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Exploring the link between consumer behaviour and brand associations

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TO MUM AND DAD.

'In the end, I've come to believe in something I call 'The Physics of the Quest'. A force in nature governed by laws as real as the laws of gravity. The rule of Quest Physics goes something like this: If you're brave enough to leave behind everything familiar and comforting, which can be anything from your house to bitter, old resentments, and set out on a truth-seeking journey, either externally or internally, and if you are truly willing to regard everything that happens to you on that journey as a clue and if you accept everyone you meet along the way as a teacher and if you are prepared, most of all, to face and forgive some very difficult realities about yourself, then the truth will not be withheld from you.'

From the novel 'Eat, Pray and Love' by Elizabeth Gilbert, writer

Acknowledgements

The day I received an email from the Ehrenberg-Bass Institute confirming that I could come to Australia and start a PhD was a cold winter day, 'Italian-Alps' cold. The sky was pale and pearl grey, of such a fine shade that everything looks boring and static. That shade used to make me feel mildly oppressed, like stepping into a crowded elevator: you simply can't wait to get out. By then, I had been infatuated with Australia since my first visit in 2007. Everybody who knew me had heard a million stories about how wonderful, wild and amazing this country was. It sounded a lot like the story of the neighbours' grass always being greener. Still, it was my favourite place to let my mind wander.

After that very cold day, in just under two months, I said my goodbyes, cried a river and got on a plane to Australia. I was very sick that day; I had high fever and a bad flu. But I was also sick deeply inside, because for the very first time in my life I was really scared. I had left so many times before, spending months abroad here and there, yet it felt quite different. It felt like I was leaving behind a lot more than I could have possibly imagined. While staring at the bright orange and turquoise colours of the Australian outback during the last few hours of my flight, I realised I had no idea about what I was about to start.

Now that I am at the end of this journey, I regard it as the most life-changing and intense one I ever took (and perhaps ever will take). It has helped me explore my mind to an extent I would have never been able to, if I had not taken it. Therefore, I don't regret any part of this journey, regardless the difficulties faced or how many times I have felt lost, sad or frustrated. It has changed who I am and made me realise who I really want to be: an academic.

For these reasons, I thank everyone I have met along this journey and I do regard you all as teachers. First and foremost, I thank my amazing supervisors Malcolm Wright and Carl Driesener for their guidance and support. It means more than words can express knowing that you have always believed in me. I also thank my colleagues at the Ehrenberg-Bass Institute for their help and friendship, in particular Armando Corsi, who has constantly mentored and encouraged me. I thank my brilliant office mate Jasha Bowe, who has shared most of this journey and helped me with all my 'second language issues'. I thank my beloved friends Darren, Merve and Natasha for looking after me and accepting me for who I am. And finally, I thank my family, especially my father, for loving me so unconditionally.

P.S. Carl, thank you for that Italian style rice cake at Lucia's at the Central Markets!

I declare that this thesis does not incorporate, without acknowledgement, any material previously submitted for a degree or diploma in any university; and that to the best of my knowledge it does not contain any materials previously published or written by another person except where due reference is made.



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LARA STOCCHI

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Abstract

This thesis examines the degree of similarity between two sets of metrics: (i) *behavioural metrics*, representative of purchase propensities measured with past purchases; and (ii) *brand salience metrics*, representative of retrieval propensities measured with brand image data.

This comparison examines an implied claim of Customer Based Brand Equity (CBBE) research, i.e. consumer choice is largely based on the set of brand associations held in memory (Keller (2003). This claim suggests the existence of a single set of latent variables underlying both purchase and retrieval propensities. The thesis tests this assumption using a set of theoretical considerations linking three areas of marketing research: memory theory, CBBE research and consumer behaviour. These considerations generate a set of crucial descriptions of consumer choice and memory relevant to CBBE, but often overlooked. Among these, the existence of different layers of stochastic processes characterising memory, as described in neuropsychology literature, and demonstrated to be quite close to a well-known stochastic theory of consumer behaviour, the Dirichlet model. Therefore, the Dirichlet model is used in this thesis to quantify the degree of similarity between the two sets of metrics analysed. Three competing views on the degree of similarity are tested, given some likely theoretical differences identified between purchase and retrieval propensities in terms of: stochastic processes, latent variables and bias.

The key outcome is that purchases and brand associations show different underlying structures, such as distinct stochastic processes, two separate sets of latent variables and differing bias. Therefore, they are best seen as two separate components of consumer choice, rather than being two expressions of a single set of latent variables. The degree of separability between purchase and retrieval propensities is quantifiable by examining the difference between the two sets of metrics in both the description of the market (i.e. ranking of brands and correlations between metrics) and at the individual brand level.

The main conclusion is that metrics based on CBBE components, such as brand salience metrics, need to be used as a *supplement* and not as a substitute for behavioural metrics. The insights that can be obtained from these metrics are, in fact, quite different and perhaps more accurate indicators of the effects of branding activities on brand memory structures. They allow the tracking of a key brand equity component by capturing ‘cognitive snapshots’ of the brand from consumer memory. However, despite common beliefs in CBBE research, these snapshots are unlikely to be directly predictive of brand choice.

This research also highlights a set of limitations that provide scope for future research: (i) a replication of this study across data collected from the same sample for multiple time periods; (ii) extending the interpretative approach beyond consumer behaviour benchmarks; and (iii) investigating explicitly the interaction between purchase and brand retrieval propensities at a latent level.

Chapter 1 – Introduction

1.1 Thesis overview

This thesis examines the link between purchases and brand associations. In particular, it discusses and tests the theoretical and empirical validity of a key underlying assumption of brand equity research: the belief that brand associations will lead into purchases (Keller 1993; 2003). This widely accepted belief implies some strong untested assumptions such as:

- The existence of very similar (if not identical) underlying structures in purchases and memory, which underpin the chance to think of a brand and ultimately the chance that the brand will be purchased;
- The existence of very similar (if not identical) empirical patterns in metrics representative of purchases and brand associations.

To test the validity of these assumptions, this thesis presents an overarching theoretical discussion of some key oversights of brand equity research, and an empirical analysis that compares patterns in purchases and brand associations.

The theoretical discussion is drawn from a comprehensive review of neuropsychology literature and has two fundamental objectives. First, it is aimed to outline a set of key underlying assumptions on the way consumers choose and on the nature of memory that are relevant to brand equity research. Second, it is aimed to clarify the key characteristics of the underlying structures of memory (e.g. different layers of stochastic processes, latency and bias) and its stochastic nature (Anderson, 1973). These aspects are then compared against the underlying structures of purchases described by the Dirichlet Theory (Goodhardt et al. 1984). This theory is a widely recognised stochastic model of purchase behaviour, which is extremely robust in explaining and simplifying empirical patterns and underlying structures of purchases (Ehrenberg, Uncles and Goodhardt, 2004). Moreover, this theory is also suitable for modelling brand associations measured with brand image data. Therefore, in this thesis it is applied as a common underlying 'mathematic abstraction' to examine the link between purchases and brand associations, by comparing patterns and underlying structures that characterise these two aspects of consumer choice.

The key outcome of this comparison is that brand associations and purchases are configured as two separate components of consumer choice, as they display distinct underlying structures, which result in different empirical patterns. This outcome is a major contribution to knowledge, because it sheds light on the theoretical and

empirical limitations of a widely accepted marketing belief. The major implications of this outcome are in terms of the strategic use of the insights obtainable from measuring brand associations and brand equity in general. These include, above all, the impossibility to draw inferences about future purchase behaviour.

An explanation of the content of each chapter included in this thesis now follows, specifying:

- The organisation of the literature review (i.e. the areas of literature covered and the reason why they are included in the thesis, especially in relation to the overarching theoretical argument presented);
- The various levels of empirical analysis used to compare purchases and brand associations and the research methods used for each level of analysis;
- The outline of the discussion of the research outcomes.

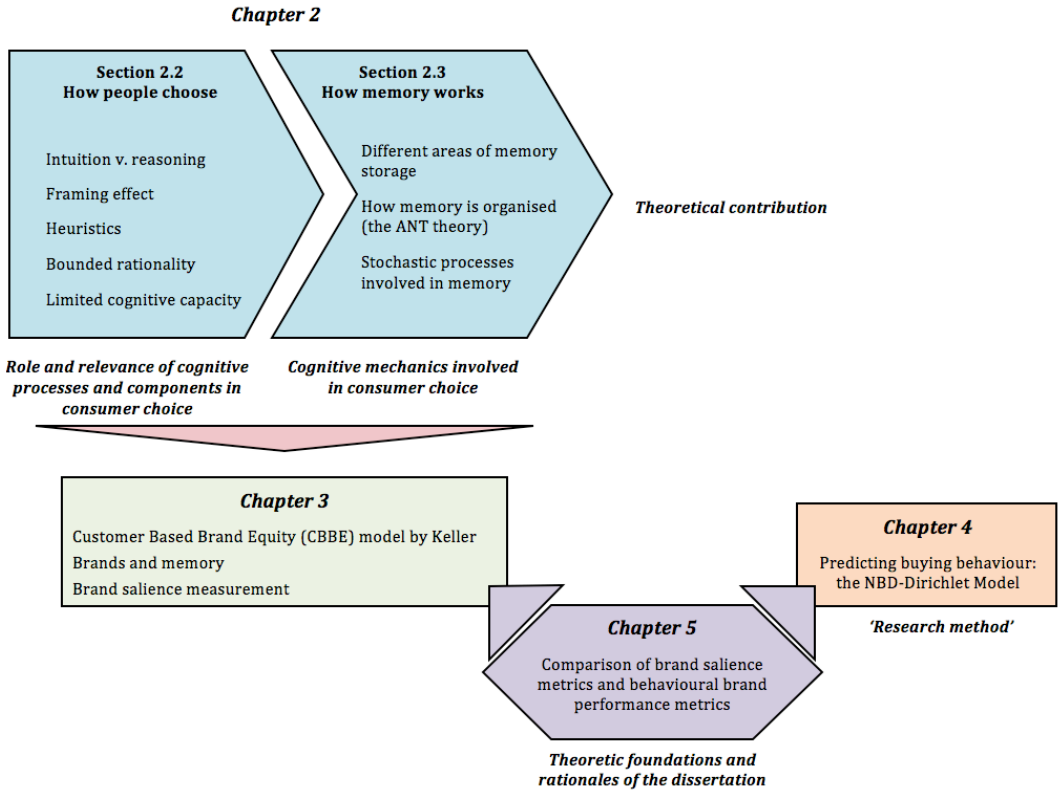
1.2 Organisation of the literature review

'To know all things is not permitted'

Horace (Roman poet, 65BC – 8BC)

The purpose of this thesis is to explore the link between two key components of consumer choice: *purchase behaviour* and *brand associations*. Therefore, each literature review chapter (see Figure 1) is designed to develop the theoretical arguments necessary to establish a conceptual link between two areas of marketing literature: Customer Based Brand Equity (CBBE) and purchase behaviour.

Figure 1 – Literature review organisation



Chapter 2 investigates human memory and it is organised into two main sections: § 2.2 explores how people choose and § 2.3 describes how memory works.

§ 2.2 is designed *to justify a set of assumptions about how people choose* and clearly position the perspective adopted in this dissertation with respect to the traditional concept of utility maximization. The purpose is to justify the role and relevance of cognitive components and processes in human decision-making processes, as well as how environment affects people's decisions. The section mostly draws from Tversky and Kahneman's studies from the early 1970s onwards, which critique the economic theory of choice (utility maximization). The literature drawn from these authors is used to clarify the difference between intuition and reasoning, the role of heuristics and the framing effect, that is, how the environment influences human decision-making. Moreover, some key concepts from cognitive psychology are described, such as limited cognitive capacity and bounded rationality. The section ends with a checklist of the key assumptions about how people choose as is relevant to brand equity research and adopted in this dissertation.

§2.3 includes a detailed description of *how memory works and is organised.* Here, the key theoretical framework dicussed is the Associative Network Theory of memory by Anderson and Bower (1973). This framework is commonly used in the marketing literature to conceptualise how brands are stored in memory and how brand

information is processed. Drawing mainly upon Anderson and Bower's empirical work and some key studies of the Carnegie Mellon University, this section presents a technical discussion of the stochastic models that describe retrieval, working memory performance, heterogeneity, bias and latent variables in memory. This section ends with a checklist of the key assumptions about how memory works as is pertinent to brand equity and used in this dissertation.

Chapter 2 serves as a theoretical background to **Chapter 3**, which presents a well-known framework for brand equity sources and outcomes: Keller's (1993; 2003) CBBE (Customer Based Brand Equity) model. A clarification of the framework components and of some major pitfalls in measuring brand equity elements is also included. Afterwards, the focus of the discussion is on brand memory structures, including how they are organised and the role of brand associations in underpinning consumer choice. The chapter finishes with an overview of Romaniuk's (Forthcoming) method for measuring brand equity, which is based on the count of brand associations modelled with the same stochastic theory that is commonly used to describe purchase behaviour: the Dirichlet model.

Chapter 4 looks extensively at the Dirichlet, which is a robust stochastic model of purchase behaviour. The various components of the model are described: the statistical distributions, the parameters, the metrics and the deviations. This model also explains a key trend: the Double Jeopardy pattern, which typically affects brand purchases, as well as brand associations.

Finally, **Chapter 5** conceptually links the two key areas reviewed (CBBE and purchase behaviour). As such, it maintains the key theoretical arguments to be considered when drawing the comparison between patterns in purchases and brand associations held in memory (particularly in terms of stochastic processes, latent variables and bias), the broad research question tested and the different research propositions on the possible research outcomes.

1.3 Four levels of analysis

As described in **Chapter 6**, the empirical investigation presented in this thesis is organised into four different levels of analysis. The description of the methods necessary for each level of analysis is preceded by a *research preamble*, which includes: (i) an overview of the data sets analysed (§ 6.2); and (ii) an overview of the key methods for calculating and modelling the two sets of metrics considered (§ 6.3 and § 6.4), with particular detail to Romaniuk's (forthcoming) guidelines for brand salience metrics. Then, the description of the research methods applied in every level is presented as follows (§ 6.5):

- Methods necessary for LEVEL 1 of the analysis, the comparison of the values of the Dirichlet parameters obtained from fitting the Dirichlet model to the two sets of metrics analysed;
- Methods necessary for LEVEL 2 of the analysis, the direct comparison of the two sets of metrics;
- Methods necessary for LEVEL 3 of the analysis, to assess the consistency of deviations from the Double Jeopardy pattern across the two sets of metrics;
- And finally LEVEL 4, a decision-tree combining the research outcomes of the previous levels into a single outcome.

1.4 Research outcomes and discussion

The final chapters of this thesis present (**Chapter 7**) and discuss (**Chapter 8**) the results obtained from data analysis and the key implications of these results for academia and practitioners. The theoretical contribution of this thesis is also clarified, differentiating between the contribution generated with the literature review and that generated analytically. Finally, a set of research limitations and the resulting opportunities for future research directions are also presented, before drawing a set of conclusions.

1.4.1 Overview of Chapter 7 (results)

Chapter 7 presents an overview of the research outcomes for all levels of analysis. The key outcomes discussed can be summarised as follows:

- The differences in the values of the parameters *M*, *K* and *Phi* obtained from modelling purchases versus brand associations (including the different degree of stability over time) suggest the existence of two sets of latent variables that shape purchase and retrieval propensities.
- For a given market, behavioural metrics and brand salience metrics show substantially different values (i.e. display large and systematic Mean Absolute Errors for analogous metrics) and provide a different description (rank) of the performance of brands.

- Given the Dirichlet benchmarks, deviations are broadly inconsistent (in magnitude and valence) across behavioural and brand salience metrics, with only few instances of consistent deviations.
- Finally, the combination of these research outcomes forms a decision tree, which is then used to validate one of the two research propositions introduced at the end of Chapter 5, hence one of the three competing views tested in this dissertation. The third competing view tested (stating that behavioural metrics and brand salience metrics are substantially different) has been accepted.

These results were robust across both data sets, i.e. robust within and between chains, same and different sample, single and multiple time periods.

1.4.2 Overview of Chapter 8 (discussion)

Chapter 8 presents a comprehensive discussion of the results displayed in Chapter 7, the most relevant managerial implications of these results and the theoretical contribution of this thesis.

First, it clarifies that the results obtained have broadly confirmed what was suggested at a theoretical level (in Chapter 5), i.e. the existence of two distinct stochastic processes and two different sets of latent variables shaping purchase and retrieval propensities as two separate components of consumer choice, when measured with past purchases and brand associations respectively.

Second, it explains how the differences identified at aggregate and individual brand level between behavioural and brand salience metrics can be used to quantify the degree of separability between purchase and retrieval propensities. This also includes a discussion about whether brand salience metrics are leading or lagging indicators of brand sales.

Third, the discussion presents an overview of:

- The key managerial implications of the results, with particular attention to clarifying the use of brand salience metrics as a *supplement* (and not substitute) to behavioural metrics;
- The contribution to academia, distinguishing between the contributions developed from the literature review (theoretical contribution) and that originated analytically (methodological and empirical contribution).

Lastly, two key sets of limitations are discussed: (i) limitations linked with the nature of the data sets analysed; and (ii) limitations linked with the interpretative approach used in the discussion of results. With regards to the first set of limitations, scope for

replication of this study is provided by the opportunity to collect and analyse purchasing and brand associations data from the same sample across multiple time periods. With regards to the second set of limitations, scope for *extending* this research would include trying to understand patterns in memory-based metrics such as brand salience metrics whilst considering further benchmarks from memory theory (rather than buying behaviour). Lastly, another possible future research direction would be investigating further (and more explicitly), the existence of any potential form of interaction between purchase propensities and retrieval propensities at latent level.

Chapter 2 – Exploring human memory

2.1 Chapter overview

This chapter reviews some key theories of *how people choose* and *how memory works* that are pertinent to brand equity research.

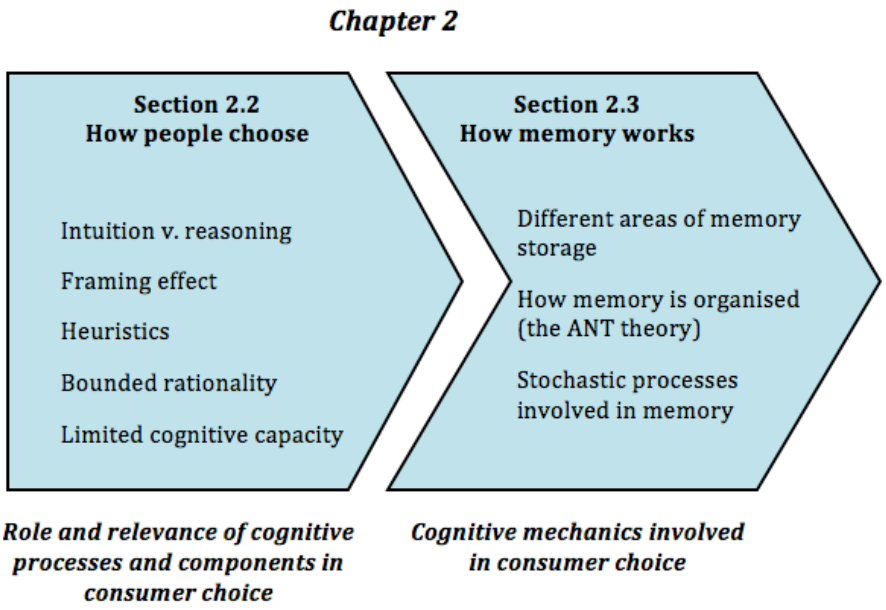
A key belief in the brand equity literature (particularly Customer Based Brand Equity) is that memory has a crucial role in determining consumer response to marketing initiatives (Keller, 2003). Therefore, in this area of marketing literature, there is a strong reference to knowledge and concepts about human memory and how it is organised. However, in many cases there is no clear and rigorous clarification of the relevant theoretical assumptions underpining the concept of brand equity and its sub-components. Often, the review of concepts from neuropsychology constitutes simplistic interpretations of commonly used frameworks for describing human memory. Moreover, most authors discuss the relevance of brand knowledge, but do not acknowledge which paradigm of purchase must hold to justify a strong influence of information held in memory on purchase decisions, nor review empirical studies on the stochastic nature of memory. This oversight represents a key theoretical gap in the advancement of brand equity literature.

As part of the theoretical contribution of this dissertation, this chapter addresses this oversight and discusses relevant theoretical assumptions underpinning the measurement of brand equity. This is achieved with reviewing pertinent literature from neuropsychology to clarify the following aspects:

- Which key assumptions about how people choose and how memory works are crucial to justify measurement of Customer Based Brand Equity components (CBBE) (Keller, 2003);
- Which key empirically driven studies about stochastic models of memory in the neuropsychology literature are crucial to understanding patterns in memory and memory mechanics.

These two aspects are organised into two separate sections as per Figure 2:

Figure 2 – Chapter 2 organisation



§ 2.2 assesses *a set of assumptions about how people choose* with respect to the traditional concept of utility maximization. The purpose is to justify the role and relevance of cognitive components and processes in human choice, as well as determine how the environment affects choice. The section is broadly based on Tversky and Kahneman's critique of the economic theory of choice (utility maximization). Some key concepts from cognitive psychology are also covered, namely limited cognitive capacity and bounded rationality. The section ends with a checklist of the key assumptions about how people choose as is relevant to brand equity research and adopted in this dissertation.

§ 2.3 includes a detailed description of *how memory works and is organised.* The key theoretical framework chosen is the Associative Network Theory of memory by Anderson and Bower (1973a). This section also includes a technical discussion of the stochastic processes taking place in memory and describes working memory performance, individual differences, sources of cognitive bias, latency of retrieval and the meaning of latent variables in memory. These are covered whilst drawing upon Anderson and Bower's empirical studies on memory, as well as some other relevant studies from Carnegie Mellon University. The section ends with a checklist of the key assumptions about how memory works as is pertinent to brand equity research and used this dissertation.

Lastly, **§ 2.4** draws an analogy between the terms from neuropsychology literature and brand equity.

2.2 How do people choose?

In this section, the key objectives are:

- Explaining and justifying the role and relevance of cognitive components and processes in human decision-making processes;
- Clarifying how the environment affects people's decisions.

The key authors chosen to accomplish these objectives are two Nobel-award winning psychologists: Amos Tversky and Daniel Kahneman, with their critique of the economic theory of choice (utility maximization). The work of these authors is an important area of literature for this dissertation: not only because they represent a bridge between two disciplines, economics and psychology, but also because their findings validate the role of cognitive components in consumer choice and the existence of varying levels of rational involvement in decision-making.

2.2.1 Tversky and Kahneman: a bridge between two disciplines

Amos Tversky and Daniel Kahneman started their experimental studies challenging traditional economic principles of utility maximization in the early 1970's at the Hebrew University in Jerusalem. Their work has narrowed the gap between economists and psychologists in relation to human decision-making and has been the subject of over 50 years of academic debate. The appeal of their work is their criticism of the traditional economic principles of utility maximization, which is both *systematic* (i.e. considering all non-psychologically plausible assumptions of utility maximization), as well as *empirically* supported.

In an introductory note in the 2003 article published in the American Economic Review, Kahneman comments:

> *'…Psychological theories of intuitive thinking cannot match the elegance and precision of formal normative models of belief and choice, but this is just another way of saying that rational models are psychologically unrealistic.'*
>
> *(p. 1449)*

The research of Tversky and Kahneman has analysed the various axioms of utility theory[1] and discussed the limitations of its leading propositions. The main underlying argument for their discussion is that human rationality is bounded by memory and computational capabilities of the individual (Quattrone and Tversky, 1988), which is in line with the *cognitive psychology* stream of thought established by Simon (1955, 1978), then developed by Neisser (1967).

Tversky and Kahneman have explored the systematic biases that separate the choices assumed in a rational agent model and actual choices, proposing a descriptive psychological analysis of choice formalized in 1979 and 1984 (Kahneman, 2003). The main explanation or conceptual framework used for the formulation of their research hypotheses was having traditional utility maximization axioms as null hypotheses and proving them wrong by highlighting: (i) the differences between two generic cognitive modes (*intuition and reasoning*); (ii) the role of the context in shaping decision-making processes (*framing effect*); and (iii) a hedonistic approach to choice (*prospect theory*)[2] (Kahneman, 2003). The first two points are now covered, as the last is not directly pertinent to this dissertation.

2.2.1.1 Two systems of cognition: intuition and reasoning

An intuitive cognitive system is based on *anything* stored in memory (Kahneman, 2003). Impressions about objects will not be voluntary, or necessarily verbalized; they will rather be *intuitive* (Kahneman, 2003). Intuition is particularly effective in the presence of distractions, such as a busy environment or performing other activities at the same time, which are common components of any realistic choice scenario. Reasoning, instead, is usually an explicit and intentional cognitive process, regardless of being expressed or not, and regardless of originating from deliberate reasoning or impressions (Kahneman, 2003).

Apart from being *cognitively* different from reasoning, intuition is also characterized by *accessibility*, i.e. the ease with which mental content comes to mind (Kahneman, 2003). Putting aside the more specific description of how mental content is organized and conceptualized, Kahneman (2003) reminds us that some thoughts are more

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[1] The mathematician Daniel Bernoulli first introduced the *theory of expected utility* (*utility theory* in brief) in the 18th century (Tversky, 1975). Von Neumann and Morgesten formalized it into axioms (self-evident propositions) and Savage (1954). integrated the concept of probability (Tversky, 1975). This theory has been extensively used in economics, where the main assumption of individuals being rational is central. Individuals are assumed to 'obey to the maxims of consistency and coherence leading to the maximization of utility' (Quattrone and Tversky, 1988). There are also a series of assumptions about the nature of alternative 'choice options', as well as information available to a decision maker. As such, utility theory has been widely used to describe how consumers, entrepreneurs, voters, and politicians make decisions.

[2] Rather than focusing on utility maximization, in prospect theory what matters is the *change of utility (hedonic utility),* i.e. utility that is the result of the transition from one state to another, e.g. 'this product is better quality than the other one', rather than 'this product is the best available option' (Kahneman, 2003) .

accessible than others. Particularly when generated by contact with the physical properties of the surrounding world (the so-called *natural assessment*), memory content will be processed more quickly and efficiently (Kahneman, 2003).

Intuition seems to be well adapted to the environment: it is the component of the cognitive system that assesses reality and allows information to be used for immediate quasi-instinctive decisions or more complex and effortful cognitive processes (Kahneman, 2003). The contextual setting of the choice usually determines which cognitive system prevails in choices; this is known as the *framing effect*.

2.2.1.2 Framing effect

The context within which a decision is made usually affects the degree of reasoning involved. This concept is defined in the literature as the *framing effect* (Kahneman, 2003).

In a decision-making scenario, equivalent contexts or descriptions of a problem may lead to different choices by altering the relative salience of different aspects of the problem (Kahneman, 2003). An example typically used to explain the framing effect is the following scenario. Let one assume that there are 600 people affected by a deadly disease and that there are two possible alternatives: (i) alternative A saves 200 people's lives; and (ii) alternative B has a 33% chance of saving all 600 people and a 66% possibility of saving no one. Despite the fact that both alternatives imply the same expected value of 200 lives saved, alternative B appeals as being riskier. Therefore, the vast majority of people would tend to prefer and select alternative A (in the original experiments conducted by Tversky and Kahneman, the proportion of people selecting alternative A was about 70%, versus 30% of respondents selecting alternative B). However, the choice pattern would be quite different if these other alternatives were presented: (i) alternative C implies that 400 people will die; and (ii) alternative D implies that there is a 33% chance that no people will die and a 66% probability that all 600 will die. In this second instance, the vast majority of people (about 80% in the original experiments) would tend to prefer alternative D (equivalent of B), instead of C (equivalent of A) (about 20% in the original experiments). The discrepancy between these two choice patterns resulting from the four alternatives presented is the framing effect.

Therefore, framing effect can be defined as a preliminary ‘screening’ of a decision by looking at all contingencies and possible outcomes (Tversky and Kahneman, 1986). Framing the context of a decision is performed according to *heuristic criteria* or simply *heuristics* (Kahneman, 2003), which are defined in the following section.

2.2.1.3 Definition and role of heuristics in human choice

The Greek meaning of the word heuristic is the following: an incomplete yet useful idea or knowledge component, which 'serves to find' (Gigerenzer, 2004). As such, in comparison to the more complex knowledge held by individuals, heuristics are the more basic and simple components of knowledge (Gigerenzer, 2004). They can also be defined as cognitive representations of information collected from the environment, determining how individuals browse through alternatives and assess or compare alternatives (Selten, 2002). Therefore, heuristics are the 'attributes' of a set of alternatives screened during decision-making processes (Newell and Simon, 1972). These are mostly used to simplify complex problem-solving activities, such as choosing among alternatives (Kahneman, 2003).

Many alternatives can be described by similar attributes, and hence similar heuristics (Bettman et al., 1991). Therefore, a decision-making task may become more difficult with a larger number of attributes, or if the attributes are more difficult to process (Bettman et al., 1991). Moreover, according to Bettman (1980), knowledge and *experience* are both implemented heuristically in the process leading to choice. As such, individuals may not always have comprehensive sets of heuristics that are pertinent to a choice. Often, in memory, only some fragments are available, which can be 'put together' and processed during decision-making (Bettman and Park, 1980). The degree to which these elements are combined largely depends on what information is available in the environment. Therefore, whenever an individual has extensive prior experience, the need to acquire information from the environment and build new heuristics will decrease (Bettman and Park, 1980). This links to numerous experiments focusing on different strategies used by people to make decisions, i.e. different degrees of reliance on heuristics, which result in two opposed choice protocols: *stimulus-based* and *memory-based*, as per Lynch and Srull (1982).

2.2.2 Stimulus versus memory-based choice protocols

According to Lynch and Srull (1982), active consideration and acknowledgement of the role and relevance of cognitive components and processes may not be as simple as it sounds in theory. The degree of involuntary and unconscious processes implied in human choice complicates theory development and empirical analysis of human choice. Reviewing some key empirical cognitive psychology studies, the authors provide an important distinction between two diametrically opposed choice protocols: *stimulus-based* and *memory-based.*

Stimulus-based choices occur when all information is available in the environment, such as when buying from a mail-order catalogue or standing in front of a supermarket shelf (Lynch and Srull, 1982). Pure memory-based choices occur when none of the relevant information is physically present, so that individuals mainly draw upon information held in memory, such as when creating a grocery list (Lynch and Srull, 1982). Mixed choice-protocols are rather frequent, i.e. when some information is physically available and some is held in memory (Lynch and Srull, 1982). Therefore, human choice can be defined as *stimulus-based* whenever an external stimulus from the environment somehow activates cognitive processes, creating new heuristics. Alternatively, whenever choice is derived from existing heuristics stored in memory, the choice protocol is defined as *memory-based*.

