	0.0000
Variance Equation				
C	0.002336	0.000375	6.223329	0.0000
RESID(-1)^2	0.204530	0.062005	3.298597	0.0010
GARCH(-1)	-0.108889	0.136872	-0.795554	0.4263

R-squared	0.509042	Mean dependent var	7.93E-05
Adjusted *R*-squared	0.506930	S.D. dependent var	0.072561
S.E. of regression	0.050952	Akaike info criterion	-3.146087
Sum squared resid	1.207170	Schwarz criterion	-3.092901
Log likelihood	742.1843	Hannan-Quinn criter.	-3.125158
Durbin-Watson stat	2.080702		

Inverted AR Roots	-.01
Inverted MA Roots	.97

As can be seen from Tables 5.5 and 5.6, for the FMCGBR returns series, in both cases the GARCH(-1) coefficient is not significant at the 0.01 level of confidence, and it is negative in the ARMA case, suggesting a different structure for the variance. In the ARMA structure for the mean equation, the coefficient of AR(1) is not significant, indicating that price volatility is affected by the marketing structure in different periods of the economic calendar, which also suggests a different ARMA combination. It was found that in both cases a GARCH(2,1) model was selected to capture the variance in volatility.

Table 5.7 GARCH(2,1) Brands Index returns (FMCGBR)

Dependent Variable: FMCGBR
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Sample (adjusted): 1/11/2004 12/30/2012
Included observations: 469 after adjustments
Convergence achieved after 60 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-2)^2 + C(5)*GARCH(-1)

Variable	Coefficient	Std. Error	*z*-Statistic	Prob.
C	-0.001182	0.002441	-0.484138	0.6283
		Variance Equation		
C	0.000212	9.34E-05	2.267389	0.0234
RESID(-1)^2	0.476393	0.073708	6.463281	0.0000
RESID(-2)^2	-0.465950	0.069657	-6.689190	0.0000
GARCH(-1)	0.951152	0.025989	36.59788	0.0000

R-squared	-0.000373	Mean dependent var	0.000218
Adjusted *R*-squared	-0.000373	S.D. dependent var	0.072546
S.E. of regression	0.072559	Akaike info criterion	-2.578363
Sum squared resid	2.463943	Schwarz criterion	-2.534114
Log likelihood	609.6262	Hannan-Quinn criter.	-2.560953
Durbin-Watson stat	3.022866		

Table 5.8 GARCH(2,1) Brands Index returns with MA(1) structure (FMCGBR)

Dependent Variable: FMCGBR
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Sample (adjusted): 1/11/2004 12/30/2012
Included observations: 469 after adjustments
Convergence achieved after 57 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 1/04/2004
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*RESID(-2)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	*z*-Statistic	Prob.
C	0.000405	6.19E-05	6.550880	0.0000
MA(1)	-0.976553	0.009436	-103.4887	0.0000
		Variance Equation		
C	0.000167	6.35E-05	2.627542	0.0086
RESID(-1)^2	0.166191	0.053594	3.100940	0.0019
RESID(-2)^2	-0.177641	0.050699	-3.503857	0.0005
GARCH(-1)	0.947245	0.027304	34.69258	0.0000

R-squared	0.509659	Mean dependent var	0.000218
Adjusted *R*-squared	0.508609	S.D. dependent var	0.072546
S.E. of regression	0.050854	Akaike info criterion	-3.159549
Sum squared resid	1.207722	Schwarz criterion	-3.106449
Log likelihood	746.9142	Hannan-Quinn criter.	-3.138656
Durbin-Watson stat	2.083690		

Inverted MA Roots	.98

Tables 5.7 and 5.8, for FMCGBR returns series, show that all coefficients are highly significant at the 0.01 level of confidence as their *p*-values are very close to zero. The sum of the ARCH and GARCH coefficients in each equation is near unity, implying significant persistence in volatility. It means that the coefficients can be used to analyse and predict the sales value volatility of FMCGs in Australia. The models should use the weighted average of the past sales value returns data to estimate the expected risks in the industry. A coefficient of one implies that sale value volatility will persist for longer periods in the FMCG industry. ARCH and GARCH coefficients of 1 provide a long-run solution to the GARCH modelling process. The probability is almost one, meaning that the sales value volatility is present and will determine the consumption trend of FMCG products.

The final step in this procedure is to ensure that the ARCH effects are no longer present as the data has been filtered for ARCH dependencies. The presence of heteroscedasticity indicates that there is a misspecification of the model. Thus, the following ARCH test results are provided in Tables 5.9a – 5.10b, below.

Table 5.9a ARCH Test - GARCH(2,1) Brands Index returns (FMCGBR)

Heteroscedasticity Test: ARCH

F-statistic	1.094957	Prob. F(5,458)	0.3623
Obs*R-squared	5.480989	Prob. Chi-Square(5)	0.3600

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Sample (adjusted): 2/15/2004 12/30/2012
Included observations: 464 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.942380	0.135647	6.947276	0.0000
WGT_RESID^2(-1)	0.071395	0.048585	1.469494	0.1424
WGT_RESID^2(-2)	-0.043011	0.048731	-0.882619	0.3779
WGT_RESID^2(-3)	-0.024213	0.048759	-0.496575	0.6197
WGT_RESID^2(-4)	-0.004944	0.048718	-0.101476	0.9192
WGT_RESID^2(-5)	0.071682	0.048565	1.475990	0.1406

R-squared	0.011812	Mean dependent var	1.012643
Adjusted R-squared	0.001024	S.D. dependent var	1.863076
S.E. of regression	1.862122	Akaike info criterion	4.094157
Sum squared resid	1588.114	Schwarz criterion	4.147690
Log likelihood	-943.8444	Hannan-Quinn criter.	4.115229
F-statistic	1.094957	Durbin-Watson stat	1.915399
Prob(F-statistic)	0.362340		

Table 5.9b Correlogram of squared residuals - GARCH(2,1) Brands Index returns (FMCGBR)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.064	0.064	1.9264	0.165
		2	-0.038	-0.042	2.6182	0.270
		3	-0.032	-0.027	3.0938	0.377
		4	-0.001	0.001	3.0946	0.542
		5	0.068	0.066	5.2726	0.384
		6	-0.017	-0.027	5.4072	0.493
		7	-0.033	-0.026	5.9410	0.547
		8	-0.051	-0.046	7.2087	0.514
		9	-0.055	-0.052	8.6431	0.471
		10	-0.033	-0.037	9.1749	0.516
		11	-0.004	-0.004	9.1831	0.605
		12	0.088	0.087	12.898	0.377
		13	-0.038	-0.047	13.604	0.402
		14	0.051	0.069	14.871	0.387
		15	0.121	0.118	22.045	0.107

Table 5.10a ARCH Test - GARCH(2,1) Brands Index returns MA(1) (FMCGBR)

Heteroscedasticity Test: ARCH

F-statistic	0.706854	Prob. F(5,458)	0.6185
Obs*R-squared	3.553152	Prob. Chi-Square(5)	0.6154

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Sample (adjusted): 2/15/2004 12/30/2012
Included observations: 464 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.950777	0.135220	7.031360	0.0000
WGT_RESID^2(-1)	0.017225	0.047855	0.359931	0.7191
WGT_RESID^2(-2)	0.014436	0.047743	0.302373	0.7625
WGT_RESID^2(-3)	-0.053363	0.047690	-1.118958	0.2637
WGT_RESID^2(-4)	0.069265	0.047737	1.450979	0.1475
WGT_RESID^2(-5)	0.009864	0.047829	0.206233	0.8367

R-squared	0.007658	Mean dependent var	1.007487
Adjusted R-squared	-0.003176	S.D. dependent var	1.869643
S.E. of regression	1.872610	Akaike info criterion	4.105390
Sum squared resid	1606.054	Schwarz criterion	4.158923
Log likelihood	-946.4504	Hannan-Quinn criter.	4.126462
F-statistic	0.706854	Durbin-Watson stat	1.953606
Prob(F-statistic)	0.618519		

Table 5.10b Correlogram of Squared Residuals- GARCH(2,1) Brands Index MA(1) (FMCGBR)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.014	0.014	0.0957	0.757
		2	0.015	0.014	0.1976	0.906
		3	-0.049	-0.050	1.3415	0.719
		4	0.065	0.066	3.3220	0.505
		5	0.010	0.009	3.3670	0.644
		6	0.019	0.015	3.5412	0.738
		7	-0.033	-0.028	4.0628	0.773
		8	-0.003	-0.005	4.0662	0.851
		9	-0.045	-0.044	5.0424	0.831
		10	-0.013	-0.017	5.1285	0.882
		11	-0.008	-0.003	5.1618	0.923
		12	0.029	0.027	5.5778	0.936
		13	0.006	0.011	5.5972	0.960
		14	-0.012	-0.011	5.6625	0.974
		15	0.066	0.072	7.7614	0.933

Both ARCH specifications (with GARCH / MA) show satisfactory results indicating that sales value volatility exists in the FMCG industry. The *F*-test and the LM-statistic were not significant at the 0.01 level of confidence, and the autocorrelation has been substantially removed as per the correlogram results in Tables 5.9b and 5.10b for the

FMCGBR returns series. The ARMA(1) structure model seems to be stronger. as assessed by the *F*-test and *p*-values, meaning that there is close relationship between the model and the observed FMCG sales value data.

The results from Tables 5.5 to 5.10b reveal that a GARCH (1,1) structure is not able to remove the autocorrelation of the squared residuals. Same outcome is attained after introducing the mean equation calculated according to an autoregressive moving average (ARMA) procedure for the same GARCH(1,1) model. Thus, different alternative GARCH structures were tested to finally arrive to a satisfactory GARCH(2,1) model with a mean equation ARMA(0,1) able to remove the autocorrelation of the squared residuals.

The next set of results to be discussed are presented in Tables 5.11 – 5.15b and correspond to the Brands Index FMCGBR_RF returns series, i.e. including the risk-free rate component.

Table 5.11 GARCH(1,1) Brands Index (RF) returns (FMCGBR_RF)

Dependent Variable: FMCGBR_RF
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Sample: 1/04/2004 12/30/2012
Included observations: 470
Convergence achieved after 19 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.078735	0.002214	35.56174	0.0000
Variance Equation				
C	0.000676	0.000236	2.868701	0.0041
RESID(-1)^2	0.262676	0.070674	3.716728	0.0002
GARCH(-1)	0.483346	0.137769	3.508385	0.0005

R-squared	-0.010360	Mean dependent var	0.083877
Adjusted R-squared	-0.010360	S.D. dependent var	0.050576
S.E. of regression	0.050837	Akaike info criterion	-3.190415
Sum squared resid	1.212094	Schwarz criterion	-3.155072
Log likelihood	753.7475	Hannan-Quinn criter.	-3.176510
Durbin-Watson stat	1.558054		

Table 5.12 GARCH(1,1) Brands Index (RF) returns (FMCGBR_RF), ARMA(1,1) structure

Dependent Variable: FMCGBR_RF
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Sample (adjusted): 1/11/2004 12/30/2012
Included observations: 469 after adjustments
Convergence achieved after 41 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 1/04/2004
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.083787	0.007961	10.52425	0.0000
AR(1)	0.948870	0.024968	38.00283	0.0000
MA(1)	-0.810345	0.050068	-16.18495	0.0000
		Variance Equation		
C	0.002211	0.000593	3.727541	0.0002
RESID(-1)^2	0.184352	0.070548	2.613157	0.0090
GARCH(-1)	-0.206619	0.260862	-0.792061	0.4283

R-squared	0.133795	Mean dependent var	0.084056
Adjusted R-squared	0.130078	S.D. dependent var	0.050481
S.E. of regression	0.047083	Akaike info criterion	-3.301678
Sum squared resid	1.033049	Schwarz criterion	-3.248578
Log likelihood	780.2434	Hannan-Quinn criter.	-3.280785
Durbin-Watson stat	2.096528		

Inverted AR Roots	.95
Inverted MA Roots	.81

From Tables 5.11 and 5.12, it can be seen that the GARCH(-1) coefficient is not significant at the 0.01 level of confidence in the ARMA structure case, while it is highly significant in the regression against the mean. The result implies that the model is unable to account for sales value volatility in the FMCG industry. The GARCH model lacks the ability to predict sales value volatility, the extent to which it will affect the next time series lag, and when it dies. Therefore, a GARCH (2,1) model was tested to ensure that sales value volatility was eliminated.

Table 5.13 GARCH(2,1) Brands Index returns with ARMA(1,1) (FMCGBR_RF)

Dependent Variable: FMCGBR_RF
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Sample (adjusted): 1/11/2004 12/30/2012
Included observations: 469 after adjustments
Convergence achieved after 77 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 1/04/2004
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*RESID(-2)^2 + C(7)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.083690	0.007691	10.88215	0.0000
AR(1)	0.939420	0.026296	35.72475	0.0000
MA(1)	-0.788365	0.051657	-15.26140	0.0000
		Variance Equation		
C	0.000253	0.000154	1.641296	0.1007
RESID(-1)^2	0.164736	0.073084	2.254057	0.0242
RESID(-2)^2	-0.166340	0.062840	-2.647068	0.0081
GARCH(-1)	0.885772	0.083645	10.58966	0.0000

R-squared	0.132170	Mean dependent var	0.084056
Adjusted R-squared	0.128445	S.D. dependent var	0.050481
S.E. of regression	0.047128	Akaike info criterion	-3.302880
Sum squared resid	1.034987	Schwarz criterion	-3.240931
Log likelihood	781.5255	Hannan-Quinn criter.	-3.278506
Durbin-Watson stat	2.119275		

Inverted AR Roots	.94
Inverted MA Roots	.79

As just discussed, the results in Table 5.11 show that all coefficients are highly significant at the 0.01 level of confidence as their *p*-values close to zero. However, the results in Table 5.13 for the GARCH(2,1) model with an ARMA (1,1) structure shows that all coefficients except C were also highly significant at the 0.01 level of confidence. Looking at the AIC and SIC values, it can be concluded that a GARCH(2,1) model with a mean equation of ARMA(1,1) is the best option for removing the autocorrelation of squared residuals in the FMCGBR_RF series.

Table 5.14a ARCH Test - GARCH(1,1) Brands Index (RF) returns (FMCGBR_RF)

Heteroscedasticity Test: ARCH

F-statistic	1.063882	Prob. F(5,459)	0.3797
Obs*R-squared	5.327206	Prob. Chi-Square(5)	0.3773

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Sample (adjusted): 2/08/2004 12/30/2012
Included observations: 465 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.010423	0.128205	7.881278	0.0000
WGT_RESID^2(-1)	-0.016108	0.046579	-0.345826	0.7296
WGT_RESID^2(-2)	-0.054448	0.046566	-1.169268	0.2429
WGT_RESID^2(-3)	0.027617	0.046611	0.592515	0.5538
WGT_RESID^2(-4)	-0.041847	0.046566	-0.898669	0.3693
WGT_RESID^2(-5)	0.077408	0.046568	1.662241	0.0971

R-squared	0.011456	Mean dependent var	1.003142
Adjusted R-squared	0.000688	S.D. dependent var	1.473934
S.E. of regression	1.473426	Akaike info criterion	3.625878
Sum squared resid	996.4824	Schwarz criterion	3.679323
Log likelihood	-837.0165	Hannan-Quinn criter.	3.646914
F-statistic	1.063882	Durbin-Watson stat	2.000242
Prob(F-statistic)	0.379680		

Table 5.14b Correlogram of Squared Residuals - GARCH(1,1) Brands Index (FMCGBR_RF)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.020	-0.020	0.1954	0.658
		2	-0.050	-0.051	1.3971	0.497
		3	0.026	0.024	1.7091	0.635
		4	-0.042	-0.044	2.5461	0.636
		5	0.076	0.077	5.2920	0.381
		6	0.021	0.018	5.4939	0.482
		7	-0.050	-0.040	6.6990	0.461
		8	0.035	0.030	7.2874	0.506
		9	-0.021	-0.019	7.4959	0.586
		10	-0.014	-0.014	7.5922	0.669
		11	0.044	0.034	8.5269	0.665
		12	-0.002	0.008	8.5282	0.743
		13	0.039	0.039	9.2479	0.754
		14	-0.033	-0.035	9.7864	0.778
		15	-0.005	0.006	9.8010	0.832

Table 5.15a ARCH Test - GARCH(2,1) Brands Index with ARMA(1,1) index (FMCGBR_RF)

Heteroscedasticity Test: ARCH

F-statistic	0.887223	Prob. F(5,458)	0.4894
Obs*R-squared	4.451119	Prob. Chi-Square(5)	0.4865

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Sample (adjusted): 2/15/2004 12/30/2012
Included observations: 464 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.900343	0.128249	7.020276	0.0000
WGT_RESID^2(-1)	0.030613	0.046607	0.656833	0.5116
WGT_RESID^2(-2)	0.003634	0.046610	0.077966	0.9379
WGT_RESID^2(-3)	-0.004855	0.046608	-0.104163	0.9171
WGT_RESID^2(-4)	-0.017516	0.046607	-0.375827	0.7072
WGT_RESID^2(-5)	0.092307	0.046589	1.981300	0.0482

R-squared	0.009593	Mean dependent var	1.004105
Adjusted R-squared	-0.001219	S.D. dependent var	1.678396
S.E. of regression	1.679419	Akaike info criterion	3.887620
Sum squared resid	1291.766	Schwarz criterion	3.941153
Log likelihood	-895.9278	Hannan-Quinn criter.	3.908692
F-statistic	0.887223	Durbin-Watson stat	1.997471
Prob(F-statistic)	0.489412		

Table 5.15b Correlogram of Squared Residuals - GARCH(2,1), ARMA(1,1) Index (FMCGBR_RF)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.030	0.030	0.4147	0.520
		2	0.004	0.004	0.4240	0.809
		3	-0.005	-0.005	0.4343	0.933
		4	-0.016	-0.015	0.5502	0.968
		5	0.091	0.092	4.4707	0.484
		6	0.015	0.009	4.5733	0.600
		7	-0.037	-0.040	5.2454	0.630
		8	-0.019	-0.016	5.4163	0.712
		9	-0.083	-0.080	8.7550	0.460
		10	0.012	0.009	8.8245	0.549
		11	0.037	0.034	9.4824	0.577
		12	0.001	0.004	9.4825	0.661
		13	0.007	0.008	9.5067	0.734
		14	-0.030	-0.017	9.9424	0.766
		15	0.016	0.018	10.071	0.815

Both ARCH specifications (with GARCH / MA) show that volatility clustering exists among FMCG goods, as the *F*-test and LM-statistic were not significant at the 0.01 level of confidence. The autocorrelation has been substantially removed, as per the correlogram in Tables 5.14b and 5.15b. However, the ARMA structure model seems to more powerful for checking the presence of FMCG sales value volatility according to the *F*-statistics and *p*-values. The ARMA model is convenient for testing data on the volatility clustering for different time series of Australian FMCG data. The *F*-statistic of 0.887 is close to unity, meaning there is a high probability that volatility clustering is present in the FMCG industry in Woolworths and Coles retail outlets in Australia.

In summary, this section provides evidence for volatility clustering in the Brands Index. The ARCH tests strongly suggest the presence of autocorrelation in the squared residuals for both the FMCGBR and FMCGBR_RF series, indicating that the amplitude of the returns variation changes over time. However, a GARCH (2,1) model with a mean equation of ARMA(0,1) was able to remove the autocorrelation of the squared residuals for the FMCGBR series, while a GARCH(2,1) model with a mean equation of ARMA(1,1) was the best option for removing the autocorrelation of the squared residuals for the FMCGBR_RF series.

5.1.2 IS THERE ANY EVIDENCE OF ASYMMETRY IN RETURNS?

The ARCH/GARCH models thus far have ignored the direction of returns and have only considered their magnitude. That is to say, GARCH models impose a symmetric response to volatility in positive and negative returns. This arises since the conditional variance is a function of the magnitudes of the lagged residuals and not their signs. Thus, by squaring the lagged error, the sign is lost. As discussed in Chapter 4, this thesis explores the EGARCH model (Nelson, 1991) and the threshold GARCH model known as TGARCH (Glosten et al., 1993) as methods of investigating volatility clustering in FMCG data. Results from these models for both return calculation methodologies are shown. An EGARCH and TGARCH model are tested with the results in Table 5.7 and the results are presented in Tables 5.16 and 5.17.

Table 5.16 EGARCH(2,1) output Brands Index returns (FMCGBR)

Dependent Variable: FMCGBR
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Sample (adjusted): 1/11/2004 12/30/2012
Included observations: 469 after adjustments
Convergence achieved after 40 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
*ABS(RESID(-2)/@SQRT(GARCH(-2))) + C(5)*RESID(-1)
/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.001212	0.002351	0.515531	0.6062
		Variance Equation		
C(2)	-5.769787	3.997514	-1.443344	0.1489
C(3)	0.855804	0.095028	9.005793	0.0000
C(4)	0.067025	0.573859	0.116797	0.9070
C(5)	**0.056601**	**0.078203**	**0.723772**	**0.4692**
C(6)	0.071610	0.651464	0.109922	0.9125

R-squared	-0.000188	Mean dependent var	0.000218
Adjusted R-squared	-0.000188	S.D. dependent var	0.072546
S.E. of regression	0.072552	Akaike info criterion	-2.605464
Sum squared resid	2.463488	Schwarz criterion	-2.552364
Log likelihood	616.9813	Hannan-Quinn criter.	-2.584571
Durbin-Watson stat	3.023424		

Table 5.17 TGARCH(2,1) output Brands Index returns (FMCGBR)

Dependent Variable: FMCGBR
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Sample (adjusted): 1/11/2004 12/30/2012
Included observations: 469 after adjustments
Failure to improve likelihood (singular hessian) after 78 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0) +
C(5)*RESID(-2)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.002195	0.002428	-0.904207	0.3659
		Variance Equation		
C	0.000215	5.19E-05	4.149895	0.0000
RESID(-1)^2	0.439825	0.071519	6.149806	0.0000
RESID(-1)^2*(RESID(-1)<0)	**0.066593**	**0.020074**	**3.317404**	**0.0009**
RESID(-2)^2	-0.487564	0.070881	-6.878638	0.0000
GARCH(-1)	0.975364	0.012086	80.70067	0.0000

R-squared	-0.001109	Mean dependent var	0.000218
Adjusted R-squared	-0.001109	S.D. dependent var	0.072546
S.E. of regression	0.072586	Akaike info criterion	-2.588357
Sum squared resid	2.465756	Schwarz criterion	-2.535258
Log likelihood	612.9698	Hannan-Quinn criter.	-2.567465
Durbin-Watson stat	3.020644		

For both the EGARCH and TGARCH specifications, the asymmetry terms (in bold) are positive, suggesting that negative movements imply a higher conditional variance in the next period compared to positive movements of the same sign. It is also clear that the asymmetry coefficient in the EGARCH case is not significant. Whereas it is very significant at the 0.01 level of confidence in the TGARCH model, it is not supported by the EGARCH results. This implies that it is possible to smooth the positivity constraints in the beta values. The cyclical movements in the Brands Index returns are allowed, as are the negative and positive impacts on volatility, depending on the size of the FMCG movement. The EGARCH and TGARCH results in Tables 5.18 and 5.19 are achieved from the results previously presented in Table 5.8.

Table 5.18 EGARCH(2,1) output Brands Index returns MA(1) (FMCGBR)

Dependent Variable: FMCGBR
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Sample (adjusted): 1/11/2004 12/30/2012
Included observations: 469 after adjustments
Convergence achieved after 39 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 1/04/2004
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)
*ABS(RESID(-2)/@SQRT(GARCH(-2))) + C(6)*RESID(-1)
/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000419	6.72E-05	6.237953	0.0000
MA(1)	-0.971379	0.009761	-99.51546	0.0000
Variance Equation				
C(3)	-10.66548	0.854580	-12.48038	0.0000
C(4)	0.458897	0.100630	4.560240	0.0000
C(5)	0.395245	0.115693	3.416329	0.0006
C(6)	**0.169021**	**0.056110**	**3.012302**	**0.0026**
C(7)	-0.656010	0.127441	-5.147548	0.0000

R-squared	0.509526	Mean dependent var	0.000218
Adjusted R-squared	0.508476	S.D. dependent var	0.072546
S.E. of regression	0.050861	Akaike info criterion	-3.182069
Sum squared resid	1.208048	Schwarz criterion	-3.120120
Log likelihood	753.1953	Hannan-Quinn criter.	-3.157695
Durbin-Watson stat	2.093825		
Inverted MA Roots	.97		

Table 5.19 TGARCH(1,1) output Brands Index returns MA(1) (FMCGBR)

Dependent Variable: FMCGBR
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Sample (adjusted): 1/11/2004 12/30/2012
Included observations: 469 after adjustments
Convergence achieved after 44 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 1/04/2004
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*RESID(-1)^2*(RESID(-1)<0) +
C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000384	7.37E-05	5.213019	0.0000
MA(1)	-0.970873	0.010395	-93.40160	0.0000
Variance Equation				
C	0.002718	0.000410	6.633569	0.0000
RESID(-1)^2	0.367695	0.114089	3.222880	0.0013
RESID(-1)^2*(RESID(-1)<0)	**-0.322601**	**0.118846**	**-2.714442**	**0.0066**
GARCH(-1)	-0.268007	0.133733	-2.004047	0.0451

R-squared	0.509443	Mean dependent var	0.000218
Adjusted R-squared	0.508392	S.D. dependent var	0.072546
S.E. of regression	0.050865	Akaike info criterion	-3.172971
Sum squared resid	1.208254	Schwarz criterion	-3.119871
Log likelihood	750.0616	Hannan-Quinn criter.	-3.152078
Durbin-Watson stat	2.094520		
Inverted MA Roots	.97		

For both the EGARCH and TGARCH specifications, the asymmetry terms (in bold) are highly significant at the 0.01 level of confidence, suggesting there is asymmetry in the returns. However, the coefficient in the TGARCH case is negative, suggesting that positive movements imply a higher next-period conditional variance than negative movements of the same sign, which is the opposite to what was concluded in the previous outputs. Therefore, asymmetry in the returns is supported by both models but the opposite sign is depicted in their coefficients. The conclusion, then, can only be validated if the models are treated separately rather than conjointly. The same models are applied now to the Brands Index FMCGBR_RF returns series. The difference in this case is that, as proposed in Chapter 4, the research in this section explores an ACD(1,1) model as proposed by Engle and Russell (1998) to model irregularly-spaced financial transaction data, as seen in risk-free rate returns. Since duration is necessarily non-negative, the ACD model has also been used to model time series data that consist of positive observations. Following this order, Table 5.20 shows the outputs for an EGARCH(1,1) specification. Results for the TGARCH model follow in Table 5.21.

Table 5.20 EGARCH output Brands Index returns (FMCGBR_RF)

Dependent Variable: FMCGBR_RF
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Sample: 1/04/2004 12/30/2012
Included observations: 470
Convergence achieved after 31 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
*RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.079192	0.002235	35.43030	0.0000
Variance Equation				
C(2)	-1.886279	0.774455	-2.435621	0.0149
C(3)	0.298634	0.109907	2.717143	0.0066
C(4)	**0.109496**	**0.062070**	**1.764078**	**0.0777**
C(5)	0.729397	0.118310	6.165159	0.0000

R-squared	-0.008600	Mean dependent var	0.083877
Adjusted R-squared	-0.008600	S.D. dependent var	0.050576
S.E. of regression	0.050793	Akaike info criterion	-3.201061
Sum squared resid	1.209983	Schwarz criterion	-3.156883
Log likelihood	757.2494	Hannan-Quinn criter.	-3.183681
Durbin-Watson stat	1.560772		

Table 5.21 TGARCH output Brands Index (RF) returns (FMCGBR_RF)

Dependent Variable: FMCGBR_RF
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Sample: 1/04/2004 12/30/2012
Included observations: 470
Convergence achieved after 24 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0) +
C(5)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.079470	0.002241	35.46784	0.0000
Variance Equation				
C	0.000777	0.000289	2.691464	0.0071
RESID(-1)^2	0.317160	0.098014	3.235884	0.0012
RESID(-1)^2*(RESID(-1)<0)	**-0.198968**	**0.115841**	**-1.717605**	**0.0859**
GARCH(-1)	0.465399	0.156253	2.978486	0.0029

R-squared	-0.007611	Mean dependent var	0.083877
Adjusted R-squared	-0.007611	S.D. dependent var	0.050576
S.E. of regression	0.050768	Akaike info criterion	-3.195893
Sum squared resid	1.208796	Schwarz criterion	-3.151715
Log likelihood	756.0349	Hannan-Quinn criter.	-3.178512

Durbin-Watson stat	1.562304

For both model specifications (EGARCH and TGARCH), the asymmetry parameters (in bold) are weakly significant at the 0.1 level of confidence. The coefficient's signs also move in opposite directions. It suggests that positive movements imply a higher next-period conditional variance than negative movements of the same sign. Therefore, asymmetry in the returns is supported by both models, but there is an opposite sign in their coefficients. The conclusion, then, can only be validated if the models are treated separately rather than conjointly. Consequently, evidence of asymmetry is unconvincingly supported. The ARMA structure from Table 5.13 follows.

Table 5.22 EGARCH output Brands Index returns ARMA structure (FMCGBR_RF)

Dependent Variable: FMCGBR_RF
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Sample (adjusted): 1/11/2004 12/30/2012
Included observations: 469 after adjustments
Failure to improve likelihood (singular hessian) after 90 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 1/04/2004
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*ABS(RESID(-2)/@SQRT(GARCH(-2))) + C(7)*RESID(-1)
/@SQRT(GARCH(-1)) + C(8)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.084697	0.006275	13.49865	0.0000
AR(1)	0.949621	0.017468	54.36278	0.0000
MA(1)	-0.851077	0.033864	-25.13252	0.0000
		Variance Equation		
C(4)	-0.432645	0.133287	-3.245964	0.0012
C(5)	0.213570	0.134980	1.582238	0.1136
C(6)	-0.315790	0.130630	-2.417446	0.0156
C(7)	**0.088193**	**0.026439**	**3.335741**	**0.0009**
C(8)	0.916780	0.022044	41.58798	0.0000

R-squared	0.134647	Mean dependent var	0.084056
Adjusted R-squared	0.130933	S.D. dependent var	0.050481
S.E. of regression	0.047060	Akaike info criterion	-3.324010
Sum squared resid	1.032033	Schwarz criterion	-3.253211
Log likelihood	787.4803	Hannan-Quinn criter.	-3.296153
Durbin-Watson stat	2.016208		

Inverted AR Roots	.95
Inverted MA Roots	.85

Table 5.23 TGARCH output Brands Index returns ARMA structure (FMCGBR_RF)

Dependent Variable: FMCGBR_RF
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Sample (adjusted): 1/11/2004 12/30/2012
Included observations: 469 after adjustments
Convergence achieved after 57 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 1/04/2004
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*RESID(-1)^2*(RESID(-1)<0) +
C(7)*RESID(-2)^2 + C(8)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.084511	0.004865	17.37134	0.0000
AR(1)	0.904983	0.031847	28.41620	0.0000
MA(1)	-0.786175	0.056397	-13.93998	0.0000
		Variance Equation		
C	0.000153	5.71E-05	2.684450	0.0073
RESID(-1)^2	0.159327	0.088251	1.805374	0.0710
RESID(-1)^2*(RESID(-1)<0)	**-0.097654**	**0.034850**	**-2.802164**	**0.0051**
RESID(-2)^2	-0.146637	0.080692	-1.817236	0.0692
GARCH(-1)	0.963179	0.030494	31.58598	0.0000

R-squared	0.129849	Mean dependent var	0.084056
Adjusted R-squared	0.126114	S.D. dependent var	0.050481
S.E. of regression	0.047190	Akaike info criterion	-3.319611
Sum squared resid	1.037755	Schwarz criterion	-3.248812
Log likelihood	786.4488	Hannan-Quinn criter.	-3.291754
Durbin-Watson stat	2.046627		

Inverted AR Roots	.90
Inverted MA Roots	.79

As was the case for the FMCGBR returns series, the same conclusion is reached here for the FMCGBR_RF returns series. In both model specifications (EGARCH and TGARCH), the asymmetry terms (in bold) are highly significant at the 0.10 level of confidence, suggesting there is asymmetry in the returns. However, the coefficient in the TGARCH case is negative, suggesting that positive movements imply a higher next-period conditional variance than negative movements of the same sign. The opposite also holds for the EGARCH model where the coefficient is positive. Accordingly, asymmetry in the returns is supported by both models but opposite signs in their asymmetry coefficients are seen. Once again, in order to support evidence of asymmetry, the TGARCH and EGARCH models need to be considered separately rather than jointly. Finally, as discussed in Chapter 4, an exponential ACD(1,1) is considered next. This study makes use of the open-source software R to calculate the EACD(1,1) model. The specific package used is 'rugarch' (Ghalanos, 2014). Appendix 3 shows the script and code used to run this package. The EACD results are provided below in Tables 5.24 and 5.25. The autocorrelation charts and model fit are presented in Appendix 4, while the residuals chart is given in Appendix 5.