Explicit consideration of the underlying cognitive processes is crucial to any theoretical analysis of pure memory-based and mixed judgments, which are prevalent in the literature as well as in real life (Lynch and Srull, 1982). However, pure memory-based and mixed judgments tend to be more complex from a theoretical perspective, since it is necessary to consider different strategies adopted by individuals using heuristics and the factors affecting one's ability to execute a choice (Lynch and Srull, 1982). For example, theorists of human choice often explore not only cognitive components and processes and their different degrees of involvement in decision-making processes; they also consider the level of attention or cognitive engagement (Lynch and Srull, 1982). The key finding being that individuals are incapable of considering more than a few items of information at a time, regardless of whether these items are external (gathered from the environment) or internal (held in memory) (Lynch and Srull, 1982). This is known as *limited cognitive capacity* (Newell and Bröder, 2008).

2.2.3 Limited cognitive capacity

Limited cognitive capacity (also defined in the literature as '*span of short-term memory*[3]' or '*limited attentional capacity*') refers to the fact that each individual can physiologically[4] process only a limited amount of information at a time (Newell and Bröder, 2008). It affects both the information available in the environment and the information held and processed in memory (Lynch and Srull, 1982).

Cognitive experiments show that the maximum number of items that can be considered simultaneously is somewhere between four (Shiffrin and Atkinson, 1969)

[3] See § 2.3 for a definition of short-term memory.

[4] This refers to different areas of memory storage and the definition of working memory, see § 2.3.

and seven (Miller, 1956). This empirical evidence convinced researchers to reject hypothesized choice rules that require individuals to process large quantities of information; it also made more plausible the role of heuristics and their 'strategic' implementation in decision-making tasks (Lynch and Srull, 1982).

Limited cognitive capacity is quite close to the concept of *bounded rationality*, although the two terms are often used erroneously and interchangeably in the literature. Limited cognitive capacity simply implies that individuals can only process a certain amount of information at the time. Bounded rationality, instead, assumes that an individual will not process all possible alternatives until the best one is chosen, but will be rather prone to satisfying behavior (Simon, 1967).

2.2.4 Bounded rationality

According to Selten (2002), assuming full rationality and full exploitation of all cognitive components in the human decision-making process is unrealistic:

> *'Full rationality would require unlimited cognitive processing. Fully rational man is a mythical hero who knows the solutions to all mathematical problems and can immediately perform all computations, regardless of how difficult they are'*
>
> *(p. 14)*

Simon's (Simon) concept of bounded rationality is based on the following assumptions: (i) from a physiologic perspective the nervous system operates in a *serial fashion*; (ii) human behavior is ruled by a hierarchy of *goals*; these goals are *aspiration levels* to be reached or surpassed while undergoing the information search processes that may lead to satisfaction, dynamically adjusted to the contingency of any situation.

Establishing a precise definition of bounded rationality is somewhat problematic. It is therefore easier to establish what bounded rationality is *not* (Selten, 2002):

- **It is *not* irrationality**: just because the ultimate goal of a decision-making process does not conform to the concept of utility maximization, it cannot be asserted that no rational motive is underpinning the decision-making process. However, the driver of the decision will be a dynamic response to various aspirations or goals, with a varying degree of rational involvement and cognitive processes;
- **It is *not* optimization**: browsing through alternatives can be suspended whenever individual satisfaction is met;
- **It is *not* conscious**: the result of thinking becomes conscious, but the act of thinking remains mostly unconscious and cannot be observed.

Therefore, the concept of bounded rationality somehow suggests a more dynamic approach to the way people choose, without leaning towards the optimal choice, but rather a 'satisfying' or 'adjusting' behavior.

2.2.5 Summary of the assumptions about how people choose

The picture of human choice presented so far is the following: every time a decision is made, a trade-off between available information in memory and new information acquired from the environment will be established, bounded by the amount of information that can be cognitively processed and by a dynamic adjustment towards satisfaction in a hedonistic fashion (aiming for a change in utility, rather than maximum utility).

This description is broadly applicable to consumer choice. Therefore, in this dissertation consumer choice is a paradigm of human choice *à la* Tversky and Kahneman with the following assumptions:

- There is a varying level of involvement of cognitive processes and components, which are the key drivers of human choice;
- The context within which a choice is made shapes and affects that choice (framing), which is performed and simplified heuristically;
- Individuals do not aim for utility maximization; what matters is the change in utility (e.g. option A is better than option B, with option A not necessarily being the best available alternative);
- Mixed choice protocols prevail, with a mixture of reliance on information held in memory and information available in the environment;
- Only a certain amount of information can be processed cognitively at a time (limited cognitive capacity);
- Tendency towards satisfaction and dynamic adjustment of goals (bounded rationality).

These assumptions are identified as theoretical underlying assumptions needed to justify brand equity conceptualization and measurement. As such, they will be implicit through this dissertation for any theoretical discussions that will follow, for the formulation of research propositions and for the data analysis.

A technical discussion about the relevant assumptions about how memory works crucial to brand equity now follows.

2.3 How does memory work?

Table 1 presents an overview of the key authors and the topics covered in this section.

Table 1- Overview of section 2.3

Topic	Key authors
How memory works and how it is organized.	Anderson and Bower (1973a)
How associations are formed (a stochastic process).	Anderson and Bower (1973b)
Differences between working memory and long-term memory, characteristics of working memory (included stochastic processes shaping differences in the performance of working memory).	Anderson, Reder and Lebiere (1996); (1988); Reder, Park and Kieffaber (2009); Daily, Lovett and Reder (2001); Lovett, Reder and Lebiere (1997)
Latency of retrieval; sources and nature of cognitive bias.	
Meaning of latent variables in neuropsychology.	

This section starts with a description of how memory works and is organized, focusing on Anderson and Bower's (1973a) Associative Network Theory (ANT), a framework commonly used in the marketing literature to explain cognitive components and processes.

Then, it presents the distinction between two different types of memory: working memory and long-term memory, focusing on some characteristics of working memory and the mechanics of information activation and processing. This leads into a technical sub-section describing the stochastic processes occurring in memory. The emphasis is on two models: (i) the stochastic model of how associations are formed in

memory as developped by Anderson and Bower (1973b); and (ii) the ACT-R theory of working memory performance by Anderson (1976) and its variants. These models lead to a discussion of: (i) heterogeneity of working memory performance; (ii) cognitive bias; (iii) latency of retrieval; and (iv) the meaning of latent variables in neuropsychology.

The section ends with a set of relevant assumptions about how memory works as is pertinent to this dissertation and to brand equity, divided into general assumptions and local processing of information assumptions.

2.3.1 Daring to peek inside the 'black box'

An abundance of empirical studies across disciplines have explored how memory works and how it is organised. The basic principles of human memory operations can be understood by looking at them as if they are optimisation processes (Anderson and Milson, 1989). Anytime a problem-solving context is presented (e.g. a purchase decision), memory will screen the information available and determine what is relevant to that context on the basis of past experience. This is similar to having a database of information organised by keywords that can be used to browse for relevant information, trying to reduce the cost of retrieving irrelevant ones. In the literature on human memory, these keywords are usually referred to as 'cues'.

Cues are mainly acquired externally, and in the case of brands they may arise from buying situations, marketing communication or any brand-consumer interaction. Once there has been exposure to a cue, the likelihood of processing pertinent information is stochastic in nature and influenced by several factors, such as how often items have been processed in the past, and the presence of competing concepts (Anderson et al., 1994). Therefore, the probability of retrieving a concept from memory usually ranges between 0 (before the presentation of a cue) and 1 (straight after exposure).

The epistemological base to better understand the organisation of memory concepts and retrieval cues is provided by the Human Associative Memory (HAM) framework. This theory describes memory as a network of nodes linked together, with the nodes representing concepts and the links denoting relationships between concepts (associations) (Anderson and Bower, 1973a, Morton, 1969, Morton, 1979, Bower, 1986, Bower, 1996).

Given the HAM framework, according to the *Associative Network Theory (ANT)* processing a concept in memory implies the activation of the node where it is stored and the spreading of such activation to the networked nodes via the connecting links (Anderson and Bower, 1973a). Therefore, nodes serve to spread activation from one

unit to another within a network of associated information, determining retrieval of concepts from long-term memory (Collins and Loftus, 1975).

2.3.1.1 Working memory and long-term memory

§ 2.2.3 covered the concept of limited cognitive capacity, which refers to the physiological characteristics of human memory that limit the amount of information that can be processed at any one time. This is linked with the definition of different types of memory storage systems, namely *working memory* and *long-term memory* (Bettman, 1979a). Working memory usually facilitates processing of information in the short run and is triggered by sensorial inputs. The information at this stage can be easily lost, unless it is further processed (Bettman, 1979a). Long-term memory, instead, has virtually unlimited storage capacity and it is composed of semantic, auditory and visual information (Bettman, 1979a).

Working memory, although limited in capacity and less permanent, is the key hub for cognitive processing of information and it is thus extremely relevant to understanding patterns in memory (Daily et al., 2001). Miller (1956) first hypothesised that working memory had limited capacity and provided evidence that approximately 7-8 items can be processed at one time. Consequently, various pieces of information are usually grouped or 'chunked' together (e.g. when memorising telephone numbers, we tend to group digits to facilitate remembering them). This implies working memory being inherently 'limited' and that increasing the cognitive load of working memory is likely to cause errors in cognitive performance (Daily et al., 2001). Nevertheless, working memory has been shown empirically to be crucial in influencing how people perform cognitive tasks (Daily et al., 2001).

In relation to the Associative Network Theory (ANT), working memory can also be defined as the portion of information that is above a certain threshold of neural activity, referred to as *memory activation* (Anderson et al., 1996).

2.3.1.2 Activation in memory

Activation usually determines the information that is cognitively available (Anderson et al., 1996) and the *ease* with which the information is accessed and processed in memory (Reder, 1988). Activation usually affects *declarative components* of knowledge (Miller, 1956). Declarative knowledge is defined as applicable to a task (e.g. some numbers), as opposed to *procedural knowledge*, which is, instead, used to perform a task (e.g. knowing how to sum numbers) (Anderson et al., 1996). Stimuli of

activation can be either internal (thinking of something) or external (cue-based) (Reder, 1988).

The pace at which information is processed depends on the *level* and *strength* of the activation of declarative components of knowledge in working memory (Reder, 1988). The level of activation is described as the total number of activated concepts, whereas the strength of activation is described as the number of times certain concepts have been activated (Reder, 1988). More specifically, according to Reder (1988), the level and strength of activation are determined by the *frequency* of memory associations (i.e. how many times concepts have been activated before), which determines which declarative knowledge will be prominent cognitively, i.e. salient (Reder, 1988). Thus, from this simple framework, it is clear that these two factors (strength and level of activation) shape the chance of retrieving declarative knowledge from long-term memory (Reder, 1988).

However, suggesting that retrieval depends solely on the level and strength of activation would be incorrect (Reder, 1988). In fact, declarative knowledge is organised in dense networks of linked concepts (Anderson and Bower, 1973a). Therefore, besides the level and strength of activation of declarative knowledge components pertinent to a task, the relative strength of an association between those components also matters. This means that the number of competing associations pertinent to the task also affects information retrieval (Reder, 1988). This is usually known as competition for activation or '*fan effect'*.

2.3.1.1 Competition for activation: the 'fan' effect and the 'paradox of the expert'

The strength of an association relative to the number of competing links is usually called *interference* (Reder, 1988). For example, the chance of retrieving the fruit 'apple' will depend not only on the activation of the conceptual node where 'apple' resides, but also the strength of the link with the node 'fruit'. It will also depend on how strongly the other fruits, such as 'peach', 'pear' or 'pineapple' are linked to the node 'fruit'.

Strength and interference will have an opposite impact on retrieval performance: more interference reduces the ease of retrieval, while stronger associations increase it (Anderson, 1983). The various nodes shared by multiple concepts 'fan out' from these concepts, thus dissipating activation and increasing monotonically the time necessary for retrieval (known as *reaction time* or *cognitive bias*, see § 2.3.2.4). In the literature, this is referred to as the '*fan effect*' (Anderson, 1983).

This is also linked to what is commonly known as '*the paradox of the expert*', which means that 'knowing a lot' about something can make it harder to retrieve specific information about it (Reder, 1988).

These two concepts complete the description of activation and processing of information.

The strategies adopted by individuals to 'manage' the flow of information in memory, commonly referred to as memory control processes (Shiffrin and Atkinson, 1969) are now discussed.

2.3.1.2 Different memory control processes

Memory control processes are 'strategies' habitually used by individuals to control the input and output of information (Shiffrin and Atkinson, 1969). Bettmann (1979b) provides a simplified and clear description of six different memory control processes as follows:

- *Encoding* is the process with which individuals structure information for retrieval; this links back to the description of memory as a network of concepts associated or linked to each other. Tulving and Thomson (1973) provide a slightly more comprehensive definition of the encoding process, as the process that results in internal representations in memory of perceptual inputs.
- *Transfer* is the process that governs the form of the information, which is stored in memory, as well as its priority in cognitive processing.
- *Placement* refers to where information is stored in an existing associative network, drawing upon existing networks of concepts associated and linked to each other.
- *Rehearsal* refers to the maintenance of the information (keeping it activated in working memory) and transfer of the information into long-term memory. Usually there is a direct relationship between rehearsal time and retention of information in long-term memory. The longer the rehearsal time, the higher the chance to retain information in long-term memory.
- *Retrieval* is a fundamental control process. It includes both the immediate access to information, as well as extended browsing for information and problem solving. Tulving and Thomson (1973) provide a definition of retrieval which also includes *remembering*, thus the process of response generation. Therefore, retrieval is often regarded as the process that completes the act of remembering, combining information stored in memory in the past and information that is cognitively prominent.

- *Response generation* is the last information control process and it implies reconstruction of information from memory traces, thus bringing to mind a piece of information.

Memory control processes are usually measured empirically *ex post*, assessing the unconscious transformation of what is remembered, into behavior (Tulving and Thomson, 1973). From an experimental perspective, measuring retrieval is quite complex. Free recall or free associations, however, as a behavioral outcome of cognitive processes, are often considered a valid empirical proxy for measuring retrieval (Tulving and Thomson, 1973).

Retrieval appears to be the most relevant memory control process. In order to be included in any decision-making process, information stored in memory has to be retrieved (Lynch and Srull, 1982). This leads to the typical distinction present in the literature between *availability* and *accessibility* of information, as per Tulving and Pearlstone (1966).

Information encoded into long-term memory is assumed to be always available in memory, thanks to the physiological mechanisms of the central nervous system that permanently maintain information in memory. However, only a small fraction of encoded information will be *accessible* at a specific point in time and it will change contextually, according to two key factors: (i) the number of competing concepts; and (ii) the chances of the retrieval to take place (Tulving and Pearlstone, 1966, Lynch and Srull, 1982).

Keeping in mind the difference between working memory and long-term memory, the explanations of activation and information processing, and memory control processes, it is now possible to discuss some other important aspects of how memory works: the stochastic processes shaping memory performance.

2.3.2 Stochastic processes in memory

Anderson and Bower (1973b) are the first authors who have developped an empirically-based stochastic theory of memory processes. Their theory presents itself as an explicit stochastic model describing how input information is stored in long-term memory (i.e. how associations are formed) and how it is subsequently retrieved.

Later empirical studies were then aimed at modelling the *individual differences in working memory performance,* see for example the Adaptive Control of Thought theory by Anderson (1976) and its derivates, describing working memory performance and the activation process in memory.

These models demonstrate and explain the existence of different layers of stochastic processes taking place in memory, individual differences in memory performance under different cognitive loads and varying characteristics of memory tasks. They also include consideration of the concepts of latency of retrieval and cognitive bias. They constitute a crucial theoretical building block for this dissertation that will help in formulating the research propositions tested.

2.3.2.1 Converting information in long-term associations: a stochastic model

Anderson and Bower (1973b) developed a theory regarding the process of encoding information into memory. This theory is an explicit stochastic model of this cognitive process and describes how input information is stored in long-term memory and how it is subsequently recalled.

The authors assert that, despite the complexities of human memory, complicating factors can be reduced if the process of converting input information into long-term memory is treated as a stochastic process.

A stochastic model can deliver detailed predictions about patterns in information recall based on the following simple assumptions: (i) the probability of encoding information into long-term memory solely depends on how long that link resides in working memory; (ii) this probability is independent of how many times other links are being encoded from working memory or how many were successfully coded (i.e. resulted in an association) (Anderson and Bower, 1973b).

There is a limitation in the formation of associations: the model must take into consideration the limited capacity of working memory in both processing newly acquired information before passing it onto long-term memory, and bringing back to mind 'old' concepts from long-term memory (Anderson and Bower, 1973b). This restriction is crucial for parsimony in the formulation of the theory (Anderson and Bower, 1973b).

A simple relationship between the time and input information determines the probability that the input is encoded into memory; this probability follows an exponential distribution with mean *a* (constant) (Anderson and Bower, 1973b). This means that the chances of encoding are continuous and independent (i.e. following a Poisson stochastic process), with actual encoding of inputs occurring at a constant average rate over time. Therefore, *f(t)* will be the probability density function of forming an association in a specific point in time, as per the following equation (Anderson and Bower, 1973b):

$$f(t) = \frac{1}{a} e^{-\frac{t}{a}}$$ ***Equation 1***

p(t) is the probability of forming an association by time *t* (Anderson and Bower, 1973b):

$$p(t) = 1 - e^{-\frac{t}{a}}$$ ***Equation 2***

When an input has *n* pre-existing associative links, the number of associations formed *(k)* is binomially distributed with the parameters $1 - e^{-\frac{t}{a}}$ and *n* (Anderson and Bower, 1973b). This means that the *n* links affect the chances of an association being formed. The mean number of associations formed will be equal to (Anderson and Bower, 1973b):

$$E(k) = n\left(1 - e^{-\frac{t}{a}}\right)$$ ***Equation 3***

Regarding the time necessary to encode *n* associations *T(n)*, the probability density function will depend upon: (i) intra-association intervals being exponentially distributed and independent; (ii) the sum of the inter-association intervals being gamma distributed (Anderson and Bower, 1973b).

This model has one main limitation: it assumes that the parameter *a* is constant. This implies systematic under-prediction of the *frequency* at which a subject will form associations (Anderson and Bower, 1973b). The parameter *a* should be randomly distributed, as a mean value of sample heterogeneity, following an exponential distribution of the rate *1/a*, of mean *b* (Anderson and Bower, 1973b):

$$f\left(\frac{1}{a}\right) = \frac{1}{b} e^{-\frac{1}{ba}}$$ ***Equation 4***

Consequently, the probability density *f(a)* of *a* can be determined as a change of variable as follows(Anderson and Bower, 1973b):

$$f(a) = \frac{1}{ba^2} e^{-\frac{1}{ba}}$$ ***Equation 5***

With the expected value of the probability distribution *p(t)* of forming an association in *t* seconds being (Anderson and Bower, 1973b):

$$E[p(t)] = \frac{tb}{tb+1}$$ ***Equation 6***

This formula is a special case of a beta distribution (Anderson and Bower, 1973b):

$$f(x) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} x^{\alpha-1}(1-x)^{\beta-1}$$ ***Equation 7***

This means that the mean rate of encoding will increase when this distribution is close to 1 (as *tb* increases), i.e. the probability of forming an association will increase with an increase of the encoding time *t* and the mean encoding rate of the population *b*.

The model explains and describes how associations are formed and the stochastic processes that determine the establishment of associations in long-term memory. However, the authors also consider recall patterns.

The average recall pattern of any construct is determined by the probability of encoding a particular *k* of the *n* associations in working memory *Q (k,n)* (Anderson and Bower, 1973b):

$$Q(k,n) = \int_0^1 p(t)^k \left[1-p(t)\right]^{n-k} f\left[p(t)\right] d p(t)$$ ***Equation 8***

Calculating this probability implies first determining the probability $p(t)^k\left[1-p(t)\right]^{n-k}$ of forming a particular *k* association for each value of *p(t)*, weighting such probability by the probability density function *f[p(t)]* at a certain *p(t)* value and integrating this over the 0 to 1 range of *f[p(t)]* as follows (Anderson and Bower, 1973b):

$$Q(k,n) = \frac{1}{tbn+1} \prod_{i=1}^{k} \frac{tbi}{tb(n-1)+1}$$ ***Equation 9***

Whenever the mean rate of encoding *tb* will be close to 1, the mean probability to form an association will be .5 and the probability of forming *n* associations greater than 0.5^n. Figure 3 shows how the probability density *f[p(t)]* changes according to different values of *tb* (Anderson and Bower, 1973b):

***Figure 3* –f[p(t)] *for different values of* tb**

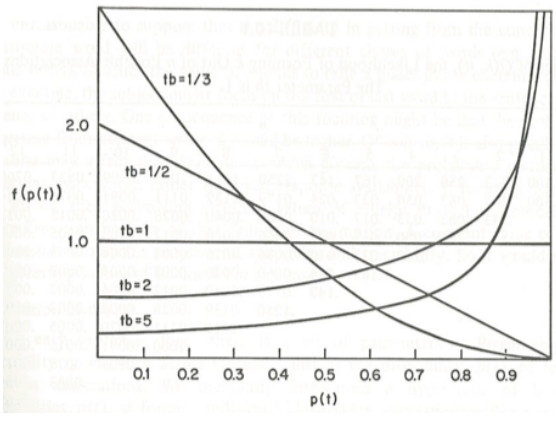


Table 2 shows, instead, different values for the probability of forming *k* out of *n* possible associations when the parameter *tb* is 1 (Anderson and Bower, 1973, p. 290):

Table 2 – Different values of* Q(k,n) *when* tb = *1

	n											
k	1	2	3	4	5	6	7	8	9	10	11	12
0	.500	.333	.250	.200	.167	.143	.1250	.1111	.1000	.0909	.0833	.0769
1	.500	.167	.083	.050	.033	.024	.0179	.0139	.0111	.0091	.0076	.0064
2		.333	.083	.033	.017	.010	.0060	.0040	.0028	.0020	.0015	.0012
3			.250	.050	.017	.007	.0036	.0020	.0012	.0008	.0005	.0003
4				.200	.033	.010	.0036	.0016	.0008	.0004	.0003	.0002
5					.167	.024	.0060	.0020	.0008	.0004	.0002	.0001
6						.143	.0179	.0040	.0012	.0004	.0002	.0001
7							.1250	.0139	.0028	.0008	.0003	.0001
8								.1111	.0111	.0020	.0005	.0002
9									.1000	.0091	.0015	.0003
10										.0909	.0076	.0012
11											.0833	.0064
12												.0769

This model was tested empirically with a set of four cue-recall experiements on individual subjects[5] (Anderson and Bower, 1973b). Goodness of fit was appraised with *Chi square* tests as well as analysis of covariates. Across all four experiments, the models accurately modelled memory patterns (Anderson and Bower, 1973b). The stochastic nature of the model accurately captured differences in potential activation and processing of memory traces and therefore in the formation of discrete all-or-none connections (Anderson and Bower, 1973b). The probability of these discrete connections being formed was proven to be *independent* within a memory network, but covarying across various networks (Anderson and Bower, 1973b).

In summary, this stochastic model explains that there are *empirically measurable patterns of associations' formulation* and provides clear guidelines to anticipate the chances to recall a concept from long-term memory (as depending upon the formation of a number of *discrete connections* in memory) (Anderson and Bower, 1973b).

This model does not, however, explicitly include any description of the stochastic processes involved in information processing, i.e. the activation of concepts and working memory performance. These were covered in later models explaining the performance of working memory and differences in individuals: the ACT (Adaptive Control of Thought) theory and its variations.

[5] Location-agent-verb-object, atomic propositions, imagery instructions and physical contiguity (Anderson and Bower, 1973)

2.3.2.2 Modeling working memory performance: ACT theory and its variations

The ACT theory (Adaptive Control of Thought) was formalised by Anderson (1976) and describes working memory performance and the activation process in memory. The central postulate of this theory is that the total amount of activation of a memory network of associated concepts is usually equal to the sum of the activation carried by all the components of declarative knowledge of this network. This is calculated accounting for both limited cognitive capacity and the performance of working memory being quite heterogeneous (i.e. for the fact that individuals do not support identical cognitive loads) (Anderson, 1976).

Anderson (1993) has successively developed this theory into the ACT-R theory. The ACT-R theory assumes that each memory network of associated concepts has a base level of activation equal to zero and also considers the role of external cues, which will determine the probability of retrieval from long-term memory (thus the 'R' in the theory's acronym). More specifically, it theorises that the activation A_i of any declarative knowledge component i of a memory network depends on the semantic similarities held with an external cue, as per the following equation (Anderson, 1993):

$$A_i = \sum_j W_j S_{ji} \qquad \textbf{Equation 10}$$

where W_j is the cognitive prominence of the declarative memory component j determined by the semantic similarity with the external cue and S_{ji} is the strength of the association of that component to the memory network of associated concepts. This approach formalises the activation of the declarative components' influence on retrieval from long-term memory, given the compatibility with external cues. Moreover, W_j determines the probability of retrieval from long-term memory.

The model also explains that there is a constant amount of information that can be activated at the time (limited cognitive capacity) and thus assumes the following (Anderson, 1993):

$$\sum_j W_j = K \qquad \textbf{Equation 11}$$

with K being a constant value, often assumed equal to 1 in empirical studies (Daily et al., 2001).

The model's last key assumption is that activation patterns are often *non-linear*, due to some latency in matching the network of associated concepts' information (i.e. its declarative knowledge components) and the task components (procedural knowledge).

This theory has been the subject of numerous subsequent experiments and resulting variants, which are now discussed in a logical rather than chronological order, to highlight the key theoretical aspects pertinent to this dissertation.

Reder, Park and Kieffaber's (2009) most recent revision of the ACT-R theory takes into consideration the level of familiarity and the decay of activation over time. Repeated exposure to a task implies that the declarative knowledge components pertinent to this task will be activated quite frequently, and thus strengthened (i.e. a stronger link between the concepts and the task and also between the various concepts) (Reder et al., 2009). Over time, however, this strength will decrease, dropping off from the baseline of the last activation. This is explained by this formula (Reder et al., 2009):

$$B = B_w + cN\sum t_i^{-dN} \qquad \textbf{Equation 12}$$

where B_w is the base-level of activation, cN and dN are constants (dN stands for decay of activation) and t_i is the time passed since the last instance of activation ith.

Regarding the strength $S_{s,r}$ of the link between any two declarative knowledge components s and r pertinent to a specific task (Reder et al., 2009):

$$S_{s,r} = cL\sum t_i^{dL} \qquad \textbf{Equation 13}$$

t_i is the time passed since the last instance of association between two concepts, cL and dL are constants (dL stands for decay of link strength).

When the fan effect is also considered (i.e. the activation 'loss' due to a number of competing declarative knowledge components), the incremental amount of activation above baseline that can be carried by a specific declarative knowledge component is (Reder et al., 2009):

$$\Delta A_r = \sum\left(\frac{A_S \times S_{s,r}}{\sum S_{s,I}}\right) \qquad \textbf{Equation 14}$$

where ΔA_r is the amount of activation above baseline, A_s is the activation of the declarative component s, $S_{s,r}$ is the strength of the link between any two declarative knowledge components s and r, and lastly, $\sum_{s,I}$ is the sum of the strength of all declarative components linked to a specific task (the 'fan' of a memory node) (Reder et al., 2009).

Prior to the work of Reder, Park and Kieffaber, (2009), Lovett, Reder and Lebiere (1997) also worked on the ACT-R theory, developing a computational version of the model that explicitly accounts for the *individual differences* in working memory performance. This model allowed formalising that limitations in cognitive capacity vary from individual to individual and people show different levels of cognitive performance.

In order to capture these aspects, the authors have included in the ACT-R model an underlying parameter capturing heterogeneity in working memory performance. This parameter varies in a *random fashion*, thus following a probability density distribution and providing many insights about the *response patterns* (retrieval and response formulation) observable in task-accomplishments based on cognitive processes (Lovett et al., 1997).

The inclusion of an underlying parameter of heterogeneity in a computational theory such as the ACT-R allows a better understanding of the distribution of the variation working memory capacity across individuals, as well as aggregated patterns of working memory performance in information processing and retrieval (Lovett et al., 1997). Lastly, such a parameter also allowed the authors to obtain a better empirical fit, i.e. the model embodying the parameter was significantly more reliable in capturing actual retrieval patterns (Lovett et al., 1997).

Put simply, with respect to Equation 11, Lovett, Reder and Lebiere (1997) have theorised K is not a constant, but a *random variable*, i.e. a variable whose value is not fixed, but can be described by a probability distribution. Therefore, this parameter should follow a density distribution that when normalised, would be centred at 1 (the original value of K) (Daily et al., 2001).

Besides including the heterogeneity parameter, Lovett, Reder and Lebiere (1997) also provide a *non-linear* formula of the base level activation B_i:

$$B_i = \log\left(\sum t_j^{-d}\right) \qquad \textbf{\textit{Equation 15}}$$

with t_j being the time lag since the last activation j^{th} and d being the decay rate.

The authors support this formula by demonstrating a better empirical fit and with the explanation that linear-based analyses of performance do not capture heterogeneity. Furthermore, non-linear functions are usually more accurate descriptors of relationships where the output (retrieved information) is not directly proportional to the input (activated declarative knowledge components).

This discrepancy between input and output leads to the definition of latency of retrieval.

2.3.2.3 Latency of retrieval

Further discussion of the role of the underlying parameter explaining individual differences in the performance of working memory can be found by Daily, Lovett and Reder (2001), in another computational model based on the ACT-R framework. This model also explains the concept of *latency of retrieval*, as the amount of information

above a certain threshold of activation, which determines the odds of retrieval, and the decay of activation over time.

Daily, Lovett and Reder (2001) theorise that given the total level of activation A_i of a memory network of associated concepts *i*, the probability of retrieving any information from the network is determined by the following formula:

$$\Pr(retrieval) = \frac{1}{1 + e^{-(A_i - \tau)/S}} \qquad \textbf{Equation 16}$$

where τ is a constant threshold of activation necessary for retrieval and S is a constant measure of interference or 'noise'. If the total activation of a network of associated concepts is above τ, *latency of retrieval* will be the total amount of information activated above the threshold (Daily et al., 2001):

$$L(retrieval) = Fe^{-fA_i} \qquad \textbf{Equation 17}$$

where F and f are constants, 'transforming' the total level of activation into actual retrieved information.

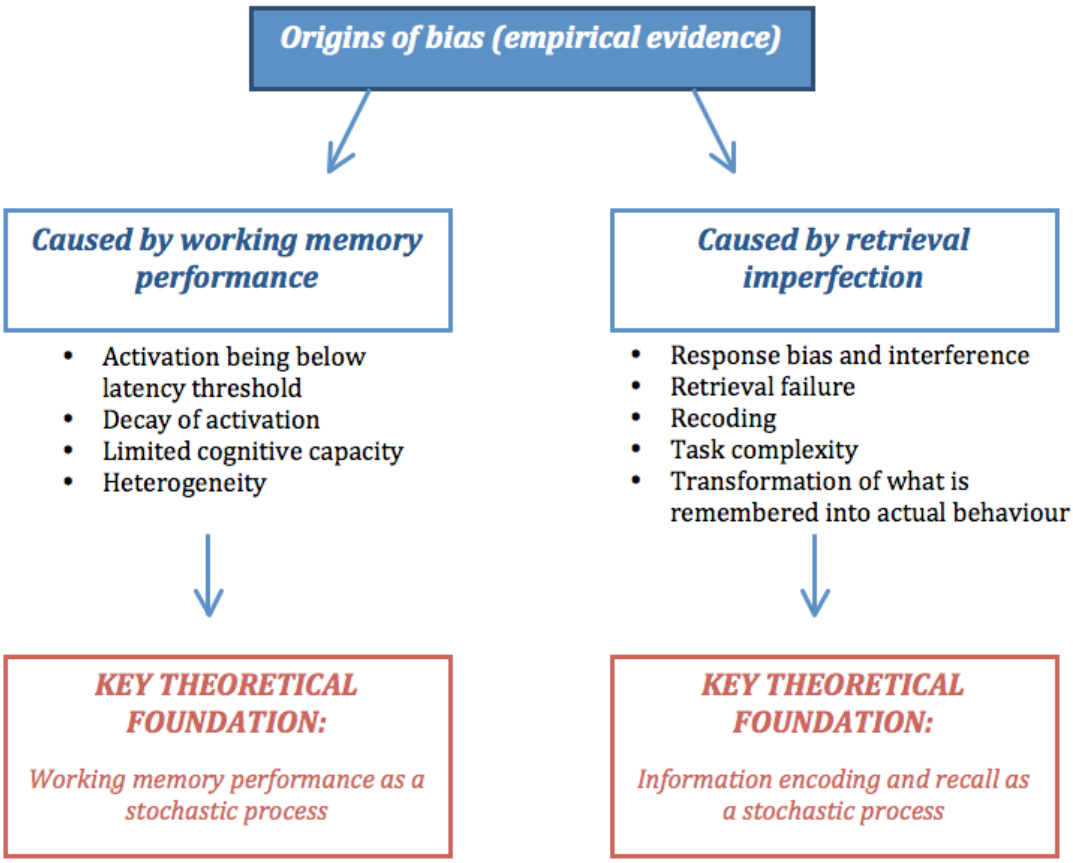
Put simply, latency of retrieval is the difference between the total level of activation A_i and the threshold τ, and A_i, moderates the chances of retrieval (Daily et al., 2001). Therefore, solving the equations of Daily, Lovett and Reder's (2001) model, it is possible to estimate retrieval propensity. Higher values of W_i (salience of declarative knowledge components of the network *i*) also imply a higher A_i, which may impact speed and ease of retrieval (Daily et al., 2001). Therefore, this model predicts that individuals with higher W_i are able to retrieve information more quickly and accurately, than individuals with lower W_i (Daily et al., 2001). This does not mean that the relationship between W_i and the accomplishment of a task given a certain amount of activated declarative knowledge components is linear: small changes in W_i linearly affect A_i, but changes in A_i have *exponential effects on retrieval* (Daily et al., 2001).

This last point leads to another important aspect linked to latency of retrieval: cognitive bias. Having a level of total activation A_i *below* a certain threshold τ causes bias in retrieval (Daily et al., 2001).

2.3.2.4 The origins of cognitive bias

As shown in Figure 4, there are two key recurring topics in the empirical research on the origins of cognitive bias: working memory performance and retrieval imperfection.

Figure 4 – Overview on the origins of cognitive bias



Cognitive bias caused by working memory performance

Working memory has a prominent influence on the biases affecting cognitive processes and latency of information retrieval (Daily et al., 2001). According to Reder (1988), the origins of cognitive bias are embedded in the nature and performance of working memory as follows:

(i) *Activation being below the latency threshold*: if the portion of declarative knowledge components activated in working memory is below a certain threshold, i.e. τ as per Daily, Lovett and Reder (2001), there is not enough activation spread through the memory network and the necessary information to complete the task may not be processed;

(ii) *Decay of activation*: over time, the level of activation will decrease, thus reducing and impairing working memory performance (Anderson, 1996);

(iii) *Limited cognitive capacity*: increasing the cognitive load on working memory is likely to cause errors in cognitive performance (Daily et al., 2001);

(iv) *Individual heterogeneity in working memory performance*: limitations in cognitive capacity vary from individual to individual and people tend to show different performance decrements (different response biases), as per Lovett, Reder and Lebiere (1997).

Cognitive bias caused by retrieval imperfection (reaction time or response bias)

Experiments on retrieval performance assess the time necessary for individuals to retrieve information under different circumstances, known as *reaction time* or *response bias*. The key finding that can be taken from this stream of research is that the broader the network of concepts related to a principal concept, the higher level of noise or interference, and thus the slower retrieval (Reder, 1988).

Lovett, Reder and Lebiere (1997) focused on assessing empirically the nature of noise or interference in response patterns. They found that *interference in retrieval* usually follows a Gaussian distribution (values clustered around the mean). The total level of activation that persists despite the existence of the interference can be incorporated into a 'performance metric' expressed as *retrieval propensity* or odds to retrieve a piece of information *i* from a network of associated concepts, with A_i being the level of activation and S being the noise:

$$\textbf{P(retrieve i)} = \frac{\left(e^{\frac{A_i}{S}}\right)}{\left(\sum_j e^{\frac{A_j}{S}}\right)} \qquad \textbf{Equation 18}$$

Conversely, the odds not to retrieve will be an explicit measure of *bias* (Lovett et al., 1997):

$$\textbf{1 – P(retrieve i)} \qquad \textbf{Equation 19}$$

What can be noted is that retrieval propensity is a *non-linear* function of the total activation A_i and thus of the heterogeneity parameter W_i (Lovett et al., 1997); this justifies the logical link between the two key sources of cognitive bias (working memory performance and retrieval imperfection) assumed in this dissertation (see Figure 5).

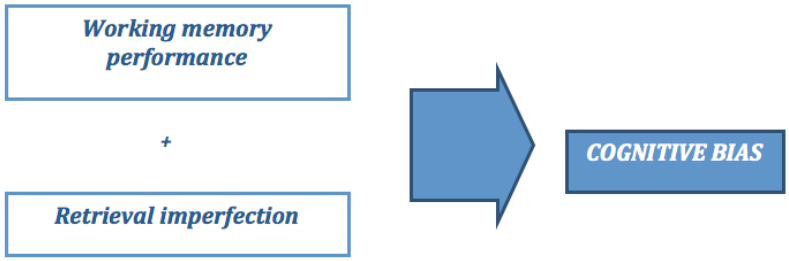
Other topics that can be found in the literature about cognitive bias being caused by retrieval imperfection in addition to retrieval failure and interference are: recoding, i.e. the modification of the original memory traces (Tulving and Thomson, 1973), and task complexity (Lynch and Srull, 1982). The experiments conducted on these two issues are relatively limited in number (in comparison to those on retrieval failure and interference) and are of limited relevance to this dissertation, thus they are not discussed.

Assumptions on cognitive bias for this dissertation

Cognitive bias linked to the performance of working memory is discussed in the ACT theory and its variations (see previous sections), whereas retrieval imperfection appears to be linked to the stochastic nature of retrieval. However, empirical studies on cognitive bias caused by retrieval imperfection do not include any explicit link to Anderson and Bower's (1973b) stochastic model of information encoding and recall. Although the first topic is more prominent in literature, the two topics appear to be logically linked, since working memory performance ultimately shapes retrieval chances. Bias in the information that is brought back to mind and used to accomplish a certain task not only depend on the memory control processes and their variation (stochastic process of information encoding and recall), but also on the 'volatility' of information processing as determined by working memory performance (activation being above threshold and individual heterogeneity).

Therefore, the origins of cognitive bias in this dissertation are assumed to be as follows (Figure 5):

Figure 5 – Origins of cognitive bias assumption (one layer)



Moreover, it is necessary to consider the transformation of the retrieved information into actual behaviour. This is a somewhat an additional layer of bias, in the sense that it links cognitive components and processes to actual behaviour, which is the ultimate and measurable outcome of human decision making. What is 'remembered' or 'brought back to mind' is a combination of the information encoded in memory and of its cognitive prominence; retrieval is the memory control process that completes the act of remembering (Tulving and Thomson, 1973).

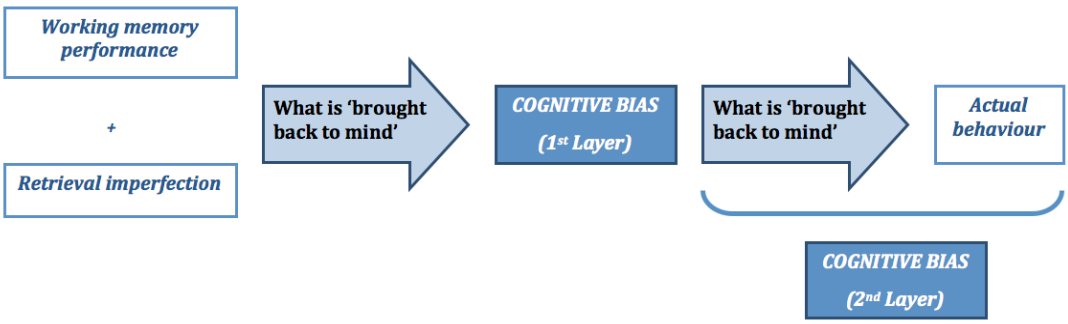
The transformation of remembered information into actual behaviour usually generates further cognitive bias, which can be assessed with extra-list cueing experiments, as per Tulving and Thomson (1973). Put simply, extra-list cueing experiments assess reaction time, i.e. time needed to recall and retrieve a formerly prompted target word with and without the presence of some retrieval cues. As such,

the effectiveness of a retrieval cue would be the difference in reaction time (Tulving and Thomson, 1973). As Tulving and Thomson (1973) point out:

> *'Some sort of a more complex interaction between stored information and certain features of the retrieval environment seems to be involved in converting a potential memory into conscious awareness of the original event and corresponding behavior.'*
>
> *(p. 353)*

Therefore, updating Figure 5 and assuming a further layer of cognitive bias, the assumptions on the origins of cognitive bias for this dissertation are (Figure 6):

Figure 6 – Origins of cognitive bias assumption (two layers)



These assumptions are particularly relevant, since drawing inferences about memory from behavioral observation will always be relative to some crucial assumptions about how memory is organized and how it works.

2.3.3 Assumptions about how memory works

The list of assumptions about memory implicitly adopted in this dissertation and relevant to brand equity is divided into *general* and *local* processing of information (drawn upon Collins and Loftus, 1975) as follows:

General assumptions:

- Concepts are stored in memory and organized as a network;
- The full meaning of a concept is represented by the whole network of linked concepts, accessed via a focal concept;
- Browsing through memory implies searching in parallel along these links, spreading activation through the network.

Local processing of information assumptions:

- Links have different strengths and elicit different levels of activation;
- There is a decreasing gradient of spreading of activation (inversely proportional to accessibility and strength of the links);
- Activation decays over time;
- There is a certain level of required activation for a concept to be considered active (threshold of activation); latency of retrieval mainly depends on the level of activation being above this threshold;
- When one concept evokes another (e.g. a semantic similarity present), the frequency of association of the two concepts is a measure of the strength of the link between them;
- Forming associations is a stochastic process, with regular empirical patterns;
- Working memory performance follows some stochastic patterns, which mainly embody heterogeneity amongst individuals;
- Retrieval chances are broadly underpinned by working memory performance;
- There are two different layers of cognitive bias: the first one regards the bias originated by working memory performance and retrieval imperfection; the second one regards the transformation of what is remembered into actual behavior.

The next chapter clarifies how these assumptions and the ones about how people choose discussed in § 2.2.5 apply to brand equity, i.e. how they apply to how brands are stored in memory, how brand information is processed in memory, how this information underpins consumer choice and the transformation of these aspects into some 'memory-based' performance metrics (brand salience metrics).

Before proceeding to this explanation, a definition of *latent variables* underpinning memory mechanics is provided. This is discussed because: (i) memory mechanics can be described and approximated with stochastic models, which typically imply the

existence of latent variables; and (ii) because the broad research issue investigated in this thesis will be approached by indirectly comparing purchase and retrieval propensities, which are shaped by latent variables.

2.3.4 Latent variables in memory

Bollen (2002) explains that there are three different definitions of latent variables in psychology and neuropsychology:

- *Non-formal definition*: latent variables are unobservable, thus impossible to measure;
- *Local independence definition*: latent variables create a relationship between observed variables;
- *Sample realization definition*: since the object of psychology and social sciences is to understand human behaviour by looking at properties or characteristics of individuals, latent variables are properties for which there is no sample realization, i.e. properties that cannot be inferred by analysis of the sample.

Clearly, all these three definitions are pertinent to memory mechanics and would translate as follows (own interpretation on the basis of Bollen's (2002) definitions):

- *Non-formal definition*: hypothetical constructs underpinning the probability of encoding and retrieving information in memory (impossible to measure and unobservable);
- *Local independence definition*: what determines the rate of extra-list cueing (e.g. free mental associations measurable empirically) or reaction time (response bias);
- *Sample realization definition*: properties of working memory such as individual heterogeneity in working memory, which cannot be inferred by analysis of the sample.

From a *theoretical perspective*, in this thesis, latent variables in memory are defined as a combination of these three definitions. This appears to be a reasonable further theoretical assumption about human memory, underlying what is assumed about how memory works.

Regarding the *empirical analysis*, however, latent variables in memory will be assessed indirectly by looking at the parameters of the stochastic model used as the research method (the Dirichlet theory). This approach is in line with the assessment

and interpretation of latent variables in buying behaviour literature and it is more intuitive than other research techniques such as Bayesian analysis, Structural Equation Modelling or Factor Analysis, which are typically used in pshychology and social sciences.

As last content in this chapter, an intuitive comparison (see Table 3) of the key terminology from the neuropsychology literature and the corresponding equivalent terms from brand equity literature is now presented.

2.4 Translation of neuropsychology terms into brand equity concepts

Brand equity literature has typically drawn on neuropsychology to explain how consumer knowledge is formed and organised, and to develop theoretical frameworks such as Keller's (1993; 2003) Customer Based Brand Equity model. However, the theoretical link between these two disciplines has become, over time, far less explicit. This chapter has reinforced this link, presenting a comprehensive overview of the theoretical insights that neuropsychology provides to brand equity conceptualisation and measurement.

Table 2 shows an intuitive comparison of the terms discussed so far and used in neuropsychology literature, and the corresponding brand equity concepts that will be defined and discussed in the next chapter (Chapter 3).

Table 3 – Comparison of neuropsychology and brand equity key terminology

Neuropsychology	**Brand equity**	
Declarative knowledge components	*Brand knowledge*	Pool of concepts linked to the brand in memory
Portion of declarative knowledge activated	*Brand awareness*	Cognitive prominence of the brand
Network of conceptual nodes	*Brand image*	Sum of brand associations
Concepts linked and networked	*Brand associations*	Concepts linked to the brand in memory
Retrieval - bringing back to mind concepts	*Brand retrieval*	Bringing a brand back to mind – cue based
Cues or external stimuli favouring retrieval	*External cues*	External stimuli favouring brand retrieval
Chance to retrieve a concept from LT memory	*Brand salience*	Chance to retrieve a brand from LT memory

2.5 Chapter summary

This chapter reviewed the key aspects of human choice and memory that are relevant to this thesis and to brand equity research. As such, it maintained a significant amount of theoretical contribution towards bridging two disciplines: neuropsychology and brand equity.

In regards to how people choose, this chapter included the description of a paradigm of human choice *à la* Tversky and Kahneman. This paradigm justifies the role and importance of cognitive components, different systems of cognition, different choice protocols and how the information available in the environment affects human choice.

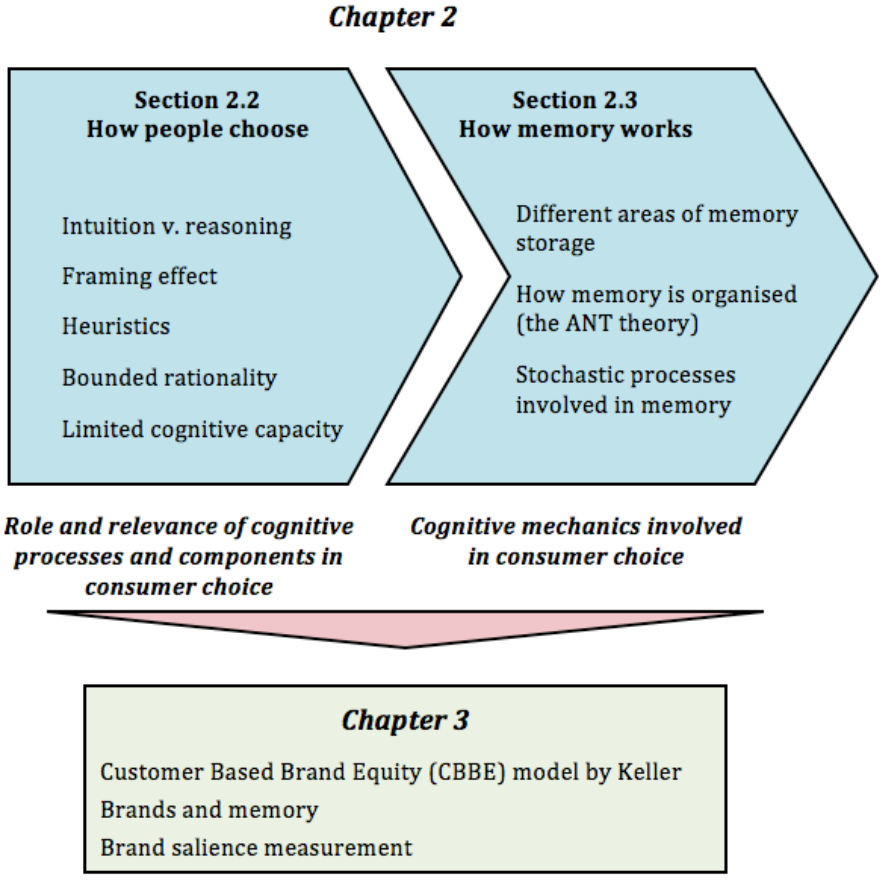
In regards to how memory works, this chapter included the description of the key empirical studies regarding how memory is organized and works from neuropsychology, with particular attention to the stochastic nature of human memory and the definition of latent variables in memory.

Chapter 3 – Brand equity

3.1 Chapter overview

Chapter 2 clarified how cognitive components and processes play a crucial role in human choice beyond mere utility maximization. It also clarified how memory works and the stochastic nature of the processes involved in memory. These theoretical foundations are the underlying assumptions that must hold in order to justify the measurement of brand equity components. Outlining and discussing these theoretical assumptions is part of the original contribution of this dissertation and creates a logical link between Chapter 2 and Chapter 3, as exemplified in Figure 7:

Figure 7 – Theoretical link between Chapter 2 and Chapter 3



Given these assumptions, this chapter presents the concept of brand equity and brand equity measurement, focusing on Keller's (1993, 2003) Customer Based Brand Equity (CBBE) framework. This framework postulates that the effectiveness of

marketing initiatives and the success of a brand largely depends on what information is memorised and processed by consumers and it is often used to 'justify' measurement of brand equity components (Keller, 2003). However, as Punj and Hillyer (2004) remark, brand equity research is not exempt from criticism, with many questioning its theoretical usefulness and whether analysis and measurement of brand equity components can extend what can be inferred about consumer behavior through the use of behavioral metrics (based on purchases). Besides the lack of a clear and *a priori* specification of which relevant assumptions about human choice and memory must hold to justify its measurement, brand equity research also lacks a record of empirical and generalisable patterns. A potential exception to this second limitation is presented in Romaniuk's (Forthcoming) approach, which applies a key empirical generalization in marketing, the Dirichlet model, to brand associations. This approach allows for the anticipation of patterns in brand associations and draws upon the Dirichlet theoretical benchmarks to track 'brand performance' over time. A pitfall, however, is that the theoretical justification for this research approach is not clear, and there is limited consideration of the stochastic models describing cognitive processes, which arise from empirical studies in neuropsychology.

Table 4 presents Erdem et al.'s (1999) summary of the most relevant conceptualizations of brand equity[6], based on two crucial distinctions: (i) focus on the *sources* (e.g. brand knowledge held by consumers in memory or consumer perceptions) or the *outcomes* of brand equity (e.g. brand attitudes and loyalty); and (ii) consideration of the components of brand equity (i.e. *component-based*) or the overall evaluation of the brand (i.e. *holistic*).

This dissertation will focus on the work of Keller, for the following reasons: (i) the explicit conceptual link between brand equity and consumer knowledge (thus cognitive components and processes involved in consumer choice); (ii) a systematic approach, which considers all possible dimensions of brand equity from a consumer perspective; (iii) its consideration of both sources and outcomes of brand equity; and (iv) the need to empirically assess drivers and underlying patterns in brand knowledge held by consumers indicated as a key future research direction.

On the basis of Keller's framework, the discussion covers the role of brand associations held by consumers, in affecting the cognitive processes that underpin consumer choice and a description of Romaniuk's (Forthcoming) approach for measuring brand associations.

[6] Reviewing all existing conceptualisations of brand equity is not pertinent to this dissertation.

Table 4 – Empirical attempts to measure brand equity

	Sources	***Outcomes***
Component based (Focusing on the components of brand equity)	Keller (1993, 1998, 2003) Aaker (1991, 1995, 1996)	Keller (1993, 1998)
Holistic (Focusing on the value of a brand)	Swain et al. (1993) Park and Srinivasan (1994) Kamakura and Russell (1991)	Simon and Sullivan (1993)

3.2 Brand equity from a consumer perspective

One of the key arguments that can be found in the literature to justify the conceptualisation of brand equity from a consumer perspective is that the information about products and brands held in memory affects consumer response to marketing initiatives (Cobb-Walgren et al., 1995):

> *'...it is important to understand how brand value is created in the memory of the consumer and how it translates into choice behaviour.'*
>
> *(p.26)*

Therefore, *anything* memorised and processed about brands in consumer memory is considered to be powerful and influential on consumer choice (Bettman, 1979). Farquhar (1989) discusses the key advantage of defining brand equity from a consumer perspective as the possibility to draw upon principles from cognitive and neuropsychology to explain how brand value is created (see also Crimmins, 1992, 1995).

Among the most relevant conceptualizations of brand equity from a consumer perspective, the best known is Keller's (1993, 2003) framework.

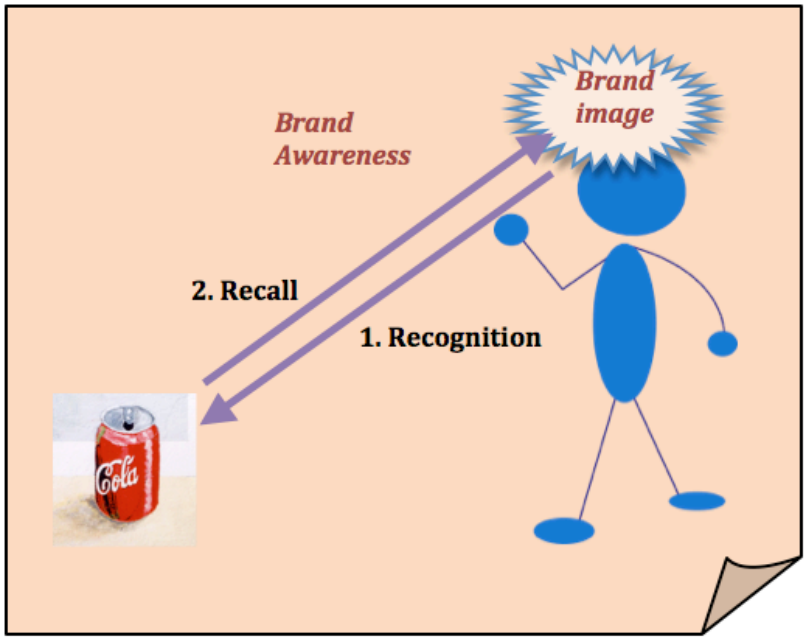
3.3 Keller's CBBE framework

Keller (1993, 2003) defines Customer-Based Brand Equity (CBBE) as the differential behavioral outcome attributable to consumers' *knowledge* about a brand, which includes feelings, perceptions, images and experiences related to a brand. As such, brand equity is derived from brand information held in memory and used heuristically by consumers to simplify choices (Biel, 1993, de Chernatony, 1991, Kirmani and Zeithaml, 1993). Consumers develop this information over time and it is in marketers' interest to nourish and control it (Na et al., 1999).

According to Keller (1993), CBBE components determine the success of a brand and its marketing strategy. The effectiveness of most product, pricing, retailing and communication strategies (thus, of any marketing decisions), ultimately resides in customers positively responding to such initiatives. Therefore, the knowledge that has been disseminated to the market about the brand, and that resides in consumers' minds, can be considered a valuable brand asset to marketers.

Keller (1993) identifies two key sub-components of consumer knowledge: (i) *brand awareness,* and (ii) *brand image* (see Figure 8).

Figure 8 – Brand knowledge components



Therefore, according to Keller (1993), *brand awareness* is the ability to actually recognize prior exposure to the brand and process it from memory whenever an

external stimulus is presented as a cue. The first process is called *brand recognition*, while the second one is called *brand recall*. *Brand image*, instead, is the other component of brand knowledge and works in synergy with brand awareness. In fact, recognition and recall of a brand (which are symptomatic of being aware of the brand) draw upon the image of a brand stored in memory, i.e. the collection of perceptions about a brand held by consumers in memory, referred to as *brand attribute associations*.

For both aspects of brand knowledge, the role of cognition is crucial. To recognize and recall a brand from memory, a cognitive effort is implied and can be conceptualized as 'browsing' through previously memorised information (Keller, 1993). The information browsed by consumers (brand image) is dependent on cognitive processes, for both the act of storing that information and subsequently accessing it.

Because of their role in the cognitive processing of brand information, most research based on Keller's framework places emphasis on *brand attribute associations*.

3.3.1 Memory and brands: the role of brand attributes

The stored information linked to a brand is commonly classified into three major categories: *attributes*, *benefits* and *attitudes* (Keller, 1993). Brand attributes are descriptive items embodying anything consumers may think about the brand or anything involved with its purchase and consumption (Keller, 2003). Benefits are related to the personal value consumers may attach to the brand attributes, whereas brand attitudes are consumers' global evaluations of a brand.

In the brand equity research stream, there has been increased interest in assessing brand attribute networks and the multidimensional network of brand associations, as the main determinant of brand knowledge and brand information processing from memory (Belén del Río et al., 2001). However, currently there is little agreement in the marketing literature about how to assess these networks of brand information effectively (Dobni and Zinkhan, 1990).

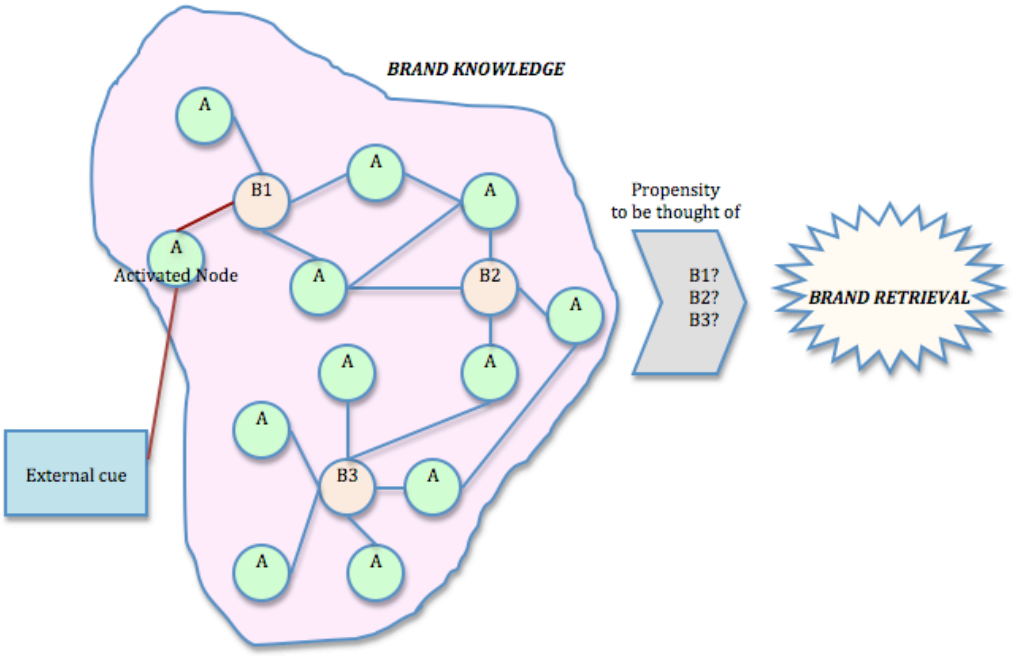
Nevertheless, brand attributes are the main sub-components of *brand knowledge* and brand information held in memory by consumers (Belén del Río et al., 2001). As such, brand attributes constitute the more permanent 'building blocks' of brand information stored in memory, and thus, are a key component of Customer Based Brand Equity (Keller, 1993, 2003).

Brand attributes play a crucial role in information processing. They often hold semantic similarities with external cues, thus functioning as connection points for

spreading activation within a brand memory structure. Therefore, brand attributes are used *heuristically* for the information processes preceding choice. Thus, in order to enhance the chances of being retrieved from memory, a brand should be linked to as many attributes as possible (Krishnan, 1996), a view entirely consitent with Anderson and Bower's (1973) ANT of memory.