Table 5.24 EACD(1,1) output Brands Index returns (FMCGBR_RF)

```
ACD model estimation by (Quasi) Maximum Likelihood

Call:

acdFit(durations=fmcg, model="ACD",dist="exponential", order = c(1,1))
Model: ACD(1,1)
Distribution: exponential
N: 470
Parameter estimate:
         Coef      SE     PV robustSE
omega  0.00522 0.00288 0.070  0.00247
alpha1 0.10970 0.04410 0.013  0.02965
beta1  0.82839 0.05999 0.000  0.04824

The fixed/unfree mean distribution parameter: lambda: 1

QML robust correlations:
       omega alpha1  beta1
omega   1.000  0.332 -0.815
alpha1  0.332  1.000 -0.810
beta1  -0.815 -0.810  1.000

Goodness of fit:
                 value
LogLikelihood  7.043510e+02
AIC           -1.402702e+03
BIC           -1.390244e+03
MSE            2.217127e-03
```

From the results in Table 5.24 above, it is clear that the conditions are satisfied; omega > 0, and alpha1+ beta1 are greater than zero and less than 1. To confirm whether or not the autocorrelation in the residuals and the ARCH effects are still present, Box-Pierce and ARCH tests were carried out. The results are shown in Table 5.25.

Table 5.25 EACD(1,1) Box-Pierce and ARCH test- Brands Index returns (FMCGBR_RF)

Box-Pierce test
data: acd_fmcg$residuals X-squared = 32.278, df = 26, p-value = 0.1841
ARCH LM-test; Null hypothesis: no ARCH effects
data: acd_fmcg$residuals Chi-squared = 15.303, df = 12, p-value = 0.2253

As can be seen from the outputs in Table 5.25, individually, the tests are satisfactory, as the *p*-values in both cases are greater than 0.05. The overall results from the ACD model are, in general terms, acceptable based on the fact that *P*-value surpasses the threshold value of 0.05. As stated in Chapter 4, it is beyond the scope of this research to investigate different ACD structures with alternative distributions, as this study focuses primarily on ARCH-GARCH-type models. Therefore, further research in this specific field will be required. Next, Section 5.2 deals with the validation of the five hypotheses specified in Chapter 3.

5.2 Hypothesis Testing

To answer the research question: *What are the antecedents of brands' sales volatility in the Australian retail sector and how do they influence brand performance overall?*, a proposed framework and set of hypothesis were developed in Chapter 3. These are now tested in this section by using outputs from Section 5.1. A comparison of the volatility measurements of the two return methodologies (FMCGBR and FMCGBR_RF) is conducted. Two alternative models were developed in both cases; the first one focuses on assessing volatility by regressing the returns against the intercept in the mean equation, while the second technique combined an ARMA process in the mean equation to capture volatility clustering. Furthermore, to evaluate asymmetry in both return calculation methodologies, the EGARCH and TGARCH models were expanded. The next step is to evaluate and choose between the two alternative models, for both return methodologies, proposed in this research. Results for both the FMCGBR and FMCGBR_RF return methodologies are given in Table 5.26.

Table 5.26 Model selection for both return methodologies, FMCGBR and FMCGBR_RF

	Model			
	FMCGBR	**FMCGBR-ARMA(0,1)**	**FMCGBR_RF**	**FMCGBR_RF-ARMA(1,1)**
Intercept	**-0.00118**	**0.00041**	**0.07874**	**0.08369**
P-values	0.62830	0.00000	0.00000	0.00000
AR(1)				**0.93942**
P-values				0.00000
MA(1)		**-0.976553**		**-0.788365**
P-values		0.00000		0.00000
ARCH-GARCH				
C	**0.000212**	**0.000167**	**0.000676**	**0.000253**
P-values	0.0234	0.00860	0.0041	0.1007
RESID(-1)^2	**0.476393**	**0.166191**	**0.262676**	**0.164736**
P-values	0.00000	0.00190	0.00020	0.02420
RESID(-2)^2	**-0.46595**	**-0.177641**		**-0.16634**
P-values	0.00000	0.00050		0.0081
GARCH(-1)	**0.951152**	**0.947245**	**0.483346**	**0.885772**
P-values	0.00050	0.00000	0.00050	0.00000
Stationarity Condition RESID(-1)^2 + GARCH(-1) < 1	**0.961595**	**0.935795**	**0.746022**	**0.884168**
R-squared	-0.000373	0.50965	-0.01036	0.13217
Akaike info criterion	-2.578363	-3.159549	-3.190415	-3.30288
Schwarz criterion	-2.534114	-3.106449	-3.155072	-3.240931
Hannan-Quinn criterion	-2.560953	-3.138656	-3.17651	-3.278506

Based on the results in Table 5.26 above, it seems that the ARMA specification gives the best results, as per its *R*-squared, Akaike information criterion, Schwarz criterion and Hannan-Quinn criterion[3], for both return calculation methodologies, FMCGBR and FMCGBR_RF. In addition, in all cases, the stationarity condition is satisfied. Thus, in

[3] *R*-squared measures the goodness of fit of the Brands Index for the Australian FMCG industry, which is a proportionate uncertainty explained by the fitted model.
Akaike information criterion measures the deviation of a model from the defined distribution of the available Brands Index data.
Schwarz criterion provides a sensible approximate value for the model under the given hypothesis and should be set before doing the computations.
Hannan-Quinn criterion is used to estimate the lag length for the Brands Index for a time series.

order to answer the hypothesis that the change in weekly sales as measured by the Brands Index follows a volatility clustering pattern similar to that of financial markets, research in this section of the thesis focus on the FMCGBR-ARMA(0,1) and FMCGBR_RF-ARMA(1,1) model specifications. A comparison of competing model specifications is then needed to finally decide on the model that best capture volatility clustering in the Brands Index. Tables 5.27 and 5.28 below show these results.

Table 5.27 Model selection for FMCGBR returns series

	Model FMCGBR-ARMA(0,1)					
	GARCH	GARCH-t	EGARCH	EGARCH*-t	TGARCH	TGARCH*-t
Intercept	**0.00041**	**0.00046**	**0.00042**	**0.00047**	**0.00039**	**0.00045**
P-values	0.00000	0.00000	0.00861	0.00861	0.00000	0.00000
AR(1)						
P-values						
MA(1)	**-0.97655**	**-0.95260**	**-0.97138**	**-0.95694**	**-0.97194**	**-0.95188**
P-values	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
ARCH-GARCH						
C	**0.00017**	**0.00017**	**-10.66547**	**-10.33963**	**0.00284**	**0.00045**
P-values	0.00860	0.40730	0.00000	0.00000	0.00000	0.49321
RESID(-1)^2	**0.16619**	**0.18829**	**0.45889**	**0.44705**	**0.37148**	**0.18506**
P-values	0.00190	0.03591	0.00000	0.00005	0.00121	0.04230
RESID(-2)^2	**-0.17764**	**-0.16967**	**0.39524**	**0.39306**	**0.03333**	**-0.17182**
P-values	0.00050	0.03794	0.00000	0.01180	0.49901	0.05383
GARCH(-1)	**0.94725**	**0.86751**	**-0.65600**	**-0.61441**	**-0.34760**	**0.80315**
P-values	0.00000	0.00000	0.00000	0.00860	0.05910	0.00710
C(6)			**0.16902**	**0.12646**		
P-values			0.00261	0.06760		
RESID(-1)^2*(RESID(-1)<0)					**-0.32760**	**0.03305**
P-values					0.00692	0.68261
T Dist		**4.52054**		**5.26335**		**4.46218**
P-values		0.00020		0.00078		0.00020
Stationarity Condition RESID(-1)^2 + GARCH(-1) < 1	**0.93580**	**0.88613**	**0.19813**	**0.22571**	**0.05721**	**0.81639**
R-squared	0.50965	0.50780	0.50952	0.50815	0.50952	0.50774
Akaike info criterion	-3.15955	-3.22240	**-3.18207**	-3.22960	-3.16986	-3.21844
Schwarz criterion	-3.10645	-3.16045	**-3.12012**	-3.15880	-3.10791	-3.14764
Hannan-Quinn criterion	-3.13866	-3.19803	**-3.15770**	-3.20174	-3.14549	-3.19058

* t- refers to t-student distribution rather than normal distribution

The EGARCH-t model is not chosen either, as its asymmetry coefficient shows a *p*-value of 0.0676, which is not significant at the 0.05 level of confidence. The standard GARCH and GARCH-t models are not considered, as the asymmetry assumption is satisfied by the TGARCH and EGARCH models. Thus, the selection of the best model for capturing volatility in the returns based on the previous period is the EGARCH model. This final choice is based on the AIC, Schwarz criterion and Hannan-Quinn criterion, which in all cases outperform the TGARCH model. Table 5.28, below, presents the results for the FMCGBR_RF returns series.

Table 5.28 Model selection for FMCGBR_RF returns

	Model FMCGBR_RF-ARMA(1,1)					
	GARCH	**GARCH-t**	**EGARCH**	**EGARCH*-t**	**TGARCH**	**TGARCH*-t**
Intercept	**0.08369**	**0.08165**	**0.08470**	**0.08449**	**0.08451**	**0.08415**
P-values	0.00000	0.00000	0.00000	0.00861	0.00000	0.00000
AR(1)	**0.93942**	**0.95057**	**0.94962**	**0.95011**	**0.90498**	**0.90855**
P-values	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
MA(1)	**-0.78837**	**-0.80652**	**-0.85108**	**-0.85089**	**-0.78618**	**-0.78779**
P-values	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
ARCH-GARCH						
C	**0.00025**	**0.00023**	**-0.43265**	**-0.42921**	**0.00015**	**0.00015**
P-values	0.10070	0.23640	0.00120	0.00290	0.00730	0.01530
RESID(-1)^2	**0.16474**	**0.17604**	**0.21357**	**0.21652**	**0.15933**	**0.16309**
P-values	0.02420	0.04070	0.11360	0.11160	0.07100	0.06940
RESID(-2)^2	**-0.16634**	**-0.17238**	**-0.31579**	**-0.31666**	**-0.14664**	**-0.14948**
P-values	0.00810	0.02270	0.01560	0.01620	0.06920	0.06820
GARCH(-1)	**0.88577**	**0.88908**	**0.91678**	**0.91763**	**0.96318**	**0.96192**
P-values	0.00000	0.00000	0.00000	0.00860	0.05910	0.00000
C(7)			**0.08819**	**0.08717**		
P-values			0.00090	0.00230		
RESID(1)^2*(RESID(1)<0)					**-0.09765**	**-0.09332**
P-values					0.00510	0.01670
T Dist		**13.30394**		**161.54660**		**69.17887**
P-values		0.03250		0.87950		0.72080
Stationarity Condition RESID(-1)^2 + GARCH(-1) < 1	**0.88417**	**0.89275**	**0.81456**	**0.81749**	**0.97587**	**0.97553**
R-squared	0.13217	0.13268	0.13465	0.13473	0.12985	0.13062
Akaike info criterion	-3.30288	-3.31033	**-3.32401**	-3.31980	-3.31961	-3.31560
Schwarz criterion	-3.24093	-3.23953	**-3.25321**	-3.24015	-3.24881	-3.23595
Hannan-Quinn criterion	-3.27851	-3.28247	**-3.29615**	-3.28846	-3.29175	-3.28426

* t- refers to t-student distribution rather than normal distribution

As the parameters for the TGARCH-t and EGARCH-t models are not significant at any level, these models were disregarded. As in the previous statement, the standard GARCH and GARCH-t models are not contemplated as the asymmetry terms in both; the TGARCH and EGARCH models is highly significant. Therefore, the EGARCH model is the one selected based on the AIC, Schwarz criterion and Hannan-Quinn criterion results, which in all cases outperform the TGARCH model. As the previous results suggest, in both return calculations, the best model for describing volatility clustering is the EGARCH, with the ARMA specification being the only difference. Thus, all elements are in place to validate *Hypothesis 1* as follows:

Hypothesis 1: The variation in the weekly sales of the proposed Brands Index follows a volatility-clustering pattern similar to that of financial market indices.

The creation of the Brands Index for the nine years of weekly data based on five categories has indicated two clear paths for capturing volatility, as previously revealed. The importance of these return calculations will be more evident when dealing with *Hypothesis 4* and *Hypothesis 5* later in this chapter. Figures 5.1 and 5.2 below shows the returns for the Brands Index.

Figure 5.1 Brands Index returns based on previous observations (FMCGBR)

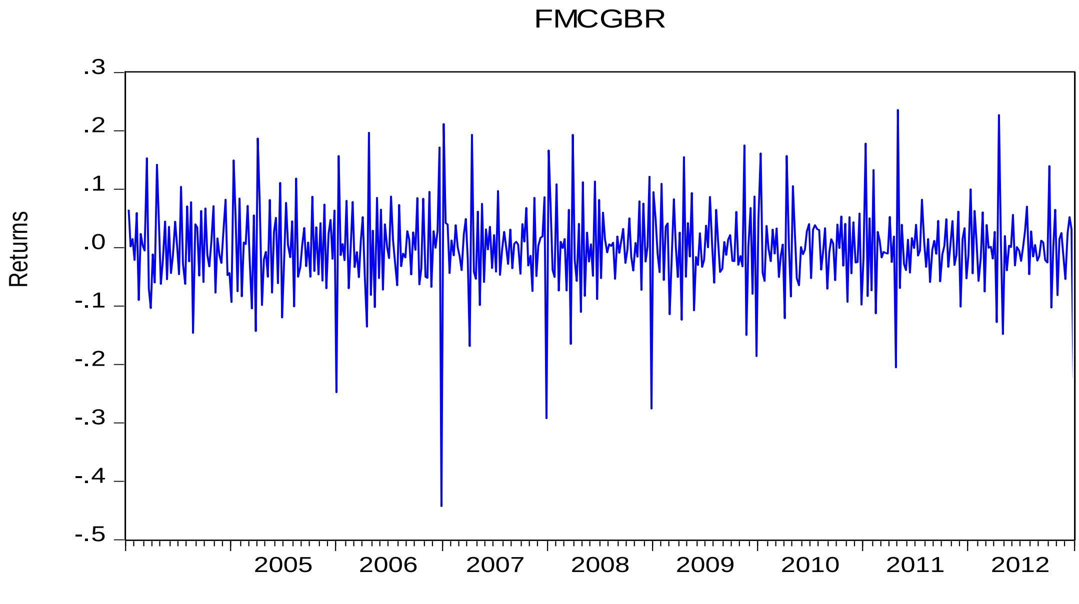
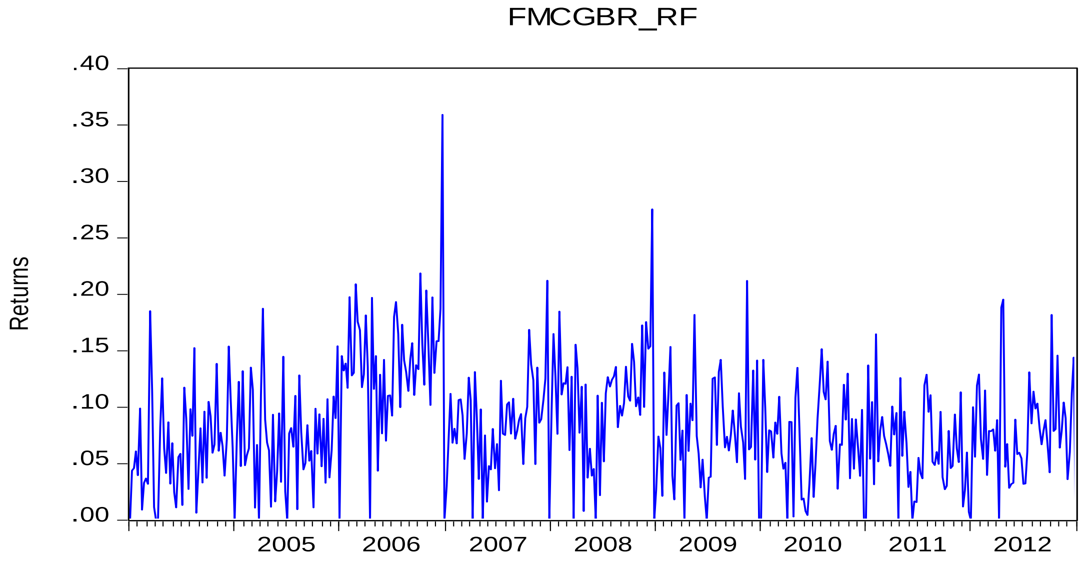


Figure 5.2 Brands Index returns based on base sales (FMCGBR_RF)



From Figure 5.1, above, it can be seen that the Brands Index returns clearly depict a similar pattern to those of financial indices, where large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes. This can be seen from the analysis presented in Figure 5.1 since we utilised the values in our target time period. The same conclusion based on the chart from Figure 5.2 is more difficult to reach, as this return methodology always generates positive returns. The graphical test in the second return calculation performed to detect volatility does not seem that obvious. Thus, the conclusion in this case needs to be supported by the use of ARCH-GARCH-type models. The phenomenon of volatility clustering has led to the introduction and extensive use of ARCH-GARCH models in financial forecasting and derivative pricing. This research has properly quantified the observed volatility and is therefore able to validate *Hypothesis 2*.

In sum, *Hypothesis 1* can be validated, as the assumed phenomenon of volatility clustering is clearly persistent in the Brands Index. Although it is less clear in the FMCGBR_RF case, it will be supported when validating *Hypothesis 2* next.

Hypothesis 2: Volatility in the created Brands Index can be forecast using ARCH/GARCH models or any of their extensions.

As stated in the previous paragraph, the visual illustration of volatility clustering is a great indication of the existence of this phenomenon in the FMCG Brands Index. However, the available techniques from the finance literature (illustrated in Chapters 2 and 3) related to ARCH-GARCH modelling deal specifically with this topic. Thus, the process presented in Section 5.1—for choosing the best model to capture volatility clustering in the FMCG Brands Index—allows this study to accept or reject *Hypothesis 2*.

The following process is a result of the two competing models that were tested. First, the two Brands Index returns were independently regressed against their respective intercepts. The residuals from these models were then squared and regressed against their squared lags for up to five periods. The conclusion reached was that the ARCH effect was present in both return calculations, as per Tables 5.1 and 5.2. Therefore, making use of a test for volatility that is mostly used in the finance field, it has been demonstrated that these techniques can be extended to other disciplines such as management and marketing. Secondly I attempted to capture the observed volatility in the Brands Index by using two returns calculation methodologies (FMCGBR and FMCGBR_RF). Accordingly, a GARCH(1,1) model was introduced for each method. However, the results show that the GARCH term was not statistically significant in all cases at the 0.05 confidence level. Third, of the different structures of standard GARCH models tested, GARCH(2,1) was the best model out of both return calculation methodologies. The same procedure was then replicated for both models; but this time, an ARMA process was brought into the mean equation.

Table 5.27 presents a summary of the outputs from these models, where the conclusion was in favour of the ARMA model. Based on the outputs, it was found that all parameters were statistically significant at the 0.01 level of confidence for both models; the FMCGBR ARMA(0,1) and the FMCGBR_RF ARMA(1,1). The models give a better understating of the Brands Index that explains the presence of volatility clustering in the Australian FMCG industry. Bollerslev and Mikkelsen (1999) assert that volatility forecasts can be improved when volatility clustering is taken into account. As the best model has been now selected for both return calculations, a set of GARCH-type models were performed in each case. Tables 5.27 and 5.28 present the output summaries for each return method. Interestingly, the asymmetry term was statistically significant for both returns. Consequently, it is concluded that the volatility clustering observed in the returns of the Brands Index can be described by adopting the same ARCH-GARCH-type models as those used in finance and economics.

In sum, *Hypothesis 2* can be validated, as the use of ARCH-GARCH models from finance theory are able to determine the best structure for measuring volatility clustering for the returns in the Brands Index. In this instance, an EGARCH (2,1) model was the best model for capturing this implicit volatility for both return adoptions.

The question that unfolds next is whether or not the volatility forecast of the Brands Index returns can be improved when volatility clustering is taken into account. If the answer to this question is "yes", then the forecasting from traditional ARMA methodologies should be improved. To accept or reject these statements, *Hypothesis 3* is examined.

Hypothesis 3: Changes in weekly sales in the created Brands Index can be simulated using the volatility forecast.

In order to validate *Hypothesis 3*, research in this section of the thesis will focus on the final ARMA structure selected for each return calculation alternative in the previous section. Two approaches are used herein; in-sample volatility forecasting and out-of-sample volatility forecasting. An in-sample volatility forecast is generated from the same set of data that has been used to estimate the model's parameters so far, whereas out-of-sample volatility forecasting requires some observations to be held back. To illustrate how the out-of-sample volatility forecast works, a new model based on eight years of data was constructed so that the final 52 observations can then be used to evaluate the volatility forecast results. The results for the FMCGBR returns series based on the ARMA(1,1) model are presented in Figure 5.3, and the outputs for the EGARCH models follow in Figure 5.4. A comparison of the main volatility forecast metrics for the ARMA(1,1) and GARCH(1,1) models is provided in Table 5.29.

Figure 5.3 Brands Index return ARMA(1,1) in-sample forecast (FMCGBR(F))

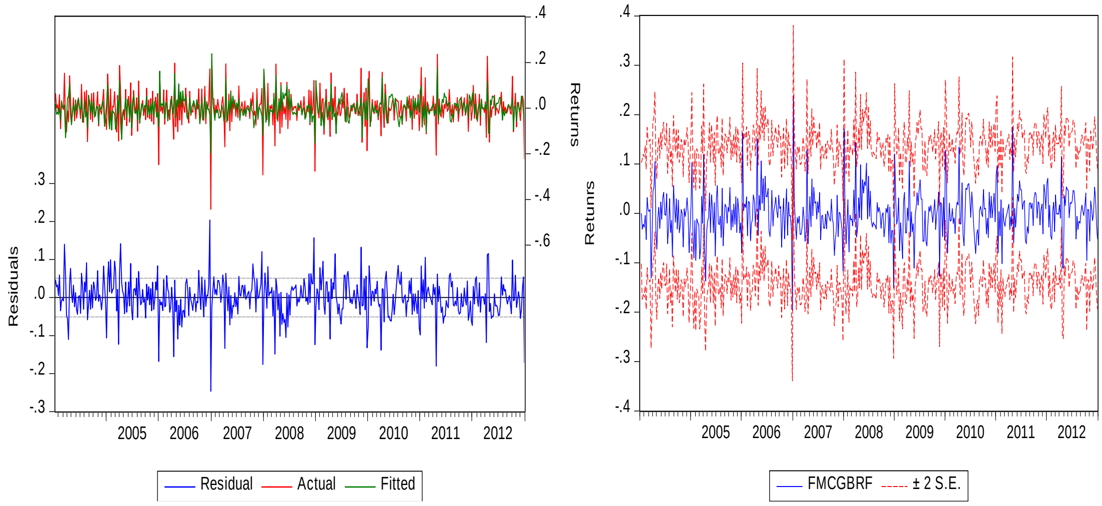


Figure 5.4 Brands Index return EGARCH(2,1) in-sample forecast

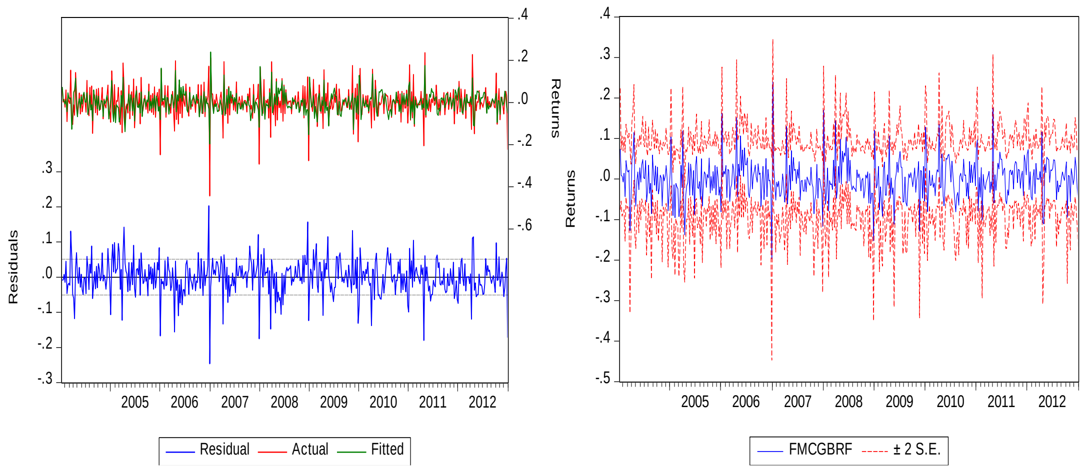


Table 5.29 Brands Index return ARIMA(1,1) in-sample forecast (FMCGBR(F))

Forecast: FMCGBRF	
Actual: FMCGBR	
Forecast sample: 1/04/2004 12/30/2012	
Included observations: 470	
Root Mean Squared Error	0.051019
Mean Absolute Error	0.037445
Mean Absolute Percentage Error	289.2074
Theil Inequality Coefficient	0.420732
Bias Proportion	0.000456
Variance Proportion	0.215442
Covariance Proportion	0.784103
Theil U2 Coefficient	0.882273
Symmetric MAPE	107.2675

Table 5.30 Brands Index return EGARCH(2,1) in-sample forecast (FMCGBR(F))

Forecast: FMCGBRF	
Actual: FMCGBR	
Forecast sample: 1/04/2004 12/30/2012	
Adjusted sample: 1/11/2004 12/30/2012	
Included observations: 469	
Root Mean Squared Error	0.050752
Mean Absolute Error	0.037188
Mean Absolute Percentage Error	285.7438
Theil Inequality Coefficient	0.418476
Bias Proportion	0.000002
Variance Proportion	0.217305
Covariance Proportion	0.782693
Theil U2 Coefficient	0.881493
Symmetric MAPE	106.2242

From Figure 5.4 and Table 5.30 above, it can be seen that across all given metrics, the EGARCH model generates a better volatility forecast. The MAPE is smaller at 285.74, the MAE has a lower value of 0.03718, and the RMSE is also lower, at 0.50752. These metrics are used to measure the accuracy of the Brands Index volatility forecast that shows that presence of volatility clustering in the FMCG data. The volatility forecasts are scale-independent and can be used to compare the Brands Indexes for the different time series in the data. The results are clearly indicative of the presence of volatility clustering in the Brand Indices.

Figures 5.5 and 5.6 present the results for the FMCGBR_RF returns series. The returns series is evolved from the concept of the risk-free rate of return, as defined in the context of the research presented in this thesis, i.e., it is the calculation of returns from total sales value to the base sales value, which is always positive. Tables 5.31 and 5.32 provide the summary statistics for the volatility forecasts of this series.

Figure 5.5 Brands Index return ARMA(1,1) in-sample forecast (FMCGBR_RF(F))

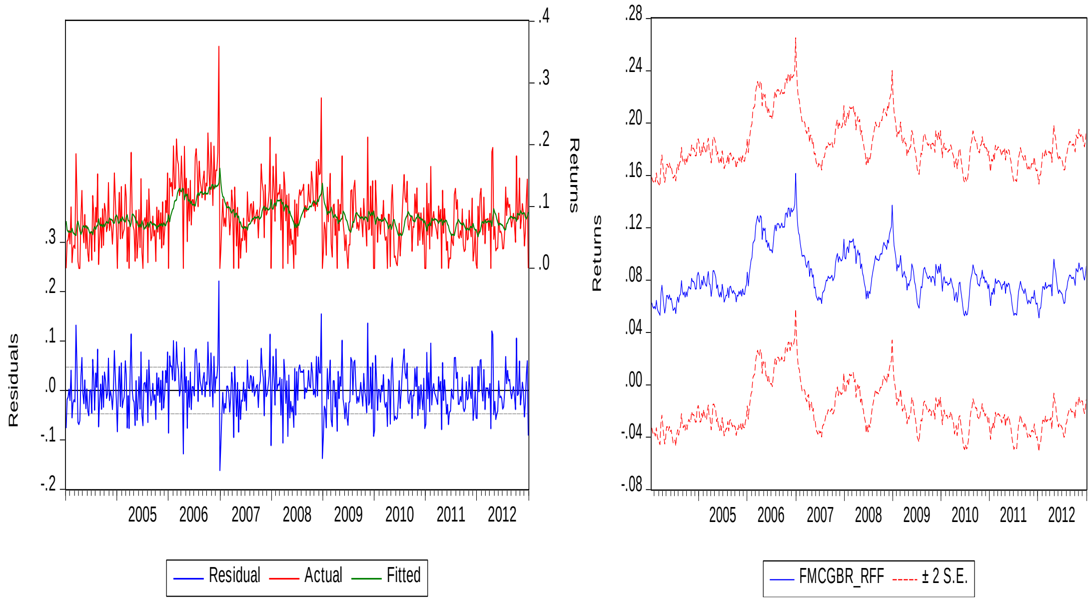


Figure 5.6 Brands Index return (RF) EGARCH(2,1) in-sample forecast (FMCGBR_RF(F))

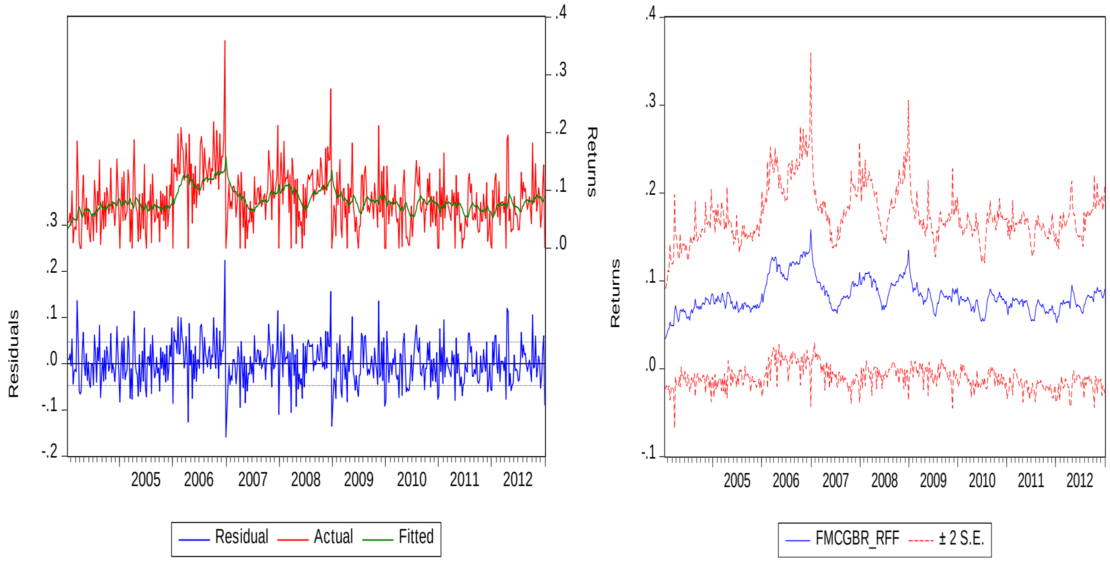


Table 5.31 Brands Index return (RF) ARIMA(1,1) in-sample forecast (FMCGBR_RF(F))

Forecast: FMCGBR_RFF	
Actual: FMCGBR_RF	
Forecast sample: 1/04/2004 12/30/2012	
Adjusted sample: 1/11/2004 12/30/2012	
Included observations: 469	
Root Mean Squared Error	0.046908
Mean Absolute Error	0.036335
Mean Absolute Percentage Error	NA
Theil Inequality Coefficient	0.255648
Bias Proportion	0.000233
Variance Proportion	0.450473
Covariance Proportion	0.549294
Theil U2 Coefficient	NA
Symmetric MAPE	50.65258

Table 5.32 Brands Index return EGARCH(2,1) in-sample forecast (FMCGBR_RF(F))

Forecast: FMCGBR_RF(F)	
Actual: FMCGBR_RF	
Forecast sample: 1/04/2004 12/30/2012	
Adjusted sample: 1/11/2004 12/30/2012	
Included observations: 469	
Root Mean Squared Error	0.046898
Mean Absolute Error	0.036297
Mean Absolute Percentage Error	NA
Theil Inequality Coefficient	0.256323
Bias Proportion	0.000684
Variance Proportion	0.453853
Covariance Proportion	0.545463
Theil U2 Coefficient	NA
Symmetric MAPE	50.62984

From Tables 5.31 and 5.32 above, the same conclusion is reached for the FMCGBR_RF(F) volatility forecast series as for the FMCGBR(F) volatility forecast series. As the MAPE formula is calculated as the sum of actual values minus forecast values divided by actual values, it can’t be assured if there are zero values, as in the case of the FMCGBR_RF series. However, the MAE is smaller at 0.03629 and the RMSE is also lower with a total figure of 0.04689. It is also observed that although the prediction metrics in this case are also more in favour of the EGARCH model, the differences in the magnitude of the volatility forecast metrics are bigger in the FMCGBR case. The main explanation for this is that the FMCGBR shows higher swings up and down as it takes into account the values in both directions without any restriction, while the FMCG_RF movement has been restricted to the base sales value so the oscillations in the movements are much smaller. The parameters for the alternative models are presented in Tables 5.33—5.36, below.