In buying situations, consumers are exposed to numerous cues that can potentially activate any piece of information stored in memory (Anderson and Bower, 1979). However, for any individual brand linked to an activated brand attribute, the chance of being brought back to mind is probabilistic in nature (Holden and Lutz, 1992). Figure 9 schematically represents a simplified example of a common activation process leading towards brand retrieval as described above, with a network of brand attributes (*A*) and brands (*B1, B2 & B3*):

Figure 9 – Brand attributes and their role in brand retrieval



An external cue (e.g. a red cylindrical shape) is likely to activate an internal concept stored in a memory node (e.g. a brand attribute such as 'Comes in a red can') on the basis of some semantic similarities (e.g. 'red' and the geometric shape). Afterwards, the activation spreads through the network of information linked to the activated node (e.g. other brand attributes such as 'refreshing', as well as other brands). However, only when a certain threshold of activation is reached will retrieval from longer-term

memory take place and a focal concept such as a specific brand (e.g. Coke) will be brought back to mind from more permanent memory traces (long-term memory).

For each brand stored in memory (as discussed in Chapter 2) the access and processing through working memory is a stochastic process (Holden and Lutz, 1992) that underlines the chance to think of the brand in buying situations, as per Romaniuk and Sharp (2002, 2004). Factors affecting this propensity are: (i) the *activation strength* of the conceptual node where the brand is memorised (Knitsch and Young, 1984); (ii) the *association strength* between the brand node and the other activated nodes according to their semantic similarities (e.g. the category node) (Hutchinson, 1983); (iii) the *availability* of the retrieval cues (Nedungadi, 1990).

As a consequence, the probability of retrieving a brand from memory is mainly ruled by the set of attributes memorised about that brand. This is the first stage of the role performed by brand attributes: they determine the prominence of a brand from a cognitive perspective, thus the likelihood of a brand to be thought of in buying situations or *brand salience*, as per Romaniuk and Sharp (2002, 2004). As such, salience can be defined as a *stable long-run retrieval probability*, or as the cognitive prominence of a brand as determined by the level of activation of brand information in memory (Alba and Chattopadhyay, 1986).This definition of brand salience, however, implies that the level of salience will have to be accounted for as a result of cueing, hence the relevance of brand attributes (Alba and Chattopadhyay, 1986).

Once a brand has been brought back to mind, brand attributes continue to be processed in memory, providing the additional *screening criteria* used for evaluating purchase alternatives (Nedungadi, 1990).

Consumer choice usually involves two stages (Nedungadi, 1990): (i) *brand consideration* and (ii) *brand evaluation*. In both steps, the role and relevance of brand equity components is assumed to be crucial.

3.3.2 Brand attributes and consumer choice

According to Nedungadi (1990), choice sets are not fixed, but are rather dynamically affected by memory processes. Consumers typically approach choice in two stages, *consideration* and *evaluation*, both driven at root by brand attributes (Nedungadi, 1990). While the consideration stage helps a consumer identify purchase options, brand evaluation represents a step closer to choice, with brand attributes appraising the identified options and hence screening them. As a result, purchase probabilities may be strongly affected by specific brand attributes. This occurs on top of the influence of brand retrieval propensity, which is dependent on the cue and the

accessibility of the linked information (Alba and Chattopadhyay, 1985, Holden and Lutz, 1992, Tulving and Pearlstone, 1966). Therefore, the link between brand attributes stored in memory and purchase propensities is quite intuitive: the chance of purchasing a brand must be driven at root by the chance of retrieving that brand from memory. Returning to Figure 9, for example, assuming the activated nodes from memory are 'comes in a red can' and 'refreshing', these attributes will determine the chance to retrieve the brand 'Coca Cola' from memory and affect the information processing leading towards choice. For example, in front of a shelf with other cans of soft-drinks, the attribute 'comes in a red can' could help to identify the brand 'Coca Cola' among the various alternatives and perheaps presents a 'reason-to-buy' or a choice criteria.

This role of brand attributes during the initial cognitive processes and the subsequent steps leading towards choice confirms their relevance in determining a brand's performance, making them a key brand equity component (Keller, 2003).

Despite the relevance of brand attributes, little is known about the nature of the relationship between brand attributes, retrieval patterns and purchase propensity. So far, there has been surprisingly little examination of empirical patterns observed in brand attributes, other than those linking frequency of associations to brand usage. Before looking at these patterns, it is necessary to clarify how brand attributes are commonly measured empirically.

3.4 Measuring the role of brand attributes: brand image surveys

Given the role of brand attributes in the cognitive processes underpinning consumer choice, it is imperative to marketers to measure and monitor brand image. This is commonly achieved with brand image surveys. These surveys typically present to respondents a list of brand attributes and brands, and with different elicitation techniques they capture brand associations held by consumers. Three different elicitations techniques are widely used: (i) rating scales; (ii) ranking measures; and (iii) pick-any free brand-attribute association measures (Driesener and Romaniuk, 2006). Rating scales require respondents to indicate on a multi-point scale (often 5 or 7 points) the extent to which they think a brand is associated with a certain attribute. Ranking measures require the ordering of brands relative to competing brands from the strongest to the weakest association (meaning that two brands can not be awarded the same rank). The pick-any technique allows respondents to provide free brand-attribute associations, given a list of brands and a set of brand attributes (multiple, as well as no associations are possible) (Driesener and Romaniuk, 2006).

The common use of this data is to draw inferences on the empirical patterns affecting consumer knowledge (Driesener & Romaniuk, 2006) and to measure the effectiveness of brand positioning and advertising (Dillon, Maddern, Kirmani & Mukherjee, 2001; Myers, 2003; Romaniuk & Nicholls, 2006; Romaniuk & Sharp, 2002). These inferences tend to be made by identifying regularities in brand image data with a direct comparison against purchase data, i.e. buying behaviour trends (Barwise & Ehrenberg, 1985). The most relevant examples of this approach and the potential pitfalls that can arise are discussed in the following sections.

3.4.1 Empirical patterns in brand image data

The most relevant example of studies appraising the empirical patterns characterising brand image data by directly comparing them against purchase behaviour is the identification of a relationship between brand image and usage (Bird et al., 1970; Bird & Ehrenberg, 1970). This pattern explains that usage or direct experience with a brand feed into brand memory structures, thus the users of a brand typically provide a higher number of brand associations. An extension of these studies is the identification of the Double Jeopardy pattern in brand image data. In purchase behaviour (see Chapter 4), this pattern maintains that small brands (low market share) are 'hit' twice, with fewer people purchasing them slightly less often than bigger brands (Ehrenberg, 1972). Barwise and Ehrenberg (1985) demonstrated that this robust pattern also affects brand image data: small brands usually obtain far fewer brand associations. These findings have been extensively replicated (Bogomolova & Romaniuk, 2006; Bogomolova & Romaniuk, 2007).

Drawing on the existence of the brand usage bias and Double Jeopardy effect in brand image data allows for differentiation between two different types of brand attributes: namely evaluative and descriptive - see Hoek et al. (2000). Evaluative attributes are generated from consumer evaluations of a brand and therefore, the response patterns for these attributes tend to clearly differentiate between users and non-users of the brand. Descriptive attributes, on the other hand, often represent common characteristics for brands competing within the same product category and are likely to elicit associations by non-users of the brand. Drawing on the Double Jeopardy pattern in brand image data allows reducing response bias in brand image data: by isolating the associations with descriptive and evaluative brand attributes, it is possible to obtain a much more representative sample of brand associations for brands of different market share (see Chapter 6).

Other patterns characterising buying behaviour found to replicate in brand image data are: (i) the study by Dall'Olmo Riley et al. (1997) on the variability over time of

consumer attitudes and associations towards brands; and (ii) the consistently with the concentration of brand purchases as per Schmittlein, Cooper and Morrison (1993) identified in brand associations (just under the half of a brand's associations is typically provided by about 20% of 'heavy mentioners', i.e. those providing the highest number of brand associations; the remaining half is, instead, spread across 80% of 'light mentioners') discussed by Romaniuk & Sharp, 2008.

All the studies mentioned in this section represent a valuable approach towards appraising the role of brand attributes, yet they provide very little information about the nature of the relationship between brand attributes, retrieval patterns and purchase propensities. On the one hand, drawing an analogy between brand image and purchases provides a large number of empirical and theoretical benchmarks borrowed from buying behaviour. On the other hand, however, it shows a number of limitations relevant to this thesis that are discussed in the next section.

3.4.2 Potential pitfalls of brand image data

The first limitation that can be identified with brand image data is linked to a certain degree of 'abstractness'. A recent work by Teichert and Schöntag (2010) points out that the more controversial aspect in assessing patterns in consumer knowledge with brand image data is caused by the risk that they may not be fully representative of the underlying cognitive structures characterising memory described in Chapter 2 (i.e. stochastic processes, latent memory structures and cognitive bias). Most studies, in fact, analyse the relationship between brand associations and the consumer response to marketing actions expressed in attitudinal and behavioural outcomes (see for example Kamakura and Russell, 1991, Cobb-Walgren et al., 1995, Yoo et al., 2000). However, they do not explicitly consider: (i) the different dimensions and processes shaping the creation and use of this knowledge (Na et al., 1999; Punj and Hillyer, 2004); (ii) how brand attributes are used heuristically in the process leading to choice (Olson and Muderrisoglu, 1979, Bettman and Park, 1980); and most importantly (iii) the various steps involved in the processing of brand information by consumers.

Second, analysing brand image data with a simple comparison against purchase behaviour ignores the numerous interpretative insights that could be potentially obtained by looking at the empirical patterns affecting memory available in neuropsychology literature. Particularly, has discussed in Chapter 2, there is a large amount of empirical evidence to draw on in the areas of: (i) encoding of information and associations formation (Anderson & Bower, 1973a); (ii) information processing and activation (Anderson, 1976; Collins & Loftus, 1975; Reder, Park & Kieffaber, 2009; Tulving & Pearlstone, 1966); (iii) working memory performance (Anderson,

Reder & Lebiere, 1996); (iv) individual heterogeneity (Daily, Lovett & Reder, 2001; Lovett, Reder & Lebiere, 1997); (v) cognitive bias (Kamas, Reder & Ayers, 1996); (vi) information retrieval (Anderson et al., 1996; Anderson & Milson, 1989; Reder, 1988; Reder et al., 1997); and (vii) retrieval propensities (Anderson & Bower, 1973a).

Third, there are only very few studies that have attempted to identify exceptions or deviations from the patterns characterising brand image data. A partial exception is Hoek et al.'s (2000) research, which separates descriptive and evaluative attributes. Nevertheless, these deviations were identified at the level of single brand attributes, rather than at the level of the overall brand image construct (or holistic brand image). This limitation is relevant because without knowing if discrepancies exist at all and especially if these are consistent with purchases, inferences become rather speculative.

The overall consequence of these limitations is fairly simple, yet so far surprisingly overlooked by academia and practitioners. The insights drawn from the empirical analysis of brand image data might not ne suitable to examine the nature of the relationship between brand attributes, retrieval patterns and purchase propensities.

Since the purpose of this thesis is to explore the link between brand associations and purchases, it is crucial to select a method to appraise the empirical patterns in brand image that can address at least some of these pitfalls. The method selected and discussed next is Romaniuk's (Forthcoming) approach to measuring and modeling brand associations.

3.4.3 Romaniuk's method

Romaniuk's (Forthcoming) approach to measuring and modelling brand associations is based on the count of brand associations captured in brand image surveys, assumed to be representative of the underlying retrieval propensities. Put simply, the count of brand associations obtained by a brand in a pick-any brand image survey is implemented in this method as a proxy for the likelihood that the brand will be thought of, i.e. its propensity to be retrieved from long-term memory or salience. As such, this method enables calculating a set of brand performance metrics (brand salience metrics, see Chapter 6) that can be modelled with the same stochastic theory used to describe purchase propensities: the Dirichlet model. These metrics can be analysed to draw inferences on the underlying structures of brand associations and the empirical patterns characterising cognitive processing of brand information.

Therefore, this method seems to be tailored to help examining the nature of the relationship between brand attributes, retrieval patterns and purchase propensities for

the following reasons. First, in line with the existing methods analyzing empirical patterns in brand image, it is conceptually based on a striking similarity with purchase behavior. As such, the possibility to draw on a number of theoretical and empirical benchmarks is guaranteed. Second, with regards to the pitfalls described so far linked to the use of brand image data to assess empirical patterns affecting consumer knowledge, this method can potentially cater for some. Most importantly, it is conceptually based on the assumption that memory is stochastic in nature. It also simplifies, yet takes into consideration how brand knowledge is likely to be processed in memory in purchase situations, by generating metrics that are representative of a full range of retrieval propensities. Therefore, it is suitable to analyse empirically the link between brand knowledge and consumer response to marketing actions.

This method, however, does not include a more specific and explicit link with Anderson and Bower's (1973) original stochastic model of memory associations or with the key stochastic models of memory mechanics discussed in Chapter 2. As such, a possible limitation is the limited consideration of the potential differences between the underlying structures in purchases and memory (e.g. different stochastic processes, latent variables and biases). These potential differences would directly reflect on the nature of the link between purchases and brand associations, as they would result in a substantial separation between purchase and retrieval propensities (see Chapter 5).

Nevertheless, because of the number of pitfalls in brand equity measurement catered for and because it includes the use of a rich stochastic theory, Romaniuk's (Forthcoming) method for measuring brand memory structures represents a suitable research approach for this dissertation. Therefore, it will be used to analyse brand image data, to assess the underlying characteristics of brand associations and to examine their link with purchases.

3.5 Chapter summary

This chapter presented a comprehensive overview of brand equity components whilst drawing upon Keller's CBBE framework. This included an explanation of the key terminology and processes involved in the formation and use of consumer knowledge and how this is theorised to underpin consumer choice. This is in line with the key claim of brand equity from a consumer perspective, according to which the value of a brand largely depends on the information held in memory by consumers.

However, despite: (i) the large number of studies acknowledging the role of memory structures and processes in underpinning consumer response to marketing initiative (hence generating value for brands); and (ii) the empirical patterns characterising

brand image data, there are several issues that can be identified in the translation of brand image data into empirically-validated measures of brand equity components.

A notable exception is represented by Romaniuk's (Forthcoming) approach for transforming the frequency of brand associations obtained from brand image data into a set of metrics. Among the strengths of this method, there is the application of a stochastic model from buying behaviour, the Dirichlet theory. This leads intuitively to the following chapter, which presents an overview of this model.

Chapter 4 – Predicting buyer behaviour and consumer choice

4.1 Chapter overview

The previous chapters have covered some important theoretical 'building blocks' fundamental to brand equity conceptualisation and to examining its link with purchases. These were: (i) a clarification of the key underlying assumptions about how people choose and how memory works; and (ii) a clarification of the key characteristics of the underlying structures of memory (i.e. stochastic processes, latent variables and biases). These aspects have then been linked explicitly to brand equity research. In particular, the previous chapter included an explanation of: (i) the key components of brand equity conceptualisation, given Keller's (1993; 2003) Customer Based Brand Equity model; and most importantly (ii) the typical approaches used to draw inferences on how consumer knowledge is processed. Among these approaches, Romaniuk's (Forthcoming) method seems more robust and is thus selected for this thesis. The key advantage of this method is that it includes the use of the Dirichlet model to explain the underlying characteristics of brand associations and to facilitate analyse the link with purchases.

This chapter is focused on describing the Dirichlet model and how it is commonly applied in purchase behaviour. The purpose is to clarify the theoretical and empirical benchmarks that characterise this model that will be implemented to examine the nature of the relationship between brand attributes, retrieval patterns and purchase propensities. The description includes covering the most relevant underlying assumptions of the model, which are: (i) the nature of the market where the model applies and holds; (ii) the statistical distributions and processes constituting the model and their parameters; (iii) the key inputs and outputs of the model, including a description of behavioural brand performance metrics such as market share, penetration and purchase frequency; and (iv) the Double Jeopardy pattern, a key market regularity accounted for by the Dirichlet model.

The validity of using a stochastic theory to describe the underlying characteristics of purchase behaviour can be summarised as follows. Stochastic models such as the Dirichlet are configured as probabilistic laws. As such, they consider purchases as the result of a stochastic process. In that, the plausible notion of heterogeneity (consumers are different and behave differently in response of influences such as mix variables) is considered endogenous to this process, whereas all other factors are considered

exogenous (Wagner and Taudes, 1987). Because they describe purchase behaviour in this way, stochastic models tend to be parsimonious, easy to estimate, and usually fit and predict the data well (Gupta, 1991). Therefore, their primary use is as a measurement tools crucial to understand generalisable regularities and statistical properties of purchase behaviour relevant to marketing strategies (Gupta, 1991).

4.2 A stochastic model of buying behaviour: the NBD-Dirichlet Model

The NBD-Dirichlet theory of buying behaviour (hereafter the Dirichlet) models the purchase timing of the product class and brand choices (Jeuland et al., 1980, Goodhardt et al., 1984). Essentially, the model describes *how* frequently bought branded goods are purchased under the general assumption of markets being *stationary* in the medium-long term (Goodhardt et al., 1984). Therefore, in this type of market we usually observe little variation in individual brand sales levels and no market partitioning or segmentation. Ehrenberg (1988) justifies this assumption by claiming that typically, markets are broadly stable, despite being fairly irregular at the individual buyer level. In fact, most Fast Moving Consumer Goods (FMCG) markets show similar repeat purchase patterns, with only minor deviations that generally fail to persist over multiple analysis periods (Ehrenberg and Uncles, 1999). This means that in these markets there are a number of consumer characteristics that can be regularly observed in purchase behaviour. For example, the observed repeat-buying rates are relatively low and similar for all brands. This implies that brands do not continuously 'lose' or 'acquire' customers, but rather people usually buy quite infrequently. Also, consumers tend to develop small portfolios of brands among which they split their loyalty, selecting brands as if randomly and regardless of the prior purchase (the so called 'zero-order' effect). Moreover, individual preferences are largely heterogeneous, with consumers differing greatly in their choices.

As a result, there are fixed on-going *as-if random* propensities of individual purchases to take place. These propensities are highly predictable from standard statistical distributions, which take a similar shape from brand to brand (Bound, 2009). These statistical distributions assume the role of probabilistic laws and have converged in an empirically based stochastic theory (Bass et al., 1976) that is discussed over three decades of marketing literature, the Dirichlet model.

The Dirichlet model is presented in the form of a set of probability density functions that capture buying behaviour patterns (Rungie and Goodhardt, 2004). The model predicts how many purchases each consumer will make in a given period and which brands will be chosen. The model's main output is a set of theoretical brand

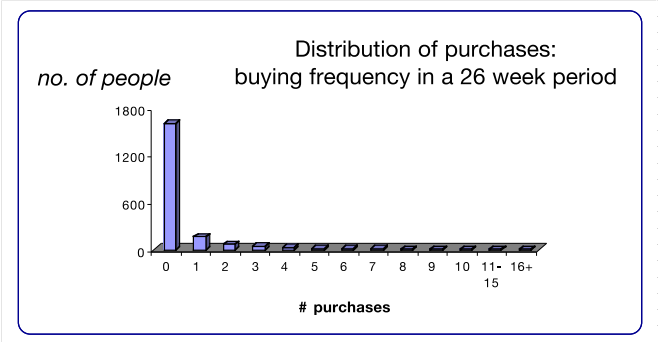
performance metrics, such as market share, penetration, average purchase frequency and so forth, enabling one to anticipate future buying behaviour and compare current with expected behaviour.

A detailed description of the two main components of buying behaviour as modelled by the Dirichlet (purchase incidence and brand choice) and their respective distributions now follows. The mathematics of the model are also included, following closely Driesener's (2005) doctoral dissertation on the Dirichlet model's parameters.

4.2.1 Modelling purchase incidence

In early empirical work, purchase incidence models for frequently purchased goods focused on modelling subsequent individual purchases as a *poisson process* with an exponential distribution of the inter-purchase intervals (i.e. purchase pace being mostly infrequent and irregular) (Banerjee and Bhattacharyya, 1976). These models also accounted for population heterogeneity (i.e. consumers are different with respect to their mean rate of product class purchase), allowing the shape parameter of the exponential distribution to follow a *gamma distribution* (Banerjee and Bhattacharyya, 1976). With the combination of these two components (the poisson process and the gamma distribution) it is possible to estimate the probability of making a certain number of purchases over a period of time, and this probability follows a *Negative Binomial Distribution* (NBD) (see Figure 10).

Figure 10 – typical shape of a Negative Binomial Distribution



Schmittlein, Bemmaor and Morrison (1985) in a technical note explain that:

> *"…consumers making poisson purchases in a product category with the individual purchasing rates being distributed gamma across the population of consumer…lead to an observable histogram of purchases across consumers*

which has a Negative Binomial Distribution over any fixed period of observation"

(p. 255)

The basic idea underpinning the model is quite simple: consumers buy infrequently (most are *non-buyers* or *light-buyers* of the product class) and independently of previous purchases (zero-order effect). Yet, under the general assumption of linear conditional expectations, at aggregate level future purchase probabilities can be estimated on the basis of the number of observed past purchases (Schmittlein et al., 1985).

Mathematically, a NBD function can be simplified as follows.

The probability density function of the poisson process is:

$$f_{x_i}(r) = \frac{e^{-x} x_i^r}{r!} \qquad \textbf{Equation 20}$$

where x_i is the constant mean purchase rate for an individual i, and $r = 0,1,2,...,\infty$ (Driesener, 2005, Johnson et al., 1993). x_i are unobservable variables gamma distributed across a population of shoppers (Driesener, 2005, Goodhardt et al., 1984). The gamma distribution is defined by two parameters: the scale parameter β (A in Dirichlet modelling) and the shape parameter α (K in Dirichlet modelling). The gamma's third parameter ,γ, is not included in the Dirichlet theory (Driesener, 2005).

The probability density function of the gamma distribution is:

$$f_{A,K}(x_i) = \frac{e^{-\frac{x_i}{A}} x_i^{K-1}}{A^K \Gamma(K)} \qquad \textbf{Equation 21}$$

with A, K and x_i assumed greater than 0 and Γ being the gamma density function (Driesener, 2005, Chatfield and Goodhardt, 1970, Chatfield and Goodhardt, 1975, Goodhardt et al., 1984, Johnson et al., 1994).

If the expected values of the individual shoppers' poisson processes change according to the parameters A and K, the resulting stochastic process is a Negative Binomial Distribution (NBD) (Driesener, 2005, Goodhardt et al., 1984, Johnson et al., 1993).

For $r = 0,1,2,...,\infty$ purchases, the probability density function of the NBD is:

$$f_{A,K}(r) = \left(\frac{A}{1+A}\right)^r \frac{\Gamma(K+r)}{r!\Gamma(K)}(1+A) \qquad \textbf{Equation 22}$$

with Γ being the gamma density function (Driesener, 2005, Ehrenberg, 1959, Chatfield and Goodhardt, 1975, Goodhardt et al., 1984).

This model of consumer purchase incidence was formally introduced by Ehrenberg (1959) and further developed by Goodhardt and Ehrenberg (1967), Chatfield and Goodhardt (1975), Morrison and Schmittlein (1981) and Goodhardt et al. (1984).

Jarvis, Habel and Rungie (2003) support the robustness of the model in providing benchmarks of heterogeneity, market penetration predictions and some valuable inferences about category partitioning.

Following the original empirical works on the NBD, consumer behaviour literature focussed on trying to assess whether the same model could be generalised to a multi-brand choice and a joint distribution of purchase frequencies for different brands of a given product category (Chatfield and Goodhardt, 1975). This is the other component of the Dirichlet theory, modelling brand choice.

4.2.2 Modelling brand choice

A crucial aspect of buying behaviour patterns is brand choice. There are a multitude of approaches and stochastic models proposed to study brand choice in consumer behaviour literature (Gupta, 1991). The first studies were mainly focused on Bernoulli models and did not account for population heterogeneity (Gupta, 1991). The Dirichlet model, however, does account for heterogeneity.

At any buying occasion, each brand has a probability of being chosen, which is independent from the other brands' probability of being chosen and different for each consumer. A *multivariate beta distribution* (also known as a Dirichlet distribution) can model this aspect of consumer choice (Ehrenberg and Uncles, 1999). Moreover, consumers are typically polygamously loyal, that is, they buy several brands in a product category and develop small *repertoires* (Ehrenberg and Uncles, 1995). These are termed repertoire markets. The allocation of consumer choice across g brands within a specific product category can be described by a *multinomial distribution* with a probability vector $P = \{P_1,P_2,...,P_g\}$ (Driesener, 2005). The multinomial distribution models n independent Bernoulli trials distributed across g mutually exclusive events E_j (brand choices in this instance) that have a probability P_j $(j=1, 2, 3,...,g)$ to take place (Driesener, 2005).

The multinomial probability density function is (Driesener, 2005, Johnson et al., 1994):

$$f_{p_1,p_2,\ldots,p_g}(r_1,\ldots,r_g) = r_\cdot! \prod_{j=1}^{g} \frac{p_j^{r_j}}{r_j!} \qquad \textit{Equation 23}$$

In this, the parameters (P_j) are distributed Dirichlet over the population, accounting for heterogeneity in consumer choice probabilities across shoppers (Driesener, 2005). The parameters of the Dirichlet distribution are α_j *(j=1, 2, 3,...,g)* (non-zero, positive real numbers) (Driesener, 2005).

The Dirichlet probability density function is:

$$f\alpha_1,\alpha_2,\ldots,\alpha_g(P_1,\ldots,P_g) = \frac{\Gamma(S)P_g^{\alpha_g-1}}{\prod_{j=1}^{g}\Gamma(\alpha_j)} \qquad \textit{Equation 24}$$

with $P_j \geq 0$, $\sum_{j=1}^{g} P_j = 1$, $S = \sum \alpha_j$ and Γ being the gamma density function (Driesener, 2005, Chatfield and Goodhardt, 1975, Goodhardt et al., 1984).

Allowing the multinomial distribution to change according to its parameters α_j *(j=1, 2, 3,...,g)* results in a Dirichlet multinomial distribution (DMD) (Driesener, 2005, Goodhardt et al., 1984, Johnson et al., 1997).

The probability density function of the DMD is:

$$f\alpha_1,\alpha_2,\ldots,\alpha_g(r_1,\ldots,r_g \mid r_1+\ldots+r_g = r_\cdot) = \frac{r_\cdot!\Gamma(S)}{\Gamma(S+r_\cdot)}\prod_{j=1}^{g}\frac{\Gamma(\alpha_j+r_j)}{r_j!\Gamma(\alpha_j)} \qquad \textit{Equation 25}$$

where $r_j \geq 0$ is the count of the purchase occasions for g brands, $r_\cdot = \sum_{j=1}^{g} r_j$ is the rate at which the population has purchased the category and Γ is the gamma density function (Driesener, 2005, Johnson et al., 1997, Rungie, 2000).

4.2.3 Latent selection rates and the model's parameters

The parameters of the distributions involved in a stochastic model like the Dirichlet are not simple *ad-hoc* numerical coefficients, but rather embody specific aspects of the described behaviour identified empirically (Goodhardt et al., 1984).

A comprehensive explanation and analysis of the Dirichlet parameters can be found in Driesener's (2005) doctoral dissertation. From a theoretical perspective, the Dirichlet parameters (except *A* and *M*) are the shape parameters of the gamma distribution underpinning the Dirichlet model (NBD and DMD). Therefore, a correct

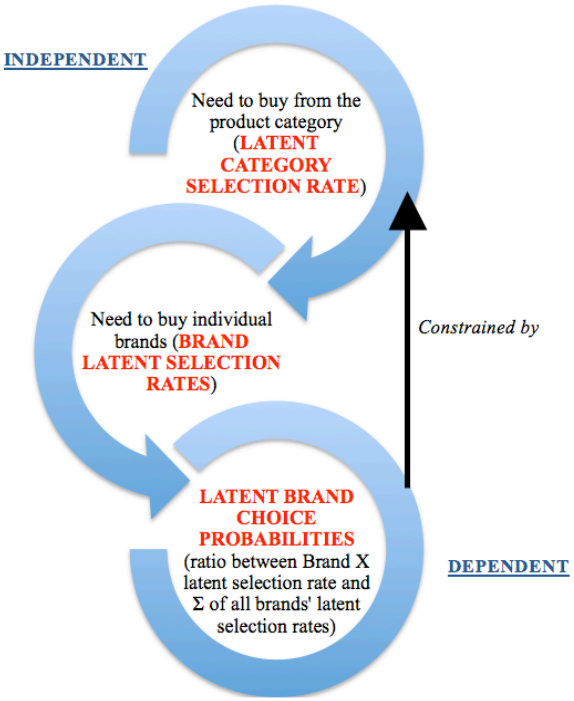
understanding of the parameters requires the consideration of the *latent selection rates* underpinning the gamma distribution (Driesener, 2005).

As explained by Driesener, (2005), latent selection rates are non-observable random variables, which are gamma distributed over a population of shoppers. The poisson and multinomial stochastic processes included in the Dirichlet theory actualise these latent variables into discrete ones, i.e. observed behaviour or actual purchases. As such, latent selection rates can be considered as a valid proxy of the individuals' propensity to respond to marketing strategies and of individual category needs.

Being unobservable, however, the analysis of these latent variables can only be inferred by analysing the values of the parameters of the distributions included in the Dirichlet model.

For every product category, individual consumers will have: (i) an independent *latent selection rate* for the product category itself (need to buy from that category); and (ii) a *latent brand selection rate* for each brand. The latent category selection rate acts as a 'constraint' (in terms of volume or rate of purchase) to *latent brand choice probabilities*, which are, for each brand, the ratio between the brand latent selection rates and the sum of all brands' latent selection rates (Driesener, 2005). Figure 11 shows the logical link between latent selection rates and brand choice probabilities:

Figure 11 – Link between latent selection rates and brand choice probabilities



This can be also explained with the following equations.

Let the latent selection rates of the g individual brands in a category for a population of n shoppers be y_{ij} $(j=1, 2, 3,..., g; i=1, 2, 3,...,n)$. (positive, non-zero and fixed) (Driesener, 2005, Goodhardt and Chatfield, 1973, Chatfield and Goodhardt, 1975, Goodhardt et al., 1984). Y_j will be the distribution of the latent selection rates for the population of shoppers for a specific brand j.

w_i is defined as follows (central block in Figure 11) (Driesener, 2005):

$$w_i = \sum_{j=1}^{g} y_{ij} \qquad \textbf{Equation 26}$$

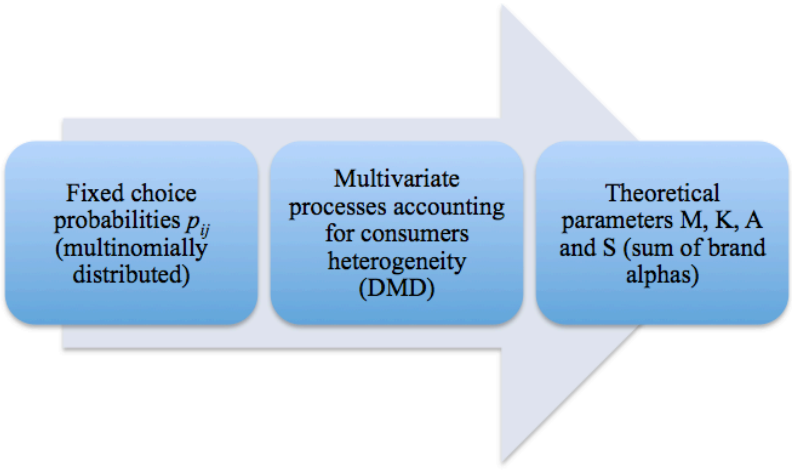
It it important to remember that w_i is different to the latent selection rates for the category and that it determines individual brands' choice propensities as follows (bottom circle in Figure 11) (Driesener, 2005):

$$p_{ij} = \frac{y_{ij}}{w_{ij}} \qquad \textbf{Equation 27}$$

with p_{ij} being the shopper i's probability of purchasing brand j, which is dependent of the latent category selection rate.

Latent brand choice probabilities are also unobservable, but result in the observable purchase rates by the stochastic process described by the DMD, hence the possibility of understanding latency in purchases by looking at the parameters of the model's distributions (see Figure 12).

Figure 12 –Link between latent brand choice probabilities and the parameters



In regards to the category latent selection rate, its further interpretation is that of being a proxy for individual shoppers unobservable desired rate of category purchasing or product category attractiveness (Driesener, 2005, p. 64).

This brief excursus on the theory of latent selection rates has been necessary to justify how relevant the Dirichlet parameters are to understanding trends and how latent variables shape purchase propensities, which underpin buying behaviour.

The parameters of the Dirichlet model are usually used to calculate a set of theoretical Brand Performance Metrics (BPMs) that describe the size and the level of loyalty of individual brands.

4.3 Brand Performance Metrics

Marketers commonly use brand performance metrics to assess a brand's market size and loyalty levels. These metrics are also used to track the performance of a brand in the market. The key brand performance metrics are (adapted from Ehrenberg et al., 2004):

- **Market share** (%) is the proportion of a market (in terms of sales) allocated to each brand.
- **Penetration** (%) is the proportion of a population of potential brand customers that have bought a brand *at least once*, i.e. the brand's buyers. Over time the measure increases (but not lineraly), because in the long term probabilities to buy a brand at least once grow due to the increasing number of purchase occasions.
- **Average Purchase Frequency** is the purchase rate averaged by the number of a brand's buyers, i.e. the average number of times a brand has been bought by its buyers. It is a measure of brand loyalty and is usually similar for all the brands of the category in a repertoire market, subject to the Double Jeopardy effect (see next section for an explanation of this).
- **Share of Category Requirements** (SCR)(%) is a measure of 'split loyalty': it measures the portion of category purchases buyers of a brand have 'devoted' to that brand.
- **Sole loyal buyers** (%) measures the portion of a brand's buyers purchasing that brand exclusively.

In a Dirichlet-type market (stationary and unpartitioned), we normally observe a large number of regularities or patterns in how brands compete, and in loyalty and brand growth. Typical regularities, for example, are (Uncles et al., 1995, Ehrenberg and

Uncles, 1999): (i) average purchase frequencies being very similar from brand to brand; (ii) most customers tend to be multi-brand buyers (they buy from a repertoire of brands) with steady split loyalty across the category; (iii) repeat-buying levels (proportion of individuals buying more than once in a period) tend to be largely steady over time; and (iv) the size of a brand will determine its level of loyalty, known as Double Jeopardy pattern.

As a comprehensive theory of buying behaviour, the Dirichlet model incorporates these well-known market regularities. The most relevant one to this dissertation is the Double Jeopardy pattern, which is now discussed in detail.

4.4 The Double Jeopardy pattern

The Double Jeopardy pattern first appeared in buying behaviour empirical studies as an application of McPhee's (1963) theory to buying behaviour data, as proposed by Ehrenberg (1972, 1988). The basic idea of the Double Jeopardy pattern is that there is a statistical effect favouring 'bigger' brands, i.e. brands with higher market share (Ehrenberg, 1972). Due to asymmetries in popularity and distribution, bigger brands usually show a higher level of market penetration (more buyers) and *slightly* higher levels of loyalty (they are also bought slightly more often). Conversely, smaller brands are penalised twice, with less buyers and *slightly* lower loyalty (Ehrenberg, 1972), hence the term 'Double Jeopardy'.

Stochastic models of buying behaviour should include and predict the presence and direction of Double Jeopardy. This is the case in the Dirichlet, which, when used, shows the existence of the Double Jeopardy pattern in traditional brand performance metrics (Bhattacharya, 1997). The theoretical brand performance metrics obtained from the Dirichlet model (i.e. expected behaviour) can be matched against the observed value, which is obtainable from panel data. A direct comparison *à la* Bass and Wind (1995), that implies benchmarking observed brand performance metrics against their theoretical correspondent, can highlight typical deviations from the Double Jeopardy pattern.

There are four typical deviations from the Double Jeopardy pattern that are usually identified by the literature: (i) *niche brands*, (ii) *change-of-pace brands*, (iii) *private labels*, and (iv) *excess behavioural loyalty* for large brands. *Niche brands* usually cater for consumers' special requirements and are positioned to serve a small base of highly loyal customers (i.e. low penetration, but high purchase frequency) (Kahn et al., 1988). *Change-of-pace brands*, on the other hand, meet consumers' variety-seeking behaviour, being purchased relatively infrequently (i.e. low purchase frequency) (Kahn et al., 1988). Retailers, wholesalers and distributors can create

private labels, which are sold exclusively in their stores (Bushman, 1993, De Wulf et al., 2005). Bound and Ehrenberg (1997) and Uncles and Ellis (1989) demonstrated that private labels usually perform in line with the Dirichlet model's norms. Being available only in specific stores, however, individual private labels can experience unusual loyalty patterns (Scriven and Bound, 2004). Pare, Dawes and Driesener (2006) and Pare and Dawes (2007) provided evidence that among deviating private labels, the majority showed excess loyalty (i.e. *within chain*, private labels show low penetration and higher than expected purchase frequency). Ehrenberg, Goodhart and Barwise (1990) observed that some market leaders obtained higher-than-expected levels of repeat buying (given the theoretical benchmarks of the Dirichlet model), resulting in a loyalty premium (i.e. high penetration and higher than expected purchase frequency). Fader and Schmittlein (1993) found that causes of *excess behavioural loyalty* were unlikely to be endogenous factors (e.g. advertising, pricing or promotion activities), but rather systematic deviations from the Dirichlet model's underlying assumptions (e.g. segmentation and partitioning) or brand availability (extensive distribution strategies and strong shelf presence).

The Double Jeopardy pattern has also been observed to hold in brand image data**.** Barwise and Ehrenberg, (1985) showed that smaller brands (low penetration) usually result in fewer brand associations than larger brands, even among brand users. Barwise and Ehrenberg's (1985) findings were robustly supported (Bogomolova and Romaniuk, 2007, Bogomolova and Romaniuk, 2006) when measuring image data with a 'pick-any' approach, i.e. presenting respondents with a list of brand attributes and brands and allowing for multiple free brand associations (Driesener and Romaniuk, 2001, Driesener and Romaniuk, 2006) as per Romaniuk's (Forthcoming) method.

4.5 Chapter summary

This chapter presented an overview of the Dirichlet theory of buying behaviour, focusing on the various sub-components of the model and the key theoretical benchmarks offered by the model (parameters and metrics).

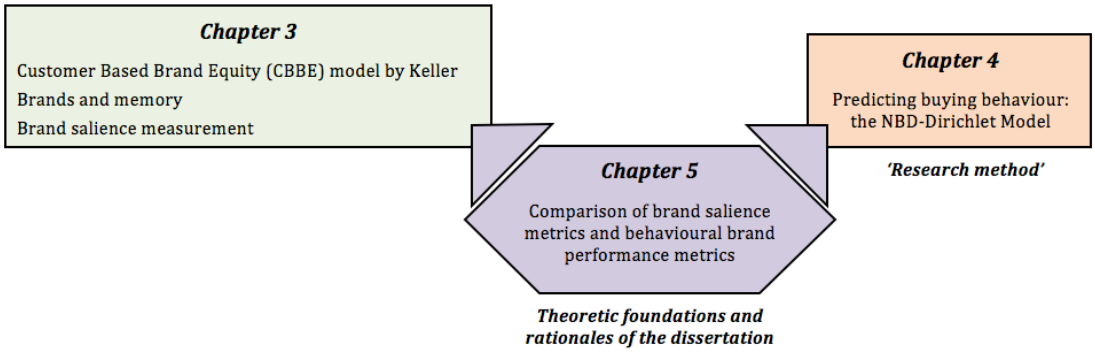
This topic has been covered because the benchmarks offered by this stochastic model will be applied in this dissertation for the direct comparison between memory and consumer behaviour, which is necessary in answering the broad research question that is introduced in the following chapter.

Chapter 5 – Testing competing views

5.1 Chapter overview

This chapter (see Figure 13) presents the logical link between the two key areas of marketing literature reviewed, brand equity and buying behavior. This link is imperative, as it leads towards the broad research question and discussion of the expectations of the research outcomes and it is discussed in three sections.

Figure 13 – Logical link between Chapters 3, 4 and 5



§ 5.2 includes: (i) a description of the comprehensive paradigm of consumer choice that is adopted in this dissertation, which includes the relevant evidence on the stochastic nature of memory from neuropsychology literature; (ii) a mathematical justification of why the Dirichlet model is a suitable approximation of memory mechanics; and (iii) a clarification of the reason why the Dirichlet theory of purchase behavior is a suitable research approach.

Then, **§ 5.3** introduces and describes the broad research question that is investigated in this dissertation. It also clarifies the potential research issues identified; in particular the differences between purchase propensities and brand salience (as propensity to retrieve a brand from memory). These include a discussion of the potential differences in terms of the stochastic processes, latent variables and bias between purchases and memory.

Lastly, the discussion in § 5.3 sets out the necessary arguments to outline in **§ 5.4** the two key research propositions of this thesis and the three competing views on the possible research outcome.

5.2 A comprehensive paradigm of consumer choice

One of the key theoretical limitations of brand equity as discussed in the previous chapters was the absence of a rigorous and upfront clarification of the key underlying assumed paradigm of consumer choice that applies.

Therefore, in this thesis, the relevant assumptions about how people choose and how memory is organized and works presented in Chapter 2 will serve two purposes: (i) they represent part of the *theoretical contribution* of this thesis, addressing the gap identified and discussed in the brand equity literature; and (ii) they represent a set of underlying assumptions for the analytical approach presented in this thesis.

The stochastic theories of memory (discussed in Chapter 2) will be implemented in two ways: (i) for a deductive comparison of traditional stochastic theories of memory with a 'competing' stochastic model, the Dirichlet, to understand if this model can be a suitable approximation of memory processes (further *theoretical contribution*); and (ii) indirectly testing whether the empirical patterns described by traditional stochastic theories of memory are apparent in brand salience metrics (*empirical contribution*).

More detail about the first point now follows, whereas the second one will be addressed in the methodology chapter (Chapter 7).

5.2.1 Is memory 'Dirichlet-like'?

Reviewing the relevant stochastic models of human memory mechanics has highlighted the existence of various layers of stochastic processes that underpin how memory works and shape retrieval propensities. Given an ANT framework of memory, as per Anderson and Bower (1973a), it appears that three key layers of stochastic processes characterise memory:

(i) A stochastic process describing the *chances to encode information*, i.e. how associations are formed in memory, as per Anderson and Bower (1973b);

(ii) A stochastic process describing the *chances to activate and process information* in the more transient part of memory, i.e. describing the

performance of working memory as per Lovett, Reder and Lebiere (1997) derived from the ACT-R theory by Anderson (1993);

(iii) A stochastic process describing the *chances to retrieve information* from the more permanent memory traces (long-term memory) as per Daily, Lovett and Reder (2001).

These three processes generate three sub-sets of latent variables that concurrently shape retrieval propensities, which have been conceptualised as being *as-if-random* independent variables by Anderson and Bower (1973b).

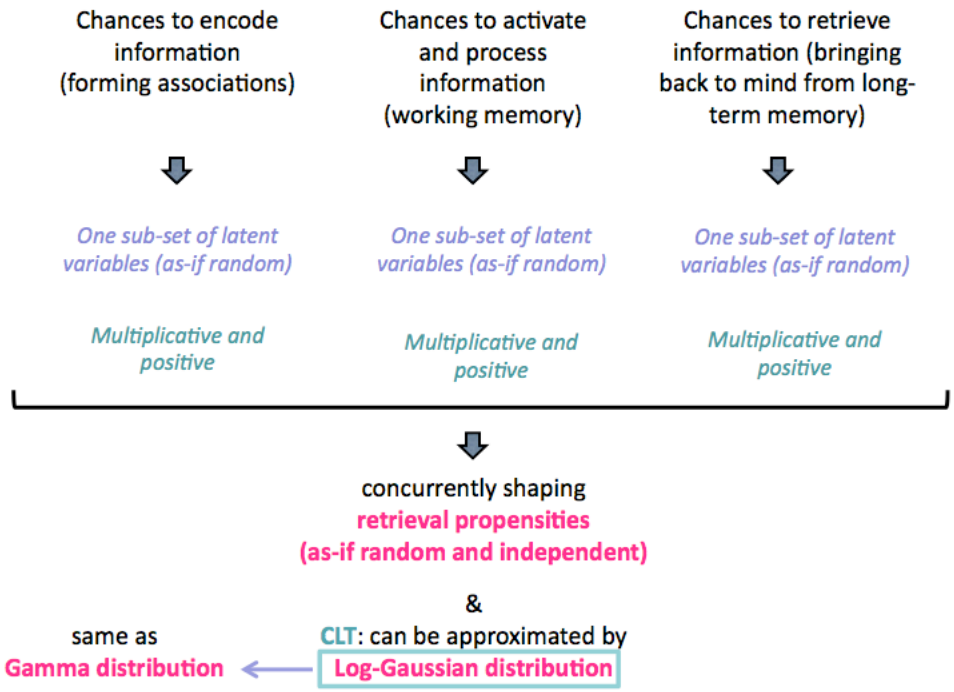
From a technical perspective, it is reasonable to look at the comprehensive result of these three processes as though they were 'Dirichlet-like', i.e. similar to the stochastic processes included in the Dirichlet theory of buying behaviour. Three key reasons for this can be identified as follows:

- *Empirical evidence*: as discussed in Chapter 3, there is evidence from Romaniuk (Forthcoming) showing that the Dirichlet model can be used to model a set of metrics representative of retrieval propensities and cognitive processing of brand information; although this research does not include formal testing of the underlying assumption of the Dirichlet theory, the good fit statistics would suggest that this theory provides a reliable description of memory patterns.
- *Theoretical evidence*: retrieval propensities are determined by: (i) the probability to form an association, which follows a Beta Binomial Distribution[7] (see Anderson and Bower (1973b)); and (ii) a non-linear relationship with the total level of activation of a focal memory chunk, which results in retrieval chances being exponentially distributed (see Lovett, Reder and Lebiere (1997)). The combination of these two distributions is very similar in nature (if not *technically* identical) to those included in the Dirichlet model. The Beta Binomial Distribution, in fact, describes the same stochastic process as a Dirichlet Multinomial Distribution, which is part of the Dirichlet. As per the exponential distribution, the Negative Binomial Distribution component of the Dirichlet also includes an exponential distribution (the poisson mixing distribution).

[7] The Beta Binomial Distribution implies probabilities being similar to a 'coin toss' Schmittlein Bemmaor and Moprrison (1985) : in a scenario where two alternatives are presented (e.g. forming or not forming an associations), there is a probability *p* for the successful event to take place and a *1-p* probability not to Morrison and Schmittlein (1988). The number of successful events obtained over *n* trials (e.g. *n* exposures to an environmental stimuli) can be modeled by a Binomial distribution Schmittlein Bemmaor and Moprrison (1985). Then, the Beta distribution accounts for the population heterogeneity Chatfield and Goodhardt (1970). Looking at brand associations elicited in a consumer survey, a Beta Binomial Distribution models the number of actual associations occurring over *n* possible brand-attribute mentioning matches or mentioning occasions, given the list of prompted brand attributes.

- *Mathematical explanation* (see Figure 14): since the three layers of stochastic processes characterising memory mechanics shape retrieval propensities as a set of *as-if-random* independent variables (Anderson and Bower, 1973b), the sub-sets of latent variables created by each layer must be multiplicative and positive, since they are concurrently shaping another set of variables. Therefore, the degree of variance showed in these multiplicative and positive variables should display *geometric means*. In probability theory, the Central Limit Theorem (CLT) states that when a group of random variables show geometric means, a Gaussian distribution is a valid mathematic approximation for these variables (Johnson et al., 1994). Since this distribution is technically close to a gamma distribution, a key component of the Dirichlet model (see Chapter 4), this provide further evidence that the stochastic processes included in the Dirichlet model seem suitable for describing patterns in memory (when measured with metrics representative of retrieval propensities).

Figure 14 – Memory being 'Dirichlet-like'



Given the reasons clarified above, in this thesis the patterns characterising brand memory associations and retireval propensities are analysed using the Dirichlet model as a mathematic abstraction and overall research approach.

5.2.2 The research problem

In buyer behaviour research, using stochastic models based on empirical evidence has provided: (i) a great understanding of purchase patterns; (ii) useful benchmarks for managers; and foremost (iii) validation of behavioural indicators of brand performance. In brand equity research, instead, there is only spurious consideration of the empirical evidence on the stochastic processes affecting memory. As a result, it is often hard to: (i) appraise empirical patterns in consumer memory; (ii) validate brand equity metrics based on consumer memory mechanics; hence (iii) generate valid benchmarks for managers.

Therefore, in this thesis the proposed research approach is to use the theoretical benchmarks offered by the Dirichlet model discussed in Chapter 5 (i.e. assumptions, distribution, parameters and metrics) to develop empirical knowledge for brand equity (*methodological contribution*). More specifically, this thesis presents a direct comparison of the empirical patterns in consumer memory and purchase behaviour by looking at the patterns observable in: (i) *behavioural metrics*, based on past purchases and representative of purchase propensities; and (ii) *brand salience metrics*, based in brand associations and representative of retrieval propensities.

5.2.3 The research approach

In this thesis, the use of stochastic theories is particularly relevant for the following reasons. First, as explained in Chapter 2, the key underlying characteristics of memory and the empirical patterns affecting it can be best understood if one assumes that: (i) memory is stochastic in nature; and that (ii) different layers of stochastic processes determine how information is processed cognitively. Second, as clarified when introducing Romaniuk's approach (Forthcoming) for measuring brand associations, likewise its application to purchase behaviour, the Dirichlet model can be applied to analyse the underlying characteristics of brand associations. This has been demonstrated to be robust from a theoretical, as well as empirical perspective in Section 5.2.1. Therefore, it seems a plausible research approach to use the Dirichlet model as a common underlying mathematic abstraction to explore the link between purchases and brand associations. The theoretical and empirical benchmarks of the model will be used to address the broad research question that is discussed next.

5.3 Broad research question

The broad research question addressed in this dissertation is:

> ***RQ1**: What is the degree of kinship between the empirical patterns in purchases and memory as reflected in behavioural and salience brand performance metrics?*

This research question also implies a comparison of two key components of consumer choice that are often implicitly claimed to be related in brand equity research:

*The **chance to buy a brand** or purchase propensity*

Vs.

*The **chance to think of a brand** or brand salience, conceptualised as retrieval propensity (chance to retrieve a brand from long term memory).*

The difference (or similarity) between these two components of consumer choice is appraised deductively. This means it is quantified by looking at:

(i) *Aggregate patterns*, hence the difference between behavioural and brand salience metrics in describing a certain market. This will be determined through the ranking of brands, correlations between metrics and so forth. This facilitates an understanding of how similar retrieval and purchase propensities are in different markets and whether their similarity depends on certain characteristics of the product category.

(ii) The description of *individual brand performance* provided by the two sets of metrics (e.g. deviations from expected benchmarks for brand purchases and brand salience). This allows for an understanding of whether the similarity of brand retrieval and purchase propensities depends on brand specific characteristics.

A number of research issues and potentially confounding factors to be considered when comparing behavioural performance metrics that are based on purchases, with brand salience metrics that are based on associations held in memory.

5.3.1 Confounding factors and research issues

The first set of issues has to do with understanding what these metrics measure. Behavioural metrics are computed on the basis of the discrete count of the observed past purchases. On the other hand, Romaniuk (Forthcoming) brand salience metrics are based on the discrete count of brand associations elicited in a pick-any survey scenario. The number of associations scored by a brand relative to competing brands is used to calculate the observed and estimated performance of the brand.

Whilst both are based on the count of discrete events (purchases versus brand associations), clearly there is a difference in the *time perspective* across the two sets of metrics. Behavioural metrics are historical performance metrics computed from a string of past purchases, whereas brand salience metrics are representative of a brand's cognitive prominence at the time of the collection of brand image data.

The second issue to be considered is that when salience is conceptualised as long-term retrieval propensity, it is computed on the basis of how likely a brand is to be retrieved from long-term memory given a network of brand attribute associations (Romaniuk, 2010). Retrieved information, however, undergoes three layers of stochastic processes, as summarised in § 5.2.2. The way salience is measured and modelled does not explicitly consider these further layers of stochastic processes. Although it appears reasonable to assume that the stochastic processes included in the Dirichlet theory should be a good approximation of the stochastic processes underpinning memory, it is also possible that it does not reflect accurately the nature of cognitive patterns. In fact, the use of a behavioural decision theory to appraise memory patterns should require such a theory to be placed in a broader psychological context that considers the role of attention, memory and cognitive representations (Einhorn and Hogarth, 1981).

The third issue concerns the possible existence of different sets of latent variables underlying purchase and retrieval propensities.

Within the Dirichlet theory, it is assumed that long-run purchase propensities are underpinned by *latent selection rates*, which are non-observable random variables turned into discrete variables by the stochastic processes included in the model (Driesener, 2005). Latent selection rates are calculated for the category as well as for individual brands. As discussed in Chapter 4, inferences about latent selection rates can be drawn from an analysis of the parameters of the distributions included in the Dirichlet model (Driesener, 2005). This interpretation (and use) of the parameters is in line with Jeuland's (1979) point about analysing the parameters of a stochastic model to uncover the statistical properties of the explained behaviour. Nevertheless, despite the relevance of the Dirichlet parameters in understanding some key aspects of buying behaviour, there are other aspects of buying behaviour, which are assumed to be

exogenous, such as consumer heterogeneity or the role of memory structures and cognitive components.

In the stochastic models describing how associations are formed in memory and how information is processed in working memory, the most important parameter is that accounting for the individual heterogeneity in working memory performance. Similarly, latent variables underpinning retrieval propensities are also linked to the performance of working memory and more specifically by the level of activation of a focal chunk of information being above a certain threshold.

Therefore, it appears that the meaning of the parameters and the definition of the set of latent variables underpinning retrieval propensity (hence memory patterns) could be potentially different to those characterising purchases. The discrepancy could be caused by assuming heterogeneity being *endogenous* in memory (differences in working memory performance affect retrieval propensity), whereas in purchases it is considered an *exogenous* factor. This difference at a latent level would most likely be reflected in the two sets of metrics.

Lastly, analogous issues can be inferred about the origins and causes of bias in buying behaviour versus memory. However, it must be clarified that bias in memory and purchases will be approached only by looking at deviations between the observed and theoretical metrics. More specifically, differences (or similarities) in bias between memory and purchase patterns will be assessed by looking at the consistency of deviations from the Dirichlet benchmarks across the two sets of metrics (see Chapter 4 for examples of deviations in behavioural metrics). This is a reasonable methodological approach that enables the drawing of some conclusions about the origins and nature of bias across purchases and memory, without complicating the data analysis.

Causes of deviations in buying behaviour are usually identified as being exogenous factors mostly linked to the size of the brand (market share) and consequently its level of popularity and loyalty. Causes of deviations in salience metrics have not been previously investigated. Therefore, in this thesis there will be an assessment of the consistency of deviations in brand salience and behavioural metrics, as a proxy for the comparison of origins and causes of bias in memory versus purchases. That is, if latent biases are similar, observed biases should also be similar.

The issues described so far suggest there are potentially different research outcomes to the research question introduced in § 5.3, which are now described.

5.4 Three competing views

Drawing upon McFadden's (1986) *path diagram* of decision protocols leading to choice, it is possible to illustrate a combined behavioral and memory-based paradigm of consumer decision-making (Figure 1, 2 and 3).

Latent or unobservable variables are represented in light blue circles (non-dashed); variables that can be directly measured/observed or simulated empirically are, instead, represented in light blue squares.

Bias is represented in yellow circles (dashed) and is conceptually differentiated according to the two levels explained in Chapter 2 (bias generated by working memory performance and retrieval imperfection, and bias generated by the transformation of retrieved information into actual behaviour).

Stochastic processes are represented with direct rectangular streams highlighted in different colors to distinguish between those included in the Dirichlet theory (the theoretical benchmark used for the analysis) and those describing memory patterns:

(iv) ***Blue*** for the stochastic processes described by the Dirichlet theory (see Chapter 4), applied to purchases as well as brand associations;

(v) ***Orange*** for the stochastic process determining how associations are formed in memory, as per Anderson and Bower (1973a) (see Chapter 2);

(vi) ***Purple*** for the stochastic processes embedded in the performance of working memory as per Lovett, Reder and Lebiere (1997) derived from the ACT-R theory by Anderson (1993) and determining latent variables underpinning retrieval propensities as per Daily, Lovett and Reder (2001) (see Chapter 2).

It is assumed that the stochastic processes described above should determine the set(s) of latent variables shaping purchase and retrieval propensities, and hence underpin the empirical patterns in purchase and memory that are apparent in behavioural and brand salience metrics.

Given this framework, three **competing views** are tested as follows:

1. There is **no detectable similarity** between behavioural and brand salience metrics; the patterns in the two sets of metrics are underpinned by distinct stochastic processes and two distinct sets of latent variables, thus purchase and retrieval propensities are two separate aspects of consumer choice, as per Figure 15;
2. Behavioural metrics and brand salience metrics are **quite similar**, but with detectable differences caused by some *confounding factors* acting upon the

stochastic processes shaping purchase and retrieval propensities, which are somewhat related aspects of consumer choice, as per Figure 16;

3. Behavioural metrics and brand salience metrics are **very similar** and the patterns characterising the two sets of metrics are underpinned by the same stochastic process, shaping only one set of latent variables and thus making purchase and retrieval propensities virtually inseparable aspects of consumer choice, as per Figure 17.

These will be supported via validation of one of the following research propositions:

Rp0: *The patterns underlying memory are **different** to those underlying purchases.*

Rp1: *The patterns underlying memory are **similar** to those underlying purchases.*

Partial acceptance of Rp1 (***quite similar***) is also accepted.

Table 5 summarises the link between the three research outcomes presented, the research propositions and the elements of the diagram exemplifying the consumer decision-making framework.