Table 5.33 Brands Index return ARMA(0,1) new model (FMCGBR)

Variable	Coefficient	Std. Error	*t*-statistic	Prob.
C	0.000422	5.96E-05	7.083347	0.0000
MA(1)	-0.977062	0.010656	-91.68711	0.0000

Table 5.34 Brands Index return EGARCH(2,1) new model (FMCGBR)

Variable	Coefficient	Std. Error	*z*-statistic	Prob.
C	0.000430	6.48E-05	6.633472	0.0000
MA(1)	-0.972996	0.009625	-101.0926	0.0000
		Variance Equation		
C(3)	-10.59014	0.908449	-11.65739	0.0000
C(4)	0.431962	0.101039	4.275189	0.0000
C(5)	0.366262	0.120651	3.035718	0.0024
C(6)	0.162388	0.054871	2.959437	0.0031
C(7)	-0.645254	0.134909	-4.782873	0.0000

Table 5.35 Brands Index return ARMA(0,1) new model (FMCGBR RF)

Variable	Coefficient	Std. Error	*t*-statistic	Prob.
C	0.082921	0.007997	10.36934	0.0000
AR(1)	0.957258	0.022197	43.12457	0.0000
MA(1)	-0.837583	0.042156	-19.86854	0.0000

Table 5.36 Brands Index return EGARCH(2,1) new model (FMCGBR RF)

Variable	Coefficient	Std. Error	*z*-statistic	Prob.
C	0.082482	0.007255	11.36944	0.0000
AR(1)	0.954680	0.019030	50.16610	0.0000
MA(1)	-0.840438	0.035795	-23.47917	0.0000
		Variance Equation		
C(4)	-0.408877	0.187593	-2.179601	0.0293
C(5)	0.262476	0.147758	1.776385	0.0757
C(6)	-0.336724	0.144897	-2.323883	0.0201
C(7)	0.075100	0.032058	2.342667	0.0191
C(8)	0.924135	0.031589	29.25470	0.0000

The outputs of the preceding four models present some consistent parameters that have importance for brand managers' decision making. The standard error values in the four tables are positive, meaning that the model has accurately predicted the presence of Brands Index volatility in the FMCGs in Australia. The *t*-statistics show both negative and positive values, implying that the swings in the different time series affect the Brands Index differently. The time-varying volatility is dictated by the market returns of the different brands. This allows this thesis to perform out of sample volatility forecasts for the last 52 observations and then compare them with actual returns. Tables 5.37 and 5.38 present the main volatility forecast metrics for the FMCGBR returns.

From Tables 5.37 and 5.38, it can be seen that the MAPE and MAE are lower in the EGARCH model but that the RMSE is slightly higher at 0.048845. The in-sample and out-of-sample volatility forecasts provided by the EGARCH model have better performance, as indicated by their main volatility forecast metrics—MAPE and MAE. However, it is evident that volatility forecasts based on returns without the a risk-free component converge to actual returns. The metrics suggest that based on the results, the EGARCH model is best able to capture the observed volatility.

Table 5.37 Brands Index return new ARMA(0,1) out-of-sample forecast (FMCGBR(F))

Forecast: FMCGBRF	
Actual: FMCGBR	
Forecast sample: 1/08/2012 12/30/2012	
Included observations: 52	
Root Mean Squared Error	0.048833
Mean Absolute Error	0.034774
Mean Absolute Percentage Error	521.9197
Theil Inequality Coefficient	0.441631
Bias Proportion	0.014396
Variance Proportion	0.263368
Covariance Proportion	0.722236
Theil U2 Coefficient	0.663007
Symmetric MAPE	110.8515

Table 5.38 Brands Index return new EGARCH(2,1) out-of-sample forecast (FMCGBR(F))

Forecast: FMCGBRF	
Actual: FMCGBR	
Forecast sample: 1/08/2012 12/30/2012	
Included observations: 52	
Root Mean Squared Error	0.048845
Mean Absolute Error	0.034686
Mean Absolute Percentage Error	508.0970
Theil Inequality Coefficient	0.442461
Bias Proportion	0.010779
Variance Proportion	0.265543
Covariance Proportion	0.723678
Theil U2 Coefficient	0.637897
Symmetric MAPE	111.3120

Table 5.39 Brands Index return new ARMA(0,1) out-of-sample forecast (FMCGBR(F))

Forecast: FMCGBR_RF(F)	
Actual: FMCGBR_RF	
Forecast sample: 1/08/2012 12/30/2012	
Included observations: 52	
Root Mean Squared Error	0.044421
Mean Absolute Error	0.033199
Mean Absolute Percentage Error	NA
Theil Inequality Coefficient	0.262600
Bias Proportion	0.004014
Variance Proportion	0.529009
Covariance Proportion	0.466977
Theil U2 Coefficient	NA
Symmetric MAPE	44.02472

The following Tables 5.40—5.42 present the results for the FMCGBR_RF returns series.

Table 5.40 Brands Index return new EGARCH(2,1) out-of-sample forecast (FMCGBR_RF(F))

Forecast: FMCGBR_RFF	
Actual: FMCGBR_RF	
Forecast sample: 1/08/2012 12/30/2012	
Included observations: 52	
Root Mean Squared Error	0.043947
Mean Absolute Error	0.033016
Mean Absolute Percentage Error	NA
Theil Inequality Coefficient	0.258448
Bias Proportion	0.001642
Variance Proportion	0.584112
Covariance Proportion	0.414245
Theil U2 Coefficient	NA
Symmetric MAPE	43.79155

The results in Tables 5.38 to 5.40 favour the EGARCH model. The RMSE is less than that of the ARMA model and the MAE is also smaller, with a value of 0.033016 compared with 0.033199. In-sample volatility forecasts and out-of-sample volatility forecasts with the EGARCH model indicate better performance, as revealed by the

RMSE and MAE values, respectively. The error metrics suggest that, based on the results, the model best able to capture the observed volatility in the Brands Index is an EGARCH model. As previously suggested, it is evident that volatility forecasts based on returns without a risk-free component converge to the actual returns. The implication of this is that if the only objective was to calculate the volatility forecast of the Brands Index based on returns, the best return calculation methodology is then to use returns without the risk-free component.

Figures 5.7 and 5.8, below, present the volatility forecast charts for both return calculation methodologies (FMCGBR and FMCGBR_RF) with the EGARCH model specification.

Figure 5.7 Brands Index return EGARCH(2,1) out-of-sample forecast (FMCGBR)

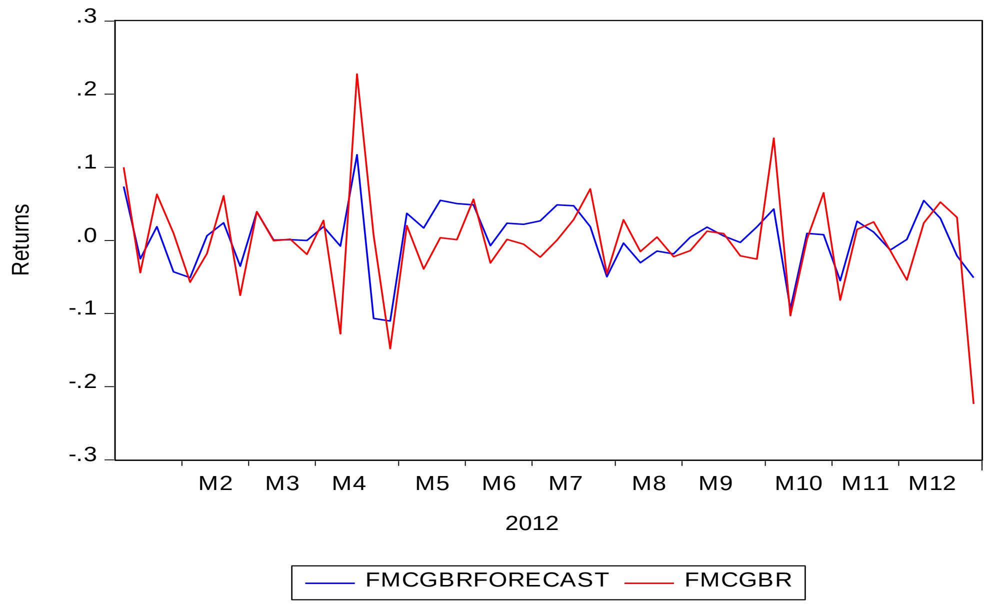
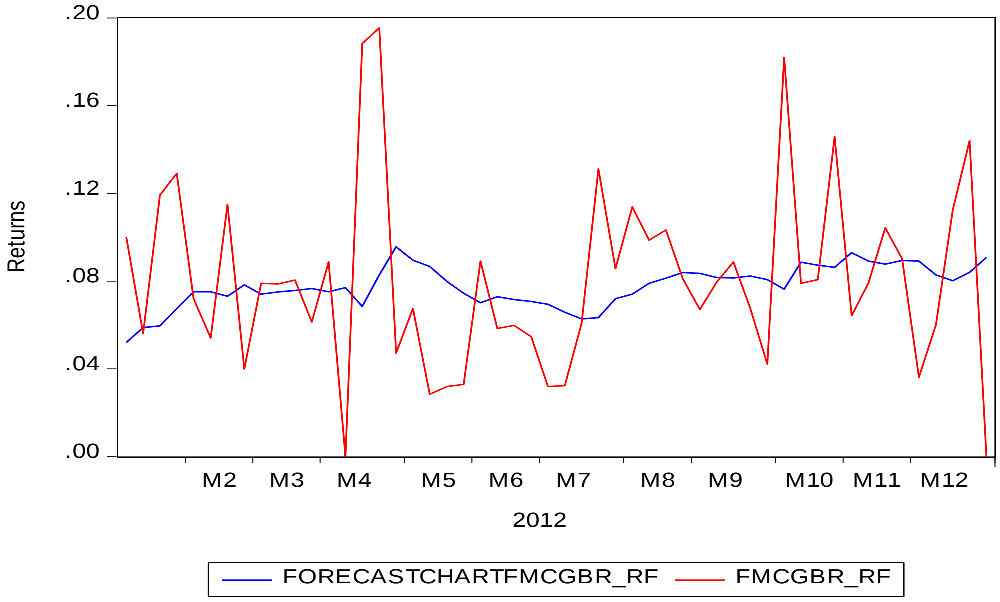


Figure 5.8 Brands Index return EGARCH(2,1) out-of-sample forecast (FMCGBR RF)



In sum, *Hypothesis 3* is upheld based on the previous outcomes. For both return calculation methodologies (FMCGBR and FMCGBR_RF), in-sample volatility forecasts and out-of-sample volatility forecasts using the EGARCH model indicate better performance according to their MAPE, RMSE and MAE values. However, it is evident that volatility forecasts based on returns without the risk-free component converge to the actual returns. Thus, the conclusion reached is that if the only objective is to forecast the volatility of the Brands Index based on returns, the best return calculation methodology is then to use returns without the risk-free component, because it provides more accurate and reliable predictions of upward and downward return swings.

So far, this thesis been has devoted to the creation of a Brands Index, to the design of two distinct methodologies to compute returns for the index, and has demonstrated that both return calculation methodologies clearly exhibit volatility clustering similar to that commonly seen in financial indices. Based on the results, the model best able to capture the observed volatility is an EGARCH(2,1) model for return calculation methodologies (FMCGBR and FMCGBR_RF). An EACD(1,1) model was introduced as an alternative method for capturing volatility in the FMCGBR_RF returns series, where the returns are always positive. The rest of this chapter will be devoted to the presentation of the CAPM. It will be tested through the use of first-pass and second pass-regressions, as suggested in Chapter 4. The same two alternative returns calculations will be used at the brand level for this purpose. To validate the use of the CAPM within the FMCG industry in Australia, *Hypothesis 4* and *Hypothesis 5* are examined thereafter.

Hypothesis 4: The calculation of beta (as a measure of volatility or systematic risk) allows a brand or set of brands to be compared with the market as a whole.

In Chapter 3, an analogy between modern finance theory and the research in this thesis, in regards to the implementation of the CAPM, was presented. The main insight from that section was the modified CAPM formula developed for the FMCG industry for dealing with the concept of the risk-free rate of return. In the absence of the risk-free rate, the CAPM formula remains the same. Including the risk-free component in the FMCG context, the CAPM-FMCG can be expressed as:

Equation 5.1

$$\tilde{r}_{it} - \tilde{r}_{bft} = \alpha_i + \beta_i(\tilde{r}_{mt} - \tilde{r}_{Mft}) + \tilde{\varepsilon}_{it}$$

As discussed in Chapter 3, the risk-free component for any given brand is different to that of the market, as their respective base sales need to be subtracted on both sides of the equation. The risk-free component for any given brand is different to that of the market, as their respective base sales have been subtracted on both sides of the equation. Risk-free is understood as the theoretical rate of return on an investment with no risk of financial loss (Engle & Russell, 1998). Risk-free returns give the required adjustments to the CAPM formula in order to adapt it to the FMCG context. When the risk-free component rate of return is assumed to be zero, then the formula remains unchanged, as originally presented in Equation 2.1.

Equation 5.2

$$\tilde{r}_{it} = \alpha_i + \beta_i(\tilde{r}_{mt}) + \tilde{\varepsilon}_{it}$$

In summary, two main modifications of the original CAPM formula including a risk-free component have been elaborated for the calculation of incremental returns in the FMCG industry, as explained from Equation 3.1. First, the denominator in the case of the FMCG industry is not the previous sales period (*t* - 1). In the FMCG instance, it is the base sales figure in period (*t*). Second, in the CAPM theory, the risk-free rate is the same value on both sides of the equation; whereas in the FMCG industry, the risk-free component (base sales) on the left-hand side of the equation is the corresponding base sales for any given brand under analysis, and on the right-hand side of the equation, the risk-free component always refers to the base sales of the overall Brands Index.

The discussion in Chapter 4 presented the process for calculating brand returns within the CAPM context. Having examined the different return calculation methodologies, I now turn to demonstrating the applicability of CAPM within the FMCG industry, with respect to calculating brand betas. Chapter 4 reported that a total of 296 brands were analysed, of which 156 satisfied the inclusion criteria for the Brands Index. In addition, Category E was introduced in Year 6 with the intention of reworking the index, so the change in divisor methodology was applied. Table 4.2 [Returns summary statistics for five brands and the Brands Index] and Table 4.3 [Table 4.3 – Returns (Rf) summary statistics for five brands and the Brands Index] in Chapter 4 presented both return calculation methodologies. The data in these tables were used to perform two independent regressions of A-Brand1 against the Brands Index returns as prescribed by the CAPM. The results are presented in Table 5.41, below.

Table 5.41 Beta calculation for A-Brand1 from Table 4.2

Regression Statistics					
Multiple R	0.407318489				
R Square	0.165908352				
Adjusted R Square	0.161859363				
Standard Error	0.494168808				
Observations	208				
ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	10.00627316	10.00627	40.97526	1.02242E-09
Residual	206	50.30577896	0.244203		
Total	207	60.31205212			
	Coefficients	*Standard Error*	*t Stat*	*P-value*	
Intercept	-0.00116451	0.034264863	-0.03399	0.972922	
A-Brand1 Return	3.363586334	0.525462504	6.401192	1.02E-09	

Table 5.41 shows that the intercept is negative and not significant at the 0.10 level (p = 0.973). It is expected that the intercept should be non-significant as the risk-free component's rate of return was set to equal to zero in this formulation. Conversely, the coefficient for A-Brand1 is positive and highly significant at the 0.01 level of confidence. The slope coefficient under the two-variable regression under the CAPM context is the beta, which is a measure of systematic risk that compares the returns of A-Brand1 to the overall Brands Index over the 209 weeks. The above calculations are based on 209 observations, starting from the week where (the new) Category E was introduced.

Table 5.42 Beta calculation for A-Brand1 using data from Table 4.3

Regression Statistics					
Multiple R	0.35764871				
R Square	0.1279126				
Adjusted R Square	0.123699617				
Standard Error	0.330597146				
Observations	209				
ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	3.318347481	3.318347	30.36153	1.05867E-07
Residual	207	22.62395592	0.109294		
Total	208	25.9423034			
	Coefficients	*Standard Error*	*t Stat*	*P-value*	
Intercept	0.154563706	0.045538617	3.394124	0.000825	
A-Brand1 Return	2.989672072	0.54257743	5.51013	1.06E-07	

In order to obtain the beta values for more brands, the process just described needs to be carried out for each brand independently. Again, using data from Chapter 4, Tables 4.2 and 4.3, the following results are achieved (Tables 5.43 and 5.44).

Table 5.43 Beta calculation for five brands from Table 4.2

Table 4.2	**A-Brand1 Return**	**B-Brand1 Return**	**C-Brand1 Return**	**D-Brand1 Return**	**E-Brand1 Return**
Intercept	**-0.0012**	**0.0014**	**-0.0015**	**0.0008**	**-0.0005**
Standard Error	**0.0343**	**0.0195**	**0.0036**	**0.0083**	**0.0062**
t-Value	-0.0340	0.0741	-0.4224	0.0951	-0.0774
slope (Beta)	**3.3636**	**1.3486**	**0.6376**	**0.7828**	**0.7887**
Standard Error	**0.5255**	**0.2990**	**0.0558**	**0.1274**	**0.0954**
t-Value	6.4012	4.5103	11.4230	6.1455	8.2652
R-squared	0.1659	0.0899	0.3878	0.1549	0.2490

Table 5.44 Beta calculation for five brands from Table 4.3

Table 4.3	**A-Brand1 Return (RF)**	**B-Brand1 Return (RF)**	**C-Brand1 Return (RF)**	**D-Brand1 Return (RF)**	**E-Brand1 Return (RF)**
Intercept	**0.1846**	**0.1749**	**0.0207**	**0.0520**	**0.0372**
Standard Error	**0.0464**	**0.0295**	**0.0075**	**0.0133**	**0.0099**
t-Value	3.9812	5.9377	2.7744	3.8958	3.7669
slope (Beta)	**2.98971**	**1.7369**	**0.4118**	**0.7086**	**0.7907**
Standard Error	**0.5525**	**0.3510**	**0.0891**	**0.1590**	**0.1177**
t-Value	5.4373	4.9484	4.6227	4.4578	6.7177
R-squared	0.1250	0.1058	0.0936	0.0876	0.1790

With the purpose of describing the results for the intercept and slope in all regressions, Tables 5.43 and 5.44 above report on the coefficients, standard errors, *t*-values, and overall *R*-squared values.

In absence of the risk-free component, the intercept is not significant for any of the brands (Table 5.43). However, all betas in this model are highly significant at the 0.01 level of confidence, as their *t*-values are greater than two. Comparison with the results for the risk-free component model specification (Table 5.44), the coefficients for intercept and slope are both significant. However, the beta and *R*-squared values are higher in Table 5.43 than in Table 5.44, except for B-Brand1, where the opposite is true. The concept of a risk-free rate is generally understood as the theoretical rate of return of an investment with no risk of financial loss. The beta values are used to predict the Brands Index values for the different base periods responsible for volatility clustering in the FMCG.

Overall, the above results suggest that in both cases, A-Brand1 is the most risky brand, followed by B-Brand1, E-Brand1, D-Brand1 and C-Brand1, respectively. Before validating *Hypothesis 4*, it will be necessary to show results for more than these five brands, so a larger sample will be taken from the 156 available brands. To this end, the top ten brands for each Category (except Category D, which only gets nine brands), were selected, resulting in a total of 49 brands for analysis. This is because the risk-free component has been accounted for in the Brands Index computation. The main focus is in the significance of the slope, which is the beta for the brand under evaluation, and the overall *R*-squared value. The slope and the *R*-squared values show the relationship between the different volatility forecasts for the Brands Indexes of the selected FMCG. In the calculations taking into account the risk-free component both coefficients, the intercept and the slope depict the main statistics; their standard errors and their corresponding *t*-values in combination with the overall *R*-squared. Returns based on calculations that disregard the risk-free component only report statistics for the slope, as the intercept is not statistically significant at the 0.10 level of confidence. Tables 5.45 and 5.46 present the summary results for the 49 brands in five categories.

Table 5.45 Beta calculations for 49 brands excluding the risk-free component

Brand	Beta	S.E	*t*-value	*R*-squared
A-Brand1	**3.36**	3.36	6.40	0.17
A-Brand2	**0.67**	0.67	7.26	0.20
A-Brand3	**1.15**	1.15	2.87	0.04
A-Brand7	**0.07**	0.07	0.20	0.00
A-Brand13	**0.41**	0.41	0.88	0.00
A-Brand18	**0.26**	0.26	1.10	0.01
A-Brand20	**0.27**	0.27	0.47	0.00
A-Brand22	**0.99**	0.99	2.54	0.03
A-Brand24	**0.50**	0.50	1.77	0.02
A-Brand16	**0.55**	0.55	2.42	0.03
B-Brand4	**1.35**	1.35	4.51	0.09
B-Brand5	**0.99**	0.99	5.15	0.11
B-Brand14	**0.57**	0.57	2.25	0.02
B-Brand15	**0.70**	0.70	5.68	0.14
B-Brand16	**0.81**	0.81	4.37	0.08
B-Brand17	**0.56**	0.56	1.93	0.02
B-Brand18	**0.85**	0.85	1.90	0.02
B-Brand20	**0.87**	0.87	4.46	0.09
B-Brand31	**0.81**	0.81	4.67	0.10
B-Brand36	**0.38**	0.38	0.99	0.00
C-Brand4	**0.73**	0.73	9.45	0.30
C-Brand18	**0.65**	0.65	6.38	0.17
C-Brand19	**0.61**	0.61	7.65	0.22
C-Brand24	**0.64**	0.64	11.42	0.39
C-Brand33	**0.71**	0.71	4.76	0.10
C-Brand34	**0.61**	0.61	13.50	0.47
C-Brand41	**0.69**	0.69	8.52	0.26
C-Brand43	**0.63**	0.63	6.66	0.18
C-Brand76	**0.45**	0.45	3.55	0.06
C-Brand77	**0.60**	0.60	3.19	0.05
D-Brand1	**0.78**	0.78	6.15	0.15
D-Brand14	**0.67**	0.67	8.72	0.27
D-Brand3	**0.70**	0.70	7.12	0.20
D-Brand5	**0.54**	0.54	12.00	0.41
D-Brand9	**0.71**	0.71	7.73	0.22
D-Brand10	**0.52**	0.52	8.55	0.26
D-Brand12	**0.55**	0.55	5.50	0.13
D-Brand15	**0.66**	0.66	9.09	0.29
D-Brand16	**0.54**	0.54	6.18	0.16
E-Brand1	**1.03**	1.03	5.51	0.13
E-Brand2	**0.79**	0.79	8.27	0.25
E-Brand6	**0.78**	0.78	2.87	0.04
E-Brand8	**0.71**	0.71	9.03	0.28
E-Brand9	**0.75**	0.75	3.16	0.05
E-Brand10	**0.72**	0.72	6.86	0.19
E-Brand13	**0.52**	0.52	3.87	0.07
E-Brand26	**0.96**	0.96	13.88	0.48
E-Brand27	**0.61**	0.61	2.01	0.02
E-Brand28	**0.43**	0.43	5.79	0.14

All the beta signs in Table 5.45 are positive, implying that there is a correlation between the different brands' volatilities. However, the *t*-value for six of the brands is less than 1.96, which makes these slopes not significant at the 0.05 level. However, A-Brand24 and B-Brand18 are weakly significant at the 0.10 level. Figures 5.9 and 5.10 below show the betas and *R*-squared values.

Figure 5.9 Beta values of 49 brands, excluding the risk-free component

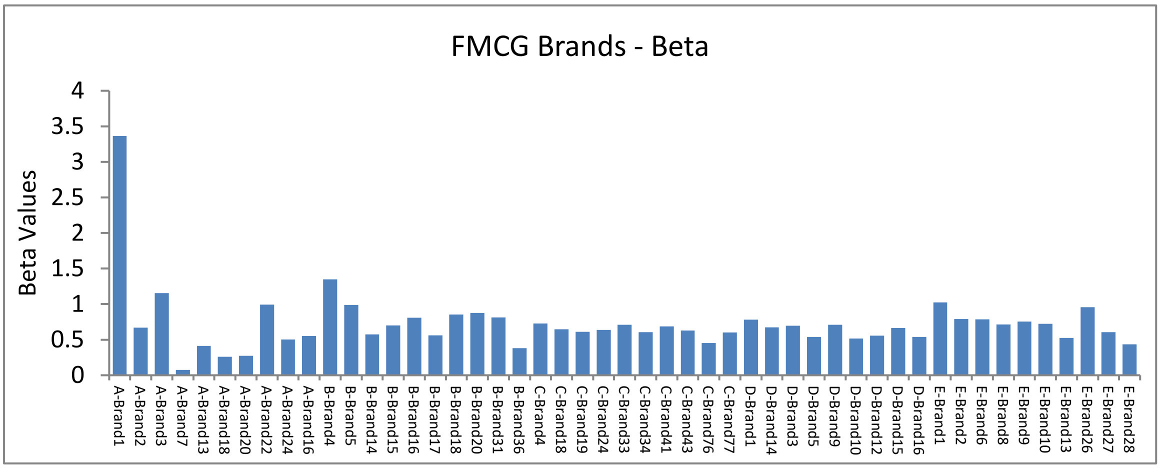
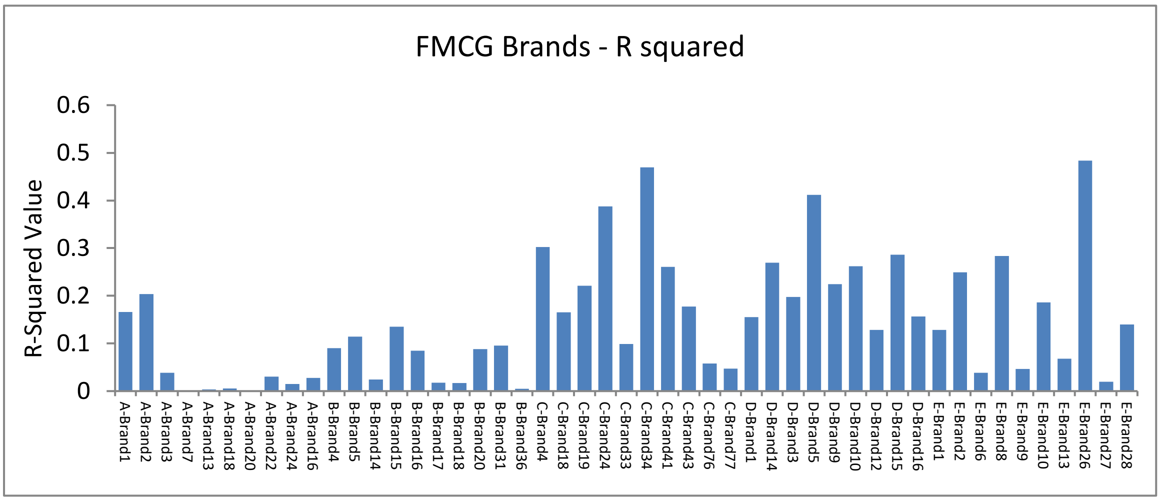


Figure 5.10 *R*-squared values of 49 brands, excluding the risk-free component



It can be seen from Figures 5.9 and 5.10 above that there is a dominant beta (A-Brand1) with a value greater than three, though with a corresponding *R*-squared value of less than 20%. One explanation of this result is that the risk-free component of the brands has been overlooked. The calculation of the beta as a measure of volatility or systematic risk allows a brand or a set of brands to be compared with the market as whole. This beta is a measure of systematic risk that compares the returns of A-Brand1 to the overall Brands Index over the 209 weeks. The above calculations are based on 209 observations, starting from the week where the new category was introduced. The different brands with lower beta values show higher *R*-squared values than the dominant A-Brand1.

The results in Table 5.46 contain two betas with negative signs. Based on their *t*-values, 16 of the beta vlaues are not statistically significant at the 0.05 level of confidence, with just six intercept figures showing the same pattern. This implies that the swings in the different lags of the Brands Index computations can yield both negative and positive values. This is clear evidence that volatility clustering exists in the FMCG industry, which accounts for the sale value returns across the different brands. Nevertheless, eight slopes are weakly significant, with *t*-values greater than 1.3. Figures 5.11 and 5.12 show the beta and *R*-squared values.