Table 5 – The three proposed competing views

		Comparison of the stochastic processes	
Competing view 1	***Rp 0***	***Blue*** on the side of purchases ***Orange*** + ***purple*** + ***blue*** on the memory-side	≠
Competing view 2	***Rp 1 (partially)***	***Blue*** on the side of purchases ***Orange*** + ***purple*** + ***blue*** on the memory-side	≈
Competing view 3	***Rp 1***	***Blue*** on the side of purchases ***Orange*** + ***purple*** + ***blue*** on the memory-side	=

Figure 15 – Competing view 1

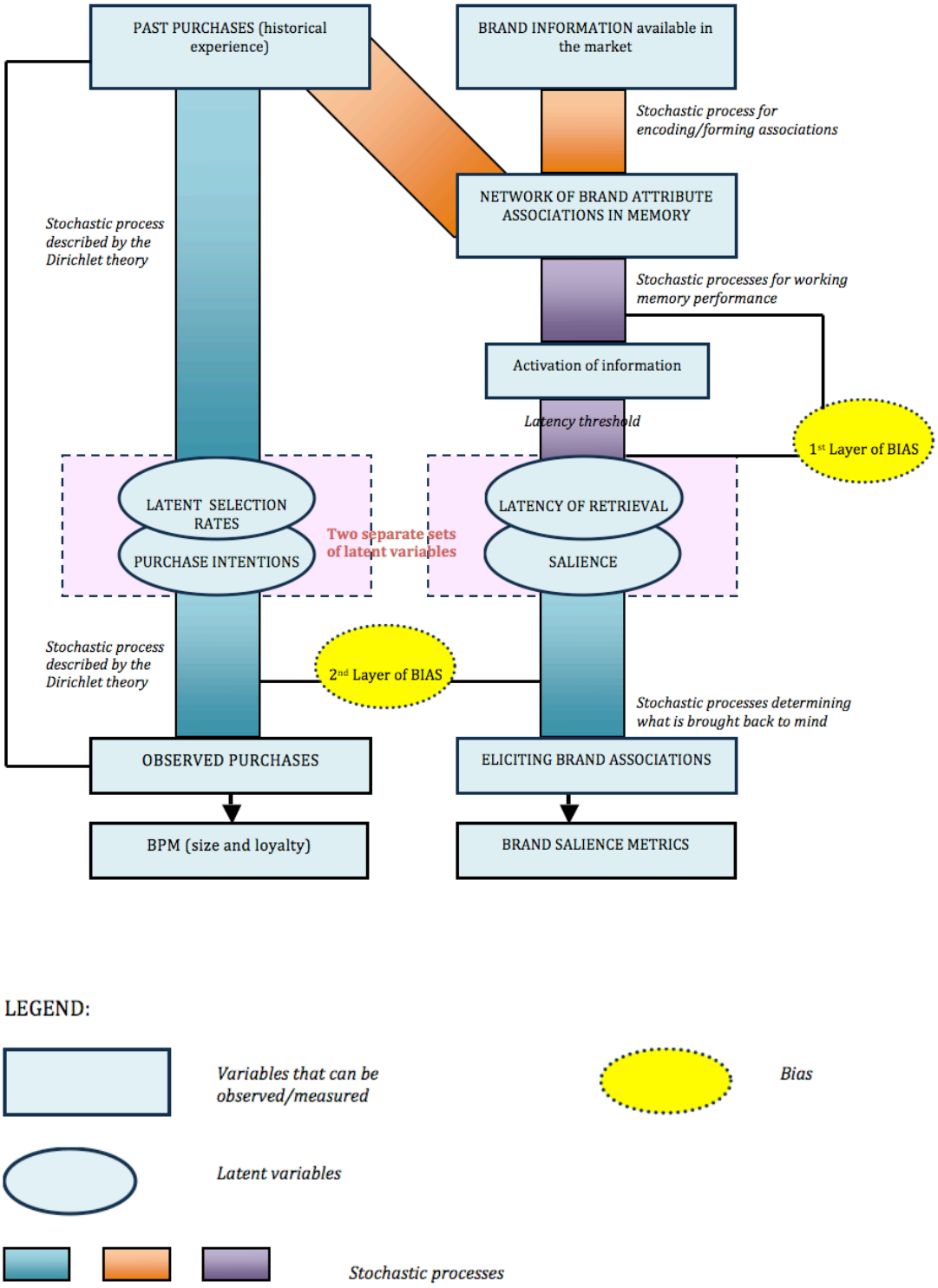


Figure 16 – Competing view 2

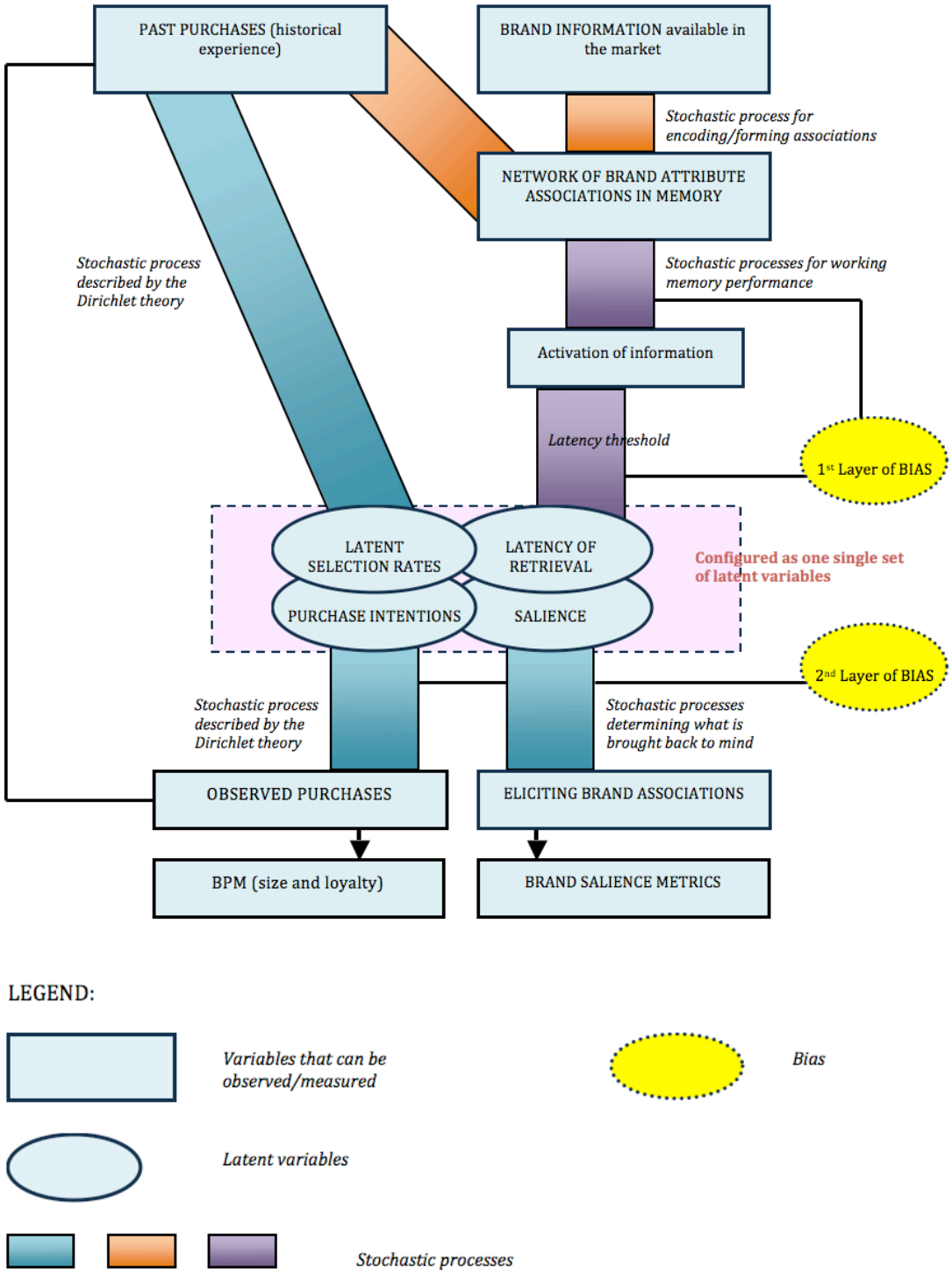
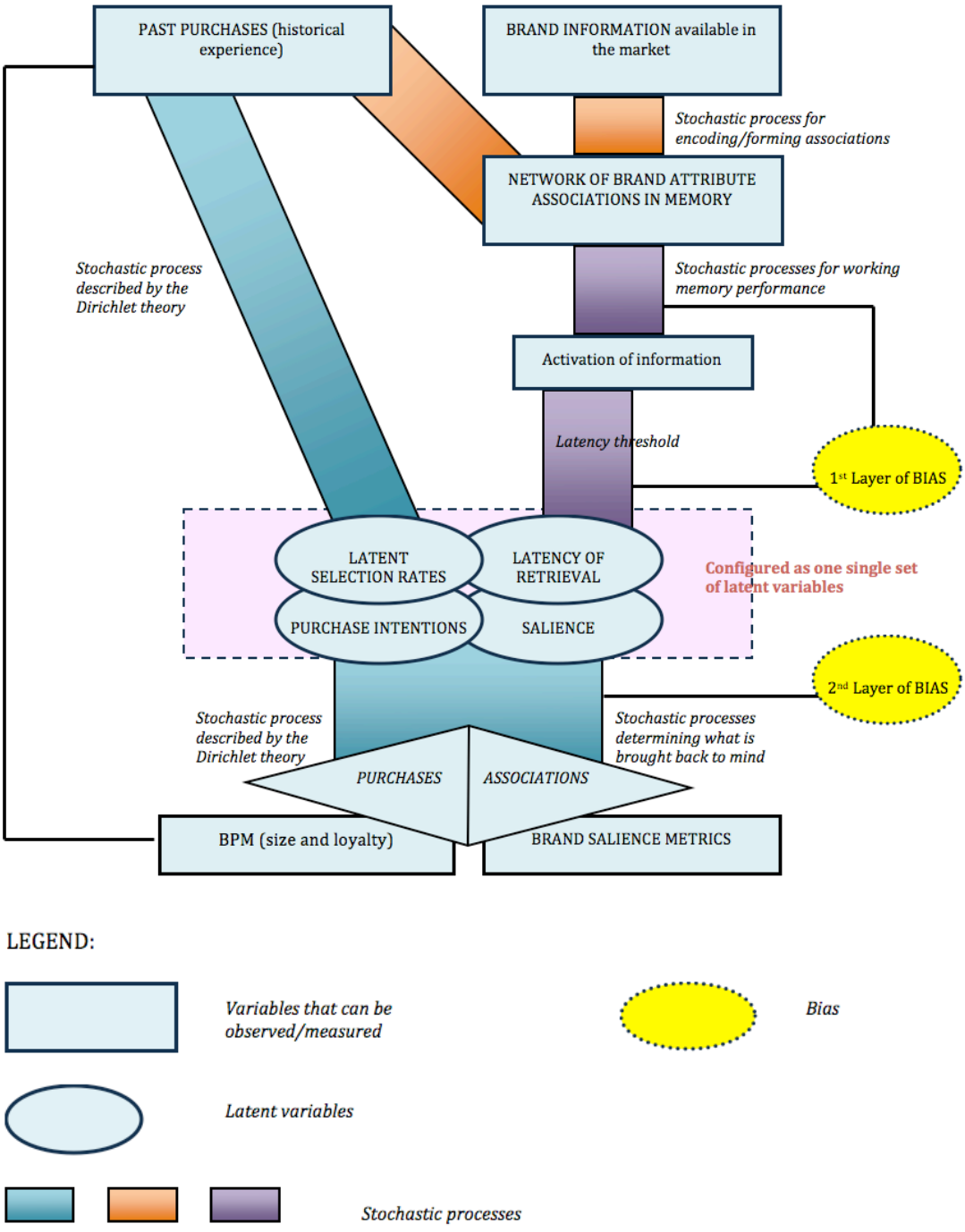


Figure 17 – Competing view 3



5.5 Chapter summary

The theoretical components presented in the previous chapters have highlighted the following. Even though it may be an acceptable empirical compromise to assume that the stochastic processes included in the Dirichlet theory are a good approximation of those underpinning memory (especially given the empirical evidence of a good fit of the Dirichlet model for brand salience metrics and some theoretical and mathematical considerations), some potential difference in terms of: (i) stochastic processes; (ii) latent variables; and (iii) bias may result in different empirical patterns in purchases and in memory. Therefore, the two sets of brand performance metrics obtained when modelling purchases versus brand associations could be: (i) substantially different, thus lacking the ability to capture certain aspects of consumer decision-making patterns and yet accounting for others; or (ii) essentially very close from a stochastic perspective and hence related to each other and reflected in buying behaviour, but expressed differently.

These considerations result in three potential research outcomes for the broad research question investigated in this thesis. The comparison between behavioural and brand salience metrics will be drawn upon the benchmarks of the Dirichlet theory (Goodhardt et al. 1984) and used to test the three competing views discussed so far. This approach requires a structured method of data analysis, which is described in the next chapter.

Chapter 6 – Research methods

6.1 Chapter overview

'We can't solve problems by using the same kind of thinking we used when we created them'

Albert Einstein – Physicist and philosopher (1879-1955)

This chapter covers a description of the research methods used in the analysis, in four main sections.

§ 6.2 includes a description of the data sets analysed and the built-in control, as only robust findings across the two different data sets will be reported.

§ 6.3 and **§ 6.4** include a description of how the two sets of metrics analysed are calculated and modelled. § 6.3 describes how **behavioural metrics** are calculated and modelled. § 6.4 presents an overview of Romaniuk's (Forthcoming) key methods for developping and modelling **brand salience metrics**. These include: (i) how to identify and why to avoid the use of overlapping mental structures; (ii) the use of the usage-image relationship to discriminate between descriptive and evaluative brand attributes; (iii) fitting the Negative Binomial Distribution to the frequency of brand associations to determine the number of brand attributes to use; and (iv) how to model brand salience metrics with the Dirichlet model. § 6.3 and § 6.4 serve as a *research preamble* for the validation of the analysis presented in this dissertation and do not represent a source of original contribution.

§ 6.5 presents a detailed description of the methods necessary for the four different levels of data analysis.

§ 6.5.1 includes the methods applied in **LEVEL 1** of the analysis, which compares the values of the Dirichlet parameters obtained by fitting the Dirichlet model to the two sets of metrics analysed. It also includes methods for assessing the temporal stability of the parameter values over time.

§ 6.5.2 includes the methods applied in **LEVEL 2** of the analysis used to compare behavioural and brand salience metrics, i.e. Spearman's rank correlation coefficient and Mean Absolute Errors (MAEs).

§ 6.5.3 includes the methods applied in **LEVEL 3** of the analysis to assess the consistency of deviations from the Double Jeopardy pattern across the two sets of

metrics analysed. Single brand instances are considered (i.e. niche, change of pace, excess behavioural loyalty and private labels).

Lastly, § 6.5.4 presents a 'decision-tree' combining the research outcomes of the previous levels of analysis into a single outcome, which represents the last level of analysis, **LEVEL 4**. The decision-tree is used to validate one of the two research propositions introduced at the end of Chapter 5. The accepted research proposition will confirm which of the three competing views tested in this dissertation, on the similarity/difference between behavioural and brand salience metrics, has been supported empirically.

6.2 Description of the data

The analysis for this thesis is performed on data from two sources (see Table 6):

(i) US repeated cross-sectional data (three years of panel and survey data) for toothpaste, providing brand purchases and brand associations from different samples;

(ii) UK panel data for three product categories (all hot beverages), providing brand purchases and brand associations from the same sample.

Table 6 – Data sets description

	Sample size *N*	**Behavioural metrics**	**Brand salience metrics**
US cross-sectional data (three years) **TOOTHPASTE**	Year 1 (2006) *N* = 2,644 Year 2 (2007) *N* = 5,228 Year 3 (2008) *N* = 5,236	AC Nielsen panel	IPSOS consumer survey on brand image
UK panel data (one year) **HOT BEVERAGES**	Tea *N* = 8,219 Instant coffee *N* = 7,974 Roast coffee *N* = 6,532	Dunnhumby panel data (within chain)	Dunnhumby panel data (within chain)

This data covers the following analytic conditions: *same* and *different samples*, *single* and *multiple time periods*, and *within* and *between chain*. This allows for the development of a built-in control, which increases the robustness of any empirical finding of this dissertation, since only findings robust across both data sets are considered in relation to their support of the research propositions.

For both data sets, two sets of brand performance metrics have been calculated and analysed as follows:

- For the set of **behavioural metrics**, for each brand available in the data sets, the % of *Market Share*, *Penetration* (%), *Average Puchase Frequency* and *Share of Category Requirement* SCR (%) (see Chapter 4 for a description of these metrics);
- For the set of **brand salience metrics**, for each brand available in the data sets, the % of *Brand Salience*, *Salience Penetration* (%), *Association Rate* and *Share of Mind* SOM (%) (see § 6.4.4 for a description of these metrics).

It is important to remind that while these metrics have been calculated for all brands available in the two data sets, the analysis performed across the four levels has been conducted only for the brands for which both purchase and brand associations data were available. This included all brands for the UK data, and only some brands for the US data, where brand associations were not available for all the brands for which purchase data were accessible. Moreover, for some levels of the analysis (namely for LEVEL 1 and 3), some of these metrics (i.e. Penetration and Average Purchase Frequency for behavioural metrics, Salience Penetration and Association Rate for brand salience metrics) have been further processed with the Dirichlet model software by Kearns to generate the theoretical outputs used for the analysis (i.e. parameters and theoretical metrics).

A description of how these metrics are calculated and how they can be modelled with the Dirichlet model now follows, starting with behavioural metrics.

6.3 Modelling behavioural metrics

Chapter 5 included a description of the typical behavioural brand performance metrics, based on the count of purchases and used as key input/output of Dirichlet modelling techniques. The count of past purchases is most often obtained from panel data, which provides records of individual consumer purchases for a number of brands within a certain category.

The key behavioural metrics calculated and used to fit the Dirichlet model are: the % of *Market Share*, *Penetration* (%), *Average Purchase Frequency* and *Share of Category Requirement* SCR (%). A description of these metrics is provided in Chapter 4.

Fitting the Dirichlet model to these metrics implies the following subsequent steps:

(i) Inputting *observed* Penetration and Average Purchase Frequency for each individual brand (ranked according to the % of Market Share), as well as for the overall category in the Excel software for Dirichlet analysis by Kearns.

Using the Means and Zeroes estimation approach, this procedure enables an estimate of the parameters of the Dirichlet Model distributions to be formed, and generates the Dirichlet parameters, hence the corresponding *theoretical* behavioural metrics;

(ii) Comparing observed and theoretical metrics, calculating commonly used fit statistics (Wright et al., 2002, Scriven and Bound, 2004) such as Mean Absolute Deviations (MADs) and Mean Absolute Percentage Errors (MAPEs):

- Mean Absolute Deviations (MADs) are the average size of deviations - ignoring their negative or positive sign (Kennedy and Ehrenberg, 2001). Based on the variance between two numbers, a MAD is calculated from raw unrounded numbers by the following formula (Driesener et al., 2012):

$$MAD = \frac{\sum_{j=1}^{g} |O_j - T_j|}{g} \qquad \textbf{Equation 28}$$

- Mean Absolute Percentage Errors (MAPEs) are the average of the sum of all the percentage errors ignoring their negative or positive sign (Scriven and Bound, 2004). Based on the variance between two numbers, a MAPE is calculated from raw unrounded numbers by the following formula (Driesener et al., 2012):

$$MAPE = \frac{\sum_{j=1}^{g} \frac{|O_j - T_j|}{T_j}}{g} \qquad \textbf{Equation 29}$$

In this thesis, the theoretical outputs obtained by fitting the Dirichlet model to behavioural metrics and the observed behavioural metrics are compared against brand salience metrics, which are described in the following section.

6.4 Modelling brand salience metrics

According to Romaniuk's (Forthcoming) guidelines, brand salience metrics are based on the the discrete count of brand associations derived from brand image data. Brand image data can be collected in different ways. However, as discussed in Chapter 4, 'pick-any' consumer surveys are widely used as they capture free associations between brands and attributes. The set of free associations obtained should then be analysed to identify an appropriate sub-set of brand attributes in order to measure

brand salience. Romaniuk's (Forthcoming) approach for salience measurement maintains the following steps:

(i) *Avoid overlapping mental structures*: the response patterns obtained from a range of brand attributes included in the survey must be analysed to reduce the number of attributes included in the range. By looking at systematic, positive and large correlations, it is possible to identify brand attributes that are somewhat 'similar' or simply capture overlapping mental structures. Out of a set of highly correlated attributes, only one attribute should be included in the set for measuring brand salience.

(ii) In selecting the range of brand attributes to be used, it is crucial to draw upon the consistency of the brand-usage relationship and to *isolate major deviations*. Variations from the normal usage-image relationship suggest that consumer cognitive responses and processes may differ, thus different attributes are not measuring comparable retrieval situations. Therefore, those attributes are not suitable for inclusion in the range for measuring brand salience.

(iii) As per Romaniuk and Stocchi (2009) A *frequency distribution* (e.g. *Negative Binomial Distribution*) should be used to ensure that the number of attributes included covers, at minimum, the response patterns for highly salient brands and a representative sample of less salient brands. When the frequency distribution of the brand associations obtained with a certain sub-set of attributes shows a good fit with a theoretical frequency distribution (e.g. Negative Binomial Distribution), this is indicative of an adequate number of attributes for brand salience measurement.

These steps are now described in more detail.

6.4.1 Correlations amongst brand attributes: avoiding overlapping mental structures

Brand attributes that represent overlapping mental structures should be isolated from the range for salience measurement, since they would alter the underlying distribution of retrieval propensities, by tapping into the same concept (Romaniuk, Forthcoming).

As explained by Romaniuk (Forthcoming), a possible approach is verifying if the response patterns (frequency of associations) of the various attributes are correlated by running *two-tailed Kendall's Tau-b correlations*.

The typical output of this analysis provides (at brand level) a double entry table of the correlations across all attributes and the level of statistical significance of these. The following step involves calculating, for each brand, the averages of these correlations. These values are then implemented to structure a second double entry table

displaying, for each attribute, the deviation from the average correlation. A positive difference of 0.15 to 0.20 from the average would indicate a set of correlated attributes. If two (or more) attributes show a positive and significant correlation across all brands, it is possible to infer that those attributes are most likely tapping into very similar memory constructs (e.g. 'Something fresh' and 'Refreshing'). Therefore, for each set of correlated attributes only one should be included in the battery for brand salience measurement.

6.4.2 Usage-image relationship: isolating descriptive and evaluative attributes

As explained in Chapter 3, there are two robust empirical patterns in brand image data: (i) a quantifiable relationship between brand usage and brand associations (brand usage bias), as per Bird and Channon (1969) and Bird et al. (1970); and (ii) a Double Jeopardy effect, as per Barwise and Ehrenberg (1985) and Dall'Olmo Riley et al. (1997). It is also known that drawing upon these two key patterns allows differentiating between *evaluative* and *descriptive* attributes - see Hoek et al. (2000).

For an accurate measurement of brand salience, it is important to identify evaluative and descriptive attributes and eliminate them from the sub-set for salience measurement, since they would alter the overall level of brand salience of all brands (Romaniuk, Forthcoming).

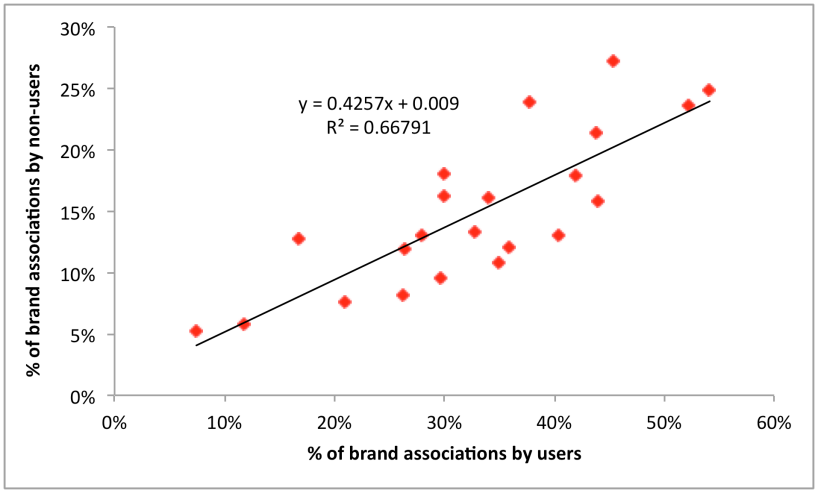
In order to identify evaluative and descriptive attributes, it is necessary to establish what is the 'normal' usage bias for each attribute included in a consumer survey. A possible method is to *cross-tabulate* (see Table 7) brand associations for individual attributes (these are often dummy variables in consumer surveys, so respondents can either provide or not provide a brand association for the various attributes) and brand usage variables (also dummy variables that indicate, for each respondent, whether he/she used the brand or not). For each attribute, this method allows the proportion of associations provided by users and non-users of a brand to be calculated (see Table 7).

Table 7 – Cross-tabulation between brand associations and usage

	Non-users	*Users*
Not mentioned	80%	25%
Mentioned	20%	75%

These proportions can then be implemented in a linear regression (Romaniuk, Forthcoming). Plotting users against non-users' responses and calculating a 'best-fit' line allows the expected proportion of responses for non-users to be estimated using the *b*-coefficients (see Figure 18).

Figure 18 – Example of regression in brand image data



In this example, the *b*-coefficient would be implemented to calculate the expected level of non-users' responses as follows: observed response level of users * 0.43. Deviations between the observed and expected level of response for non-users greater (smaller) than 5% suggest that the attribute is deviating from the usage-image constraint, hence that it should not be included in the set of attributes to be used for salience measurement (Romaniuk, Forthcoming). Large negative deviations represent evaluative attributes and large positive deviations represent descriptive attributes. If deviations are consistent across all brands, the deviating attribute must be removed from the range for salience measurement.

6.4.3 Fitting the Negative Binomial Distribution to the frequency of brand associations

Once the attributes that are overlapping (highly correlated) and deviating from the usage-image pattern have been removed, it is still necessary to determine *how many* attributes should be included in the range for salience measurement. The number of attributes should be sufficient to describe retrieval propensities for all brands (Romaniuk, Forthcoming). It is necessary to ensure that smaller brands are not under-

represented. In marketing, frequency distributions such as the negative binomial distribution (hereafter NBD) are commonly used and represent a valuable method to assess the ideal number of items required to describe a full range of propensities (Romaniuk, Forthcoming). Moreover, a NBD has been proven to enable prediction of the incidence of brand attribute associations (Romaniuk and Stocchi, 2009). The key inputs for fitting the NBD to brand image data are: (i) the observed average number of associations for an individual brand (given the sub-set of attributes obtained after eliminating over-lapping and descriptive/evaluative attributes); and (ii) the observed proportion of people providing at least one association (again, given the identified sub-set of attributes). Fitting the NBD (finding a feasible solution to the density function included in the model with common methods of estimation, e.g. means and zeros) allows calculating the *theoretical* correspondents to (i) and (ii) above. By comparing the deviations between estimates and observed values (e.g. calculating Mean Absolute Deviations, MADs), it is possible to appraise whether the NBD 'fits' and if the number of attributes included in the set is suitable to describe brand associations of all brands. Fit is based on a benchmark of MADs smaller than 5% (Romaniuk and Stocchi, 2009).

Table 8 shows an example of the NBD fitting for a single brand. Small MAD values (between 0 and 1%) indicate that the number of attributes appears adequate to capture retrieval propensities for this brand. By repeating this for all individual brands assessed in a brand image survey, it is possible to understand if the number of attributes is suitable for measuring brand salience for all brands.

Table 8 – Example of NBD fitting for a single brand (8 brand attributes)

	Frequency	**Total associations**	**Observed (%)**	**Theoretical (%)**	**MADs (%)**
0	6348	0	78	78	0
1	817	817	10	11	1
2	351	702	4	5	0
3	219	657	3	3	0
4	135	540	2	1	0
5	99	495	1	1	0
6	59	354	1	1	0
7	45	315	1	0	0
8	31	248	0	0	0
Tot.	**8104**	**4128**			
	1756				
22% Proportion of people providing at least one association **2.4** Average number of associations					

6.4.4 Computing brand salience metrics

At this stage, the range of brand attributes to be included for salience measurement should be reduced through the following conditions (Romaniuk, Forthcoming): (i) NOT including over-correlated attributes; (ii) NOT including evaluative and descriptive attributes ; (iii) the frequency distribution of resulting associations (for each brand) follows a Negative Binomial Distribution (NBD).

Given the resulting sub-range of brand attributes, as explained by Romaniuk (Forthcoming), it is possible to calculate a set of brand salience metrics as follows:

- *Brand Salience* (%), which is is defined as the share of associations a brand holds in the category relative to competing brands (conceptually similar to Market Share);
- *Salience Penetration* (%), which is is defined as the proportion of respondents providing at least one association for a specific brand (conceptually similar to purchase Penetration);
- *Association Rate*, which is is the average number of associations for a specific brand (conceptually similar to Average Purchase Frequency)
- *Share of Mind SOM* (%), which is is defined as the share of associations held by those with at least one association to a specific brand, in relation to competing brands (conceptually similar to Share of Category Requirement).

Then, for the purpose of the data analysis performed in this dissertation, these metrics are modelled with the Dirichlet theory, as per Romaniuk's (Forthcoming) guidelines.

6.4.5 Fitting the Dirichlet model to brand salience metrics

Research by Romaniuk (Forthcoming) applied the Dirichlet model to brand salience metrics for multiple product categories. The author reported that the model shows good fit statistics (e.g. *Chi Square*) for various product categories, as well as for the individual brands analysed within the categories. Therefore, the model can be implemented for predicting the theoretical equivalents of the observed brand salience metrics. Fitting the Dirichlet model to salience metrics involves the following steps:

(i) Inputing the *observed* salience metrics (namely Salience Penetration and Association Rate) for individual brands (ranked according to the % of Brand Salience) and for the overall category in the Excel software for Dirichlet analysis by Kearns. Using the Means and Zeroes estimation approach

(Goodhardt et al., 1984, Morrison and Schmittlein, 1988), this procedure enables an estimate of the parameters of the Dirichlet model distributions to be formed and generates the Dirichlet parameters, hence the corresponding *theoretical* brand salience metrics;

(ii) Comparing observed and theoretical metrics, producing a report of fit statistics. For the purpose of this thesis, the same fit statistics described for behavioural metrics will be considered, i.e. MADs and MAPEs.

Table 9 shows an example of a typical modeling output when fitting the Dirichlet to brand salience metrics by Romaniuk (Forthcoming) that will be used as a benchmark for appraising fit statistics for the data sets analysed in this thesis.

Table 9 – Example of brand salience modelling (Romaniuk, 2010)

	Salience %		**Salience Penetr. %**		**Association Rate**		**Share of Mind %**	
	O	**T**	**O**	**T**	**O**	**T**	**O**	**T**
Brand A	22	23	87	88	5.1	5.0	29	24
Brand B	21	21	88	86	4.6	4.7	24	23
Brand C	14	14	78	76	3.6	3.7	19	17
Brand D	13	13	69	72	3.6	3.5	16	16
Brand E	10	10	59	62	3.2	3.0	14	14
Brand F	9	9	57	60	3.1	3.0	14	13
Brand G	7	6	47	48	2.7	2.6	14	12
Brand H	5	5	47	40	2.1	2.4	10	11
Average	**12**	**13**	**67**	**67**	**3.5**	**3.5**	**18**	**16**

Fit statistics

	Salience	**Salience Penetr.**	**Association Rate**	**Share of Mind**
MADs	0 %	3 %	0.1	2 %
MAPEs	1 %	5 %	5 %	9 %

6.5 Four levels of analysis

The analysis of literature from neuropsychology (see Chapter 2) has highlighted how the stochastic processes characterising memory appear to be quite similar to those included in the Dirichlet theory (see also Chapter 5). However, despite being described by the same mathematic abstraction, it is not possible to confirm *a priori* that purchase and retrieval propensities underlying purchases and memory are generated from common latent structures and processes, nor that they will result in analogous empirical patterns in the representative metrics.

Nevertheless, from a technical perspective, drawing upon the same theoretical benchmarks of the Dirichlet model, it should be possible to understand: (i) if there are two distinct stochastic processes, with the Dirichlet abstractions providing a suitable to model for two distinct phenomena (i.e. purchases and memory patterns); (ii) if the two propensities (purchase and retrieval propensities) result into two distinct sets of latent variables or not; and (iii) if the sets (or the set) of latent variables cause similar empirical patterns in the metrics.

The following section describes the methods necessary to address these research issues and to test the three competing views outlined in Chapter 5 on the possible research outcome of this thesis.

Four levels of analysis are included, starting with the comparison of a first key theoretical Dirichlet benchmark: the parameters.

There are three reasons why the parameters are compared first: (i) for every stochastic model, the parameters can be considered as a proxy of the structural characteristics of the modelled behaviour; (ii) the parameters can also be considered direct expression of the latent variables; and (iii) for the Dirichlet model, the parameters are actually embodied in the other crucial theoretical outputs of the model, i.e. the theoretical metrics. Therefore, comparison of the parameters assesses the existence of distinct sets of latent variables that underpin purchases and brand associations.

The outcome of this first level of analysis is then followed by a comparison of the metrics and the deviations. Finally, to ensure the robustness of findings, a further level of analysis will combine deductively the outcomes of the other levels, validating either Rp0 or Rp1 with a ‘decision-tree’.

6.5.1 LEVEL 1: Comparing the Dirichlet parameters

The parameters involved in the distributions of a stochastic model are not simple *ad-hoc* coefficients, but embody specific aspects of the described behaviour (Goodhardt et al., 1984). The interpretation of the values assumed by the parameters allows for the distribution of latent variables to be explained, hence providing insights on the underlying patterns of the modelled behaviour (Goodhardt et al., 1984). Therefore, a better understanding of the differences in the parameter values and the trends of these values over time can highlight more implicit differences (or similarities) not only between the two sets of metrics, but also in terms of the underlying latencies in purchases and brand associations. More specifically, this level of analysis is aimed at drawing inferences on the existence of *one* or *two* separate sets of latent variables, by: (i) considering the meaning of some key Dirichlet parameters for purchases and brand associations; (ii) comparing the values of the parameters obtained with both sets of metrics analysed; and (iii) assessing the stability over time of the parameter values (time series).

6.5.1.1 Meaning of the parameters M, K *and* Phi

Empirical research on the Dirichlet parameters tends to be focused on three key parameters that carry the most explicit insight about purchase behaviour:

(i) The ***M* parameter** describes the overall weight of category purchases by all shoppers; typically reflecting seasonality, promotions, stockouts and other demand fluctuations;

(ii) The ***K* parameter** is the shape parameter of the gamma distribution underlying the Negative Binomial Distribution and a measure of heterogeneity in the category latent selection rates. As such, it expresses behavioural characteristics of a group of shoppers and the distribution of light and heavy buyers (lower *K* values imply a greater proportion of heavy buyers) or customer concentration;

(iii) The **parameter *Phi*** is a transformation of the traditional ***S* parameter**, *1/(1+S)*, and measures the variance in shoppers' choice probabilities, hence capturing the degree of switching or brand loyalty (a *Phi* of 0 represents no loyalty, while a *Phi* of 1 represents 100% loyalty).

The potential meaning of these parameters when obtained by fitting the Dirichlet model to brand salience metrics has, to date, no empirical evidence nor theoretical discussion, even within Romaniuk's research (Forthcoming).

Given the common interpretation and meaning of these parameters in buying behaviour, it is possible to provide some interpretation of the parameters when applied to the modelling of brand salience metrics (see Table 10):

Table 10 – Meaning of the parameters M, K and Phi in brand associations

	Purchases	**Salience**
M	Average level of demand	Average level of knowledge about a certain product category or market
K	Customer concentration	Proportion of high-knowledgeable customers or concentration of knowledge about a product category
Phi	Loyalty (level of switching)	How scattered/concentrated knowledge about a product category is (one brand vs. many brands)

Besides this rather speculative consideration on the potentially different meaning of the parameters for purchases and brand associations, this level of analysis also includes a comparison of the parameters as follows: (i) a direct comparison of the *value range* across the two sets of metrics modelled; and (ii) a test of *temporal stability*.

The first point is addressed with a simple comparison of the parameter values, which is obtained by fitting the model to the two sets of metrics across both data sets and does not require further methodological explanation. The second point is addressed by calculating the Coefficient of Variation for the parameter values over time (time series analysis).

6.5.1.2 Temporal stability of the parameters

One of the key assumptions of the Dirichlet model is that the latent selection rates are fairly stable over time, given the condition of market *stationarity* (Ehrenberg, 1988). Therefore, from a theoretical perspective, all parameters of the Dirichlet model should embody this underlying characteristic (Banerjee and Bhattacharyya, 1976). As such, the values of the parameters should not change over time (for *K* and *Phi*) or should change linearly with increasing time length (as for the parameter *M*). This implies that

by looking at the time series of the parameters estimated from subsequent and identical (in length) time periods (e.g. quarters), it is reasonable to expect that the size of variation relative to the size of the observations should be minimum or nil. This is tested calculating the ratio of the standard deviations to the means of the parameters (the *Coefficient of Variation*). This standardised measure of variation allows for comparison across different product categories, as well as across purchases and brand associations, since it is independent of the units of observation. To calculate the Coefficient of Variation, it is necessary to calculate the mean value of the parameters and the standard deviation. The ratio of the standard deviation to the mean is the coefficient of variation (Armstrong and Hubbard, 2010). In this analysis, this ratio is considered: (i) a test of the stability over time of latent variables shaping purchase and retrieval propensities (thus confirming a key underlying assumption of the Dirichlet model, that of stationarity); and (ii) a test to prove, in combination with the direct comparison of the parameter values, the existence of one or two separate sets of latent variables shaping purchase and retrieval propensities.

6.5.2 LEVEL 2: Direct comparison of salience and behavioural metrics

This second level of analysis presents a direct comparison of the two sets of metrics. The comparison concerns the observed values of behavioral and brand salience and the overall description of the market provided by these metrics in terms of: (i) the *rank* of the brands; and (ii) the *values* of the metrics for each individual brand.

6.5.2.1 Ranking of brands

The method used to compare the rank of brand performance in behavioural and brand salience metrics (from top brand in the market down) is calculating a Spearman's rank correlation coefficient or Spearman's ρ (rho). From a practical perspective, ρ (rho) is a non-parametric measure of statistical dependence between two observations, expressed as follows (Armstrong and Hubbard, 2010):

$$r_s = 1 - \theta \sum d^2 / \left(n^3 - n\right) \qquad \textbf{Equation 30}$$

with n being the number of measurements in each of the two observations in the correlation $\sum d^2 = \sum_i^n d_i^2$, and d_i being the ranked difference between the ith measurements for the two observations.

In terms of comparing behavioral and brand salience metrics, correlations between 'pairing' metrics are tested, i.e. between the metrics conceptually similar in the way they are computed, which are:

- Brand Salience (%) and Market Share (%);
- Salience Penetration (%) and Penetration (%);
- Association Rate and Average Purchase Frequency;
- Share of Mind SOM (%) and Share of Category Requirement SCR (%).

Significant correlation coefficients close to 1 across all four pairs of metrics imply that the two sets of metrics are 'alike' in depicting the rank of brand performance for a given market. Conversely, correlation coefficients close to 0 and significant imply that the two sets of metrics are providing very different descriptions of brand performance.

A further component of the second level of analysis includes the calculation of simple Mean Absolute Errors (MAEs) between the pairs of metrics listed above.

6.5.2.2 Mean Absolute Errors (MAEs)

Mean Absolute Error (MAE) is an accuracy measure commonly defined as the average error when ignoring sign, or average size of deviations ignoring their negative or positive sign (Armstrong and Hubbard, 2010). Therefore, based on the arithmetic difference between two numbers or measures, MAE is calculated from raw unrounded numbers by the following formula:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | f_i - y_i | = \frac{1}{n}\sum_{i=1}^{n} | e_i | \qquad \textbf{Equation 31}$$

In this level of data analysis, MAEs values are calculated to further appraise the difference (or similarity) between the two sets of metrics analysed. Therefore, this technique is applied in this thesis to compare the observed values of the two sets of metrics for 'pairing' metrics. If MAE values were systematically large (e.g. greater than 5%) for most brands across both data sets analysed, this would be a further clue that the two sets of metrics are substantially different, and so were the propensities they embody.

The outcome of this method of analysis will supplement the analysis of the correlation coefficient and provide a formal direct comparison of the metrics, which, when combined with the analysis of parameters, can provide insight into the broad research question tested in this thesis. More specifically, the methods described in these first

two levels of analysis allow for the comparison of the two sets of metrics *between* groups (i.e. observed and observed).

The next level of analysis, instead, includes the methods necessary to compare *within* groups (i.e. observed against theoretical for each set), drawing more explicitly upon the Dirichlet benchmarks and purchase behaviour empirical methods.

6.5.3 LEVEL 3: Assessing deviations from the Double Jeopardy pattern

The key aspect of the comparison of the two sets of metrics within groups will be assessing the consistency of deviations from a common underlying pattern, the Double Jeopardy.

In buying behaviour, the difference between observed and theoretical values (Dirichlet estimates) of Penetration and Purchase Frequency is usually used to identify deviations from the Double Jeopardy pattern (Ehrenberg et al., 1990, Ehrenberg et al., 2004). In this level of data analysis, this research approach is extended to identifying deviations from the Double Jeopardy pattern in brand salience metrics. Then, to assess the consistency of the identified deviations with behavioural metrics, two aspects are compared: the *magnitude* (how large) and *valence* (excess or deficit) of the identified deviations across both sets of metrics. If the origins and causes of bias are similar in purchases and brand associations, then when comparing behavioural and brand salience metrics, a brand that deviates for one set of metrics should also deviate for the other.

It is important to remember that while this comparison is extremely relevant for testing further the differences between behavioural and brand salience metrics, it also represents a new area of empirical contribution, since the analysis of the existence of deviations from the Double Jeopardy pattern in brand image data has not been thoroughly investigated so far.

Three typical deviations from the Double Jeopardy pattern (as per empirical evidence in behavioural data) are investigated: (i) *niche brands*; (ii) *change-of-pace brands*; and (iii) *excess behavioural loyalty* (see Chapter 4 for a description of these typical deviations from Double Jeopardy pattern in buying behaviour). The last type of deviation also includes private labels, since within chains these brands usually show excess behavioural loyalty.

6.5.3.1 Identifying deviations from Double Jeopardy

The method used to indentify deviations from the Double Jeopardy pattern across the two sets of metrics analysed includes calculating Absolute Percentage Errors (APEs) values for every brand. Drawing upon Wright et al. (2002) the formula for calculating APEs is the following (for every brand):

$$APE = Abs\left(\frac{Obs - Th}{Obs}\right) \qquad \textbf{Equation 32}$$

This measure identifies large discrepancies between observed and theoretical metrics (Wright et al., 2002). APEs values are calculated for the following metrics: (i) for behavioral metrics, *Penetration* and *Average Purchase Frequency*; and (ii) for brand salience metrics, *Salience Penetration* and *Association Rate*.

In the literature, there is no cohesive specification of how large APEs should be in order to determine an actual deviation from the Dirichlet benchmark. Therefore, in this thesis a benchmark of an APE value equal to or greater than 15% of the observed metrics to identify actual deviations (or 'large enough' discrepancies between observed and theoretical metrics) is used. This value is in line with the summary of benchmarks from literature in a recent discussion on the methods of assessing the fit of the Dirichlet model (Driesener et al., 2012).

6.5.3.2 How to determine consistent deviations

Consistent deviations across both sets of metrics would be identified as follows:

- For *niche brands* (typically low Penetration and higher than expected Purchase Frequency as per purchase data), also observing low Salience Penetration and higher than expected Association Rate;
- For *change-of-pace brands* (typically medium-to-high Penetration and lower than expected Purchase Frequency as per purchase data), also observing medium-to-high Salience Penetration and lower than expected Association Rate;
- For *private labels* within chain (typically high Penetration and higher than expected Purchase Frequency as per purchase data), also observing higher than expected Salience Penetration and high Association Rate.

To determine consistent deviations, there are two aspects that must be assessed simultaneously for every deviation identified in the two sets of metrics analysed:

- Whether a brand showed an actual deviation, i.e. showing an APE value equal to or greater than 15% in *both* sets of metrics or *only in one*;
- Whether the direction of the deviation (referred to as 'valence' of the deviation) between observed and theoretical metrics (excess or deficit purchase frequency and association rate) was *same* or *opposite*.

Comparing valence of deviations will not be possible in any instance when in one of the two sets of metrics *Obs = Th*.

Consequently, only when a brand is an actual deviation across both metrics and is showing the same valence in the deviation, it is possible to identify an instance of a consistent deviation across both sets of metrics.

6.5.4 LEVEL 4: The decision-tree

As displayed in Table 11, each level of analysis has multiple research outcomes and each outcome validates one of the two research propositions tested in this thesis.

Therefore, the last level of analysis combines the various research outcomes of each previous level of analysis into a 'decision-tree' showing graphically which research outcomes validate the research propositions of this thesis (Rp0 or Rp1), hence which of the following three competing views tested is supported (see also Chapter 5):

(i) There is no detectable similarity between behavioural and brand salience metrics; the patterns in the two sets of metrics are underpinned by distinct stochastic processes and two distinct sets of latent variables, thus purchase and retrieval propensities are two separate aspects of consumer choice (supported by the validation of **Rp0**).

(ii) Behavioural metrics and brand salience metrics are quite similar, but with detectable differences caused by some confounding factors acting upon the stochastic processes shaping purchase and retrieval propensities, which are somewhat related aspects of consumer choice (supported by the **partial** validation of **Rp1**).

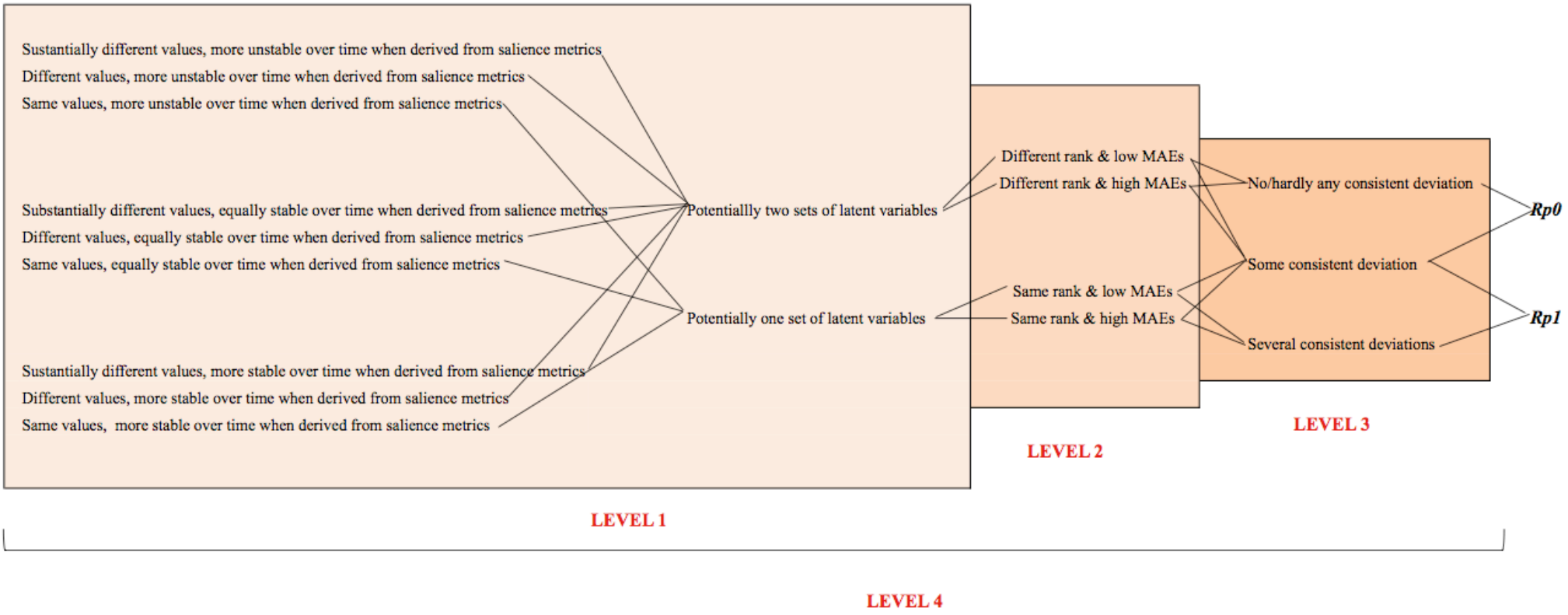
(iii) Behavioural metrics and brand salience metrics are very similar and the patterns characterising the two sets of metrics are underpinned by the same stochastic process, shaping only one set of latent variables and thus making purchase and retrieval propensities virtually inseparable aspects of consumer choice (supported by the validation of **Rp1**).

Table 11 – Overview of the four levels of analysis

		Competing view 1 (Rp0)	*Competing view 2 (Rp1 partially)*	*Competing view 3 (Rp1)*
LEVEL 1: Parameters	Values	Substantially different values	Different values	Same values
	Temporal stability	Higher coefficient of variation when derived from salience metrics	Same coefficient of variation when derived from salience metrics	Lower coefficient of variation when derived from salience metrics
LEVEL 2: Metrics	Spearman's correlation coefficients	Sig. correlation ≠ +/-1 for all analogous metrics	Non - Sig. correlation for all analogous metrics	Sig. correlation = +/-1 for all analogous metrics
	MAEs values	Greater than 5% for all analogous metrics	Around 5% for all analogous metrics	Smaller than 5% for all analogous metrics
LEVEL 3: Deviations	Consistency in the deviations	No consistency / hardly any consistency	Some instances of consistency	Several instances of consistency

An intuitive way to outline of the logical process is selecting which research outcomes validate one of the two research propositions and support one of the three competing views is the following decision tree (Figure 19):

Figure 19 – Level 4 of the analysis



6.6 Chapter summary

This chapter presented an overview of the research methods used for the data analysis.

It started with an overview of the data sets analysed and the analytic built-in control. Then, it included a description of how the two sets of metrics are calculated and modelled, particularly for brand salience metrics.

Afterwards, the research methods used across four levels of data analysis have been described as follows:

- The methods necessary for LEVEL 1 of the analysis, which compares the values of the Dirichlet parameters obtained by fitting the Dirichlet model to behavioural and brand salience metrics (including the methods for assessing the temporal stability of the parameter values over time);
- The methods necessary for LEVEL 2 of the analysis, which includes the direct comparison of behavioural and brand salience metrics (Spearman's rank correlation coefficient and Mean Absolute Errors) between the 'pairing' metrics;
- The methods necessary for LEVEL 3 of the analysis, which assesses the consistency of deviations from the Double Jeopardy pattern across the two sets of metrics;
- The decision-tree combining the research outcomes of the previous levels of analysis into a single outcome, for LEVEL 4.

Chapter 7 – Results

7.1 Introduction

'The search for truth is more precious than its possession'

Albert Einstein – Physicist and philosopher (1879-1955)

This chapter presents the results of the four different levels of analysis for this thesis, preceded by the results of the research preamble.

§ 7.3 presents the results of LEVEL 1 of the analysis, including the comparison of the values of the Dirichlet parameters *M*, *K* and *Phi* and of the analysis of temporal stability (Coefficients of Variation).

§ 7.4 presents the results of LEVEL 2 of the analysis on the direct comparison of the two sets of metrics. The results are divided according to the two key methods used, i.e. analysis of the rank (Spearman's Rho correlation coefficients), and analysis of the Mean Absolute Errors (MAEs) between the metrics.

§ 7.5 presents the results of LEVEL 3 of the analysis, assessing the consistency of deviations from the Double Jeopardy pattern.

Finally, **§ 7.6** presents the results of LEVEL 4 of the analysis, i.e. the 'decision-tree' combining the outcomes of the previous levels of analysis to validate one of the two research propositions, hence one of the three competing views tested in this thesis.

7.2 Results for behavioural metrics

For the two data sets analysed, Table 12 indicates the total sample size and the number of brands available in the data set and analysed.

Table 12 – Descriptive statistics for behavioural data

	Sample size N	***Product categories***	***# of brands***
US cross-sectional data (three years)	Year 1 (2006) $N = 2{,}644$ Year 2 (2007) $N = 5{,}228$ Year 3 (2008) $N = 5{,}236$	Toothpaste	Between 25 and 28 brands each year
UK panel data (one year)	Tea $N = 8{,}219$ Instant coffee $N = 7{,}974$ Roast coffee $N = 6{,}532$	Hot beverages	9 for tea and instant coffee; 8 for roast coffee

The set of behavioural metrics analysed in this thesis were: the % of *Market Share*, the % of *Penetration*, the *Average Purchase Frequency* and the *Share of Category Requirement* SCR (%). The calculation of these metrics did not require any sub-selection of the range of brand purchases available in the data sets. The theoretical equivalents of these metrics have been obtained by fitting the Dirichlet model to the observed values.

Table13 shows, as an example, observed and theoretical behavioural metrics for the one product category available in the UK data, i.e. tea.

The results for all other categories and data are available in Appendix C.

Results are ordered according to the observed % of Market Share.

Table 13 – Observed and theoretical behavioural metrics – TEA (UK)

	Market share %	Penetr. %		Purch. Freq.		SCR %	
		O	T	O	T	O	T
Tesco Std	29	38	48	5.8	4.5	22	46
PGTips	21	37	37	4.2	4.1	55	41
Tetley	19	40	35	3.5	4.1	53	40
Twinings	13	26	27	4.0	3.8	42	37
Typhoo	5	17	12	2.5	3.5	34	33
Yorkshire	5	9	11	4.4	3.5	49	33
Clipper	4	10	9	3.3	3.5	33	32
TescoFinst	3	8	8	3.5	3.4	35	32
Punjana	0	3	2	2.1	3.3	27	31
Average	**11**	**21**	**21**	**3.7**	**3.7**	**39**	**36**

In this category (tea), the average % of Market Share was 11%, ranging between 29% for the largest brand in the market (Tesco Standard) and less than 1% for the smallest share brand (Punjana). The average Penetration was 21% percent and the Average Purchase Frequency was 3.7 times per year. The average observed Share of Category Requirement was around 39%, and the theoretical value was 36%. The observed values were close to the theoretical metrics for all the behavioural metrics calculated.

Similar results were found across all of the other categories analysed in the UK data set, as well as for all years analysed in the US data set. Hence, the values obtained for behavioural metrics broadly conformed to prior empirical evidence from consumer behaviour literature, as shown in the overview of the fit statistics (Mean Absolute Deviations and Mean Absolute Percentage Errors) in Table 14:

Table 14 – Report of fit statistics for behavioural metrics for both data sets

Fit statistics (UK tea)

	Penetration	Purch. Freq.	SCR
MADs	3 %	0.6	9%
MAPEs	14 %	16 %	23%

Fit statistics (UK instant coffee)

	Penetration	Purch. Freq.	SCR
MADs	2 %	0.5	9%
MAPEs	38 %	22 %	22%

Fit statistics (UK roast coffee)

	Penetration	Purch. Freq.	SCR
MADs	1 %	0.4	17%
MAPEs	14 %	17 %	30%

Fit statistics (US average 3 years)

	Penetration	Purch. Freq.	SCR
MADs	1.5 %	0.3	7.3 %
MAPEs	10 %	13 %	20 %

Share of Category Requirement represents the only partial exception for roast coffee, where the discrepancy between observed and theoretical metrics seems quite large. However, prior empirical evidence showed that the Dirichlet model might provide less robust estimates for this metric (Scriven and Bound, 2004).

Moreover, the results obtained for behavioural metrics showed a clear Double Jeopardy pattern across both data sets, with larger share brands also systematically showing higher Penetration, Average Purchase Frequency and Share of Category Requirement.

7.3 Results for brand salience metrics

As explained in § 6.4, there are three key steps that must be undertaken in order to analyse brand image data and to obtain a sub-set of attributes to calculate brand salience metrics. These were: (i) analysis of correlations among brand attributes to avoid overlapping mental structures; (ii) analysis of the usage-image relationship to isolate descriptive and evaluative attributes; and (iii) analysis of the frequency of brand associations. These steps have been implemented for both data sets analysed. An example of the outcome of these steps for one product category (tea from the UK data) is shown below.

Table 15 shows the results for Kendall Tau's correlations for the whole sample of brand image data for tea. Average correlations across all brands analysed are presented; and positive and large (> 15%) correlations are bolded in red. Negative large correlations (bolded in blu) were not considered, since they actually represent concepts that are tapping into very different mental constructs (significantly different response patterns). The correlations for all categories analysed are available in Appendix A.

Table 15 – Kendall Taub's correlations – TEA (average of all brands)

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
A		**0.23**	0.12	0.12	0.02	**0.20**	**0.15**	0.13	0.08	0.02	0.07	0.01	0.03	-0.03	0.02	0.04	0.02	0.03
B	**0.20**		0.09	0.08	0.00	0.14	0.10	0.08	0.05	0.00	0.03	0.00	0.03	-0.05	0.00	0.03	0.01	0.02
C	0.07	0.06		0.10	0.12	0.06	**0.20**	0.02	-0.04	-0.06	-0.04	-0.06	-0.02	0.03	-0.01	-0.02	0.01	-0.04
D	0.09	0.07	0.12		0.12	0.12	0.12	0.06	0.01	-0.02	-0.01	-0.01	-0.01	0.01	0.01	-0.02	-0.01	-0.02
E	-0.09	-0.08	0.06	0.05		-0.08	0.01	-0.09	-0.09	-0.05	-0.13	-0.03	-0.05	0.06	0.00	-0.10	-0.02	-0.07
F	**0.20**	**0.17**	0.11	**0.16**	0.04		**0.18**	**0.16**	0.09	0.01	0.09	0.01	0.02	-0.03	0.03	0.05	0.02	0.05
G	**0.15**	0.13	**0.25**	**0.16**	0.12	**0.17**		0.11	0.05	-0.01	0.04	0.00	0.02	0.01	0.04	0.01	0.03	0.01
H	0.06	0.04	0.00	0.03	-0.05	0.09	0.04		-0.01	-0.04	0.02	-0.05	-0.04	-0.03	-0.04	0.08	-0.02	0.00
I	0.08	0.08	0.01	0.04	0.02	0.08	0.05	0.06		0.09	**0.23**	**0.17**	0.09	0.01	0.11	0.04	0.05	0.07
J	-0.13	-0.12	**-0.15**	-0.13	-0.08	-0.14	-0.16	-0.12	-0.06		-0.07	0.01	-0.05	-0.02	0.00	-0.06	-0.09	-0.03
K	0.06	0.04	-0.01	0.02	-0.03	0.08	0.02	0.07	**0.22**	0.06		**0.16**	0.08	0.00	0.08	0.06	0.05	0.09
L	-0.04	-0.02	-0.06	-0.02	0.03	-0.04	-0.05	-0.03	0.12	0.12	0.12		0.10	0.04	0.10	-0.02	0.06	0.03
M	-0.05	-0.02	-0.05	-0.06	-0.03	-0.07	-0.06	-0.05	0.01	0.02	0.01	0.07		0.03	0.04	0.00	0.03	0.00
N	**-0.25**	**-0.24**	-0.14	**-0.18**	-0.05	**-0.25**	**-0.21**	**-0.18**	**-0.21**	-0.09	**-0.21**	-0.14	-0.11		-0.11	-0.14	-0.04	**-0.17**
O	-0.03	-0.02	0.00	0.00	0.06	-0.02	-0.01	-0.02	0.07	0.10	0.05	0.10	0.07	0.07		-0.02	0.02	0.00
P	-0.13	-0.11	-0.13	-0.15	**-0.15**	-0.12	**-0.15**	-0.02	-0.13	-0.07	-0.10	-0.14	-0.09	-0.08	-0.14		-0.05	0.06
Q	-0.09	-0.07	-0.05	-0.08	-0.02	-0.10	-0.08	-0.07	-0.06	-0.06	-0.05	-0.01	0.00	0.07	-0.04	0.01		-0.02
R	-0.11	-0.10	-0.14	-0.13	-0.11	-0.10	-0.14	-0.08	-0.08	-0.03	-0.05	-0.07	-0.07	-0.09	-0.10	0.08	-0.06	

As shown, there were multiple sets of brand attributes that showed positive and large correlations across all brands. These were:

- *'Would warm me up' and 'Satisfy thirst';*
- *'First thing in the morning', 'When I want to relax' and 'Would warm me up';*
- *'Calm me down', 'When I want to relax' and 'After dinner';*
- *'A brand I can trust', 'Taste good' and 'High quality ingredients'.*

For each set listed above, only one attribute has been selected for salience measurement. This approach was replicated for all categories and both data sets.

The remaining brand attributes then underwent usage-image regression analysis. Attributes with a higher than expected number of responses from non-users was identified as highly *descriptive* attributes, whereas attributes showing lower than expected responses were identified as highly *evaluative*. Both types were removed from the set of attributes for salience measurement. Table 16 shows the results of the usage-image regression analysis for the category chosen as an example (% of associations by users, by non-users, % of expected associations by non-users and deviations). All results of the usage-image regression are reported in Appendix B.

Table 16 – Usage-Image regression analysis – TEA (average of all brands)

	% users	**% non-users**	**Exp. %**	**Deviations**
Satisfy thirst	44	16	19	-2.9
Warm me up inside	42	18	18	0.0
Calm me down	26	8	11	-3.0
After dinner	30	10	13	-3.1
To indulge myself	21	8	9	-1.3
1st thing in the morning	40	13	17	-4.2
When I want to relax	35	11	15	-4.1
Good value for money	36	12	15	-3.2
Would taste good	52	24	22	1.4
Strong flavour	30	16	13	3.5
A brand I can trust	54	25	23	1.8
High qual. ingredients	44	21	19	2.7
Natural	34	16	15	1.6
Doing new things	12	6	5	0.8
Great aroma	33	13	14	-0.7
Down to earth	30	18	13	**5.2**
Up-to-date	28	13	12	1.1
Traditional	38	24	16	**7.8**

The table highlights that in this product category (tea) there were two outliers which deviated from the usage-image relationship across all brands analysed and elicited more associations from non-users than expected: '*Down to earth*' and '*Traditional*'. These two attributes were not included in the set for measuring brand salience. The same analysis was replicated for all categories, across both data sets.

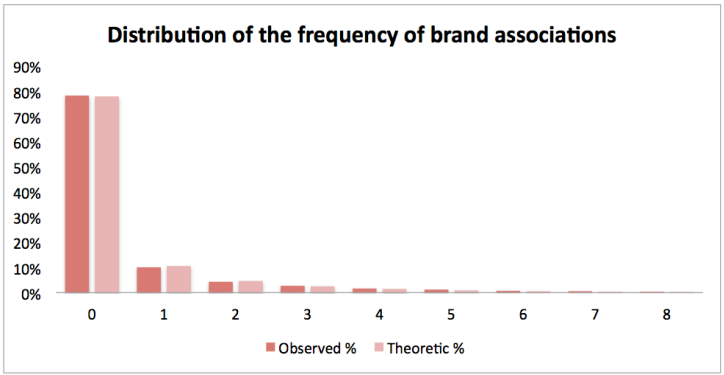
The final step of analysis was fitting a frequency distribution, the Negative Binomial Distribution (NBD), to identify a suitable number of brand attributes to be used.