Table 5.46 Beta values for 49 brands, excluding the risk-free component

Brand	Beta	S.E	*t*-value	Intercept	S.E	*t*-value	*R*-squared
A-Brand1	**2.99**	0.54	5.51	0.15	0.05	3.39	0.13
A-Brand2	**0.54**	0.11	4.75	0.03	0.01	3.51	0.10
A-Brand3	**1.38**	0.38	3.59	0.08	0.03	2.37	0.06
A-Brand7	**-0.22**	0.37	-0.61	0.16	0.03	5.17	0.00
A-Brand13	**0.13**	0.39	0.33	0.14	0.03	4.40	0.00
A-Brand18	**-0.05**	0.26	-0.18	0.16	0.02	7.31	0.00
A-Brand20	**0.28**	0.50	0.55	0.16	0.04	3.78	0.00
A-Brand22	**0.57**	0.37	1.57	0.11	0.03	3.51	0.01
A-Brand24	**0.47**	0.33	1.42	0.15	0.03	5.26	0.01
A-Brand16	**0.68**	0.27	2.54	0.12	0.02	5.39	0.03
B-Brand4	**1.59**	0.34	4.71	0.12	0.03	4.22	0.10
B-Brand5	**0.84**	0.21	3.98	0.09	0.02	5.07	0.07
B-Brand14	**0.14**	0.30	0.47	0.13	0.03	5.11	0.00
B-Brand15	**0.64**	0.24	2.67	0.08	0.02	3.95	0.03
B-Brand16	**0.55**	0.19	2.86	0.05	0.02	3.36	0.04
B-Brand17	**0.57**	0.30	1.91	0.09	0.02	3.52	0.02
B-Brand18	**0.81**	0.37	2.18	0.12	0.03	3.84	0.02
B-Brand20	**0.44**	0.22	2.03	0.07	0.02	3.91	0.02
B-Brand31	**0.80**	0.21	3.78	0.06	0.02	3.33	0.06
B-Brand36	**0.01**	0.44	0.03	0.16	0.04	4.45	0.00
C-Brand4	**0.49**	0.10	5.07	0.02	0.01	1.88	0.11
C-Brand18	**0.31**	0.15	2.09	0.05	0.01	3.90	0.02
C-Brand19	**0.04**	0.19	0.22	0.08	0.02	4.80	0.00
C-Brand24	**0.34**	0.08	4.44	0.00	0.01	0.63	0.09
C-Brand33	**0.48**	0.18	2.60	0.08	0.02	5.39	0.03
C-Brand34	**0.27**	0.05	5.08	0.01	0.00	1.25	0.11
C-Brand41	**0.25**	0.16	1.60	0.05	0.01	4.12	0.01
C-Brand43	**0.22**	0.09	2.45	0.00	0.01	0.47	0.03
C-Brand76	**0.27**	0.16	1.67	0.08	0.01	5.80	0.01
C-Brand77	**0.33**	0.21	1.55	0.09	0.02	5.20	0.01
D-Brand1	**0.54**	0.15	3.68	0.03	0.01	2.71	0.06
D-Brand14	**0.40**	0.21	1.94	0.04	0.02	2.52	0.02
D-Brand3	**0.19**	0.12	1.64	0.06	0.01	6.03	0.01
D-Brand5	**0.21**	0.05	3.92	0.01	0.00	2.05	0.07
D-Brand9	**0.34**	0.14	2.48	0.03	0.01	2.98	0.03
D-Brand10	**0.29**	0.10	2.76	0.04	0.01	3.99	0.04
D-Brand12	**0.13**	0.11	1.22	0.04	0.01	5.03	0.01
D-Brand15	**0.29**	0.07	4.41	0.02	0.01	3.47	0.09
D-Brand16	**0.31**	0.25	1.23	0.06	0.02	2.76	0.01
E-Brand1	**0.97**	0.21	4.60	0.05	0.02	2.70	0.09
E-Brand2	**0.57**	0.09	6.20	0.01	0.01	0.70	0.16
E-Brand6	**0.67**	0.28	2.43	0.11	0.02	4.64	0.03
E-Brand8	**0.29**	0.08	3.58	0.02	0.01	3.60	0.06
E-Brand9	**0.79**	0.24	3.27	0.10	0.02	4.78	0.05
E-Brand10	**0.61**	0.12	5.04	0.03	0.01	3.12	0.11
E-Brand13	**0.59**	0.21	2.87	0.04	0.02	2.50	0.04
E-Brand26	**0.49**	0.07	6.85	0.01	0.01	1.72	0.18
E-Brand27	**0.14**	0.39	0.36	0.11	0.03	3.45	0.00
E-Brand28	**0.37**	0.12	3.03	0.02	0.01	2.29	0.04

Figure 5.11 Beta values for 49 brands, excluding the risk-free component

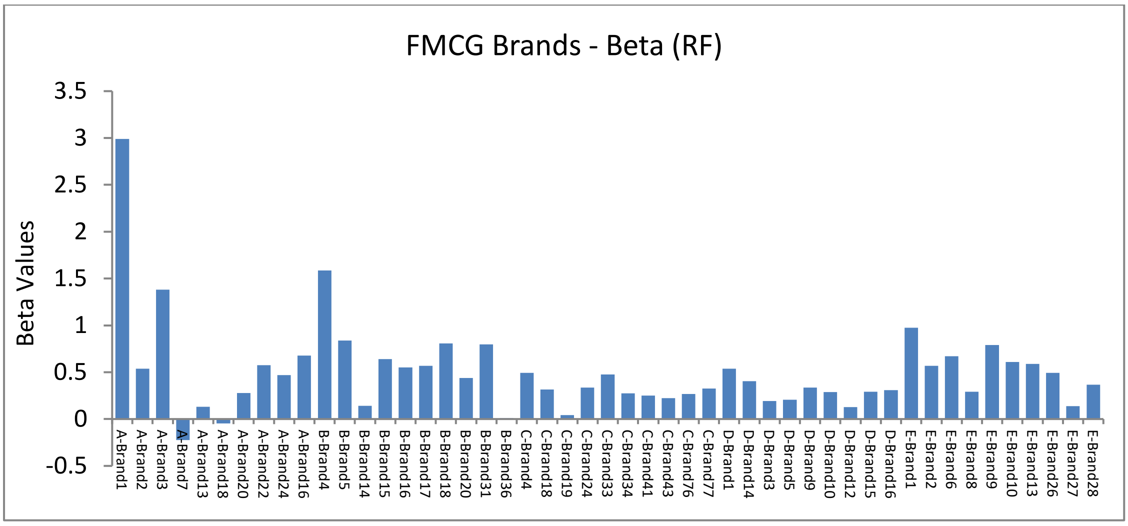
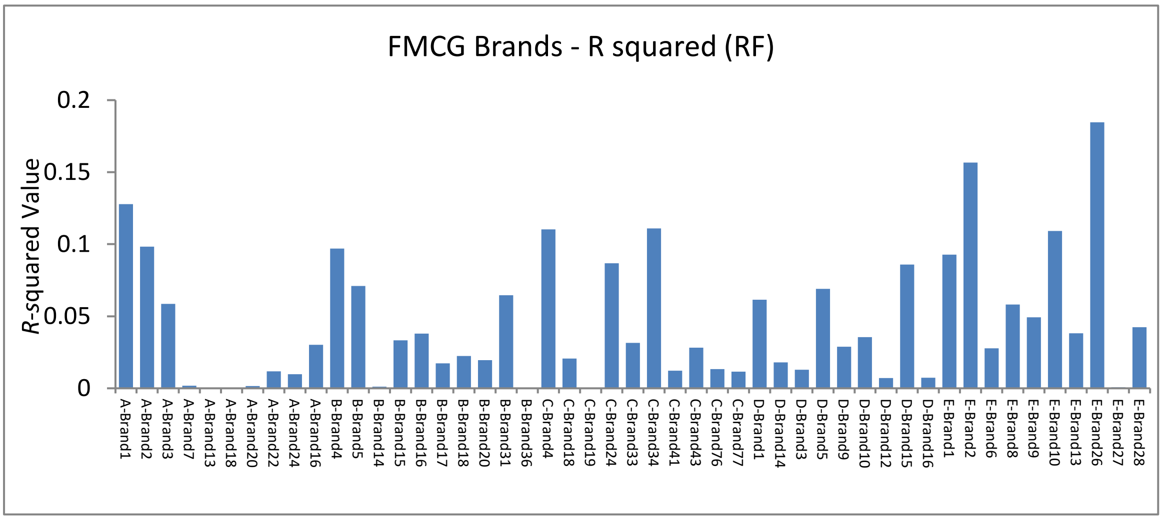


Figure 5.12 Beta values for 49 brands, including the risk-free component



The same conclusion as for the model specification without a risk-free component can be reached here with a risk-free specification. There is a dominant beta (A-Brand1) with a value close to three. The calculation of the beta as a measure of volatility or systematic risk allows a brand or a set of brands to be compared with the market as a whole. This beta is a measure of systematic risk that compares the returns of A-Brand1 to the overall Brands Index over the 209 weeks. Since the beta calculations moved from five brands where all results were very satisfactory to a 49 brands option, it can be seen that in the case where the risk-free component is disregarded, most of the betas were highly significant at the 0.01 level of confidence. Therefore, the first-pass regressions, on average, show a *t*-value of 5.49, which is very significant. However, when the risk-free return methodology is analysed, a few more betas are not significant at the 0.05 level. The first-pass regressions' average *t*-value is lower, at 2.7, but the average intercept *t*-value is 3.66. Both values are highly statistically significant. The conclusion made then is that *Hypothesis 4* can be validated based on the significance of the average *t*-values of the first-pass regressions in both return calculations. It can also be determined that the betas are a good representation of brands' risk, so these values can be used as a metric for comparison against the market as a whole.

Though the results so far are quite optimistic—as the first-pass regression test has been accepted—the second-pass regression also needs to be satisfied in order to validate the CAPM. Thus, *Hypothesis 5* will be tested next.

Hypothesis 5: The computation of the second-pass regression (the mean returns of brands on their respective betas) should be the security market line (SML-FMCG).

It will be recalled from the discussion in Chapter 3 that in order to fully test the CAPM, a second-pass regression needs to be performed. To this end, we must regress the mean returns of the 49 brands evaluated earlier in this chapter on their respective betas. If the CAPM in this descriptive format holds, then the results of the second-pass regression should be equivalent to the security market line (SML). The slope is expected to be positive and statistically significant, while the intercept must equal zero and is also assumed to be statistically significant. The next equation depicts this relationship.

Equation 5.3

$$\overline{r_i} = \gamma_0 + \gamma_1 \beta_i$$

Beta values from Table 5.45, in addition to the mean returns, are shown in Table 5.47.

Table 5.47 Beta values and mean returns for 49 brands without a risk-free component

Brand	Beta	Mean
A-Brand1	3.36	0.00
A-Brand2	0.67	0.00
A-Brand3	1.15	0.00
A-Brand7	0.07	0.00
A-Brand13	0.41	0.00
A-Brand18	0.26	0.00
A-Brand20	0.27	0.00
A-Brand22	0.99	0.00
A-Brand24	0.50	0.00
A-Brand16	0.55	0.00
B-Brand4	1.35	0.00
B-Brand5	0.99	0.00
B-Brand14	0.57	0.00
B-Brand15	0.70	0.00
B-Brand16	0.81	0.00
B-Brand17	0.56	0.00
B-Brand18	0.85	0.00
B-Brand20	0.87	0.00
B-Brand31	0.81	0.00
B-Brand36	0.38	0.01
C-Brand4	0.73	0.00
C-Brand18	0.65	0.00
C-Brand19	0.61	0.00
C-Brand24	0.64	0.00
C-Brand33	0.71	0.00
C-Brand34	0.61	0.00
C-Brand41	0.69	0.00
C-Brand43	0.63	0.00
C-Brand76	0.45	0.00
C-Brand77	0.60	0.00
D-Brand1	0.78	0.00
D-Brand14	0.67	0.00
D-Brand3	0.70	0.00
D-Brand5	0.54	0.00
D-Brand9	0.71	0.00
D-Brand10	0.52	0.00
D-Brand12	0.55	0.00
D-Brand15	0.66	0.00
D-Brand16	0.54	0.00
E-Brand1	1.03	0.00
E-Brand2	0.79	0.00
E-Brand6	0.78	0.00
E-Brand8	0.71	0.00
E-Brand9	0.75	0.00
E-Brand10	0.72	0.00
E-Brand13	0.52	0.00
E-Brand26	0.96	0.00
E-Brand27	0.61	0.00
E-Brand28	0.43	0.00

The results in Table 5.47 show that the mean returns are very close to zero with a combination of positive and negative values. Based on these values the following regression is performed, where the *Y*-variable represents mean returns and the *X*-variable represents betas. The following outputs are obtained.

Table 5.48 SML for betas and mean return excluding the risk-free component

Regression Statistics				
Multiple R	0.135964713			
R Square	0.018486403			
Adjusted R Square	-0.002396865			
Standard Error	0.002007675			
Observations	49			
ANOVA				
	df	*SS*	*MS*	*F*
Regression	1	3.56813E-06	3.56813E-06	0.885225586
Residual	47	0.000189446	4.03076E-06	
Total	48	0.000193014		
	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.000140462	0.00055143	0.254723191	0.800048175
Betas	-0.000612582	0.000651084	-0.940864276	0.351585252

An assumption of the SML is that the mean return for each brand should be linearly related to its beta. However, the above results for γ_0—the risk rate over the study period of 208 weeks—is close to zero and is not statistically different (at the 0.05 level of confidence) from zero as its *t*-value is very far from two. This result is not surprising, as the returns in this scenario were calculated without the risk-free component. The mean return term γ_1 should correspond to [*E(Rm) – Rf*] (the average weekly return of the Brands Index over the 208-week study period) yet it is negative (-0.00061), which is contrary to the CAPM theory, and it is not statistically significant (at a 0.05 level of confidence), as per its *t*-value of -0.94. Thus, the SML test has failed, as it does not describe the data used for this purpose. The most likely reason for these unsatisfactory results is the fact that most of the mean values were close to zero, making the relationship meaningless even though the betas are a good indication of each brand’s risk. One alternative possibility is that maybe the CAPM holds only if the market returns are positive (Benninga, 2008). Results including the risk-free component are presented in Table 5.49.

Table 5.49 Beta values and mean returns for 49 brands including the risk-free component

Brand	Beta	Average
A-Brand1	2.99	0.37
A-Brand2	0.54	0.07
A-Brand3	1.38	0.18
A-Brand7	-0.22	0.14
A-Brand13	0.13	0.15
A-Brand18	-0.05	0.15
A-Brand20	0.28	0.18
A-Brand22	0.57	0.15
A-Brand24	0.47	0.18
A-Brand16	0.68	0.17
B-Brand4	1.59	0.23
B-Brand5	0.84	0.15
B-Brand14	0.14	0.14
B-Brand15	0.64	0.13
B-Brand16	0.55	0.09
B-Brand17	0.57	0.13
B-Brand18	0.81	0.18
B-Brand20	0.44	0.10
B-Brand31	0.80	0.12
B-Brand36	0.01	0.16
C-Brand4	0.49	0.05
C-Brand18	0.31	0.07
C-Brand19	0.04	0.08
C-Brand24	0.34	0.03
C-Brand33	0.48	0.12
C-Brand34	0.27	0.03
C-Brand41	0.25	0.07
C-Brand43	0.22	0.02
C-Brand76	0.27	0.10
C-Brand77	0.33	0.12
D-Brand1	0.54	0.07
D-Brand14	0.40	0.07
D-Brand3	0.19	0.07
D-Brand5	0.21	0.02
D-Brand9	0.34	0.06
D-Brand10	0.29	0.06
D-Brand12	0.13	0.05
D-Brand15	0.29	0.04
D-Brand16	0.31	0.08
E-Brand1	0.97	0.12
E-Brand2	0.57	0.05
E-Brand6	0.67	0.16
E-Brand8	0.29	0.05
E-Brand9	0.79	0.15
E-Brand10	0.61	0.08
E-Brand13	0.59	0.09
E-Brand26	0.49	0.05
E-Brand27	0.14	0.12
E-Brand28	0.37	0.05

Contrary to previous results, Table 5.49 shows that the mean returns are all positive and greater than zero. Using the values from Table 5.49, the resulting regression (where the Y-variable represents mean returns and the X-variable represents beta values) is shown below.

Table 5.50 SML for betas and mean returns including the risk-free component

Regression Statistics				
Multiple R	0.663801175			
R Square	0.440632001			
Adjusted R Square	0.428730554			
Standard Error	0.048470651			
Observations	49			
ANOVA				
	df	SS	MS	F
Regression	1	0.086982918	0.086982918	37.02339791
Residual	47	0.110421987	0.002349404	
Total	48	0.197404906		
	Coefficients	Standard Error	t Stat	P-value
Intercept	0.064940753	0.009924862	6.543239561	4.03571E-08
Betas	0.087054182	0.014307096	6.084685523	2.0036E-07

From Table 5.50 above, the results for γ_0 the risk-free over the study period (209 weeks) is about 6.5% and is statistically different from zero, as its t-value is much greater than 2. This result was expected, as the returns were calculated as a value greater than or equal to zero. The mean return term γ_1 that corresponds to $[E(r_M) - r_f]$ is the average weekly return of the Brands Index over the 209-week study period. It is positive (0.08705), which is in agreement with CAPM theory, and it is highly statistically significant at the 0.05 level of confidence, as per its t-value of 6.084. Consequently, the SML test has succeeded, so it does describe the conditions regarding the structure of expected returns in the FMCG market. In this case, all returns are expected to lie on the SML. Thus, it seems that the CAPM holds only if the Brands Index returns are positive.

The conclusion achieved in regards to *Hypothesis 5* is that, based on the returns made from the previous observation (allowing negative values), the CAPM should only be used as a descriptive tool. Hence, the beta of a brand is an important measure of the brand's risk. In the second case, where the returns were calculated as being greater than or equal to zero (using the base sales) the CAPM can then be utilised as both a prescriptive and descriptive tool.

In summary, *Hypothesis 5* can be upheld, based on the returns including the risk-free component, but is only partially upheld based on returns obtained by taking into account the previous observation. The reason for this is because the second-pass regression failed in the latter case.

It should be noted that under the SML, changes in beta risk are not proportional to changes in expected return (Finch et al., 2011). Most practitioners tend to assert that a beta of two will have an expected return twice that of the market. To make this concept clear, the results from Table 5.50 are used. Following the CAPM formula in Equation 2.1, we obtain Equation 5.4, below.

Equation 5.4

$E(R_i) = R_f + \beta_i[E(R_{Mkt}) - R_f]$, where, $R_f = 0.0649 \; and \; R_{Mkt} = 0.152$

Where:

R_f is the risk-free, and

$[E(R_{Mkt}) - R_f]$ is the risk premium.

If *Beta* = 1, then

$E(R_i = 0.065 + 1[0.152 - 0.065] = 0.152$

If *Beta* = 2, then

$E(R_i = 0.065 + 2[0.152 - 0.065] = 0.239$

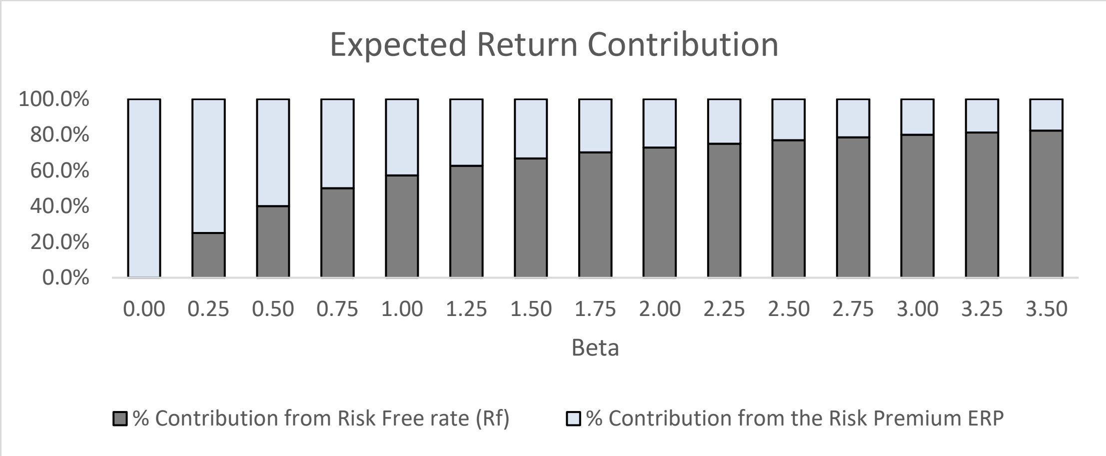
As can be seen from the results for *Beta* = 1 and *Beta* = 2 (a 100% increase in beta value) the expected return in the second case is 57.3% (0.239/0.152) greater, rather than double. This is a change in the beta estimate for the FMCG brands that will trigger a similar rise in the estimated returns of the brand. Table 5.51, below, presents the decomposition of CAPM expected returns as per Equation 5.4, above, for different beta values ranging from zero to 3.5. The objective of this procedure is to demonstrate that changes in beta risk are not proportional to changes in expected return. Therefore, a change in beta from 1 to 2 does not result in a doubling of expected returns.

Table 5.51 Decomposition of CAPM expected returns

Beta	CAPM Expected Return $E(R_i)$	% Contribution from Risk-free rate (Rf)	% Contribution from the Risk Premium ERP
0.00	0.0649	100.0%	0.0%
0.25	0.0867	74.9%	25.1%
0.50	0.1085	59.9%	40.1%
0.75	0.1302	49.9%	50.1%
1.00	**0.1520**	**42.7%**	**57.3%**
1.25	0.1738	37.4%	62.6%
1.50	0.1955	33.2%	66.8%
1.75	0.2173	29.9%	70.1%
2.00	**0.2390**	**27.2%**	**72.8%**
2.25	0.2608	24.9%	75.1%
2.50	0.2826	23.0%	77.0%
2.75	0.3043	21.3%	78.7%
3.00	0.3261	19.9%	80.1%
3.25	0.3479	18.7%	81.3%
3.50	0.3696	17.6%	82.4%

Conclusively, the results from Table 5.51, above, show that changes in beta risk are not proportional to changes in expected return. The risk premium contributes up to 73% of the expected return when *Beta* = 2. Figure 5.13 shows that the contribution of the risk premium increases with beta risk; however, it does so at a decreasing rate due to the fluctuations and other effects caused by the sale value variations of the different brands. When there are not many activities taking place, then volatility tends to be lower and increases as the activities increase. The presence of volatility also accounts for this change in beta risk.

Figure 5.13 Expected return contribution



The next section summarises the results of tests of the five hypotheses proposed in Chapter 3 and provides the underpinnings for Chapter 6.

5.3 Summary

This chapter reports on the results of the five hypotheses proposed in Chapter 3. With respect to *Hypothesis 1*, it was found that the change in weekly sales from the Brands Index illustrates volatility clustering similar to that which occurs in financial indices. Graphically, this phenomenon was more evident in the returns without the risk-free component. The second hypothesis, which involves measurement, had to rely on the use of ARCH-GARCH-type models from finance theory in order to be validated. It was established that the best structure for measuring volatility clustering for both return calculation methodologies in the Brands Index was an EGARCH(2,1) model. Examining *Hypothesis 3*—with regards to simulating performance when volatility is forecast—the hypothesis was validated based on the previous outcomes. In both cases, in-sample volatility forecasts and out-of-sample volatility forecasts using the EGARCH model performed better than the ARMA structures, as revealed by the main volatility forecast metrics of MAPE, RMSE and MAE. The exponential ACD model was also introduced as an alternative way to capture the volatility of positive returns. The results were well received, as all coefficients were statistically significant. However, further research on this topic is beyond the scope of this study. *Hypothesis 4* was confirmed for both return calculations, as in both cases, the average *t*-values of all beta computations were highly significant (> 2). The calculated betas can now be used to benchmark performance against the FMCG Brands Index, where betas greater than one are riskier than the market as a whole. The opposite also holds. To finalise application of the CAPM to the FMCG industry based on the created Brands Index, the second-pass regression needed to be satisfied, as per *Hypothesis 5*. The conclusion achieved was that the test failed in the case of returns without the risk-free component, but succeeded in the second option—where the risk-free rates of return were included. Hence, *Hypothesis 5* was partially accomplished for returns without the risk-free component.

Chapter 6 examines the results from this chapter in order to provide implications for both brand suppliers (supermarkets) and brand managers (manufacturers). From the brand suppliers' point of view, the benefits of improving volatility forecasting for the overall index will be highlighted, in combination with an interpretation of the beta values at different levels; i.e, supermarket beta, category betas and beta values inside a category, where a category index acts as a sub-index (Category Index). From the brand managers' perspective, brand portfolio management is reviewed, using betas as a risk metric rather than the standard deviation. Chapter 6 also proposes an approach to maintain the Brands Index and to track brands' betas on a weekly basis.

CHAPTER 6: FINDINGS AND IMPLICATIONS

6.0 Introduction

The findings of this thesis reported in Chapter 5 have theoretical and managerial implications for the two main participants in the Australian FMCG industry; brand suppliers (supermarkets) and brand managers (manufacturers). Theoretical developments describing the underpinning arguments in the literature have provided impetus for investigating the antecedents of volatility in the created Brands Index. By combining theoretical approaches from extant theories, a new theoretical model has been tested that captures the volatility clustering observed in the index which, until now, has not been reported. The result suggests that the overall Brands Index volatility forecast can be improved when volatility clustering is accounted for. From a brand supplier perspective, this part of the research makes an important contribution to the literature. The results and analyses further imply that improving overall sales forecasting by using the Brands Index can enhance production planning, inventory management and future capacity development, so that resources can be accurately and efficiently allocated to meet anticipated demand (Murray, 2008). In this regard, the participants in the retail market may also gain additional insights and direction in the academic body of knowledge concerned with time series forecasting theory. In addition, the creation of the Brands Index represents an excellent contribution to the management and marketing disciplines, as it allows any brand or set of brands to be compared against an overall market (i.e. the Brands Index).

This thesis has demonstrated that the capital asset pricing model (CAPM) can be applied to data from the Australian FMCG industry. The brands constituting the industry now have an overall market index with which to compare their performance. Further, betas for any brand or set of brands may be calculated based on the CAPM. A significant implication of this from a brand manager's view is that these estimated betas can then be used to manage brand risk in portfolio management, which is a definite contribution to this field. Two clear methodologies were established to evaluate returns; one excluding base sales (as a proxy for the risk-free rate of return) and a second one including base sales. In regards to the second-pass regression required to test the

CAPM, only the methodology including the risk-free rate of return proved successful. Thus, it was argued in Chapter 5 that the computation of base sales on both sides of the CAPM equation was essential to clearly see the risk-free rate of return values. A comprehensive procedure for calculating base sales, for both the Brands Index and individual brands, was described in Chapter 4 and successfully tested in Chapter 5. The remainder of this chapter is devoted to the exploration of beta value calculations at different levels and their managerial implications. A beta for each supplier, as well as category betas, will be presented is Section 6.1. Betas inside a single category or sub-category index are demonstrated in Section 6.2. Additionally, Section 6.3 deals with brand portfolio management. The last section, Section 6.4, will provide an approach for maintaining the Brands Index and tracking brands' betas on a weekly basis. It is important to clarify that all these sections only use returns based on incremental sales, known in the context of this research as returns including the risk-free component, wherein the risk-free rate of return component is base sales (FMCGBR_RF). Managerial implications will also be indicated in each section accordingly. As in Chapter 5, the data used was obtained from 209 weekly observations spanning the period 2009 to 2012.

6.1 Beta calculations at brand supplier and category levels

In the context this thesis, a *beta* value indicates whether a brand is more or less volatile than the Brands Index. As per the usual interpretation, a beta value < 1 specifies that the brand is less volatile than the Brands Index, while a beta value > 1 suggests that the brand is more volatile than the Brands Index. In the current context, beta refers to the volatility of Woolworths or Coles product sales compared with the overall Brands Index. The following three steps will be required:

Step 1: Using the methodology introduced in Chapter 4, calculate the total and base sales for each brand as depicted in Figure 6.1 and Figure 6.2 for each brand supplier.

Figure 6.1 Woolworths - total sales and base sales

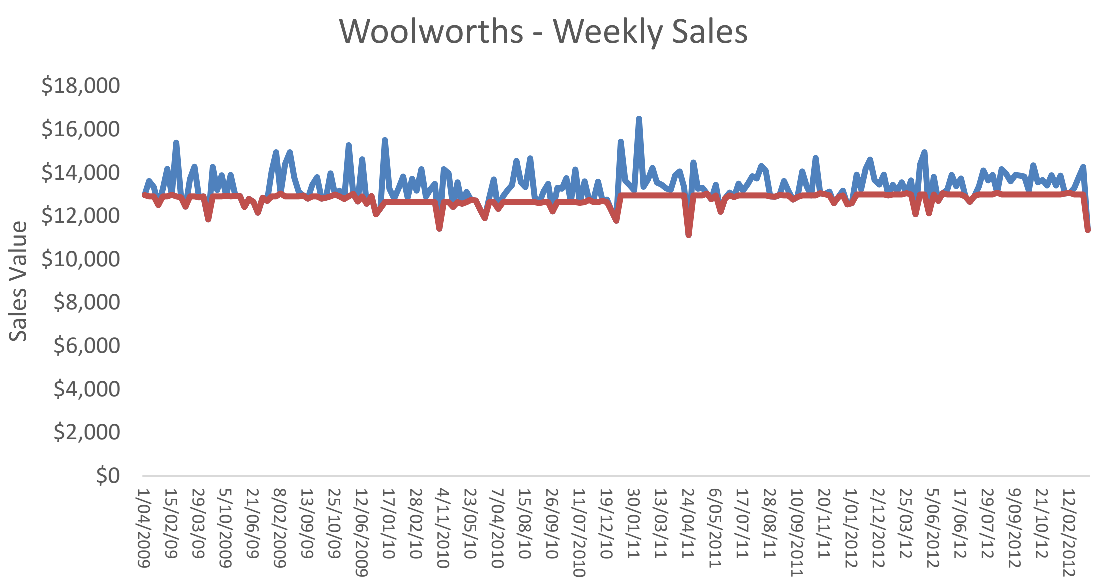
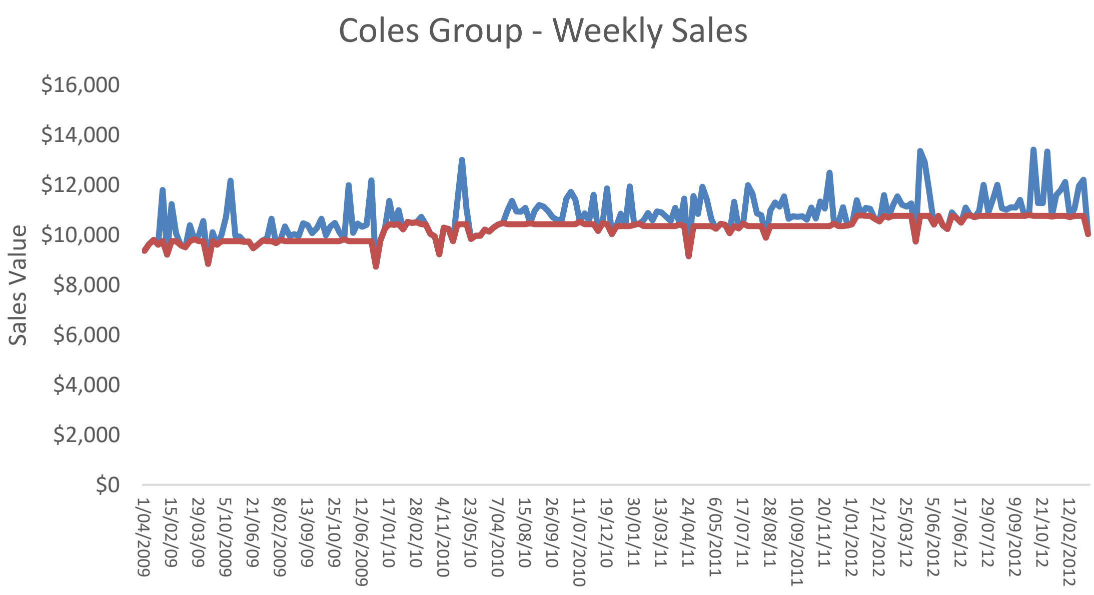


Figure 6.2 Coles Group - total sales and base sales



Step 2: Also following the procedure in Chapter 4, calculate the incremental returns—defined in this study as returns (RF) including the risk-free component. Returns (RF), which are all calculated from predetermined base sales, are presented in Table 6.1.

Table 6.1 Woolworths and Coles Group returns (RF)

Date	Woolworths Return (RF)	Coles Group Return (RF)
4/01/2009	0.0%	0.0%
11/01/2009	5.4%	0.0%
18/01/2009	3.3%	0.0%
25/01/2009	0.0%	0.0%
1/02/2009	2.6%	19.1%
8/02/2009	9.4%	0.0%
15/02/2009	0.0%	14.2%
22/02/2009	17.6%	3.2%
…	…	…
25/11/2012	**0.0%**	**11.9%**
2/12/2012	0.0%	0.0%
9/12/2012	2.3%	2.7%
16/12/2012	6.0%	10.6%
23/12/2012	9.4%	12.6%
30/12/2012	0.0%	0.0%

Step 3: Run a regression of the Brands Index and each brand supplier and make a conclusion from the results. Outputs from this regression are summarised in Table 6.2.

Table 6.2 Beta calculations - Output for Woolworths and Coles

Brand Supplier	Beta	S.E.	*t*-value	Intercept	S.E.	*t*-value	*R*-squared	Average Return (RF)
Woolworths	**0.9520**	0.0602	15.8045	**0.0101**	0.0029	3.5042	0.5468	**0.0403**
Coles Group	**1.0777**	0.0720	14.9780	**0.0090**	0.0034	2.6285	0.5201	**0.0433**

For both brand suppliers, Woolworths and Coles, the beta coefficients from Table 6.2 are statistically significant at the 0.05 level of confidence as their *t*-values are greater than two. The intercept from Table 6.2 is around 1% for both brand suppliers; however, Woolworths' intercept is slightly greater than that of Coles. The *R*-squared values in both regressions are greater than 50%. The average return is marginally higher for Coles at 4.33% compared to 4.03% for Woolworths. The implication of the above findings is that Coles appears to have a lower than 1% risk-free rate, as given by its intercept value of 0.0090, while its beta value is greater than 1 at 1.077, meaning that this retailer is slightly more volatile than the market as whole. Some 52% of the variation in Coles' returns has been captured by using the CAPM model, as measured by the *R*-squared value. Woolworths, on the other hand, shows an intercept (risk-free) slightly greater than 1% at 0.0101, whereas its beta value is less than 1 at 0.9520, indicating that this store is slightly less volatile than the market as a whole. Some 55% of the variation in Woolworths' returns was captured by the CAPM model, as measured by the *R*-squared figure. One interpretation of this result is that Coles is more dependent on tactics that drive short-term sales such as price promotions, which makes this retailer riskier if those marketing strategies slow down or do not work at all. Therefore, this thesis, through the calculation of beta values, has allowed both brand suppliers and brand managers to compare themselves against the overall market. Expanding beyond total supplier beta calculations, it is of interest to understand how each category itself compares against the overall Brands Index.

During the period under observation, the beta value for Coles is 1.08 while Woolworths has a beta value of 0.95. The market has a beta = 1 and the Brands Indexes are measured according to how they deviate from this market value. That the Coles beta is greater than 1 means that its brand sales are riskier than those of Woolworths, but they offer a higher chance of increased sales returns. That the Woolworths beta value is less than the market value of 1 means that its brands are less risky, but it has lower returns compared to Coles. The interpretation of this is that Coles is more volatile than Woolworths when compared against the overall Brands Index. In addition, if the overall market grows, Coles will grow faster than Woolworths but at a lower rate, as explained in Chapter 5. The opposite also holds, if the overall market slows down, Coles will shrink faster than the market. Thus, it seems that Coles is riskier than Woolworths based on the beta values mentioned above.

The implication of the above findings is that Coles appears to have higher ratios of spikes against base sales when compared with Woolworths. The average returns also confirm this fact, as Coles' returns are higher by about 7.5%. One interpretation of this result is that Coles is more dependent on tactics that drive short-term sales (such as price promotions), which makes this retailer riskier if those mechanics slow down or do not work at all. Therefore, this thesis, through the creation of the Brands Index, has provided brand suppliers with a way to compare themselves with other suppliers and the overall market.

Expanding beyond total supplier beta calculations, it is of interest to understand how each category itself compares against the overall Brands Index. By repeating the above three steps for the five categories used in this research, the following results are attained. Table 6.3 shows the category returns, and Table 6.4 summarises the regression outputs.

Table 6.3 Categories A, B, C, D, and E Returns (RF)

Date	**Category A Returns (RF)**	**Category B Returns (RF)**	**Category C Returns (RF)**	**Category D Returns (RF)**	**Category E Returns (RF)**
4/01/2009	0.0%	0.0%	3.4%	0.0%	3.0%
11/01/2009	5.3%	1.4%	5.7%	14.0%	5.7%
18/01/2009	9.1%	0.0%	5.0%	0.0%	3.2%
25/01/2009	4.3%	0.0%	1.7%	0.0%	0.0%
1/02/2009	32.5%	0.0%	3.7%	0.0%	1.4%
8/02/2009	9.3%	0.0%	4.9%	12.5%	5.6%
15/02/2009	10.4%	0.0%	10.4%	1.7%	12.4%
22/02/2009	27.5%	7.6%	8.4%	5.9%	5.5%
…	…	…	…	…	…
25/11/2012	3.4%	8.5%	3.3%	2.9%	12.6%
2/12/2012	1.9%	0.0%	2.7%	0.0%	4.0%
9/12/2012	3.4%	2.5%	2.0%	0.0%	6.5%
16/12/2012	15.6%	1.6%	5.1%	18.3%	8.4%
23/12/2012	14.4%	18.5%	14.8%	2.4%	6.8%
30/12/2012	0.0%	0.0%	0.0%	0.0%	0.0%

Table 6.4 Beta calculations - Output for five categories

Category	**Beta**	**S.E**	***t*-value**	**Intercept**	**S.E**	***t*-value**	***R*-squared**	**Average Return (FE)**
Category A	**1.7401**	0.0782	22.2643	**0.0157**	0.0037	4.2285	0.7054	0.0711
Category B	**1.0611**	0.1341	7.9120	**0.0461**	0.0064	7.2101	0.2322	0.0798
Category C	**0.4756**	0.0564	8.4268	**0.0220**	0.0027	8.1652	0.2554	0.0371
Category D	**0.3891**	0.0939	4.1426	**0.0316**	0.0045	7.0502	0.0766	0.0439
Category E	**0.6947**	0.0679	10.2324	**0.0319**	0.0032	9.8573	0.3359	0.0540

All the coefficients in Table 4.6 are statistically significant at the 0.05 level, as their *t*-values are greater than two. The intercept values range between 1.6% (for Category A) to 4.6% (for Category B). The *R*-squared figures are all greater than 20%, except for Category D, which is low at 8%. The minimum average return is 8% (Category B). The results suggest that the different categories of FMCG brands have varying sale values depending on their marketing strategies.

Beta values for the five categories in Table 4.6 show that two categories have betas greater than one (Categories A and B), whereas the remaining three categories have betas less than one. The interpretation of this result is that Category A is the most volatile, while Category D is the least. The same conclusion as in the brands suppliers' case is reached here. If the overall market grows, Category A will grow faster than the other ones (though at a lower rate). The reverse also holds. Based on Table 6.3, the following parameter values for the SML are obtained. Table 6.5, below, exhibits the regression results.

Table 6.5 Security market line - output for five categories

SML	Slope	S.E.	*t*-value	Intercept	S.E.	*t*-value	*R*-squared
5 Categories	**0.0258**	0.0116	2.2316	**0.0346**	0.0116	2.9871	0.6241

The second-pass regression results in Table 6.5 reveal that the intercept and slope coefficients are both statistically significant. This result should be seen as a good indication that the conclusions based on the betas values in the first-pass regression are likely to remain the same. The beta values show the relationship between brand returns and overall market returns. A high beta value indicates that a brand's sales will rise when the market is up and will fall when the market is in decline. Small beta values imply that the brand's sales values are relatively unaffected by the fluctuations in the overall FMCG market's returns.

The implication of the above findings is that brand suppliers can add this beta metric to ones they already use, such as value share, turnover and profitability, to allocate category shelf space within actual supermarkets. Thus, the category beta in this context should be seen as an additional piece of information to help in the decision-making process, rather than as a contending metric. The beta figure at the category level allows retailers to identify what could happen to these categories if the entire market grows or declines. Thus, categories with beta figures greater than one will grow or decline faster than the market, while categories with beta values less than one will grow or decline more slowly than the market. Similarly, supermarkets may use category beta values as good indicators of whether a growth strategy should be pursued. This research contributes to management and marketing theory by asserting that beta is an important metric for category managers because it measures the risk of a category that cannot be reduced by diversification. Results for one of the categories and a comparison with the brand betas from Chapter 5 are presented in the next section.

6.2 Sub-Category Index and Resulting Brand Betas

So far, this research has used an overall FMCG Brands Index made as the summation of total available brands. However, the index can be modified to be consider only the brands within a single category. This reduced 'category market' is then the foundation for creating a sub-Category Index. The term *sub-Category Index* in this context therefore refers to an index based on brand betas obtained by regressing a brand's returns against the overall category returns.

The aim in this section is to use the returns of a selected category (as already determined in Table 6.3) as a proxy for the total market instead of the Brands Index. This process is important, as it will allow the comparison of betas acquired from the FMCG Brands Index against the betas gained from the sub-Category Index. The purpose here is to substitute the returns of a specific category for the Brands Index returns to obtain the beta values for the brands within the selected category. This will be done using the same three-step process as employed in Section 6.1.

Based on the results presented in Table 6.4, it can be seen that Category A has a beta of 1.7 and Category B has a beta near one. The other three categories display betas less than one. Results for Category B and the top-10 brands in it are provided next. The decision to select Category B for the purpose of this illustrative analysis is due to the fact that its beta is in the middle point, close to one. However, any category could be selected. Category B returns are taken from Table 6.3 and the returns for the brands within the Category are taken from Table 6.6.

Table 6.6 Returns for the top-10 brands in Category B

Date	B-Brand4	B-Brand5	B-Brand14	B-Brand15	B-Brand16	B-Brand17	B-Brand18	B-Brand20	B-Brand31	B-Brand36
4/01/2009	8.5%	0.0%	0.0%	0.0%	0.0%	0.0%	48.4%	0.0%	0.0%	34.9%
11/01/2009	6.8%	0.0%	13.3%	0.0%	19.1%	15.1%	36.7%	0.0%	0.0%	33.0%
18/01/2009	24.0%	13.7%	0.0%	0.0%	0.0%	0.0%	0.0%	8.8%	25.2%	35.1%
25/01/2009	10.6%	5.1%	18.1%	0.0%	0.0%	0.0%	0.0%	0.0%	8.9%	38.0%
1/02/2009	36.8%	0.0%	22.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	53.0%
8/02/2009	0.0%	0.0%	0.0%	0.0%	13.7%	0.0%	58.3%	0.0%	12.4%	51.3%
…	…	…	…	…	…	…	…	…	…	…
4/11/2012	**38.9%**	**26.4%**	**13.2%**	**20.2%**	**0.0%**	**36.6%**	**63.7%**	**0.0%**	**33.2%**	**0.0%**
11/11/2012	34.8%	20.9%	0.0%	24.9%	0.0%	20.1%	28.6%	19.1%	0.0%	41.6%
18/11/2012	10.5%	8.9%	0.0%	12.3%	0.0%	112.0%	23.9%	22.3%	0.0%	16.5%
25/11/2012	0.0%	53.8%	0.0%	0.0%	0.0%	0.0%	33.7%	0.0%	7.2%	32.9%
2/12/2012	11.0%	6.0%	0.0%	6.2%	0.0%	31.9%	0.0%	0.0%	5.5%	22.1%
9/12/2012	7.2%	15.3%	0.0%	8.0%	0.0%	27.7%	10.7%	40.2%	0.0%	0.0%
16/12/2012	0.0%	17.6%	9.6%	9.8%	0.0%	38.8%	0.0%	40.5%	0.0%	0.0%
23/12/2012	61.5%	25.6%	12.2%	17.2%	0.0%	9.5%	19.1%	26.2%	13.6%	0.0%
30/12/2012	26.2%	0.0%	0.0%	0.0%	0.0%	0.0%	6.1%	0.0%	0.0%	0.0%

Following Step 3 from Section 6.1, ten independent regressions for each Category B which are the top-10 brands' returns against overall Category B returns were performed. The results are summarised in Table 6.7, below.

Table 6.7 Return calculations for top-10 brands inside Category B

Category B	Beta	S.E	t-value	Intercept	S.E	t-value	R-squared	Average
B-Brand4	**1.7654**	0.1465	12.0511	**0.0934**	0.0164	5.7084	0.4123	0.2343
B-Brand5	**0.7580**	0.1055	7.1866	**0.0899**	0.0118	7.6328	0.1997	0.1504
B-Brand14	**0.1500**	0.1606	0.9340	**0.1260**	0.0179	7.0252	0.0042	0.1379
B-Brand15	**0.0954**	0.1317	0.7244	**0.1186**	0.0147	8.0673	0.0025	0.1262
B-Brand16	**0.0236**	0.1063	0.2222	**0.0928**	0.0119	7.8121	0.0002	0.0946
B-Brand17	**0.4843**	0.1585	3.0549	**0.0907**	0.0177	5.1208	0.0431	0.1293
B-Brand18	**1.1973**	0.1839	6.5108	**0.0821**	0.0205	3.9962	0.1700	0.1777
B-Brand20	**0.5212**	0.1117	4.6641	**0.0610**	0.0125	4.8868	0.0951	0.1026
B-Brand31	**0.3041**	0.1160	2.6222	**0.0927**	0.0130	7.1604	0.0321	0.1170
B-Brand36	**0.7248**	0.2293	3.1607	**0.1054**	0.0256	4.1137	0.0460	0.1632
Average	**0.6024**		**4.1131**			**6.1524**		0.1433

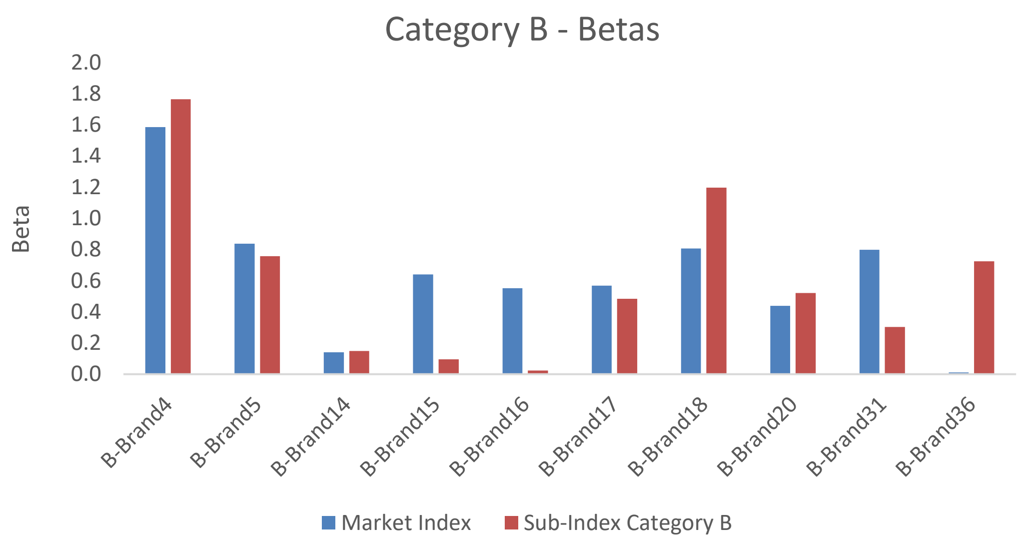
The results from Table 6.7 show that all the betas are positive. Betas for B-Brand14, B-Brand15, and B-Brand16 are, however, not statistically significant at the 0.10 level of confidence, as their *t*-values are less than two. Although all intercept values are significant, the average *R*-square for all is just 14.3%. It implies that only a small percentage of the brands' sales returns are explained by the base value for the top-10 brands in all the categories. It shows the proportion that can be predicted from the variance of the top-10 brands across the different categories of the Australian FMCG industry. Interestingly, just two betas are greater than one: B-Brand4 and B-Brand18 with values of 1.76 and 1.2, respectively. The average *t*-values for the beta values for the slope and intercept are about 4.1 and 6.2, correspondingly. Thus, the first-pass regression seems to be fulfilled. The outcome for the regression of the betas on average returns is shown in Table 6.8, below.

Table 6.8 Regression between beta values and average returns - Category B

Category E SML	**Slope**	**S.E.**	***t*-value**	**Intercept**	**S.E.**	***t*-value**	***R*-squared**
10 Brands	**0.0686**	0.0112	6.1135	**0.1020**	0.0089	11.4741	0.8237

The results from Table 6.8 suggests that the second-pass regression holds. Both the slope and intercept are highly significant at the 0.05 level of confidence as the *t*-values are greater than two. The *R*-squared value is high at 82.4%. However, these results are only based on ten observations, so they should be considered with caution. A comparison plot between the top-10 Category B brands' betas attained using the overall Brands Index and the betas achieved using the same top-10 brands from the Category sub-Index is shown in Figure 6.3.

Figure 6.3 Betas comparison of Brands Index vs. Category sub-Index: Category B



As can be seen in Figure 4.3, the B-Brand4 beta calculated on the basis of the Brands (market) Index and the Category sub-Index is the largest among all ten brands considered. Relative to their equivalent Brands Index betas, Category sub-Index betas for B-Brand15 and B-Brand16 are significantly lower. The opposite only holds for B-Brand36 where the beta obtained from the Category sub-Index is significantly greater than that obtained using the Brands Index. All the betas are positive based on the Brands Index and the Category sub-Index, but variations occur due to the prevailing market for FMCGs in Australia. The beta values will also depend on the relative volatility of the brands' sales returns compared to overall market returns, as well as the correlation of brand and market returns. The beta value compares the sale returns and not prices; therefore, the Brands Index and the Category sub-Index will show similar trends, but brand manager strategies can lead to variations, as shown by B-Brand15, B-Brand16 and B-Brand36.

The implication of the above results is that although the overall category beta is close to one (Category B beta = 1.06), there are riskier brands inside the category with beta values greater than one (B-Brand4 and B-Brand18) when measured against the Category sub-Index.

This research proposes that this information can be used by brand suppliers to reallocate shelf space inside the category share of a store. Specifically, when planning price reductions, priority should be given to brands with betas greater than one, as this will drive more sales value than for brands with betas less than one. Comparing betas calculated using the overall Brands Index with those using the Category sub-Index can confirm or redistribute shelf space among different brands, as beta values show the relative volatility of brands' sales returns as well as the correlation of the sales returns of different FMCG brands. From the sub-index, those brands depicting betas greater than those of the overall Brands Index can be recalibrated to test them for a greater shelf space.

As the overall Category B beta is around one, it is not expected that the category will grow significantly relative to the overall market. Nonetheless, benefits for the category can be achieved by rearranging the inside share composition. A similar approach can be used for categories with betas greater than one. Brands inside the Category with betas greater than one can be the focus for achieving growth targets. In the case of categories with betas less than one, the same logic can be applied, even though no growth at all is pursued for these categories. In summary, the beta value can be used as an alternative metric to allocate shelf space at both levels; the category level against the entire supermarket, and the brand levels inside those categories.

From a brand manager's point of view, beta is a great indicator of how a specific brand's risk compares against its category and also against the overall market (using the Brands Index). Inside a category, a brand manager may use the beta values obtained using the Category sub-Index as a proxy for the market, to become more or less volatile depending on the growth objectives, so that the beta target can change over time. Most of the volatility in the FMCG industry in Australia comes from price promotions, as temporary reductions in price lead to increased sales volumes. Therefore, if the target is to increase sales, then an increase in price promotion activity will be required to meet the target. This condition will make the beta of this specific brand become higher (assuming the other brands do not follow) as the volatility of this brand's returns will also increase. The CAPM theory suggests that a beta greater than one will grow/decline faster than the market, and a beta lower than one will grow/decline slower than the market. Thus, a brand with a current beta value of 0.9, for instance, can aim to achieve a beta of 1.1 by conducting more marketing activities such as price promotions, investment in advertising, or changing their number of SKUs. These marketing activities will make a positive and noticeable change in sales, albeit at a higher cost, as all these marketing activities have costs attached to them. The knowledge gained from the beta value allows a manager to know that whether a competitor does the same, as its own brand it will grow or decline faster or slower than the category or the overall market compared with its own beta value. Most importantly, the research in this thesis is the first to provide clear guidelines of how to derive a a single value that is able to compare brand risk, not only inside a category but outside it. The theoretical beta developed through the use of modern financial theory allows brand managers and brand suppliers to compare brand risk within the FMCG industry. These previous statements are an unquestionable contribution to practitioners and academic research. The knowledge gained about brand betas through this investigation can also be expanded to the managerial topic of portfolio management, as brand betas measure risk. Hence, a brand's portfolio can be reworked using beta as a measurement of risk. The following section deals with the applicability of the brand beta in this field.

6.3 Brand portfolio management

It will be recalled from Chapter 2 that one of the main conclusions of previous studies is that marketing portfolios differ from financial ones in the sense that the allocation of marketing funds affects the portfolio returns (Ryals, Dias, & Berger, 2007). In stock markets, the calculated percentage return is independent of the investment amount; but in marketing, the return is dynamic and varies depending on the investment. For instance, an investment of one million dollars or ten thousand dollars in financial securities may generate the same rate of return (e.g. 10%) for a given change in the price of the asset, so the return does not vary with the amount of money invested. In contrast, different levels of marketing investments may generate different returns, e.g., investing a million dollars in marketing strategies may generate a return of 5%, while an investment of two million dollars may generate a return of 7%. This distinction is quite important, as the incremental sales this research has used so far disregard any investment required to achieve that value when calculating the return.

This section tests and presents outputs for a portfolio made of seven brands owned by the same manufacturer. The rationale in choosing brands owned by the same manufacturer is that brand portfolio theory can be applied in the discussion of the outcomes. Although I recognise that the portfolio is not large enough to eliminate all diversifiable risk and that some unsystematic risk may remain (i.e. the portfolio contains a relatively small number of brands), the intention of this section nonetheless is employ modern portfolio theory (MPT) in a new context. The particular portfolio under examination is comprised of two brands from Category A, two brands from Category B and one brand from each of the remaining three categories. Applying the methodology discussed in Section 4.3, the variance-covariance matrix is provided in Table 6.9, below, and mean returns for the seven brands are given in Table 6.10, following.

Table 6.9 Variance-covariance matrix using brand betas and index variance

	A-Brand1	A-Brand3	B-Brand4	B-Brand5	C-Brand4	D-Brand1	E-Brand1
A-Brand1	0.12472	0.00737	0.00846	0.00447	0.00263	0.00288	0.00520
A-Brand3	0.00737	0.05815	0.00391	0.00206	0.00122	0.00133	0.00240
B-Brand4	0.00846	0.00391	0.04633	0.00237	0.00140	0.00153	0.00276
B-Brand5	0.00447	0.00206	0.00237	0.01763	0.00074	0.00081	0.00146
C-Brand4	0.00263	0.00122	0.00140	0.00074	0.00394	0.00047	0.00086
D-Brand1	0.00288	0.00133	0.00153	0.00081	0.00047	0.00845	0.00094
E-Brand1	0.00520	0.00240	0.00276	0.00146	0.00086	0.00094	0.01830

Table 6.10 Mean returns using brand betas and index variance

Brand	Mean Return
A-Brand1	37.16%
A-Brand3	17.68%
B-Brand4	23.43%
B-Brand5	15.04%
C-Brand4	5.11%
D-Brand1	7.25%
E-Brand1	11.87%

One of the main contributions of the Brands Index is that it allows brand managers to optimise brand portfolios. The composition of the optimal brand portfolio based on brand betas is provided in Table 6.11, below. The portfolio is optimal in the sense that it provides the highest level of return per unit of risk (based on standard deviation).

Table 6.11 Optimal portfolio – expected return and standard deviation based on betas

	A-Brand1	A-Brand3	B-Brand4	B-Brand5	C-Brand4	D-Brand1	E-Brand1	E(Rp)	S.D.p
Optimal Portfolio	11.4%	9.3%	18.7%	29.4%	0.8%	14.1%	16.5%	**17.67%**	**9.03%**

Further to the above specification of the optimal portfolio, the quantification of the beta for each brand provides brand managers with an additional metric for volatility beyond the standard deviation. Based on this, different portfolio scenarios can be examined if, for instance, brand betas are expected to increase or decrease. For example, if the beta for A-Brand1 in a brand portfolio was expected to decrease to 2.5 (e.g. due to a decrease in promotional activity) and the beta for E-Brand1 was expected to increase to 1.2 (e.g. as a result of greater promotional activity) then the risk and expected return of the new optimal brand portfolio can be easily calculated using the expected betas for those two brands. The result for the proposed alternative change in betas has generated a decreased in volatility (standard deviation of 8.98%) but the portfolio expected return has also decreased, as per the results in Table 6.12.

Table 6.12 Scenario – A-Brand1 beta declines and E-Brand1 beta increases

Portfolio	E(Rp)	S.D.p
Old	17.67%	9.03%
New	16.74%	8.98%

Overall, brand managers could easily change the current value of a beta for a predicted one based on greater or lower price promotional activities in order to work out the expected return and standard deviation.

In Chapter 4, it was specified that the extra cost that a brand incurs in order to generate incremental sales from price promotions has not yet been considered. So far, it has been assumed that a return that comes from incremental sales is divided by base sale values. However, if access to confidential information is granted (such as gross profit for base sales and the cost of causing incremental sales), then a more realistic return could be worked out for a given brand. Equation 4.10 shows that π_p will always generate a static profit. However, what needs to be identified is how the cost varies as the incremental sales increase or decrease. Thus, Equation 4.11 was presented as a dynamic ratio between the change in profit to trade deal discount, which varies with Δ and δ accordingly. Equation 4.11 is repeated below as Equation 6.1.

Equation 6.1

$$\pi_p - \pi_o = \Delta(M_o - \delta) - S_o\delta$$

The dynamic ratio in Equation 6.1 can be understood as the ratio of incremental profit to promotional spend. Profit and cost per unit information is considered confidential by manufacturers or brand owners and is not publicly available. However, if that information is available, the return formula of the ratio of incremental sales to base sales can be then modified to accomplish a more realistic result.

The specification in Equation 6.1 seeks to identify cost variances as incremental sales increase or decrease. Different levels of investment generate different levels of incremental uplift, which is the effect caused by increased investment strategies. In most circumstances, the incremental value is not fully taken by manufacturers, so they only take what is left after paying for that extra sale. The higher the uplift in sales, the higher the cost that a brand needs to pay to a brand supplier (retailer). Due to confidentiality agreements with manufacturers, this research is not allowed to disclose any costing information. However, the available average cost paid to retailers on promotion at different levels of price discounts is shown in Table 6.13, below.

Table 6.13 Average cost at different levels of incremental sales

Sales Uplift Range	Retailer Share of Incremental Revenue –	Manufacturer Share of Incremental Revenue
80% +	81%	19%
60-80%	72%	28%
40-60%	63%	37%
20-40%	54%	44%
10-20%	45%	55%
< 10%	41%	59%

Table 6.13 assumes that if the incremental sales are less than 10%, then the brand only gets 59% of that extra revenue and the retailer keeps 41%. As the incremental sales become higher and higher, the revenue becomes smaller and smaller. For instance, if the incremental sales are between 40% and 60%, the brand gets 37% of that extra uplift and the retailer will retain 63%. It is also assumed that the incremental sales are fully funded by the brand. Thus, the return calculations taking into account this cost are much lower. The results of the adjustments are presented Table 6.14, below.

Table 6.14 Returns adjusted by the cost of bringing incremental sales

	A-Brand1	A-Brand3	B-Brand4	B-Brand5	C-Brand4	D-Brand1	E-Brand1	Index
Mean Return	16.45%	8.34%	11.51%	8.23%	3.01%	4.13%	6.49%	4.01%
S.D.	13.73%	10.19%	9.25%	6.88%	3.58%	5.02%	6.35%	2.25%
Variance	1.88%	1.04%	0.85%	0.47%	0.13%	0.25%	0.40%	0.0505%
Beta	**2.03**	**1.13**	**1.16**	**0.87**	**0.55**	**0.58**	**0.95**	

To obtain a better view of how the return and betas values of different brands change, a comparison is presented below in Table 6.15.

Table 6.15 Returns a beta comparison with data adjusted by incremental cost

	A-Brand1	A-Brand3	B-Brand4	B-Brand5	C-Brand4	D-Brand1	E-Brand1
Mean Return [Old]	37.16%	17.68%	23.43%	15.04%	5.11%	7.25%	11.87%
Mean Return [New]	16.45%	8.34%	11.51%	8.23%	3.01%	4.13%	6.49%
Beta [Old]	**2.99**	**1.38**	**1.59**	**0.84**	**0.49**	**0.54**	**0.97**
Beta [New]	**2.03**	**1.13**	**1.16**	**0.87**	**0.55**	**0.58**	**0.95**

It is clear from Table 6.15 that the return taking into account incremental cost is much lower, and the beta values have decreased for A-Brand1, A-Brand2, B-Brand4 and E-Brand1, and have increased for B-Brand5, C-Brand4 and D-Brand1, meaning that different marketing strategies (like marketing and pricing) will affect brand volatility. This research has provided brand managers with a clear methodology to incorporate the actual cost they incur when having incremental sales, so a more realistic view of brand performance can be achieved. The implication of this methodology and its implementation is quite important for companies that place different brands in supermarkets, as they are now able to compare performance across brands and also, they gain a more realistic view of the brands' execution overall. However, this technique cannot be extended across companies, as rival manufacturers will not provide costing information to other firms. Thus, if confidential information in regards to costing information is available, this research strongly recommends to take this information into account in order to provide a more realistic return. It is left for future research the option when the market is made as the total manufacturer sales so the brands portfolio will originate their betas from inside the company's total sales value rather than from outside as it has been exposed so far all the way through this study. It means that a new sub-Index similar to the Category sub-Index is required. This sub-Index is made of total manufacturer sales. Thus, the brand's size, profitability, risk and other measures can be brought together to help in the portfolio management optimisation process.

Nevertheless, a comparison of the composition of portfolios with (new) and without (old) confidential costing information is provided in Table 6.16, below. It shows that the new expected return is lower than the old expected return, as the additional cost of running a price promotion has been taken into account in the returns calculation.

Table 6.16 Comparison of portfolio weights with data adjusted by incremental cost

Costing Information	A-Brand1	A-Brand3	B-Brand4	B-Brand5	C-Brand4	D-Brand1	E-Brand1	E(Rp)	S.D.p
Old	11.4%	9.3%	18.7%	29.3%	0.8%	14.1%	16.5%	**17.67 %**	**9.03 %**
New	12.1%	8.9%	18.9%	22.5%	8.1%	13.0%	16.4%	**8.61 %**	**3.88 %**

Focusing on the portfolio composition in Table 6.16 above, it can be seen that the foremost change is in C-Brand1 which moves from 0.8% to 8.1%. Looking at incremental sales data, the share of total incremental sales for each brand in the last year can be worked out, so a better view of this metric is obtained. In addition, knowing the incremental cost structure based on Table 6.13, the share of spend for the last year can also be calculated. The ratio between revenue share and spend share is a good indication of how a specific brand is doing in relation to the spend used to reach that incremental revenue. Table 6.17 and Figure 6.4 present those results.

Table 6.17 Revenue share vs. spend share for seven brands

Parameter	A-Brand1	A-Brand3	B-Brand4	B-Brand5	C-Brand4	D-Brand1	E-Brand1
Incremental Revenue (%)	38%	12%	21%	10%	1%	2%	14%
Spend Share	42%	13%	21%	9%	1%	2%	13%
Ratio Revenue to Spend	0.91	0.95	1.03	1.20	1.42	1.37	1.09

Figure 6.4 Revenue share vs. spend share

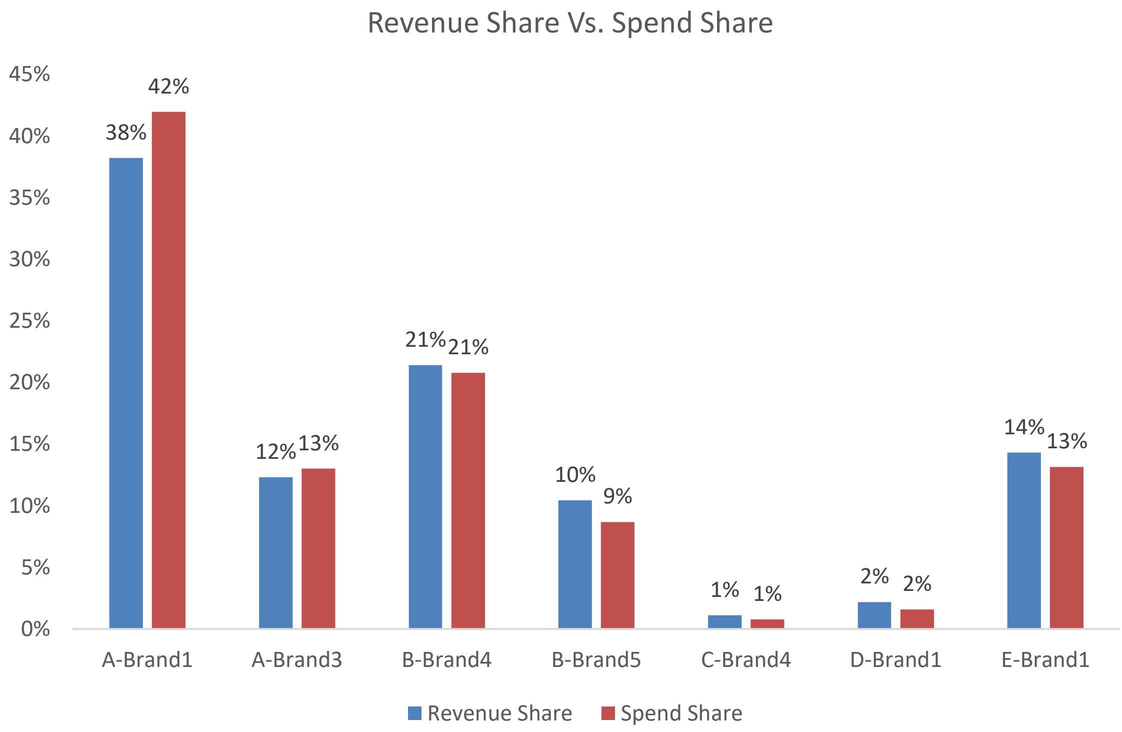


Table 6.17 shows A-Brand1 and A-Brand3 have revenue to spend ratios less than one, while the remaining brands have ratios greater than one. The result suggests that A-Brand1 and A-Brand3 are not as efficient as the other ones in driving incremental revenue. Based in this information, different portfolios should be analysed to determine whether or not the expected return can be improved for a given level of standard deviation. To this end, ten portfolios are selected for examination and, as recommended in Chapter 4, Sharpe ratios (Sharpe, 1966) will be used to rank them. Table 6.18 shows individual brand weights, portfolio expected returns and standard deviations for the ten portfolios.

Table 6.18 Expected returns and standard deviations of ten portfolios for seven brands

Portfolio	A-Brand1	A-Brand3	B-Brand4	B-Brand5	C-Brand4	D-Brand1	E-Brand1	E(Rp)	S.D.p
Portfolio 1	10%	10%	10%	10%	30%	20%	10%	**6.83%**	**3.20%**
Portfolio 2	15%	14%	14%	14%	14%	14%	15%	**8.37%**	**3.88%**
Portfolio 3	12%	8%	15%	11%	20%	22%	12%	**7.56%**	**3.47%**
Portfolio 4	**42%**	**13%**	**21%**	**9%**	**1%**	**2%**	**13%**	**12.04%**	**6.80%**
Portfolio 5	30%	11%	19%	13%	2%	5%	20%	**10.67%**	**5.46%**
Portfolio 6	39%	11%	20%	10%	1%	2%	17%	**11.67%**	**6.43%**
Portfolio 7	42%	12%	19%	9%	2%	1%	15%	**11.91%**	**6.75%**
Portfolio 8	**38%**	**12%**	**21%**	**10%**	**1%**	**2%**	**14%**	**11.69%**	**6.39%**
Portfolio 9	40%	12%	19%	10%	2%	1%	16%	**11.73%**	**6.53%**
Portfolio 10	38%	13%	20%	11%	1%	2%	15%	**11.63%**	**6.35%**

Based on the share of spend and share of incremental revenue figures from Table 6.17, Portfolios 4 and 8 (in bold) resemble those weights accordingly. Weights for the remaining portfolios have been randomly selected in order to provide a clearer view on the principle of diversification. Table 6.19 shows the results for the optimised portfolios. The principal of diversification can be clearly explained making use of Sharpe ratios to rank portfolios. The Sharpe ratio is simply the ratio of portfolio's expected return minus risk-free divided by its standard deviation, as follows:

Equation 6.2

Sharpe ratio = $\left(S = \frac{E(r_p) - Rf}{\sigma_p}\right)$.

Table 6.19 Optimised expected returns and standard deviations for seven brands

Efficient Portfolio	A-Brand 1	A-Brand 3	B-Brand 4	B-Brand 5	C-Brand 4	D-Brand 1	E-Brand 1	E(Rp)	S.D.p	Sharpe Ratio
Efficient Portfolio 1	7%	7%	13%	18%	24%	17%	14%	**7.11%**	**3.20%**	**2.223**
Efficient Portfolio 2	12%	9%	19%	23%	8%	13%	16%	**8.61%**	**3.88%**	**2.216**
Efficient Portfolio 3	**9%**	**8%**	**16%**	**20%**	**17%**	**15%**	**15%**	7.76%	3.47%	2.235
Efficient Portfolio 4	19%	11%	26%	27%	1%	1%	15%	**12.43%**	**6.80%**	**2.115**
Efficient Portfolio 5	25%	10%	31%	25%	1%	1%	7%	**11.07%**	**5.46%**	**2.027**
Efficient Portfolio 6	34%	8%	37%	19%	1%	1%	1%	**12.10%**	**6.43%**	**1.881**
Efficient Portfolio 7	37%	6%	38%	16%	1%	1%	1%	**12.39%**	**6.75%**	**1.836**
Efficient Portfolio 8	33%	8%	36%	20%	1%	1%	1%	**12.06%**	**6.39%**	**1.888**
Efficient Portfolio 9	35%	7%	37%	18%	1%	1%	1%	**12.19%**	**6.53%**	**1.867**
Efficient Portfolio 10	33%	8%	36%	20%	1%	1%	1%	**12.02%**	**6.35%**	**1.894**

Comparing the results in Table 6.18 with those of Table 6.19, it can be seen that in all cases the optimised expected return is higher—as should be anticipated. The Sharpe ratio is highest for Portfolio 3, which differs from the current spend highlighted in Portfolio 4 in Table 6.18 above. The efficient Portfolio 3 clearly allocates less weight to the first three brands and more weight to the last four brands. This implies that in terms of adjusted returns, Portfolio 3 is considered superior to the others. The excess return for Portfolio 3 over the risk-free rate, relative to the standard deviation, is high compared to the other portfolios. Portfolio 3 has the lowest standard deviation of sale returns and should generate higher returns to maintain the high Sharpe ratio. Portfolio diversification is needed for brands with small negative correlations, to reduce the overall portfolio risk and, thus, increase the Sharpe ratio. The implication of the above results is that even though the current spend share (Portfolio 4) generates the highest return among all possible portfolios, Portfolio 4 also has the highest standard deviation. On the other hand, the Sharpe ratio recommends Portfolio 3, which has the lowest standard deviation.

This section has delivered significant implications for brand managers in terms of the different methods that can be used to measure beta. It has also provided an example of how to rank portfolios based on Sharpe ratios when the incremental cost is known. Most of these implications are new in the management and marketing disciplines; there are no antecedents of the Brands Index, which has allowed novel techniques to be implemented in this thesis. This is the main reason why the creation of the Brands Index is significant for practitioners, academics, brand suppliers, brand managers and everyone involved in management and marketing. The next section develops a clear approach for maintaining the Brands Index and betas so that the values are updated weekly rather than being static.

6.4 Weekly Maintenance of the Brands Index and Brand Betas

The previous section brought together the creation of the Brands Index and its applicability through the use of the adapted CAPM methodology. Thus far, the analysis has been conducted on the basis of fixed betas, i.e., a beta for a fixed period of time, namely January 2009 to December 2012. It is believed that brand suppliers and brand managers will benefit more from having a time-varying beta rather than a fixed one. The research in this thesis suggests that betas are calculated using a moving window containing the last 52 weekly observations of available data. The estimation of betas each week requires the window to be the same size to avoid comparison bias. It means that the beta for the week ending 08-Jan-2012 is calculated from 16-Jan-2011 to 08-Jan-2012, whereas the beta for the week ending 30-Dec-2012 (52 weeks later) is computed from 08-Jan-2012 to 30-Dec-2012. This technique can be used at the category level for one or several brands. Literature on financial volatility (see, for example, Schwert & Seguin, 1990; Harvey, 1989 or Lettau & Ludvigson, 2001) indicates that there is evidence of high persistence and fluctuations in the conditional variance of asset returns and market returns that can be shown by computing time-varying betas. However, the time-varying beta methodology only provides a single beta value rather than a different one week-on-week. Thus, this specific topic is excluded from the current study and left for future research. Time-varying beta calculations were performed herein for all 49 brands. In order to save space, results are only shown in this chapter for five categories, and for the first and last brands, as an example of indicative findings. The complete set of results for all 49 brands is shown in Appendix 7. The index returns do not change they are the same as previously calculated. Table 6.20 shows the outcomes.

Table 6.20 Index returns and moving betas for all brands

From	To	Index Return	Category A	…	Category E	A-Brand1	A-Brand2	…	E-Brand28
01-Jan-12	07-Jan-12	10.0%	1.31	…	0.94	3.18	0.56	…	-0.01
08-Jan-12	14-Jan-12	5.6%	1.31	…	0.95	3.18	0.56	…	0.00
15-Jan-12	21-Jan-12	11.9%	1.29	…	0.95	3.20	0.62	…	-0.01
22-Jan-12	28-Jan-12	12.9%	1.32	…	0.95	3.01	0.60	…	-0.02
29-Jan-12	04-Feb-12	7.2%	1.31	…	0.94	3.66	0.64	…	-0.21
05-Feb-12	11-Feb-12	5.4%	1.32	…	0.95	3.57	0.64	…	-0.20
12-Feb-12	18-Feb-12	11.5%	1.27	…	0.94	3.54	0.65	…	-0.20
19-Feb-12	25-Feb-12	4.0%	1.23	…	0.95	3.31	0.69	…	-0.18
26-Feb-12	03-Mar-12	7.9%	1.23	…	0.94	3.34	0.69	…	-0.17
04-Mar-12	10-Mar-12	7.9%	1.24	…	0.93	3.47	0.69	…	-0.18
11-Mar-12	17-Mar-12	8.0%	1.24	…	0.93	3.36	0.74	…	-0.17
18-Mar-12	24-Mar-12	6.1%	1.23	…	0.94	3.30	0.74	…	-0.17
25-Mar-12	31-Mar-12	8.9%	1.18	…	0.93	3.16	0.84	…	-0.14
01-Apr-12	07-Apr-12	0.0%	1.18	…	0.91	3.29	0.89	…	-0.10
08-Apr-12	14-Apr-12	18.8%	1.12	…	0.86	2.25	0.90	…	-0.07
15-Apr-12	21-Apr-12	19.5%	1.29	…	0.76	1.77	0.92	…	-0.07
22-Apr-12	28-Apr-12	4.7%	1.28	…	0.76	1.83	0.95	…	-0.05
29-Apr-12	05-May-12	6.7%	1.27	…	0.76	1.81	0.95	…	-0.05
06-May-12	12-May-12	2.8%	1.26	…	0.78	1.75	0.84	…	-0.04
13-May-12	19-May-12	3.2%	1.26	…	0.78	1.69	0.79	…	-0.05
20-May-12	26-May-12	3.3%	1.26	…	0.79	1.87	0.79	…	-0.06
27-May-12	02-Jun-12	8.9%	1.26	…	0.81	1.85	0.75	…	-0.06
03-Jun-12	09-Jun-12	5.8%	1.28	…	0.83	1.65	0.73	…	0.01
.	.	…	…	…	…	…	…	…	…
.	.	…	…	…	…	…	…	…	…
.	.	…	…	…	…	…	…	…	…
11-Nov-12	17-Nov-12	10.4%	1.30	…	0.75	2.42	0.90	…	0.42
18-Nov-12	24-Nov-12	9.0%	1.30	…	0.72	2.59	0.89	…	0.48
25-Nov-12	01-Dec-12	3.6%	1.32	…	0.72	2.62	0.89	…	0.37
02-Dec-12	08-Dec-12	6.0%	1.34	…	0.72	2.62	0.88	…	0.32
09-Dec-12	15-Dec-12	11.2%	1.36	…	0.72	2.58	0.84	…	0.42
16-Dec-12	22-Dec-12	14.4%	1.39	…	0.70	2.93	0.72	…	0.58
23-Dec-12	29-Dec-12	0.0%	1.39	…	0.70	3.00	0.72	…	0.34

To offer a better view of the results contained in Table 6.20, Table 6.21 provides a summary for the top five brands in each category. Their corresponding average returns, average, maximum and minimum beta values, and the previous static beta figures that were calculated based on a fixed four-year period (2009—2012) to give a clear view of the variation of the lag, are also shown.

Table 6.21 Summary outputs for moving betas

	Average Return	Average Beta	Max Beta	Min Beta	Static Beta
Category A	5.3%	1.28	1.39	1.12	1.43
Category B	7.6%	0.86	1.10	0.51	0.91
Category C	5.9%	0.40	0.58	0.31	0.45
Category D	4.7%	0.33	0.53	0.20	0.42
Category E	5.3%	0.82	0.95	0.70	0.67
A-Brand1	38.3%	2.35	3.66	1.45	2.99
A-Brand2	8.4%	0.76	1.02	0.56	0.54
A-Brand3	20.3%	2.49	2.88	1.47	1.38
A-Brand7	14.9%	-0.05	0.66	-0.70	-0.22
A-Brand13	18.8%	-0.68	0.28	-1.51	0.13
B-Brand4	24.9%	0.83	1.60	0.10	1.59
B-Brand5	15.0%	0.69	1.09	0.41	0.84
B-Brand14	14.6%	-0.24	0.66	-1.28	0.14
B-Brand15	8.3%	0.92	1.20	0.67	0.64
B-Brand16	11.5%	1.06	1.36	0.77	0.55
C-Brand4	4.7%	0.58	0.84	0.34	0.49
C-Brand18	7.1%	0.15	0.45	-0.02	0.31
C-Brand19	14.4%	-0.08	0.35	-0.41	0.04
C-Brand24	2.0%	0.48	0.64	0.22	0.34
C-Brand33	11.2%	0.41	0.71	0.15	0.48
D-Brand1	7.2%	0.33	0.62	0.06	0.54
D-Brand14	15.3%	1.10	1.64	0.20	0.40
D-Brand3	8.3%	0.34	0.64	0.13	0.19
D-Brand5	3.1%	0.34	0.43	0.23	0.21
D-Brand9	8.8%	0.50	0.82	0.07	0.34
E-Brand1	12.4%	0.97	1.34	0.44	0.97
E-Brand2	4.9%	0.88	1.12	0.78	0.57
E-Brand6	16.6%	0.38	1.39	-0.53	0.67
E-Brand8	3.8%	0.27	0.41	0.16	0.29
E-Brand9	14.1%	0.40	1.14	-0.04	0.79

Table 6.21 shows that the beta values vary substantially, as observed in the maximum and minimum values. In some cases, the minimum beta value is negative even though the average value is positive. As expected, in most cases, the old beta is highly correlated with the average beta. Only A-Brand13, B-Brand14 and C-Brand19

illustrates opposite signs. It means that the beta obtained using the last four years of data (static) experienced dramatic changes during the last year, compared with the average beta calculated using just the last 52 observations (average beta). The most likely explanation for this change in sign is that the brands with opposite signs for their static and average betas had higher or lower price promotion activity. In order to test whether or not the second-pass regression for the average betas holds, a linear regression of average betas on average returns (data from Table 6.21) was carried out. The results are shown in Table 6.22.

Table 6.22 Second-pass regression test on average returns and average betas

	Coefficient	**Standard Error**	***t*-value**
Intercept	0.0887	0.01165	7.61647
Slope	0.0425	0.01398	3.04054

From Table 6.22, it can be seen that the coefficients for both intercept and slope are statistically significant at the 0.01 level of confidence, as the *t*-values are greater than two. The implication of the previous results is that the FMCG industry can be provided with a weekly figure for the Brands Index as well as a weekly beta figure for each brand. This will allow brand managers observe changes in the beta value rather than relying on a static beta value. Changes in beta figures need to be investigated further by each brand manager to understand why it may be changing. Changes could be the result of a large or small marketing activity, or a competing brand conducting large or small marketing activities. Thus, the main contribution of having weekly betas is that they can alert brand managers to the movements of the overall market and their own brand. This new information, in balance with other metrics such as market share, promotional activity, advertising investment and others, should give brand managers a better understanding of a brand's performance, not only within a category but relative to the entire industry, as the beta value is comparable across different brands. Therefore, the average betas and average returns complement the fixed beta values based on four years of data.

CHAPTER 7: SUMMARY AND CONCLUSIONS

7.0 Introduction

The research presented in this thesis has empirically investigated the phenomenon of volatility clustering in the Brands Index, within the FMCG industry context. This research encapsulates theoretical reasoning from modern finance theory and applies it to a new research setting. The central research question underpinning this thesis was: *What are the antecedents of brands' sales volatility in the Australian retail sector and how do they influence brand performance overall?* The basic objective of the research was to create a detailed Brands Index comparable to those commonly used in financial markets, for example, the Standards & Poor's 500 and All Ordinaries Indices.

The motivation for construction of the index was to determine a model that best predicts the observed sales volatility in the FMCG industry in Australia. To address the research question and to achieve the research objective, a comprehensive review of potential theories and theoretical literature was conducted in Chapter 2 with the aim of describing and identifying volatility clustering.

By consolidating the existing literature in Chapter 3, an adaptation of the capital asset pricing model (CAPM) was developed, and two alternative methodologies for calculating returns were also proposed. As this research has endeavoured to investigate real phenomena related to FMCG volatility clustering, quantitative research approaches were developed in Chapter 4.

The suggested models were tested and discussed in Chapter 5. Further, it was concluded that the model including a risk-free component[4] was the best one for fully applying the CAPM to FMCG industry data. The findings and implications of the research were considered in Chapter 6. In addition, brand portfolio management and approaches to maintaining the Brands Index and tracking brand betas on a weekly basis were

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[4] The concept of the risk-free rate of return is understood in the context of this research as the returns based on base sales; but in theory, it is the minimum return a brand manager expects from sales, since they will not accept additional risk unless the ability of the rate of return is greater than the risk-free rate.

presented in Chapter 6. The findings were summarised in that chapter, as were their theoretical and practical implications and the contributions of the study. The current chapter concludes with a discussion of the limitations of the study and future research directions.

7.1 Summary of the Research

Throughout this thesis, several statistical techniques and applied econometric methods were implemented in order to build exploratory and predictive models that produced accurate results.

There were three major objectives of this research: 1) creating a Brands Index for the FMCG industry in Australia; 2) evaluating and capturing volatility clustering in the Brands Index; and 3) investigating whether the CAPM framework could be deployed to generate betas across multiple brands.

After the creation of the FMCG Brands Index, the first major challenge encountered in selecting an appropriate methodology to capture its volatility was the number of competing models able to accurately describe it. A reasonable number of different types of models did provide acceptable outputs, and the asymmetry effect was brought into play in order to restrict the numerous possibilities. GARCH models impose a symmetric response to volatility to positive and negative returns. This arises since the conditional variance is a function of the magnitudes of the lagged residuals and not their signs. Thus, by squaring the lagged errors, the signs are lost. The second challenge was to overcome the problem where both contending return calculation methodologies (with and without the risk-free component) were effective in capturing volatility clustering. Finally, the adaptation of the CAPM approach on both return procedures had to fully be tested to decide on the best model for providing betas for the entire industry. Given this, the methodology ultimately needed to be flexible enough to update the Brands Index and betas on a weekly basis.

To narrow the research question on: *What are the antecedents of brands' sales volatility in the Australian retail sector and how do they influence brand performance overall?*, three basic models were utilised, namely: auto regressive conditional heteroscedasticity (ARCH; Engle, 1982); generalised auto regressive conditional heteroscedasticity (GARCH) and the capital asset pricing model (CAPM; Lintner, 1965; Sharpe, 1964). Furthermore, a broad review of the literature was conducted to identify the causes of volatility clustering and the foundations of the CAPM. However, limited research and applications were found in the FMCG context.

The FMCG Brands Index was designed as a cap-weighted index based on the methodology used for calculating the Standards & Poor's 500 and All Ordinaries Indices, where the weighting is determined by market capitalization. Therefore, the Brands Index is a weighted-average index where the brand with the largest market value will have the largest weight. The concept of a divisor was introduced to start the index at a value of 1,000. The initial divisor was the price of the index divided by the base level of the index at time zero. Once the index was rebased, its returns were determined. A graphical review of its returns offered the first evaluation of volatility clustering in the FMCG Index. Consequently, further assessment was needed to statistically validate this initial finding.

The first method used to capture volatility was an ARCH test. This assisted in deciding whether or not autocorrelation was present in the squared residuals of the returns. The phenomenon of volatility clustering was documented as early as Mandelbrot (1963) and later by Fama (1965). However, it was not until Engle (1982) and the advent of the ARCH and GARCH models that financial econometricians started to seriously model the phenomenon.

The results obtained support the presence of volatility clustering in the FMCG Brands Index. Hence, a pool of different GARCH-type models was developed for each return calculation alternative. A decision to disregard standard GARCH models was made, as the asymmetry terms in the TGARCH and EGARCH models were highly significant from a statistical point of view. The final model was selected based on its Akaike information criterion, Schwarz criterion and Hannan-Quinn criterion. For both return calculations, the best model for describing volatility clustering was the EGARCH model. These outcomes allowed this research to uphold *Hypothesis 1*: *The variation in the weekly sales of the proposed Brands Index follows a volatility-clustering pattern similar to that of financial market indices*, and *Hypothesis 2*: *Volatility in the created Brands Index can be forecast using ARCH/GARCH models or any of their extensions*. The conclusion reached was that volatility in the FMCG Brands Index clearly follows a similar pattern to that of financial markets, and this volatility can be effectively captured and measured by an ARCH-GARCH technique; specifically, an EGARCH(2,1) model. An additional attempt was made to describe returns based on base sales (understood as the equivalent risk-free return in the context of the study), which always depicts a value equal to or greater than zero. Accordingly, a conceptual autoregressive conditional duration (ACD; Engle & Russell, 1998) model was developed. Since duration is necessarily non-negative, the ACD model has also been used to model time series that consist of positive observations. It was found that an exponential ACD, more specifically an EACD(1,1), was, in general terms, significant at a 0.05 level of confidence.

As discussed in Chapter 3, *Changes in weekly sales in the created Brands Index can be simulated using the volatility forecast* (*Hypothesis 3*). The proposed methodology here was to produce in-sample volatility forecasts and out-of-sample volatility forecasts based on the EGARCH(2,1) model for both return calculations. The models used for comparison were based on traditional ARMA modelling techniques. Results for in-sample volatility forecast testing suggested that the EGARCH(2,1) model outperformed the traditional ARMA structures in both cases, as per its lower values of root mean squared error (RMSE), mean absolute error (MAE) and mean absolute percent error (MAPE). In order to apply the same set of tests to the out-of-sample volatility forecasts, a new GARCH(2,1) model was obtained based on eight years of weekly data. The same conclusion as for the in-sample volatility forecast was reached; namely, that the EGARCH(2,1) model gave better performance according to its lower RMSE, MAE and MAPE values. Thus, consistent with Bollerslev and Mikkelsen (1999), it was concluded that the volatility forecasting technique was accurate and reliable. In addition, if the only objective is to simulate the future value of the Brands Index based on returns, volatility forecasts based on returns calculated without the risk-free component perform better than those based on returns including the risk-free component.

Furthermore, to explore the validity of the CAPM model within the FMCG industry in Australia, a set of estimated betas for several brands was needed. Subsequently, two alternative returns calculations were completed for 49 brands. Having the 49 brands' return computations in place, and the returns for the Brands Index, this research relied on an ordinary least squares method to run independent regressions of each brand on the index. Most of the beta coefficients were statistically significant for the returns without the risk-free component. The returns including the risk-free component achieved lower average *t*-values. Therefore, it was concluded that, based on the significance of the average *t*-values, the first-pass regression (required to test the validity of the CAPM) was satisfactory in both cases. Additionally, calculation of beta figures for each brand allows a brand or a set of brands to be compared with the overall market.

On this point, the first four proposed hypotheses from Chapter 3 were successfully accepted based on both returns calculations. However, the CAPM model required a second-pass regression test to validate it. To this end, the mean returns of the 49 brands were regressed on their respective betas. If the CAPM in this descriptive format holds, then the second-pass regression should be the security market line (SML). The slope is expected to be positive and statistically significant, while the intercept does need to be equal to zero but it is assumed to also be statistically significant. The outputs achieved for the returns without the risk-free component did not inspire any confidence at all; none of the coefficients were statistically significant and the slope term was negative, which is contrary to CAPM theory. The SML test failed in this instance, as it did not describe the data used for this purpose. The most likely reason for this result is the fact that most of the mean values were close to zero, making the relationship meaningless even though the betas were a good indication of each brand's risk. An alternative possibility is that maybe the CAPM holds only if the market returns are positive (Benninga, 2008). Conversely, the results for the returns that take into account the risk-free component's rate of return were quite pleasing; both coefficients were highly significant and in agreement with the CAPM theory. It was concluded that the SML test had succeeded, so it did describe the conditions of the structure of expected returns in the FMCG market. It was also shown that changes in beta risk are not proportional to changes in expected returns.

Finally, based on the research outcomes, Chapter 6 expanded the research to identify a beta for each supplier and category. The chapter also introduced a sub-index example for Category B, dealt with brand portfolio management implications, and demonstrated an approach for maintaining the Brands Index and tracking brand betas on a weekly basis.

The findings this thesis, as reported in Chapters 5 and 6 and summarised in the previous section, have several theoretical and managerial implications, which are discussed below.

7.2 Implications for the Literature

The fundamental concepts in the literature provided impetus to investigate the causes of sales volatility in the Australian FMCG industry and to estimate betas across multiple brands in a management and marketing context. By combining the theoretical approaches of extant theories, a new theoretical model for capturing volatility clustering in the Brands Index was tested. The result suggest that asymmetry in returns needs to be accounted for, as the best model for describing volatility in the Brands Index was the EGARCH(2,1) model.

From a management and marketing perspective, this study makes an important contribution to the literature. The results and analyses imply that volatility clustering in the Brands Index has always been present, but no studies have dealt with this matter in the past. Thus, this thesis represents the first attempt to account for volatility. One of the main advantages of taking volatility clustering into account in the models is that the volatility forecast becomes more accurate and reliable, as opined by Bollerslev and Mikkelsen (1999). In this regard, practitioners may gain additional insights and direction in the field of time series theory. Similarly, the creation of a market index for the FMCG industry also allows practitioners to create betas for a range of brands for comparative purposes by using and testing CAPM theory (Lintner, 1965; Sharpe, 1964). The vast majority of these theoretical arguments were empirically validated in this study, which should be of interest to academic practitioners.

In modern finance theory, the rationale behind the CAPM is that it provides an intuitively simple and appealing model of the relationship between required rates of return and risk. The general idea of the CAPM is that investors need to be compensated in two ways: *time value of money* and *risk*. The time value of money is represented by the risk-free rate (*Rf*) and compensates investors for placing money in an investment over a period of time. The remainder of the formula represents risk and calculates the amount of compensation the investor needs for taking on additional risk, as measured by the market risk premium (*Rm-Rf*) where *Rm* is the market return (Koop, 2006). This thesis adapted the CAPM formula to model returns with and without a risk-free rate of return component. The notion of the risk-free rate of return within the context of this thesis is understood as base sales, i.e., if a brand manufacturer does nothing in terms of marketing activities (e.g. price promotions, advertising investment, etc.) it still attains its base sales. Conversely, if a marketing activity takes place, then incremental sales are attained, which are calculated as the difference between total sales and base sales. This the groundwork for the risk-free returns calculation. Therefore, future researchers can use this adaptation of the CAPM theory as applied to the FMCG industry.

While both return calculation methods—excluding and including a risk-free component (the FMCGBR and FMCGBR_RF models, respectively)—were used in parallel throughout this research, the results from CAPM theory suggest that only the method including risk-free returns (FMCGBR_RF) passed the first- and second-pass regression tests needed to validate the CAPM. This is because the outputs for both methods in regards to the first-pass regression (Brands Index returns on individuals brand returns) was successfully validated, but the second-pass regression (all betas regressed on their respective expected returns), was only validated for the risk-free return methodology. This is a significant factor in the CAPM theory, as it can definitely be applied to the

Australian FMCG industry. This further implies that the obtained FMCG brand beta figures are academically supported by CAPM theory.

By contrast, the CAPM calculation approach for the two theoretical brand returns methodologies was validated. The only difference in this process among the two competing procedures is the failure of the second-pass regression for returns without the risk-free component within the CAPM framework. This progression has provided this study with richer insights. It reveals a dilemma whereby the rejection of the method of estimating returns without the risk-free component is fully justified, as some of the theoretical arguments in terms of its validation hold. Also, some of the evidence suggests that volatility forecasts based on returns without the risk-free component produce better results. More obviously, if the only goal was to simulate the index value, then the returns calculated without the risk-free component are the best method. Since estimates of returns with and without the risk-free component have been addressed in this research as distinct alternative methods for capturing volatility in the Brands Index and to compute brand betas, the selection of which methodology to use needs to be based on the researcher's objective. The results of this thesis favoured estimates of returns that included the risk-free component, as all five hypotheses from Chapter 3 were upheld in Chapter 5.

7.3 Managerial Implications

The managerial implications of this research largely emerged from the interpretation of the findings in terms of what they mean for brand suppliers and brand managers. Based on the statistical testing approach, it can be seen that the Brands Index clearly displays similar patterns to those of financial indices. Large changes tend to be followed by large changes of either sign, and small changes tend to be followed by small changes, though this may not be used as a basis for inferential statistics. For both brand suppliers and brand managers, a cursory look at the returns suggests that some time periods are riskier than others. Moreover, these risky times are not scattered randomly across the weekly data. Instead, there is a degree of autocorrelation in the riskiness of the FMCG Brands Index returns that needs to be accounted for.

Although a visual approach provides useful initial insights on periods of high and low volatility, a more rigorous test was required to deal with the fact that the amplitude of the returns varies over time, which has been called *volatility clustering*. Hence, the ARCH and GARCH models developed by Engle (1982) and Bollerslev (1986), respectively, were employed herein. ARCH-type models have become widespread tools for dealing with heteroskedastic time series models. The goal of such models is to provide a volatility measure like a standard deviation that can be considered in financial decision making (Engle, 2001). This research findings have been supported by the use of the ARCH-GARCH-type models; specifically, an exponential GARCH, EGARCH(2,1) best described the volatility in the FMCG Brands Index. This result implies that the FMCG Brands Index, as an indicator of the total market, can be simulated accurately and reliably (Bollerslev & Mikkelsen, 1999). Therefore, brand suppliers and brand managers may benefit from it, as they can use it to enhance production planning, inventory management and future capacity requirements, and accurately and efficiently allocate resources to meet anticipated demand (Murray, 2008).

In Chapter 6, betas for Woolworths and Coles were derived and the results therein implied that Coles was more volatile than Woolworths relative to the overall Brands Index. From a brand supplier's point of view, it means that if the overall market grows/declines, Coles will grow/decline faster than Woolworths. It also implies that Coles appears to have higher ratios of spikes against the base sales compared with Woolworths. Consequently, Coles is more dependent on tactics that drive short-term sales such as price promotions, which makes this retailer riskier if such activities slow down or do not work at all. Clearly, this research, through the creation of the Brands Index in combination with the introduction of the risk-free component into the calculations, has allowed both brand suppliers a way to compare themselves with each other and against the overall market. Other factors that determine sales value volatility were also explored in this research, providing information to brand managers that will help them increase product demand.

Providing betas at the category level also has clear implications. Brand suppliers can now combine category beta values with traditional metrics such as value share, turnover, profitability, etc., to more efficiently allocate shelf space across categories within actual supermarkets. The beta figure in this context should be seen as additional piece of information that helps in the decision-making process, rather than a contending metric. The category beta can be used as a good indicator if a growth strategy is pursued. Categories with betas greater than one could be targeted for this end, while betas with values less than one might be used if no growth is anticipated for a brand. A beta value of one indicates that the sales return value has the same volatility as the market's returns. Beta is a product of the relative volatility of a brand's sale returns and the correlation returns; therefore, it allows formulation of useful conclusions about FMCGs. The computed values are good market indicators for FMCG products in Australia. Marketing strategies should comprise an in-depth analysis of the many components that affect sales return values.

This research also investigated the use of sub-indices of the Brands Index, similar to those used in financial markets. The category used for this purpose was Category B, as its beta was close to one. The results show that although the category beta is close to one, there are riskier brands inside the category with beta values greater than one (B-Brand4 and B-Brand18) when compared against the sub-index. The implication for brand suppliers in this case is that the beta values for brands in Category B can be used to reallocate shelf space according to the category share. The more volatile the brand is, the faster it will grow. Thus, when planning price reductions, priority should be given to brands with betas greater than one, as they will drive more sales than brands with betas less than one. Overall, the beta value can be used by brand suppliers as an alternative metric for allocating shelf space at both levels—at the category level across entire supermarkets and at the brand level within specific categories.

From the brand manager's perspective, the beta value is a great indicator of how a specific brand's risk compares against the category it sells in, and also against the overall market. Within a category, a brand manager may use the beta to become more or less volatile depending on growth objectives, so its beta target can change over time.

The knowledge gained via beta values allows a manager to know that if a competitor conduct the same activities, it will grow or decline more or less than the category or overall market compared with its own beta value. Most importantly, by just looking at a single beta value, brand managers will be able to compare brand risks, not only within the category they sell in, but also for brands in other categories.

Conclusively, the knowledge gained from the brand beta computations proposed by this research have been expanded to portfolio management, as brand beta is a metric for volatility that differs from the standard deviations used for comparison of different FMCG brands. Hence, brand portfolios can be reworked using the brand beta as a measurement of risk. The findings on this topic relied on the use of modern portfolio theory (Markowitz, 1952). The research created the Brands Index, which allows manufacturers and brand managers to use alternative methods such as the CAPM, which was extensively used throughout this study to improve the sales returns and profitability targets. In this specific case, the Brands Index returns are required so its variance can be processed, and the brand betas can also be executed by linearly regressing each brand's returns on the Brands Index. Thus, the clear implication for brand managers is that portfolios can be optimised based in the Brands Index and the betas of the brands making up the portfolio. Most importantly, the quantification of the beta for each brand provides brand managers with an additional metric for volatility beyond the standard deviation. Additionally, ten portfolios were optimised, taking into account a hypothetical cost involved when incremental sales are achieved, and then these portfolios were ranked using the Sharpe ratio, which refers to the average return on the risk-free rate over a certain period (Sharpe, 1966). The ratio was helpful in forming the new index of FMCG industry performance. Sharpe ratios deal with the potential risks that business entities endure in adverse market situations, and the new index works with new baseline sales figure to lessen the problem of market risk. The implication of this is that brand managers can also use the Sharpe ratio to rank portfolios and make the decision-making process easier.

Lastly, an approach to updating the Brands Index and tracking brand betas on a weekly basis was developed and presented. Betas were calculated based on the previous 52 weekly observations of Brands Index returns and each brand's returns. The use of a moving beta allows the creation of a new beta every week, so that once the new weekly data comes in, a new beta will be generated for any brand of interest. This implies that brand managers need to be vigilant for changes in the beta value rather than relying on a fixed one. Changes in beta figures need to be investigated further by each brand manager to understand why it may be changing. It could be the result of a large or small marketing activity by their own or a competing brand. Thus, the main implication of moving betas is that the weekly values can guide brand managers to be alert to the movements of the overall market and also their own brand. This new information, in balance with other metrics such as market share, promotional activity, advertising investment, etc., should give brand managers a better understanding of their brand's performance, not only within a category but also the entire industry, as the beta value is comparable across different brands. However, in order to validate the CAPM theory for the weekly betas, it would be necessary to perform a corresponding confirmatory test.

7.4 Overall Contributions

This thesis has made a number of contributions to business, management and marketing research. The creation of the Brands Index represents an important contribution to the management and marketing disciplines, as it allows any brand or set of brands to be compared against an overall market. By combining approaches from extant theories, a new theoretical model was tested that captures observed volatility clustering. This has never been reported before in the FMCG industry. As a result, the volatility forecast of the Brands Index is improved when volatility clustering is accounted for. Even though the returns computed without the risk-free rate of return component did not fully validate the CAPM theory, it was found that the Brands Index volatility forecast is more accurate when these returns are used.

This thesis clearly found that the CAPM can be implemented in the analysis of Australian FMCG industry data, as the brands acting inside it now an overall market index to compare against. Therefore, betas for any brand or set of brands may be developed following the CAPM approach. Based on the returns including risk-free returns, the CAPM theory was fully validated and tested. It was also disclosed in this study that the computation of base sales on both sides of the CAPM equation was essential to this aim.

This investigation, through the creation of the Brands Index in combination with the risk-free rate of return (base sales) calculation allows the brand suppliers Woolworths and Coles to compare themselves against each other and the overall market. This study also contributes to management and marketing theory by asserting that beta values are an important metric for consideration by category managers, because it measures the risk of a category that cannot be reduced by diversification.

Most importantly, this research is the first study providing clear guidelines for using a single value to compare risk between brands within a category and beyond it. This has management as well as manufacturing implications. The manufacturers gain a clear idea of when to increase or decrease production according to brand performance. FMCG management personnel gain information on when to increase stock levels in retail outlets so as to increase returns. The theoretical beta, developed through the use of economics and finance theory, allows brand managers and brand suppliers to compare brand risk among the different brands acting within the FMCG industry. These are unquestionable contributions to practitioners and academic research.

This thesis provides brand managers with a clear methodology for incorporating the actual incurred costs of incremental sales so a more realistic view of brand performance can be achieved. This allows them to compare performance across brands owned by the same manufacturer and gain a more realistic view of the brands' overall execution. However, this technique cannot be extended across rival manufacturers as costing information for competing firms is not publicly available. Thus, this approach is reduced to portfolio management for a specific manufacturer. As a general contribution, when comparing brands owned by the same manufacturer, the technique incorporating the cost of incremental sales is more appealing, but comparing with the overall FMCG industry or a specific category the original procedure without considering the cost of incremental sales is more applicable.

From a commercial point of view, this thesis contributes to the FMCG industry by specifying an approach for maintaining Brands Index and tracking brand betas on a weekly basis. The main contribution of the moving betas method is that the weekly values can alert brand managers to the overall movements of the market and their own brands. It was also proven that the average betas and average returns calculated over a moving window time period reinforce and complement the results derived from fixed beta values. All theoretical arguments appear valid and reliable.

7.5 Limitations

This thesis examined the creation of a detailed and theorised market index for the FMCG industry in Australia. It is able to measure the disparate sales value movements of numerous brands acting within the industry in order to better understand overall FMCG sales value behaviour. Particular attention was paid to the presence of the phenomenon known as volatility clustering, as defined by relevant theories and the literature. The specific objective of this research was to design a modelling technique able to compare individual brands' performance against the overall Brands Index. Despite their potential usefulness, the findings of the research presented in this thesis have to be considered with some prudence, as an empirical approach such as this is rare and unique in the present research setting. To the author's knowledge, there are no previous studies in the business, management or marketing disciplines related to the quantification of overall FMCG sales volatility, an index for the industry and the implementation of CAPM theory. Thus, the current findings have no equivalent academic research to be compared with. With these concerns in mind, the following important issues related to the generalisation of the findings need to be verified carefully:

- The findings were based on five product categories out of the 23 broad categories reported on the Woolworths website. This may not affect the methodologies used throughout this study; however, incorporating all the categories in the Brands Index could alter the overall results.

- Owing to data confidentially, the data used in this research were collected by anonymising actual category and brand names. This fact limits the conclusions, as information about specific categories or brands is not incorporated in the analyses.
- To maintain parsimony and rigour, only the ARCH-GARCH-type of models of asymmetry, including EGARCH and TGARCH, were included in this study. This thesis does not diminish the contributions made by the TGARCH and EGARCH models. No additional variations of these models were utilised in the research, meaning that there could be other models that are better able to capture brand sales volatility. A different type of ACD model is one example. Overall, the models used were useful in measuring temporal volatility clustering in FMCG sales data.

While acknowledging such limitations, this research provides an effective description of the creation of the Brands Index and its extensive application to Australian FMCG industry sales data. Accordingly, the study authenticates the developed framework. This also highlights how brand suppliers and brand managers can use CAPM theory to build betas and investigate their relationships with the market index in the FMCG setting.

7.6 Future Research Directions

The research in this thesis contemplated the causes of FMCG brands' sales volatility. This relied on the creation of an index, its measurement of volatility in returns and its use within the CAPM theory. This provides the foundations for future work in these three areas. More specifically, as this research strived to measure volatility clustering in the Brands Index using extant theories, this provides a solid foundation for many research avenues and, hence, several suggestions are made for further research.

First, from contextual aspects, this research envisaged a demanding context with theoretical assertions and validates most of the findings from financial theory to business, management and marketing disciplines. However, most of the findings do not have a point of reference in the business, management or marketing fields, they depend on financial applications to be compared with. Therefore, a research avenue is open for further validation with a larger market size and different category contexts. It can also be noted that as this research explores the Brands Index as a market index made up of only five categories, any similar studies including different categories in the index could facilitate a comparative study to validate the findings. Further, as there is no similar research in management and marketing to benchmark the results against, replicating the study with additional categories—all of them, or different ones—might allow the generalisation of the present findings.

Second, volatility clustering has been studied in finance theory since Engle (1982), and several alternative competing models have been proposed since then. As a result, this study only investigated ARCH-GARCH-type models. In order to capture asymmetry in the returns, the EGARCH and TGARCH models were also analysed. Therefore, in any future research, it may be appealing to compare and contrast the findings using the alternative models not explored in this research in an effort to validate the findings.

Third, as the risk-free returns calculations that were positive in nature gave the best results, an autoregressive conditional duration (ACD; Engle & Russell, 1998) model was developed. Since duration is necessarily non-negative, the ACD model was also used to model time series that consisted of positive observations. The findings suggested that an exponential EACD(1,1) model was, in general terms, acceptable. This could be included in any future research model by specifically trying a different distribution and/or different order of alpha and beta values. This might be interesting in terms of theories of the volatility process.

Fourth, all betas under the CAPM theory in this research were computed using the ordinary least squares methodology. The CAPM tests are two-pass, where weekly returns are regressed on beta estimates. However, betas under an ARCH-GARCH-type model were not developed. Therefore, it might be interesting to compare whether there is any difference between GARCH betas and unconditional betas. In other words, if there is evidence of ARCH effects in the model, the betas provided under the ARCH-GARCH framework should correct this effect, and deliver more reliable beta values to be utilised in brand management and marketing strategy.

Fifth, while this study only emphasised the application of CAPM to calculate each beta for every brand under analysis, alternative approaches may also be explored. For instance, the theory of time-varying betas was not investigated, which provides an opportunity for future research. Therefore, in any future research direction, it could be important to incorporate additional theoretical models from financial theory to compare and contrast with the findings. This is important, because there may be a significant difference in the results.

Sixth, while according to modern portfolio theory (MPT) there is no need to for a market index to calculate the efficient frontier, this research has shown that the same results can be obtained using the estimated betas and the variance of Brands Index returns. Portfolio optimisation was developed for seven brands owned by the same manufacturer, where the betas were calculated based on the returns from the overall Brands Index. To provide a more realistic return computation for the seven brands in the portfolio, the additional costs that the firms incurred in generating incremental sales were included in the returns calculations. Therefore, any future study could incorporate this aspect to encapsulate a more realistic picture of portfolio performance. It might be interesting to compare the previous results with a proxy market index made as the summation of all the brands in the portfolio. This is likely to provide a more robust understanding of portfolio management from a manufacturer point of view.

Finally, the study developed a procedure for optimising portfolios using as a risk metric—the beta figure. However, the marketing discipline is increasingly looking to demonstrate its contribution to shareholder value (Doyle, 2000) and a core component in this process will be the minimisation of risk. Thus, further research is required to provide marketers with a practical framework to both minimise the risk of marketing investments and maximise the return on marketing investments. Any similar research direction should include these concepts to test further reliability and validity.

7.7 Conclusion

To answer the basic research question: *What are the antecedents of brand sales volatility in the Australian retail sector and how do they influence brand performance overall?* To answer this question, this thesis developed a theorised market index for the FMCG industry in Australia, measured and modelled its observed volatility clustering through the use of ARCH-GARCH-type models, and made use of CAPM theory to assemble a modelling technique able to compare individual brands' performance against the Brands Index. Based on economics and finance theory, several ARCH-GARCH-type models were tested and compared. The optimal model was identified, with the purpose of capturing the observed volatility clustering in Brands Index returns. In this research, it was found that asymmetry in Brands Index returns was statistically significant and could explain this phenomenon. Evidently, the CAPM was the core theory used to obtain the beta figures for all brands analysed in this research. While two competing procedures were advanced to calculate returns, only returns including the risk-free component were able to successfully pass the CAPM test. By contrast, returns modelled without the risk-free component better simulated overall Brands Index returns.

In addition, the importance of the creation of a market index for the FMCG industry in Australia is absolute. The Brands Index itself represents an excellent contribution to management and marketing disciplines, as it allows any brand or set of brands to be compared against the overall market (via the Brands Index). Most importantly, this research is the first study to provide clear guidelines consistent with management and marketing theory for using a single value to compare brand risk, not only inside a category, but between categories.

This thesis provides brand managers with a clear methodology for considering the actual costs they incur when undertaking incremental sales activities. Thus, a more realistic view of brand performance can be achieved. This implementation allows the comparison of performance across brands owned by the same manufacturer and provides a more realistic view of brands' overall execution. However, this technique cannot be extended across rival manufacturers as costing information for competing firms is not publicly available. Therefore, this approach is reduced to portfolio management for a specific manufacturer.

From a commercial point of view, this research details an approach to maintain the Brands Index and to track brand betas on a weekly basis. First and foremost, this research also revealed that average betas and average returns, calculated as rolling computations, reinforce and complement fixed beta values based on four years of data. Here, all theoretical arguments appear valid and reliable. It is in this context that the contributions of this study can be examined and analysed.

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APPENDICES

Appendix 1 – Working Definitions

Advertised Points:
The number of Fly Buys points per item.

Advertised Price:
The price in the advertisement. For example, 1 item @ $1.69 is recorded as $1.69. Buy two items for $3.00 is recorded as $3.00.

Advertised Volume:
Normally set as 1, but will record multiple offers. For example, 2 for $3.00 will be recorded as 2. And 3 for $3.00 would be recorded as 3.

Average Price ($/Unit):
Price per unit is the average price across all stores in the selected market. It is calculated by dividing the total dollar sales by the total unit sales scanned through the account(s) or state(s) from the period Monday through Sunday inclusive.

Average Price ($/Kilo):
Price per kilogram is the average price across all stores in the selected market. It is calculated by dividing the total volume sales by the total unit sales scanned through the account(s) or state(s) from the period Monday through Sunday inclusive.

Baseline Sales:
Sales that would have been made if the product was not on promotion. This is calculated by first identifying the number of weeks it has been on price promotion by using the promotional settings of a % decrease in price for less than X consecutive weeks. For the week where a price promotion has been identified, the average of the six non-promotion weeks before and after are taken to estimate the baseline whilst assigning heavier weightings to weeks closer to the promoted week. If there are any outliers that exist, these weeks will be disregarded in this calculation.

BOGOF Flag:
Flags whether any weeks for the selected product had a Buy One Get One Free Promotion.

Category:
Refers to a set, or class, of goods by which goods, or products, are classified. For instance, in the FMCG industry, the deodorants category includes all products related to deodorants, classified by brand and form (roll-on, spray, cream, etc.).

Discount to Incremental:
Ratio of the Discount Value / Incremental Value

Discount Value:
The actual discount amount-units multiplied by the number of cents discount (price discounts).

Incidence of Advertising:
Is the item Advertised or not?   1 = Yes, 0 = No

Incremental Sales:
Incremental sales are sales that are achieved as a result of price promotional activity over and above the baseline sales expected for that time period. It will specify the actual difference in sales between total sales and baseline sales for the product in the weeks it was "On Promotion". For "Off Promotion" weeks, zeros will be shown.

Market:
Is the summation of the three main retailers in Australia Woolworths, Coles and Bilo, which represent, in most of the cases, about 75—80% of national sales.

Market Share or Share of Total "Category":
Is the share a product has of the category. e.g. Rexona's share is 21% of the total deodorants category.

Numeric Distribution %:
Measures the percentage of actual stores that sold a product in a given time period. Note: It will not include a product as being in distribution if the item is in stock at a store, but no sales are recorded for that store during the previous 4 weeks. Eg: Item A Numeric Distribution = 70% in Coles Vic (70% of Coles Vic stores had scanned item A).

Non-promoted Price:
Aims to calculate the price that the product would be sold at if it were not on promotion. The non-promoted price is the actual price in a non-promo week, in a promo week it is the average of the previous 4 non-promotion weeks' prices.

Percentage Discount:
Calculates the % difference between the "non-promoted price" and the actual price for weeks on promotion. (Average Price - Non-Promo price)/Non-Promo Price * 100.

Price Discounts:
The difference between the promoted price and the "non-promoted price" (measured in cents).

Promoted Price:
This is the price when the item is deemed to be on promotion. It will be "0" if the product is not on promotion.

Promotional Yield:
Helps to evaluate the effectiveness of a promotion in relation to cost. Calculated as incremental dollars less discount value.

Price Relative to Total Category:
Indexes the average price of a selected product total/item to the average price for the total category. The price for the total category will be given a value of 100. If the value for your selected product is above 100 (e.g. 113), then the price for the selected product total is greater than the category average price (by 13% in our example).

Store Count:
Store count information is based on that supplied by the data agents and will provide the total number of stores under each banner at the state or national level.

Sold off Promotion and On Promotion
They are actual sales if a product was “off promotion” in that week. They are the actual sales if a product was “on promotion” in that week.

Type of Advertising:
Promotional types other than price - such as Fly Buys and others.

Weeks off Promotion:
Shows if a product did not have a price discount in that week. 0 = On Promotion, 1 = Off Promotion. Sum or roll the weeks to get a total number of weeks off promotion for a range of weeks.

Weeks on non-price promotion:
This measure attempts to identify any week where there has been a 'non-price' based promotion. In any week where there has been a price promo this will always be 0.

Weeks on price promotion:
Has a value of 1 in any week where the % discount is > the nominated value e.g. 3%.

Weeks on Promotion:
Shows if a product had a price discount in that week. 1 = On Promotion, 0 = Off Promotion. Sum or roll the weeks to get a total number of weeks on promotion for a range of weeks.

Weighted Distribution %:
Weighted distribution takes into consideration the size of the stores that an item is in. E.g.: Item A has 70% numeric distribution in Coles Victoria. But those 70% of stores represent 80% of the dollar turnover for Coles Vic, then Item A has 80% weighted distribution.

Appendix 2 – Additional GARCH Results

GARCH (2,2) Brands Index returns

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.001022	0.002318	-0.441036	0.6592
		Variance Equation		
C	0.000270	9.68E-05	2.787464	0.0053
RESID(-1)^2	0.497943	0.078467	6.345865	0.0000
RESID(-2)^2	-0.473870	0.071184	-6.656958	0.0000
GARCH(-1)	0.983684	0.057008	17.25533	0.0000
GARCH(-2)	-0.055324	0.051576	-1.072682	0.2834

GARCH (1,2) Brands Index returns

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.000812	0.002251	-0.360539	0.7184
		Variance Equation		
C	0.002650	0.000289	9.161235	0.0000
RESID(-1)^2	0.529191	0.080163	6.601450	0.0000
GARCH(-1)	0.088628	0.072377	1.224524	0.2208
GARCH(-2)	-0.052641	0.041981	-1.253923	0.2099

GARCH (2,2) Brands Index returns with ARMA (1,2) structure

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000403	6.84E-05	5.894723	0.0000
AR(1)	-0.968562	0.014379	-67.35934	0.0000
MA(2)	-0.947717	0.018917	-50.09883	0.0000
		Variance Equation		
C	0.000176	7.51E-05	2.343959	0.0191
RESID(-1)^2	0.165669	0.053914	3.072848	0.0021
RESID(-2)^2	-0.178062	0.050635	-3.516538	0.0004
GARCH(-1)	0.901075	0.132681	6.791311	0.0000
GARCH(-2)	0.043633	0.119159	0.366173	0.7142

GARCH (1,2) Brands Index returns with ARMA (1,2) structure

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000390	7.46E-05	5.226462	0.0000
AR(1)	-0.967134	0.015187	-63.67967	0.0000
MA(2)	-0.942526	0.020141	-46.79540	0.0000
		Variance Equation		
C	0.002655	0.000533	4.984672	0.0000
RESID(-1)^2	0.189995	0.056593	3.357192	0.0008
GARCH(-1)	-0.105510	0.136184	-0.774764	0.4385
GARCH(-2)	-0.118914	0.128929	-0.922319	0.3564

GARCH (2,2) Brands Index (RF) returns

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.078923	0.002172	36.34022	0.0000
		Variance Equation		
C	0.001141	0.000517	2.207392	0.0273
RESID(-1)^2	0.284538	0.079454	3.581160	0.0003
RESID(-2)^2	0.125143	0.135644	0.922580	0.3562
GARCH(-1)	-0.245930	0.293656	-0.837475	0.4023
GARCH(-2)	0.404811	0.167609	2.415205	0.0157

GARCH (1,2) Brands Index (RF) returns

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.078622	0.002185	35.97935	0.0000
		Variance Equation		
C	0.000811	0.000323	2.507919	0.0121
RESID(-1)^2	0.290391	0.081396	3.567632	0.0004
GARCH(-1)	0.047212	0.134924	0.349917	0.7264
GARCH(-2)	0.352728	0.171436	2.057495	0.0396

GARCH (2,2) Brands Index (RF) returns with ARMA (1,2) structure

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.079816	0.002804	28.46294	0.0000
AR(1)	0.122409	0.054037	2.265287	0.0235
MA(2)	0.160372	0.050463	3.178035	0.0015
	Variance Equation			
C	0.001179	0.000671	1.757176	0.0789
RESID(-1)^2	0.248985	0.077385	3.217487	0.0013
RESID(-2)^2	0.069945	0.131493	0.531931	0.5948
GARCH(-1)	-0.203937	0.339174	-0.601273	0.5477
GARCH(-2)	0.401197	0.185674	2.160759	0.0307

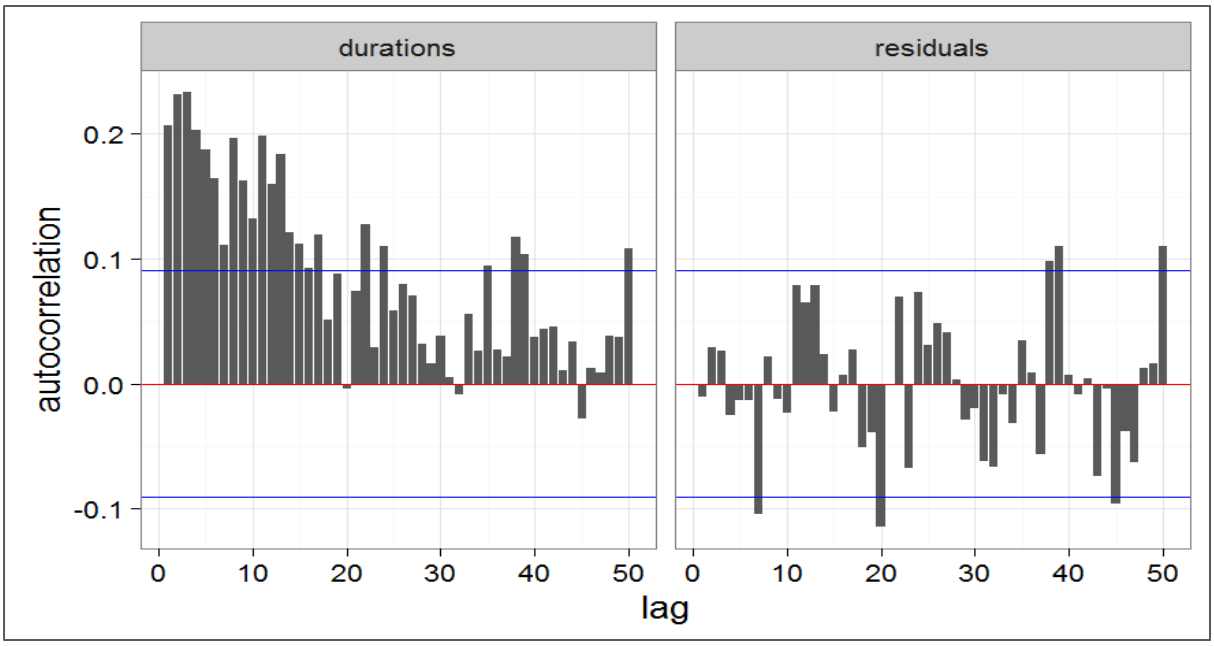
GARCH (1,2) Brands Index (RF) returns with ARMA (1,2) structure

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.079688	0.002822	28.23365	0.0000
AR(1)	0.131239	0.053527	2.451836	0.0142
MA(2)	0.154420	0.048341	3.194419	0.0014
	Variance Equation			
C	0.000962	0.000429	2.243047	0.0249
RESID(-1)^2	0.246615	0.077388	3.186725	0.0014
GARCH(-1)	-0.023299	0.144528	-0.161207	0.8719
GARCH(-2)	0.379745	0.184040	2.063381	0.0391

Appendix 3 – R Script and Code for ACD

```
library(readr)
library(dplyr)
library(FinTS)
library(timeSeries)
library(tseries)
library(ACDm)


dat <- read_csv("C:/Users/juan.franco/Desktop/UWS/Thesis/ACDData.csv")

fmcg<-dat$Return ; date<-dat$Date
plot(fmcg,type="l")
acd_fmcg<-acdFit(durations=fmcg,model="ACD",dist="exponential",order=c(1,1))

acf_acd(acd_fmcg,conf_level = 0.95,max=50)
qqplotAcd(acd_fmcg)
plotScatterAcd(acd_fmcg,x="muHats",y="residuals",colour=NULL,ylag=0,xlim=NU
LL,ylim=NULL,alpha=1/10,smoothMethod = "auto")
plotHazard(acd_fmcg)
testRmACD(acd_fmcg,pStar = 1, robust = TRUE)

par(mfrow=c(1,1))
plot(fmcg,type="l",ylab="Return",xlab="fmcgbr_rf",main="Brands Index Return
(RF)")
lines(acd_fmcg$muHats,col="red")
plot(acd_fmcg$residuals,type="l")

Box.test(acd_fmcg$residuals,lag=26)
ArchTest(acd_fmcg$residuals)
```

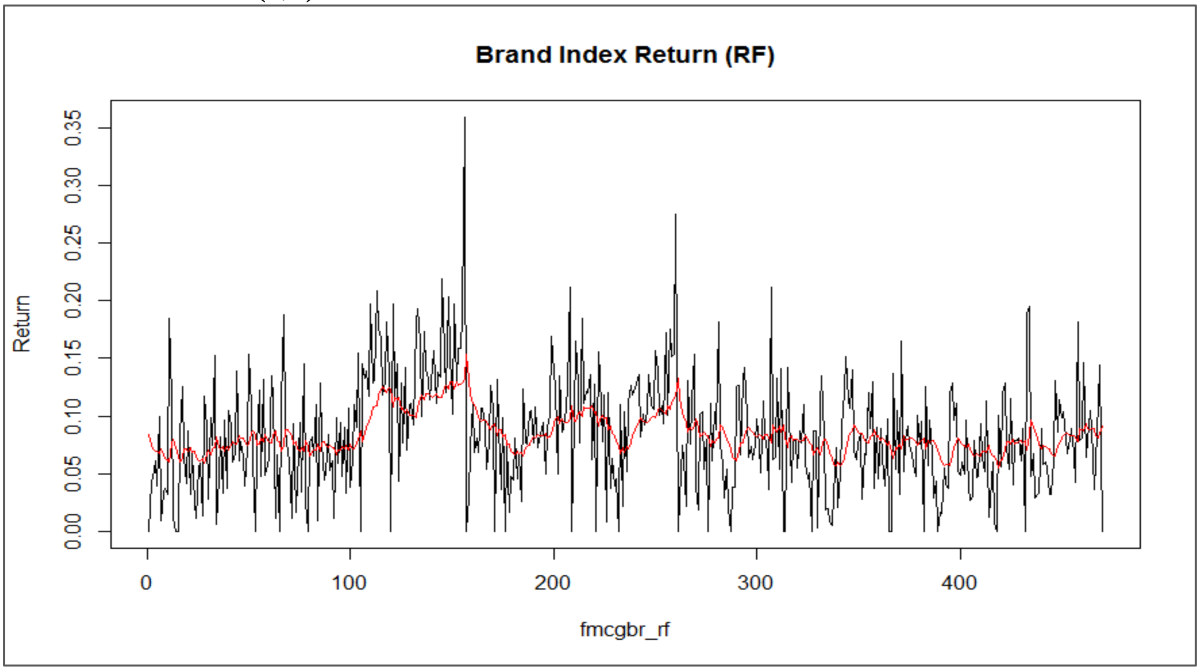
Appendix 4 -Autocorrelation Charts and Model Fit



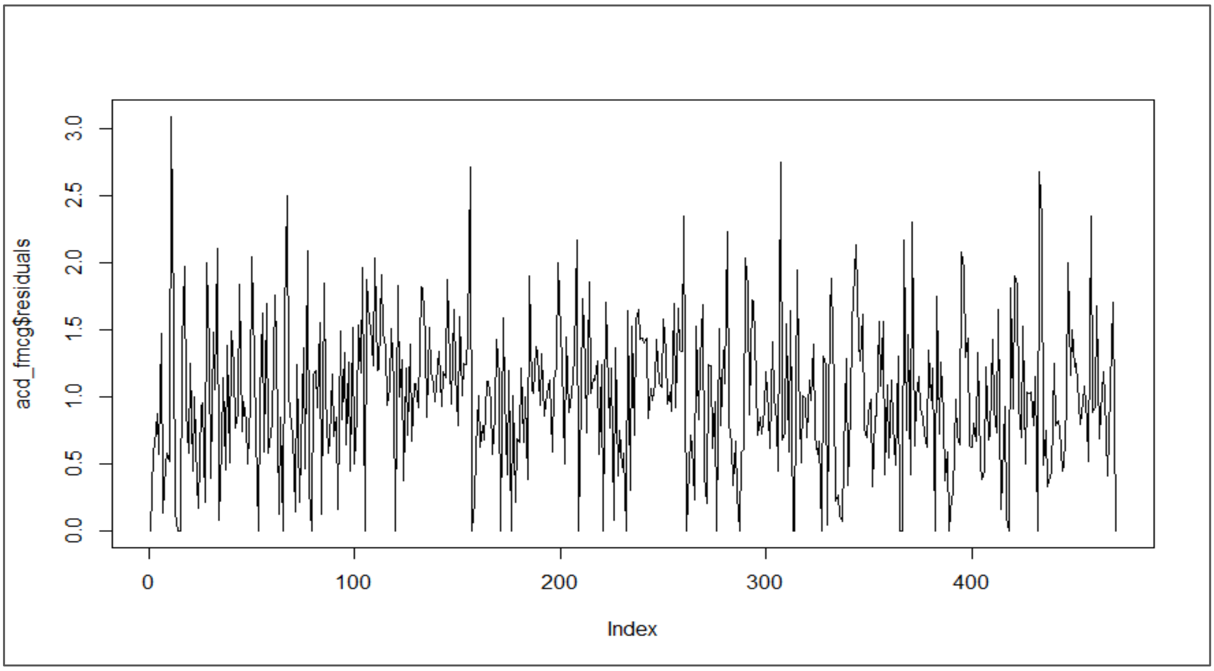
M&T (2006) test of no remaining ACD in residuals (robust version):

LM-stat: 0.169
Degrees of freedom: 1.000
P-value: 0.681

Model Fit – EACD (1,1)



Appendix 5 - ACD Residual chart



Appendix 6 – Key Statistics for the Top-10 Brand in All Five Categories

Key Stats	Category A	A-Brand1	A-Brand2	A-Brand3	A-Brand7	A-Brand13	A-Brand18	A-Brand20	A-Brand22	A-Brand24	A-Brand16
Mean	**8,114.01**	$1,165	$625	$482	$386	$619	$576	$300	$489	$333	$223
Std. Dev.	**681.42**	$527	$52	$142	$123	$216	$100	$155	$155	$115	$46
Minimum	**6,930.22**	$563	$493	$284	$259	$353	$415	$157	$278	$176	$121
Maximum	**11,398.08**	$4,084	$824	$1,022	$1,168	$1,554	$927	$1,156	$1,200	$804	$412

Key Stats	Total Category B	B-Brand4	B-Brand5	B-Brand14	B-Brand15	B-Brand16	B-Brand17	B-Brand18	B-Brand20	B-Brand31	B-Brand36
Mean	**3,419.23**	$826	$602	$164	$226	$92	$269	$496	$113	$131	$99
Std. Dev.	**363.83**	$203	$89	$42	$42	$16	$76	$162	$23	$27	$87
Minimum	**2,654.65**	$513	$449	$119	$177	$61	$163	$279	$74	$81	$5
Maximum	**4,453.43**	$1,499	$930	$589	$488	$144	$780	$1,120	$196	$238	$488

Key Stats	Total Category C	C-Brand4	C-Brand18	C-Brand19	C-Brand24	C-Brand33	C-Brand34	C-Brand41	C-Brand43	C-Brand76	C-Brand77
Mean	**$4,104**	$197	$443	$254	$614	$116	$139	$115	$119	$247	$184
Std. Dev.	**$191**	$17	$85	$43	$50	$26	$12	$20	$27	$39	$33
Minimum	**$3,453**	$158	$248	$196	$478	$70	$102	$79	$56	$166	$99
Maximum	**$4,833**	$251	$747	$505	$753	$174	$169	$206	$179	$365	$301

Key Stats	Total Category D	D-Brand1	D-Brand14	D-Brand3	D-Brand5	D-Brand9	D-Brand10	D-Brand12	D-Brand15	D-Brand16	E-Brand1
Mean	**$592**	$309	$3	$26	$46	$63	$34	$31	$25	$41	$1,016
Std. Dev.	**$44**	$33	$1	$3	$3	$14	$3	$4	$2	$9	$189
Minimum	**$474**	$246	$2	$15	$41	$36	$27	$15	$14	$22	$763
Maximum	**$736**	$425	$4	$33	$55	$99	$49	$43	$31	$58	$2,902

Key Stats	Total Category E	E-Brand2	E-Brand6	E-Brand8	E-Brand9	E-Brand10	E-Brand13	E-Brand26	E-Brand27	E-Brand28
Mean	**$9,937**	$3,785	$502	$156	$558	$843	$184	$148	$91	$226
Std. Dev.	**$520**	$302	$113	$21	$124	$85	$61	$14	$43	$24
Minimum	**$8,212**	$3,062	$333	$121	$326	$563	$68	$104	$57	$186
Maximum	**$11,479**	$5,450	$945	$217	$846	$1,119	$480	$192	$501	$323

Appendix 7 – Index Returns and Moving Betas for All 49 Brands

From	To	Index Return	Category A	Category B	Category C	Category D	Category E
01-Jan-12	07-Jan-12	10.0%	1.31	0.66	0.46	0.53	0.94
08-Jan-12	14-Jan-12	5.6%	1.31	0.66	0.46	0.53	0.95
15-Jan-12	21-Jan-12	11.9%	1.29	0.63	0.46	0.51	0.95
22-Jan-12	28-Jan-12	12.9%	1.32	0.51	0.46	0.42	0.95
29-Jan-12	04-Feb-12	7.2%	1.31	0.69	0.31	0.21	0.94
05-Feb-12	11-Feb-12	5.4%	1.32	0.69	0.31	0.21	0.95
12-Feb-12	18-Feb-12	11.5%	1.27	0.74	0.32	0.20	0.94
19-Feb-12	25-Feb-12	4.0%	1.23	0.80	0.34	0.21	0.95
26-Feb-12	03-Mar-12	7.9%	1.23	0.76	0.35	0.23	0.94
04-Mar-12	10-Mar-12	7.9%	1.24	0.73	0.35	0.24	0.93
11-Mar-12	17-Mar-12	8.0%	1.24	0.71	0.36	0.26	0.93
18-Mar-12	24-Mar-12	6.1%	1.23	0.70	0.36	0.26	0.94
25-Mar-12	31-Mar-12	8.9%	1.18	0.75	0.37	0.28	0.93
01-Apr-12	07-Apr-12	0.0%	1.18	0.77	0.42	0.32	0.91
08-Apr-12	14-Apr-12	18.8%	1.12	0.98	0.50	0.30	0.86
15-Apr-12	21-Apr-12	19.5%	1.29	0.93	0.41	0.36	0.76
22-Apr-12	28-Apr-12	4.7%	1.28	0.87	0.44	0.34	0.76
29-Apr-12	05-May-12	6.7%	1.27	0.88	0.43	0.33	0.76
06-May-12	12-May-12	2.8%	1.26	0.83	0.45	0.34	0.78
13-May-12	19-May-12	3.2%	1.26	0.85	0.45	0.33	0.78
20-May-12	26-May-12	3.3%	1.26	0.84	0.44	0.36	0.79
27-May-12	02-Jun-12	8.9%	1.26	0.81	0.41	0.38	0.81
03-Jun-12	09-Jun-12	5.8%	1.28	0.80	0.39	0.36	0.83
10-Jun-12	16-Jun-12	6.0%	1.28	0.82	0.37	0.38	0.84
17-Jun-12	23-Jun-12	5.5%	1.30	0.80	0.37	0.40	0.86
24-Jun-12	30-Jun-12	3.2%	1.31	0.81	0.40	0.38	0.84
01-Jul-12	07-Jul-12	3.2%	1.30	0.82	0.43	0.38	0.84
08-Jul-12	14-Jul-12	6.1%	1.30	0.80	0.45	0.37	0.85
15-Jul-12	21-Jul-12	13.1%	1.33	0.81	0.43	0.36	0.80
22-Jul-12	28-Jul-12	8.6%	1.36	0.79	0.44	0.40	0.74
29-Jul-12	04-Aug-12	11.4%	1.34	0.76	0.43	0.42	0.75
05-Aug-12	11-Aug-12	9.9%	1.33	0.75	0.41	0.43	0.74
12-Aug-12	18-Aug-12	10.3%	1.29	0.82	0.40	0.40	0.78
19-Aug-12	25-Aug-12	8.1%	1.27	0.85	0.38	0.38	0.78
26-Aug-12	01-Sep-12	6.7%	1.27	0.85	0.39	0.38	0.78
02-Sep-12	08-Sep-12	8.0%	1.28	0.87	0.38	0.41	0.77
09-Sep-12	15-Sep-12	8.9%	1.27	0.87	0.37	0.43	0.76
16-Sep-12	22-Sep-12	6.8%	1.27	0.91	0.37	0.41	0.75
23-Sep-12	29-Sep-12	4.2%	1.27	0.93	0.38	0.41	0.75
30-Sep-12	06-Oct-12	18.2%	1.24	1.01	0.35	0.29	0.79
07-Oct-12	13-Oct-12	7.9%	1.24	1.01	0.35	0.29	0.79
14-Oct-12	20-Oct-12	8.1%	1.25	1.03	0.36	0.27	0.78
21-Oct-12	27-Oct-12	14.6%	1.31	1.10	0.34	0.26	0.74
28-Oct-12	03-Nov-12	6.4%	1.30	1.06	0.34	0.25	0.76
04-Nov-12	10-Nov-12	7.9%	1.29	1.07	0.34	0.25	0.76
11-Nov-12	17-Nov-12	10.4%	1.30	1.08	0.35	0.23	0.75
18-Nov-12	24-Nov-12	9.0%	1.30	1.09	0.34	0.25	0.72
25-Nov-12	01-Dec-12	3.6%	1.32	1.10	0.35	0.25	0.72
02-Dec-12	08-Dec-12	6.0%	1.34	1.09	0.36	0.24	0.72
09-Dec-12	15-Dec-12	11.2%	1.36	1.05	0.37	0.29	0.72
16-Dec-12	22-Dec-12	14.4%	1.39	1.07	0.49	0.22	0.70
23-Dec-12	29-Dec-12	0.0%	1.39	1.07	0.58	0.22	0.70

A-Brand1	A-Brand2	A-Brand3	A-Brand7	A-Brand13	A-Brand18	A-Brand20	A-Brand22	A-Brand24	A-Brand16
3.18	0.56	1.48	-0.70	-0.69	0.58	-0.06	1.94	0.83	2.21
3.18	0.56	1.47	-0.62	-0.70	0.55	-0.01	1.96	0.82	2.17
3.20	0.62	1.76	-0.47	-0.72	0.50	0.61	1.89	0.89	2.13
3.01	0.60	2.09	-0.50	-0.35	0.37	1.13	1.66	0.80	1.94
3.66	0.64	2.47	-0.59	-1.02	-0.26	1.46	1.68	0.05	1.65
3.57	0.64	2.46	-0.63	-1.11	-0.28	1.66	1.68	0.07	1.67
3.54	0.65	2.67	-0.69	-0.82	-0.42	1.52	1.29	0.08	1.63
3.31	0.69	2.54	-0.61	-0.72	-0.54	1.64	1.23	0.06	1.55
3.34	0.69	2.57	-0.57	-0.81	-0.53	1.61	1.25	0.08	1.66
3.47	0.69	2.56	-0.54	-0.84	-0.56	1.59	1.26	0.05	1.71
3.36	0.74	2.76	-0.50	-0.89	-0.53	1.69	1.21	0.08	1.77
3.30	0.74	2.73	-0.54	-0.93	-0.49	1.87	1.20	0.13	1.82
3.16	0.84	2.74	-0.44	-1.24	-0.43	1.91	1.40	0.01	1.87
3.29	0.89	2.78	-0.33	-1.51	-0.20	1.89	1.45	0.09	1.95
2.25	0.90	2.27	0.58	-0.11	0.08	1.96	2.11	-0.11	1.57
1.77	0.92	2.46	0.22	-0.41	0.05	2.07	1.81	0.25	1.27
1.83	0.95	2.40	0.35	-0.26	-0.13	1.80	1.51	0.25	1.05
1.81	0.95	2.42	0.33	-0.28	-0.12	1.81	1.49	0.24	1.04
1.75	0.84	2.55	0.33	-0.52	0.02	1.82	1.44	0.22	1.11
1.69	0.79	2.47	0.11	-0.46	0.09	1.85	1.46	0.18	1.13
1.87	0.79	2.46	0.13	-0.62	0.10	1.88	1.15	0.17	1.16
1.85	0.75	2.37	0.06	-0.71	0.08	1.85	1.19	0.13	1.10
1.65	0.73	2.29	0.44	-0.67	0.22	1.86	1.16	0.23	1.16
1.48	0.71	2.22	0.66	-0.78	0.33	1.85	1.09	0.31	1.12
1.52	0.71	2.34	0.61	-0.89	0.32	1.99	1.03	0.42	1.10
1.60	0.70	2.40	0.34	-0.78	0.39	2.05	1.06	0.45	1.13
1.67	0.70	2.42	0.35	-0.91	0.31	1.88	1.13	0.46	1.16
1.76	0.67	2.39	0.31	-1.00	0.35	1.85	1.16	0.44	1.24
2.10	0.62	2.12	0.13	-1.01	0.48	1.80	1.12	0.39	1.15
2.34	0.63	2.33	0.21	-0.90	0.60	1.95	1.07	0.12	1.28
2.29	0.63	2.25	0.18	-0.93	0.48	1.92	1.31	0.07	1.20
1.74	0.66	2.66	0.20	-0.86	0.42	2.00	1.35	0.14	1.10
1.59	0.62	2.54	0.33	-0.89	0.36	1.89	1.35	0.18	1.11
1.45	0.63	2.46	0.30	-0.73	0.38	1.90	1.31	0.16	1.05
1.49	0.63	2.47	0.29	-0.74	0.38	1.88	1.30	0.19	1.04
1.59	0.64	2.49	0.23	-0.81	0.38	2.02	1.30	0.22	1.00
1.67	0.65	2.58	0.22	-0.80	0.29	2.04	1.32	0.24	0.78
1.56	0.68	2.59	0.26	-0.87	0.22	2.00	1.38	0.22	0.81
1.49	0.76	2.63	0.23	-0.68	0.25	1.93	1.38	0.21	0.73
1.99	0.98	2.75	-0.05	-0.38	-0.02	1.49	1.31	0.33	0.76
1.93	0.97	2.72	0.00	-0.37	-0.02	1.49	1.35	0.34	0.76
1.81	1.02	2.86	-0.06	-0.39	0.04	1.44	1.49	0.32	0.80
2.33	0.92	2.77	-0.19	-0.56	0.10	1.21	1.34	0.30	0.66
2.42	0.92	2.81	-0.20	-0.61	0.12	1.26	1.38	0.31	0.69
2.43	0.92	2.79	-0.18	-0.59	0.11	1.26	1.36	0.30	0.68
2.42	0.90	2.66	-0.20	-0.37	0.18	1.24	1.26	0.33	0.71
2.59	0.89	2.78	-0.16	-0.33	-0.01	1.26	1.36	0.38	0.63
2.62	0.89	2.76	-0.38	-0.34	0.19	1.25	1.21	0.34	0.41
2.62	0.88	2.74	-0.14	-0.46	0.14	1.29	1.12	0.30	0.36
2.58	0.84	2.76	-0.18	-0.54	0.18	1.37	1.05	0.29	0.29
2.93	0.72	2.88	-0.15	-0.48	0.40	1.13	0.79	0.26	0.41
3.00	0.72	2.53	-0.38	0.28	0.66	1.13	0.79	0.35	0.28

B-Brand4	B-Brand5	B-Brand14	B-Brand15	B-Brand16	B-Brand17	B-Brand18	B-Brand20	B-Brand31	B-Brand36
0.68	1.09	-0.72	1.18	1.06	-1.27	1.11	0.24	1.54	1.19
0.68	1.09	-0.70	1.18	1.06	-1.29	1.10	0.24	1.52	1.14
0.75	1.04	-0.81	1.20	1.18	-1.30	1.05	0.27	1.58	1.07
0.61	0.81	-0.80	1.17	1.24	-1.38	0.95	0.10	2.07	0.69
1.02	0.70	-1.28	1.15	0.91	-1.75	1.33	0.29	2.14	1.16
1.00	0.67	-1.25	1.16	0.95	-1.75	1.35	0.31	2.16	1.16
1.26	0.57	-0.72	1.06	1.12	-1.67	1.26	0.41	2.03	0.98
1.31	0.68	-1.00	1.08	1.06	-1.56	1.38	0.47	2.02	1.01
1.22	0.71	-1.04	1.10	1.04	-1.57	1.45	0.46	1.99	0.89
1.23	0.73	-1.08	1.14	1.01	-1.59	1.39	0.44	1.94	0.81
1.20	0.68	-1.07	1.13	1.00	-1.57	1.35	0.44	1.96	0.74
1.18	0.68	-1.09	1.13	1.03	-1.51	1.32	0.42	1.96	0.70
1.27	0.71	-1.10	0.93	1.17	-1.65	1.51	0.48	1.95	0.77
1.25	0.79	-0.90	0.92	1.23	-1.40	1.52	0.55	1.94	0.72
0.87	0.98	-1.05	1.15	1.31	0.02	1.71	0.80	2.26	0.34
0.27	0.84	-0.22	1.18	1.26	-0.13	2.13	0.44	2.19	-0.16
0.17	0.72	-0.16	1.09	1.25	-0.24	2.34	0.51	2.11	-0.64
0.17	0.75	-0.17	1.11	1.26	-0.21	2.34	0.52	2.14	-0.62
0.21	0.56	-0.06	1.14	1.33	-0.16	2.14	0.51	2.13	-0.68
0.29	0.56	-0.04	1.05	1.36	-0.10	2.16	0.51	2.01	-0.68
0.28	0.59	-0.04	1.05	1.36	-0.03	2.11	0.51	1.99	-0.36
0.15	0.52	-0.10	1.02	1.30	-0.05	2.13	0.49	1.94	-0.32
0.10	0.53	-0.20	1.00	1.29	0.09	2.25	0.43	1.96	-0.28
0.11	0.52	-0.15	0.97	1.27	0.17	2.38	0.39	1.96	-0.27
0.22	0.62	-0.15	0.96	1.26	0.11	2.29	0.54	1.95	-0.47
0.21	0.67	-0.11	0.97	1.22	0.14	2.33	0.52	1.97	-0.58
0.23	0.60	0.03	0.88	1.23	0.22	2.18	0.55	1.94	-0.42
0.17	0.60	-0.04	0.88	1.20	0.36	2.09	0.55	1.93	-0.36
0.36	0.46	-0.06	0.80	1.17	0.34	2.03	0.48	1.95	-0.50
0.33	0.41	0.01	0.78	1.04	0.43	1.97	0.48	2.10	-0.64
0.29	0.53	-0.02	0.78	1.05	0.37	1.80	0.59	1.95	-0.70
0.42	0.58	0.00	0.76	1.12	0.39	1.68	0.59	2.02	-1.07
0.71	0.55	-0.06	0.75	1.04	0.43	1.55	0.72	1.95	-0.78
0.84	0.56	-0.06	0.79	1.01	0.39	1.49	0.85	1.93	-0.65
0.84	0.55	-0.05	0.78	1.01	0.40	1.49	0.85	1.93	-0.67
0.86	0.63	-0.09	0.79	0.97	0.50	1.45	0.85	1.92	-0.73
0.83	0.61	0.02	0.78	0.93	0.59	1.55	0.78	2.01	-0.92
0.81	0.65	0.19	0.76	0.97	0.54	1.62	0.86	1.98	-0.63
0.77	0.67	0.29	0.84	0.87	0.64	1.70	0.81	1.98	-0.80
1.12	0.78	0.36	0.77	0.87	1.14	1.44	0.77	1.55	-0.46
1.10	0.77	0.36	0.76	0.87	1.14	1.46	0.75	1.54	-0.49
1.20	0.83	0.31	0.74	0.83	1.18	1.40	0.72	1.54	-0.55
1.54	0.75	0.15	0.71	0.77	1.58	1.25	0.68	1.37	-0.67
1.51	0.77	0.16	0.72	0.80	1.56	1.11	0.62	1.35	-0.68
1.53	0.75	0.15	0.71	0.79	1.59	1.11	0.64	1.33	-0.62
1.49	0.73	0.07	0.72	0.78	1.92	1.08	0.66	1.25	-0.55
1.46	0.73	0.09	0.75	0.82	1.98	1.09	0.68	1.31	-0.48
1.38	0.86	0.15	0.72	0.92	1.91	1.31	0.68	1.29	-0.62
1.41	0.79	0.20	0.69	1.01	2.01	1.25	0.59	1.27	-0.69
1.33	0.77	0.28	0.68	0.94	2.04	1.14	0.73	1.18	-0.76
1.60	0.70	0.49	0.67	0.80	1.86	1.00	0.77	1.09	-0.99
1.55	0.70	0.66	0.67	0.94	1.86	0.95	0.77	1.18	-0.99

C-Brand4	C-Brand18	C-Brand19	C-Brand24	C-Brand33	C-Brand34	C-Brand41	C-Brand43	C-Brand76	C-Brand77
0.83	0.19	-0.12	0.52	0.58	0.46	0.16	0.20	0.39	0.38
0.84	0.18	-0.14	0.52	0.56	0.46	0.17	0.19	0.40	0.35
0.83	0.16	-0.06	0.44	0.58	0.43	0.12	0.27	0.46	0.31
0.73	0.05	-0.19	0.39	0.43	0.40	0.13	0.38	0.52	0.11
0.68	0.04	0.06	0.23	0.71	0.29	-0.18	0.25	0.27	0.10
0.68	0.03	0.04	0.23	0.68	0.28	-0.20	0.24	0.26	0.07
0.61	-0.02	0.04	0.22	0.58	0.26	-0.17	0.22	0.38	-0.01
0.62	0.05	0.15	0.23	0.67	0.28	-0.17	0.24	0.32	0.08
0.62	0.04	0.17	0.23	0.64	0.27	-0.16	0.23	0.31	0.09
0.60	0.03	0.15	0.22	0.60	0.27	-0.19	0.23	0.31	0.08
0.62	0.00	0.12	0.22	0.62	0.26	-0.17	0.22	0.30	0.03
0.62	-0.01	0.08	0.25	0.60	0.26	-0.18	0.22	0.29	0.05
0.60	0.00	0.12	0.29	0.55	0.28	-0.14	0.23	0.35	0.05
0.60	0.09	0.33	0.28	0.62	0.29	-0.05	0.23	0.28	0.21
0.64	0.23	0.19	0.56	0.52	0.43	-0.01	0.17	0.36	0.40
0.66	0.13	-0.23	0.64	0.34	0.41	-0.16	0.12	0.20	0.29
0.67	0.20	-0.07	0.62	0.31	0.40	-0.10	0.14	0.26	0.24
0.66	0.19	-0.10	0.61	0.31	0.40	-0.11	0.13	0.25	0.25
0.65	0.23	0.05	0.56	0.27	0.37	-0.06	0.15	0.23	0.14
0.66	0.23	0.12	0.53	0.29	0.36	-0.03	0.15	0.18	0.10
0.64	0.21	0.11	0.51	0.31	0.35	-0.03	0.15	0.21	0.18
0.62	0.16	0.02	0.50	0.25	0.34	-0.07	0.14	0.22	0.11
0.61	0.11	-0.11	0.51	0.26	0.34	-0.12	0.14	0.28	0.00
0.59	0.07	-0.21	0.52	0.39	0.34	-0.15	0.13	0.22	-0.03
0.63	0.06	-0.14	0.53	0.46	0.34	-0.19	0.13	0.24	-0.10
0.64	0.15	0.00	0.52	0.52	0.34	-0.17	0.13	0.26	-0.05
0.65	0.27	0.23	0.52	0.58	0.36	-0.16	0.13	0.17	-0.14
0.64	0.34	0.35	0.55	0.60	0.38	-0.18	0.13	0.12	-0.16
0.66	0.27	0.11	0.56	0.62	0.39	-0.19	0.13	0.11	-0.21
0.63	0.17	-0.07	0.60	0.53	0.38	-0.16	0.14	0.21	-0.15
0.61	0.16	-0.20	0.63	0.46	0.34	-0.17	0.13	0.21	-0.21
0.62	0.12	-0.36	0.63	0.44	0.36	-0.16	0.14	0.20	-0.30
0.59	0.13	-0.38	0.63	0.41	0.37	-0.21	0.13	0.16	-0.27
0.57	0.14	-0.36	0.62	0.38	0.37	-0.23	0.12	0.15	-0.26
0.57	0.15	-0.33	0.62	0.37	0.38	-0.24	0.12	0.17	-0.22
0.55	0.16	-0.31	0.62	0.33	0.37	-0.27	0.11	0.16	-0.17
0.54	0.09	-0.41	0.61	0.31	0.34	-0.28	0.12	0.12	-0.18
0.53	0.11	-0.35	0.61	0.31	0.35	-0.29	0.11	0.18	-0.23
0.53	0.12	-0.25	0.62	0.29	0.35	-0.33	0.11	0.25	-0.38
0.39	0.11	-0.28	0.51	0.15	0.29	-0.10	0.07	0.35	-0.47
0.40	0.11	-0.29	0.52	0.15	0.29	-0.10	0.07	0.35	-0.48
0.44	0.14	-0.24	0.51	0.21	0.29	-0.03	0.07	0.31	-0.39
0.37	0.16	-0.24	0.46	0.26	0.26	0.02	0.05	0.27	-0.37
0.37	0.15	-0.27	0.47	0.24	0.26	0.02	0.05	0.29	-0.32
0.38	0.16	-0.25	0.47	0.27	0.26	0.04	0.06	0.28	-0.34
0.39	0.15	-0.23	0.46	0.27	0.25	0.11	0.05	0.25	-0.24
0.41	0.17	-0.31	0.47	0.29	0.26	0.11	0.05	0.20	-0.27
0.38	0.23	-0.19	0.47	0.28	0.26	0.12	0.05	0.20	-0.16
0.34	0.27	-0.10	0.48	0.21	0.26	0.10	0.04	0.25	-0.12
0.41	0.27	-0.08	0.47	0.28	0.26	0.23	0.05	0.19	-0.09
0.55	0.45	0.17	0.48	0.28	0.27	0.70	0.10	0.12	0.08
0.55	0.45	0.32	0.48	0.35	0.27	0.64	0.19	0.12	0.18

D-Brand1	D-Brand14	D-Brand3	D-Brand5	D-Brand9	D-Brand10	D-Brand12	D-Brand15	D-Brand16
0.62	0.24	0.27	0.39	0.08	0.39	-0.11	0.60	2.23
0.62	0.20	0.26	0.39	0.07	0.39	-0.13	0.60	2.30
0.54	0.62	0.37	0.43	0.13	0.40	-0.01	0.65	1.89
0.42	0.87	0.34	0.36	0.12	0.31	0.00	0.57	1.86
0.12	0.93	0.54	0.26	0.23	0.20	0.03	0.41	1.19
0.12	0.86	0.53	0.26	0.21	0.20	0.01	0.41	1.27
0.06	1.18	0.55	0.27	0.34	0.15	0.11	0.43	1.01
0.08	1.09	0.59	0.30	0.31	0.16	0.15	0.44	0.85
0.13	1.19	0.54	0.31	0.33	0.16	0.15	0.47	0.73
0.15	1.29	0.52	0.30	0.31	0.15	0.17	0.47	0.67
0.16	1.37	0.50	0.31	0.36	0.16	0.19	0.48	0.68
0.16	1.33	0.51	0.30	0.34	0.16	0.17	0.47	0.79
0.18	1.53	0.57	0.32	0.45	0.13	0.27	0.48	0.50
0.24	1.41	0.64	0.34	0.36	0.16	0.27	0.50	0.42
0.16	1.57	0.58	0.37	0.63	0.15	0.13	0.56	0.14
0.25	1.47	0.46	0.38	0.74	0.15	-0.08	0.53	0.17
0.25	1.57	0.44	0.36	0.81	0.10	-0.07	0.48	-0.04
0.24	1.56	0.44	0.36	0.80	0.10	-0.07	0.49	-0.02
0.27	1.62	0.35	0.37	0.82	0.07	-0.05	0.45	-0.13
0.29	1.64	0.34	0.38	0.78	0.08	-0.10	0.43	-0.17
0.35	1.61	0.31	0.39	0.79	0.09	-0.18	0.45	-0.18
0.37	1.52	0.28	0.37	0.81	0.09	-0.19	0.42	-0.14
0.34	1.48	0.30	0.40	0.77	0.11	-0.21	0.42	-0.17
0.36	1.44	0.39	0.39	0.73	0.13	-0.24	0.40	-0.20
0.39	1.40	0.42	0.41	0.69	0.15	-0.25	0.40	-0.23
0.37	1.40	0.42	0.41	0.65	0.16	-0.25	0.39	-0.22
0.37	1.41	0.44	0.42	0.65	0.17	-0.21	0.41	-0.22
0.36	1.38	0.43	0.43	0.64	0.18	-0.21	0.41	-0.23
0.34	1.34	0.27	0.39	0.65	0.16	-0.24	0.38	-0.21
0.39	1.48	0.25	0.42	0.72	0.18	-0.21	0.43	-0.24
0.42	1.42	0.24	0.39	0.76	0.18	-0.26	0.39	-0.14
0.47	1.46	0.23	0.38	0.79	0.18	-0.25	0.38	-0.08
0.42	1.34	0.23	0.36	0.71	0.18	-0.30	0.35	-0.03
0.39	1.27	0.23	0.35	0.67	0.18	-0.33	0.33	-0.02
0.40	1.27	0.23	0.35	0.67	0.18	-0.32	0.33	-0.02
0.47	1.22	0.20	0.34	0.67	0.20	-0.34	0.32	-0.03
0.53	1.21	0.14	0.32	0.60	0.21	-0.36	0.32	-0.01
0.50	1.16	0.18	0.31	0.65	0.20	-0.38	0.30	0.00
0.50	1.15	0.28	0.36	0.72	0.21	-0.37	0.33	-0.05
0.32	0.74	0.21	0.31	0.51	0.23	-0.20	0.23	-0.06
0.32	0.73	0.22	0.30	0.51	0.23	-0.20	0.23	-0.05
0.31	0.70	0.23	0.29	0.48	0.23	-0.19	0.21	-0.06
0.31	0.57	0.27	0.27	0.36	0.23	-0.21	0.16	-0.02
0.29	0.62	0.26	0.27	0.37	0.23	-0.20	0.17	0.00
0.29	0.61	0.26	0.27	0.37	0.24	-0.20	0.17	0.00
0.27	0.51	0.27	0.26	0.32	0.23	-0.24	0.15	0.04
0.28	0.54	0.29	0.23	0.34	0.23	-0.26	0.15	0.07
0.31	0.56	0.28	0.26	0.33	0.21	-0.23	0.17	0.01
0.30	0.55	0.26	0.32	0.30	0.21	-0.20	0.21	-0.07
0.40	0.47	0.23	0.32	0.24	0.25	-0.14	0.20	-0.03
0.38	0.23	0.13	0.30	0.11	0.25	-0.14	0.14	-0.02
0.38	0.61	0.13	0.30	0.11	0.25	-0.07	0.19	-0.08

E-Brand1	E-Brand2	E-Brand6	E-Brand8	E-Brand9	E-Brand10	E-Brand13	E-Brand26	E-Brand27	E-Brand28
0.94	0.92	1.00	0.34	0.37	0.88	0.85	0.65	-0.06	-0.01
0.95	0.92	0.98	0.33	0.37	0.89	0.88	0.65	-0.06	0.00
0.86	0.85	1.21	0.36	0.39	0.84	0.77	0.67	-0.24	-0.01
0.69	0.86	1.21	0.29	0.56	0.84	0.91	0.62	-0.34	-0.02
0.55	0.86	1.19	0.30	0.74	0.66	0.48	0.46	-0.58	-0.21
0.55	0.86	1.22	0.30	0.73	0.67	0.53	0.46	-0.51	-0.20
0.47	0.87	1.27	0.31	0.87	0.71	0.38	0.49	-0.61	-0.20
0.49	0.89	1.32	0.34	0.92	0.67	0.31	0.49	-0.60	-0.18
0.46	0.87	1.37	0.35	0.93	0.66	0.27	0.48	-0.61	-0.17
0.45	0.86	1.35	0.35	0.97	0.67	0.26	0.47	-0.66	-0.18
0.48	0.86	1.29	0.35	1.01	0.68	0.25	0.49	-0.67	-0.17
0.49	0.85	1.31	0.34	1.07	0.71	0.26	0.49	-0.69	-0.17
0.44	0.87	1.39	0.36	1.10	0.66	0.25	0.50	-0.68	-0.14
0.53	0.82	1.08	0.39	1.14	0.66	0.28	0.52	-0.55	-0.10
0.91	0.84	0.84	0.36	0.74	0.69	0.20	0.53	-0.59	-0.07
0.92	0.79	0.37	0.25	0.37	0.60	0.20	0.47	-0.70	-0.07
0.69	0.83	0.43	0.22	0.37	0.63	0.25	0.43	-0.71	-0.05
0.70	0.83	0.41	0.22	0.37	0.63	0.24	0.43	-0.71	-0.05
0.78	0.84	0.33	0.20	0.36	0.62	0.22	0.39	-0.70	-0.04
0.80	0.84	0.39	0.21	0.35	0.60	0.23	0.39	-0.67	-0.05
0.91	0.81	0.50	0.23	0.45	0.58	0.23	0.39	-0.84	-0.06
1.16	0.79	0.49	0.23	0.45	0.59	0.21	0.39	-0.76	-0.06
1.14	0.81	0.39	0.23	0.39	0.58	0.33	0.42	-0.90	0.01
1.15	0.84	0.31	0.26	0.33	0.58	0.43	0.43	-1.01	0.03
1.14	0.88	0.28	0.30	0.26	0.59	0.48	0.44	-1.10	0.04
1.12	0.88	0.19	0.32	0.17	0.56	0.50	0.45	-1.05	0.03
1.20	0.85	0.23	0.33	0.17	0.54	0.50	0.44	-1.03	0.03
1.24	0.85	0.27	0.35	0.18	0.53	0.50	0.43	-1.05	0.04
1.18	0.87	0.09	0.26	0.03	0.49	0.38	0.43	-0.74	0.03
1.17	0.78	0.11	0.25	-0.04	0.46	0.39	0.46	-0.67	0.05
1.23	0.82	0.05	0.20	0.08	0.44	0.38	0.48	-0.71	0.04
1.24	0.84	0.04	0.18	0.21	0.41	0.28	0.50	-0.80	0.06
1.24	0.86	0.26	0.18	0.26	0.43	0.26	0.49	-0.79	0.04
1.32	0.86	0.21	0.17	0.23	0.42	0.26	0.48	-0.71	0.03
1.34	0.85	0.20	0.17	0.21	0.42	0.25	0.48	-0.71	0.04
1.33	0.85	0.17	0.17	0.19	0.42	0.28	0.48	-0.75	0.04
1.29	0.87	0.00	0.17	0.17	0.42	0.33	0.48	-0.74	0.04
1.26	0.86	0.10	0.16	0.19	0.40	0.32	0.47	-0.79	0.03
1.23	0.86	-0.11	0.16	0.26	0.41	0.22	0.45	-0.11	0.06
1.06	1.12	-0.36	0.18	0.14	0.35	0.49	0.33	-0.13	0.20
1.04	1.12	-0.37	0.19	0.15	0.35	0.52	0.33	-0.12	0.21
1.10	1.11	-0.40	0.20	0.13	0.34	0.54	0.31	-0.15	0.22
1.11	1.04	-0.51	0.29	0.22	0.36	0.63	0.25	-0.17	0.37
1.13	1.04	-0.53	0.30	0.24	0.36	0.63	0.27	-0.17	0.35
1.11	1.04	-0.48	0.30	0.27	0.36	0.63	0.27	-0.17	0.35
1.07	1.01	-0.22	0.29	0.32	0.36	0.69	0.25	-0.19	0.42
1.12	0.93	-0.29	0.29	0.28	0.39	0.75	0.27	-0.18	0.48
1.11	0.90	-0.16	0.27	0.35	0.40	0.67	0.27	-0.20	0.37
1.16	0.93	-0.13	0.28	0.24	0.38	0.60	0.24	-0.24	0.32
1.12	0.91	-0.01	0.32	0.30	0.35	0.67	0.24	-0.29	0.42
1.10	0.84	-0.16	0.41	0.22	0.28	0.78	0.20	-0.42	0.58
1.10	0.84	-0.16	0.41	0.27	0.28	0.83	0.22	0.06	0.34