Since prior empirical research by Romaniuk (Forthcoming) identified 8 to 10 attributes as an ideal number of attributes for salience measurement, it was necessary to reduce the remaining set of 12 attributes. The following attributes were removed:

- The attribute '*Good value for money*' was removed because it may result in a over-representation of private labels or low price tier brands;
- The attribute '*Would have a strong flavour*' was removed because it may be interpreted negatively by respondents;
- The attributes '*Always doing new things*' and '*Up-to-date*' were removed because they represent two similar constructs (although they were not correlated), which could bias patterns in brand associations.

Following these additional qualitative appraisals, the NBD was fitted to the remaining 8 attributes. Figure 20 shows, in a histogram plotting observed and theoretical values, the results of fitting the NBD to one brand. The example presented in this figure shows a close fit between the observed % of brand associations and the theoretical values provided by the NBD, with overall MADs of 0%. Results were consistent across all brands analysed (largest MAD was 3%) and for both large as well as small brands.

Figure 20 – Negative Binomial Distribution (NBD) – TEA (one brand)



Therefore, the sub-sets of brand attributes used for calculating brand salience metrics for the tea category were:

- *'Would warm me up inside';*
- *'Calm me down';*
- *'After dinner';*
- *'When I want to indulge myself';*
- *'Good first thing in the morning';*
- *'Would taste good';*
- *'Natural';*
- *'Great aroma'.*

The sub-sets of brand attributes used for the other product categories are showed in the Appendix A (bolded attributes in Table 1). They were all identified in the same way described in this example.

Table 17 indicates the number of brands and brand attributes originally available in the data set and the number of attributes selected for salience measurement after implementing the necessary steps.

Table 17 – Descriptive statistics for brand salience metrics

	Sample size N	***Product categories***	***# of brands***	***# of attributes***	***# of attributes selected***
US cross-sectional data (three years)	Year 1 (2006) *N* = 2,644 Year 2 (2007) *N* = 5,228 Year 3 (2008) *N* = 5,236	Toothpaste	12 each	15 each	9 each (same sets across all three years)
UK panel data (one year)	Tea *N* = 8,219 Instant coffee *N* = 7,974 Roast coffee *N* = 6,532	Hot beverages	9 each	Tea = 18 Coffee = 25	8 each (different sets for each category)

Given the sub-set of brand attributes identified, for both data sets it was then possible to calculate the set of observed brand salience metrics for all brands. The metrics calculated were: the % of *Brand Salience*, *Salience Penetration* (%), *Association Rate*

and *Share of Mind* SOM (%). These metrics were then modelled with the Dirichlet in order to generate their theoretical equivalents.

Results for both the data sets showing the observed and theoretical brand salience metrics are reported in Appendix D. Table 18 shows the results for the product category from the UK, which has been used as an example so far. The values of the metrics are ordered according to the % of Brand Salience (observed).

Table 18 – Observed and theoretical brand salience metrics – TEA (UK)

	Salience %	**Sal. Pen. %**		**Assoc. Rate**		**SOM %**	
		O	**T**	**O**	**T**	**O**	**T**
PGTips	20	65	66	3.9	3.9	35	26
Tetley	19	62	63	3.8	3.8	32	25
Twinings	15	56	56	3.4	3.5	27	22
Yorkshir	15	41	42	3.0	3.0	22	19
Typhoo	12	48	47	3.1	3.1	21	20
Tesc Fin	9	41	39	2.8	2.9	18	18
Tesco St	7	29	33	3.1	2.8	24	17
Clipper	4	22	20	2.4	2.5	16	15
Punjana	3	19	15	1.9	2.4	12	14
Average	**12**	**43**	**42**	**3.1**	**3.1**	**23**	**20**

The values of observed and theoretical salience metrics were very close for all metrics from this category (tea). Average Brand Salience score was 12%, ranging between 20% for the most salient brand (PG Tips) and 3-4% for the least salient brands (Clipper and Punjana). The average Salience Penetration was slightly above 40% percent and the average Association Rate were around 3.1. Lastly, the average Share of Mind was about 20%.

As shown by the report of fit statistics in Table 19, similarly robust sameness between the calculated observed and theoretical brand salience metrics was obtained for all other categories analysed.

Table 19 – Report of fit statistics for salience metrics for both data sets

Fit statistics (UK tea)

	Sal. Penetr.	**Ass. Rate**	**Share of Mind**
MADs	1.6 %	0.1	4.1 %
MAPEs	3.7 %	4.9 %	17.8 %

Fit statistics (UK instant coffee)

	Sal. penetr.	Ass. Rate	Share of Mind
MADs	1.1 %	0.2	7.5 %
MAPEs	7.2 %	7.7 %	35.2 %

Fit statistics (UK roast coffee)

	Sal. penetr.	Ass. Rate	Share of Mind
MADs	1.9 %	0.5	10.5 %
MAPEs	16.2 %	16.4 %	44.8 %

Fit statistics (US average 3 years)

	Sal. penetr.	Ass. Rate	Share of Mind
MADs	2.9 %	0.3	4.2 %
MAPEs	6.6 %	7.8 %	24.2 %

The values of MADs were always considerably low and so are MAPE values, especially for Salience Penetration and Association Rate. Values of MADs and MAPEs are higher for Share of Mind, but the Dirichlet model is known to provide less accurate predictions for Share of Category Requirement (Scriven and Bound, 2004), the behavioural equivalent of Share of Mind. Therefore, higher MAPE values for Share of Mind are, to some degree, not surprising and do not affect the ability of the Dirichlet model to produce theoretical brand salience metrics. Moreover, these results are also in line with Romaniuk's (Forthcoming) prior empirical analysis on brand salience measurement.

Lastly, all metrics showed a clear Double Jeopardy pattern, with the most salient brands also showing higher Salience Penetration, Association Rate and Share of Mind.

The obtained values of behavioural and brand salience metrics described so far were then analysed across the four different levels of analysis introduced in Chapter 6. The results for each level now follow.

7.4 Results for LEVEL 1 of the analysis

As explained in Chapter 6, the comparison of the parameters allowed for an assessment of whether there were distinct sets of latent variables underpinning purchases and brand associations. This provided the first crucial clue about the potential differences (or similarities) between purchases and retrieval propensities.

Two aspects of the parameters were considered in this first level of analysis: (i) the value of the parameters; and (ii) the stability of the parameter values over time.

7.4.1 Values of the parameters

As explained in Chapter 6, a first component of the LEVEL1 of the analysis included comparing the values assumed by the Dirichlet parameters M, K and Phi. The values have been compared across behavioural and brand salience metrics in terms of the typical range they can assume and how the range is interpreted in purchase behaviour (e.g. between 0 and 1 for Phi), or in terms of how large the values were (e.g. for M). The key rationale for interpreting the values of the parameters is looking for a significant sameness across purchases and brand associations, as a potential indicator of the existence of a single set of latent variables. In fact, only if the parameter values were fairly similar it would be possible to conclude that they are representative of a single set of latent variables, despite the existence of similar underlying stochastic processes.

As shown in Table 20, the biggest differences in the values of the parameters obtained from modelling behavioural and brand salience metrics were for the parameter *M* and *Phi. Phi*, in particular, was on average nearly 6 times bigger for behavioural metrics than salience metrics.

Table 20 – Comparison of the values of the Dirichlet parameters – UK data

	M		***K***		***Phi***	
	Behav. Metrics	**Salience Metrics**	**Behav. Metrics**	**Salience Metrics**	**Behav. Metrics**	**Salience Metrics**
Tea	7.29	12.57	0.99	1.66	0.47	0.17
Roast coffee	0.87	3.43	0.09	0.08	0.40	0.04
Instant coffee	5.14	3.63	0.52	0.11	0.50	0.02
Average	**4.43**	**6.54**	**0.53**	**0.62**	**0.46**	**0.08**

These results are not surprising if one considers the following: as explained in Chapter 6, when looking at purchasing behaviour the parameter *M* is a proxy of the

overall level of demand. One possible interpretation for brand salience metrics is that *M* is a proxy of the overall level of knowledge about a certain product category. Thus, the consistency between how much, on average, a population is purchasing a certain product category, and the amount of knowledge held by that same population about that category may not be as straightforward.

Analogously, the parameter *Phi* embodies the level of brand switching in purchase behaviour (the closer to 1, the higher the level of brand loyalty), whereas for salience metrics it could be interpreted as an indicator of how dispersed the knowledge about the product category is (the closer to 1, the more concentrated around few brands category knowledge would be). Given the assumed interpretation of *Phi* for salience metrics, it appears that while brand-switching levels are moderate, the knowledge about the category is dispersed across multiple brands (values of *Phi* are always close to 0), even among non-users.

On average, the values of the parameter *K* were, instead, more similar. However, this was not the case when looking at the three categories separately (especially for tea and instant coffee). Once again, interpreting this result comes down to parameters' meaning. Since this parameter is used in buying behaviour for customer concentration analysis (distribution of light and heavy buyers), and for salience metrics could be considered a proxy of the concentration of category knowledge (distribution of highly knowledgeable versus non knowledgeable customers), it is not surprising to see a smaller difference. Possible reasons for this could be: (i) evidence of usage-image effect in brand image data, which results in a positive relationship between brand usage levels and the rate of associations as per Bird and Channon (1969), and Bird, Channon and Ehrenberg (1970); (ii) evidence of a Pareto Share distribution underpinning brand knowledge: just under half of all brand associations scored by brands is held by 20% of 'heavy mentioners' (i.e. those providing the highest number of brand associations), while the remaining half is spread across a large pool (80%) of 'light mentioners' (Romaniuk and Sharp, 2008).

In the US data, slightly different patterns in the discrepancies between values of the parameters were observed when looking across time periods (Table 21).

The largest difference was evident for the parameter *M*, suggesting that this parameter most likely embodies very different aspects of the modelled phenomena, which are not directly comparable (i.e. the level of demand versus level of category knowledge).

The difference for the parameter *Phi* was less in the US data set than in the UK data. This suggests that for this market there might be a closer relationship between the level of brand switching and the dispersion of category knowledge across a large cohort of brands (i.e. high level of brand switching constantly matched by associations being spread across many brands). One could assume that interpreting

and comparing the values of this parameter across behavioural and brand salience metrics provides category specific insights, rather than generalisable trends.

Lastly, for the parameter *K*, its value in behavioural metrics was essentially double that in brand salience metrics. Given the interpretation of the *K* parameter in purchase behaviour (lower values imply a greater proportion of heavy users), it appears that for this product category there is a smaller cohort of heavy buyers (*K* = 1.60 on average) than of heavy mentioners (*K* = 0.80 on average). Nevertheless, given the fact that these results are obtained from different samples, some care needs to be taken in drawing conclusions from this data.

Table 21 – Comparison of the values of the Dirichlet parameters – US data

	M		***K***		***Phi***	
	Behav. Metrics	**Salience Metrics**	**Behav. Metrics**	**Salience Metrics**	**Behav. Metrics**	**Salience Metrics**
Year 1	3.36	18.97	1.67	0.80	0.21	0.08
Year 2	3.31	19.52	1.56	0.80	0.10	0.10
Year 3	3.25	19.89	1.58	0.81	0.09	0.10
Average	**3.31**	**19.46**	**1.60**	**0.80**	**0.13**	**0.09**

Therefore, when simultaneously considering the results obtained from the comparison of the values of the parameters for the two data sets, the following conclusions can be drawn:

- The values of the parameters for behavioural and brand salience metrics are different for all three parameters analysed;
- Differences are more or less enhanced for each parameter analysed, with no clear generalisable pattern across the two data sets.

The first point is particularly relevant, because it suggests that despite some similarities in the way these three parameters may be interpreted, there are different meanings and insights inherent in brand image data that may not be found in behavioural data. Moreover, the substantial differences in the values assumed by these

parameters provide empirical support for the hypothesis developed in Chapter 5. It provides the first evidence that there are likely to be two sets of latent variables underpinning purchases and brand associations.

When looking separately at the values of the parameters derived from brand salience the following patterns can be identified:

- *M*: highest for toothpaste, followed by tea and then the two types of coffee's categories; these values suggest that on average, consumers hold numerous associations with the brands competing in these categories;
- *K*: highest for tea, followed by toothpaste, then all others fairly low and close to 0; these values suggest that for tea and toothpaste, a large percentage of the respondents provided a large number of brand associations (more 'heavy mentioners'), whereas for the coffee categories the vast majority of respondents provided a limited number of brand associations (more 'light mentioners');
- *Phi*: the value of this parameter is close to 0 for all categories; this indicates that for all categories brand associations where allocated across multiple brands, rather than concentrated among few brands. This is an important characteristic of brand image data that does not mirror purchase behaviour in these instances.

7.4.2 Temporal stability of the parameters

To analyse the condition of stationarity, i.e. the stability of the parameter values over time, multiple time periods must be considered. This required fitting the model repeatedly in order to obtain a time series of the parameter values. For this reason, results of this component of analysis are available only for the US data, which were longitudinal.

Two distinct components of the analysis of the temporal stability are reported:

- The analysis of a time series of 13 time periods (quarterly data) for brand salience metrics only (no quarterly data was available for purchase data) for the purpose of appraising the condition of stationarity in brand salience metrics;
- The analysis of a time series of three time periods (yearly data) for both sets of metrics, hence comparing directly the degree of stability shown in the underlying structures of purchases and brand associations.

Both time series were calculated for the parameters *M*, *K* and *Phi*, by fitting the Dirichlet model to each time period available. The stability over time of the parameter values was appraised by looking at the ratio of the standard deviations to the means of the parameters (the *coefficient of variation*). The first time series (i) was also plotted to highlight any trend and exception.

Assessment of the first time series (13 quarters for salience metrics only) provided the following results (see Figures 21, 22 and 23): a coefficient of 0.07 for the parameter *M*, 0.05 for the parameter *K*, and 0.12 for the parameter *Phi*, thus confirming broad stability over time in the parameters derived from salience metrics. This also suggests that when based on the count of brand associations, similarly to purchase propensities, retrieval propensities are stable over time.

Figure 21 – Temporal stability of the parameter* M *(brand salience) – US data

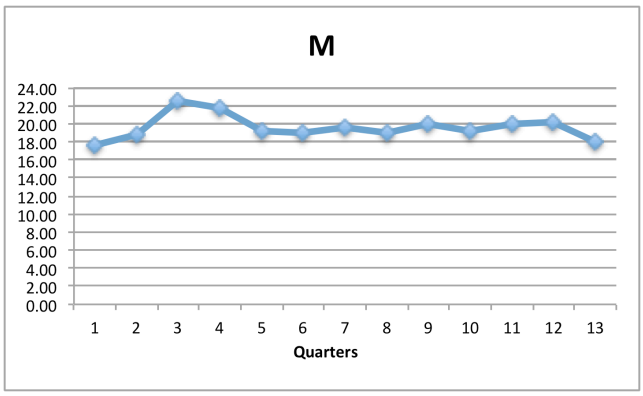


Figure 22 – Temporal stability of the parameter* K *(brand salience) – US data

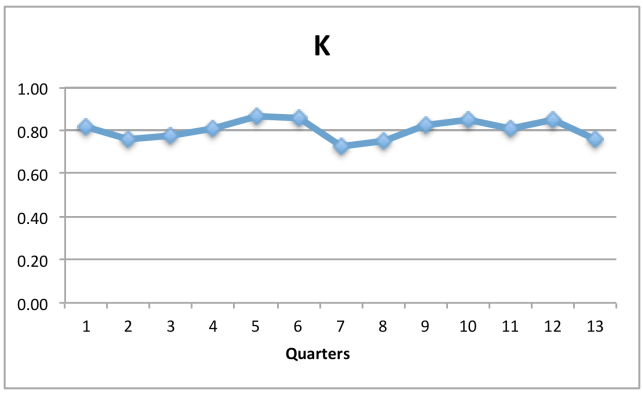
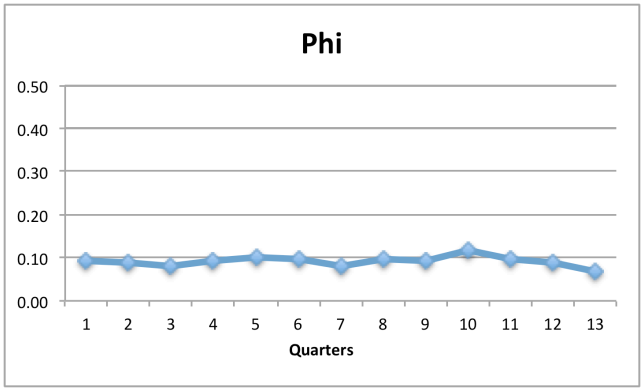


Figure 23 – Temporal stability of the parameter **Phi** *(brand salience) – US data*



Assessment of the parameter values across both sets of metrics over three years also confirmed the condition of stationarity (low coefficients of variation) for both sets of parameters.

Moreover, a close look at the coefficients of variation showed the following systematic pattern across all three parameters (see Table 22):

- The values of the parameters derived from salience metrics were systematically more stable over time than those derived from behavioural metrics;
- The most 'stable' parameter was *K*, which was virtually non-varying across both sets of metrics, whereas maximum variation was apparent for *Phi*.

Table 22 – Temporal stability of the Dirichlet parameters – US data

	M		***K***		***Phi***	
	Behav. Metrics	**Salience Metrics**	**Behav. Metrics**	**Salience Metrics**	**Behav. Metrics**	**Salience Metrics**
Coefficient of Variation	**0.26**	**0.02**	**0.03**	**0.01**	**0.54**	**0.07**

These results are extremely interesting because they not only provide insight into the condition of stationarity in retrieval propensities (which appear to be potentially more stable than purchase propensities), but they also support the potential existence of two separate sets of latent variables shaping purchase and retrieval propensities, given the

differences identified not only in the values of the parameters, but also in the coefficients of variation.

Therefore, these results complete the analysis of the Dirichlet parameters and the comprehensive research outcome of the first level of analysis as follows:

> *The Dirichlet parameters M, K and Phi obtained from modelling behavioural and brand salience metrics were substantially different in values across both data sets analysed, as well as in the degree of stability showed over time.*

7.5 Results for LEVEL 2 of the analysis

The second level of analysis included the direct comparison of the observed values of behavioral and brand salience metrics focusing on: (i) the *rank* of the brands provided by the two sets of metrics, and (ii) the actual *difference* in the values assumed by these metrics. The first aspect was appraised by looking at Spearman's rank correlation coefficients, whereas the second aspect was appraised calculating Mean Absolute Errors (MAEs).

7.5.1 Ranking of brands

The two sets of metrics calculated were used to rank the brands in each category from the top brand in the market down as follows: according to % of observed Market Share for behavioral metrics; and according to the observed % of Brand Salience for brand salience metrics. Then, for each category, calculating Spearman's rank correlation coefficients compared the ranks obtained with the two sets of metrics. The results obtained are reported in Table 23 and Table 24:

There was a consistent pattern across both data sets analysed: a positive, large and significant correlation between Share of Mind and Share of Category Requirements. These two metrics showed a positive, large (ranging between 0.7 and 0.8) and significant ($p<0.05$, even $p<0.01$ in most instances) Spearman's rank correlation coefficient. The only exception was the roast coffee category in the UK data, but the trend was robust across more than one time period and more than a single product category.

Table 23 – Spearman's rank correlation coefficients for UK data

	Market share & Brand sal.	Purch. penetr. & Sal. penetr.	APF & Assoc. rate	SCR & SOM
Tea	0.60	0.63	0.49	0.70*
Roast coffee	-0.31	-0.10	-0.31	-0.18
Instant coffee	0.64	0.65	0.11	0.80**

***Correlation is significant at the 0.01 level (2-tailed)*
**Correlation is significant at the 0.05 level (2-tailed)*

Table 24 – Spearman's rank correlation coefficients for US data

	Market share & Brand sal.	Purch. penetr. & Sal. penetr.	APF & Assoc. rate	SCR & SOM
Year 1	0.52	0.98**	0.47	0.72*
Year 2	0.19	0.96**	0.52	0.78**
Year 3	-0.03	0.68*	0.43	0.73**

***Correlation is significant at the 0.01 level (2-tailed)*
**Correlation is significant at the 0.05 level (2-tailed)*

It was not possible to identify a clear pattern in the correlation coefficients for other metrics that held across *both* data sets. However, there were minor patterns affecting the two data sets separately:

- In the UK data, for two of the three categories, there was a positive and moderate (around 0.6), but non-significant correlation coefficient for: (i) Market Share and Brand Salience; (ii) Purchase Penetration and Salience Penetration;
- In the US data, across all three years analyzed, there was a positive, large (ranging between 0.7 and 0.9) and significant ($p<0.05$, even $p<0.01$ for two out of three year) correlation coefficient for Purchase Penetration and Salience Penetration; there was also a positive, moderate (ranging between 0.4 and 0.5), but non-significant correlation between Purchase Frequency and Association Rate.

These results suggest that there was no clear pattern in the correlation coefficients that held across both sets of data analysed. Therefore, for the purposes of the broad research question investigated in this dissertation, it appears that another potential difference between behavioral and brand salience metrics has been highlighted. Only

one of the four analogous metrics analysed provided a very close rank and description of brand performance from the top to bottom brand in the market. As for two size-related analogous brand performance metrics (i.e. Market Share and Brand Salience, purchase penetration and salience penetration), there appears to be some potential similarities in the rank of brands provided by these metrics, but these similarities do not persist across all categories and time periods analysed.

These findings were supplemented by a further and even more direct test: the calculations of the Mean Absolute Errors (MAEs) values, i.e. the average size of the differences between analogous metrics.

7.5.2 Mean Absolute Errors (MAEs)

Table 25 and Table 26 report MAE values for both data sets (average of all brands), while Table 27 exemplifies results for individual brands in one product category (tea).

The following patterns were clear across both data sets:

- MAE values are, on average, reasonably large for all other metrics and extremely large for Purchase Frequency and Association Rate (even above 100% in several instance; systematically above 200% for US data);
- MAE values are smaller for Market Share and Brand Salience - around 5%; however, a close look at the values of individual brands highlights that the discrepancies across both sets of metrics are systematically distributed: the largest discrepancy occurs for the market leader.

Table 25 – MAE values (UK data)

	Market share & Brand sal.	Purch. penetr. & Sal. penetr.	APF & Assoc. rate	SCR & SOM
Tea	0.06	0.24	0.85	0.16
Roast coffee	0.09	0.08	1.14	0.32
Instant coffee	0.06	0.06	0.95	0.21

Table 26 – MAE values (US data)

	Market share & Brand sal.	Purch. penetr. & Sal. penetr.	APF & Assoc. rate	SCR & SOM
Year 1	0.06	0.40	2.07	0.08
Year 2	0.05	0.37	2.06	0.09
Year 3	0.04	0.33	2.02	0.10
Average	0.05	0.37	2.10	0.12

Table 27 – MAE values example for individual brands (UK data, TEA)

	Market share & Brand sal.	Purch. penetr. & Sal. penetr.	APF & Assoc. rate	SCR & SOM
Brand 1	0.22	0.08	2.71	0.15
Brand 2	0.00	0.28	0.24	0.27
Brand 3	0.00	0.22	0.29	0.24
Brand 4	0.02	0.31	0.56	0.17
Brand 5	0.06	0.30	0.64	0.12
Brand 6	0.11	0.32	1.31	0.12
Brand 7	0.00	0.12	0.96	0.03
Brand 8	0.06	0.33	0.77	0.06
Brand 9	0.03	0.16	0.11	0.02

Therefore, these results supplement what was highlighted by the rank correlation coefficients: brand salience metrics and behavioural metrics depict differently the performance of brands. This is obvious not only in the rankings of brand performance, but also in the substantially different values for the metrics. Even in the instance of smaller difference between the two sets of metrics, i.e. low MAEs for Market Share and Brand Salience, this is not matched with a significant and robust correlation coefficient.

These results complete the direct comparison of the metrics. The comprehensive research outcome of this second level of analysis is the following:

> *Behavioural and brand salience metrics were substantially different across both data sets. The difference was apparent in the ranking of brands provided by these metrics, as well as in the value assumed by the analogous or 'pairing' metrics.*

7.6 Results for LEVEL 3 of the analysis

The third level of analysis draws on a common underlying empirical pattern, Double Jeopardy, in a further comparison of the two sets of metrics. This involved identifying any potential consistencies in the deviations from the Double Jeopardy pattern.

The primary insights that were sought at this level of analysis were:

- Highlighting further similarities or discrepancies that could supplement research outcomes of the previous levels of analysis;
- Addressing an empirical gap in the area of brand image research, i.e. the analysis of the existence of deviations from the Double Jeopardy pattern in brand image data and relative interpretation.

The following aspects were examined: (i) using the theoretical benchmarks of the Dirichlet model (i.e. theoretical metrics) to assess deviations from expected patterns in each set of metrics; and (ii) assessing the consistency of the identified deviations across both sets of metrics.

Results for both data sets are reported with brands being ranked according to the observed % of purchase Penetration. Observed (O) and theoretical (T) values for both sets of metrics are indicated. Average Percentage Errors (APEs) for Purchase Frequency and Association Rate are also indicated in order to identify deviations and their magnitudes. To assess the consistency of deviations, for every instance of deviation in either set of metrics, the *valence* of the deviation is showed (excess or deficit Purchase Frequency and Association Rate). Possible analysis outcomes were:

- 'SAME' for an excess in purchase frequency as well as the association rate, or conversely a deficit in purchase frequency as well as association rate;
- 'OPPOSITE' for an excess in purchase frequency and a deficit in association rate, or conversely a deficit in purchase frequency and excess in association rate;
- 'n.a.' if Observed = Theoretical for one of the two sets of metrics.

Only when a brand had an actual deviation across both metrics (i.e. APE equal to or greater than 15%) and showed the same valence there was a consistency across both sets of metrics.

Table 28, Table 29 and Table 30 show the results for the UK data.

Table 28 – Comparing deviations from DJ pattern (UK data, TEA)

	Behavioral metrics					*Brand salience metrics*							
	Pen %		**APF**		**APEs**	**Sal Pen %**		**Ass Rate**		**APEs**	**Actual deviations**	**Valence**	**Consistent deviation**
	O	**T**	**O**	**T**		**O**	**T**	**O**	**T**				
Tetley	40	35	3.5	4.1	15	62	63	3.8	3.8	2	BEH	n.a.	NO
Tesco Std	38	48	5.8	4.5	22	29	33	3.1	2.8	12	BEH	SAME	NO
Pg Tips	37	37	4.2	4.1	1	65	66	3.9	3.9	1			
Twinings	26	27	4.0	3.8	4	56	56	3.4	3.5	0			
Typhoo	17	12	2.5	3.5	43	48	47	3.1	3.1	1	BEH	n.a.	NO
Clipper	10	9	3.3	3.5	4	22	20	2.4	2.5	6			
Yorkshire	9	11	4.4	3.5	20	41	42	3.0	3.0	2	BEH	n.a.	NO
Tesco Fin	8	8	3.4	3.4	2	41	39	2.8	2.9	5			
Punjana	**3**	**2**	**2.1**	**3.3**	**62**	**19**	**15**	**1.9**	**2.4**	**24**	**BOTH**	**SAME**	**YES**

In the tea category (Table 28), there were five instances of deviations in behavioural metrics, but only one brand deviated also in brand salience metrics: Punjana showed a APE of 62% for Purchase Frequency and 24% for Association Rate. This brand was also the only instance of consistency, as it was a change-of-pace brand in both sets of metrics. Among the brands that deviated in at least one of the two sets of metrics, there is one instance of same valence in the direction of the deviation (Tesco standard, a private label showing excess loyalty in behavioural metrics and slightly higher Association Rate in salience metrics). However, given that in brand salience metrics the brand did not represent an actual deviation, it was not possible to identify a consistency.

Table 29 – Comparing deviations from DJ pattern (UK data, ROAST COFFEE)

	Behavioral metrics					*Brand salience metrics*							
	Pen %		**APF**		**APEs**	**Sal Pen %**		**Ass Rate**		**APEs**	**Actual deviations**	**Valence**	**Consistent deviation**
	O	**T**	**O**	**T**		**O**	**T**	**O**	**T**				
Tesco Std	8	9	3.2	2.8	11	10	12	3.4	2.9	14			
Tesco Col	6	7	3.3	2.6	19	12	9	1.9	2.5	31	BOTH	OPP	NO
Tesco Fin	6	6	2.5	2.5	4	16	14	3.0	3.5	16	SAL	n.a.	NO
Taylors	5	5	2.6	2.5	3	10	12	3.4	2.9	14			
Percol	2	2	2.5	2.3	7	4	6	3.1	2.1	33	SAL	SAME	NO
Douwe	**2**	**1**	**1.5**	**2.3**	**55**	**19**	**15**	**2.8**	**3.7**	**31**	**BOTH**	**SAME**	**YES**
Starbucks	2	1	1.6	2.3	41	10	11	3.1	2.8	9	BOTH	OPP	NO
Carte Noi	2	1	1.8	2.2	26	14	15	3.9	3.7	5	BEH	OPP	NO

In roast coffee (Table 29), there were six instances of deviations from the Double Jeopardy pattern, which were actual deviations across both sets of metrics for three brands. Out of these three brands, only Douwe also showed the same valence, as it was a change-of-pace brand across both sets of metrics (APE of 55% for Purchase Frequency and 31% for Association Rate). There were, however, two instances of brands that were actual deviations across both sets of metrics, but showing opposite valence: Tesco Collection (excess loyalty and deficit in association rate, with APE of 19% for Purchase Frequency and 31% for Association Rate) and Starbucks (change-of-pace in behavioural metrics, with 41% APE and niche in salience metrics, with 15% APE for Association Rate).

Table 30 – Comparing deviations from DJ pattern (UK data, INST. COFFEE)

	Behavioral metrics					***Brand salience metrics***							
	Pen %		**APF**		**APEs**	**Sal Pen %**		**Ass Rate**		**APEs**	**Actual deviations**	**Valence**	**Consistent deviation**
	O	**T**	**O**	**T**		**O**	**T**	**O**	**T**				
Tesco Std	32	38	5.2	4.4	15	14	13	2.2	2.4	9	BEH	OPP	NO
Nesc Orig	27	28	4.2	4.0	5	22	19	3.1	3.6	14			
Nesc Gol	20	18	3.2	3.7	15	21	19	3.1	3.4	11	BEH	SAME	NO
Kenco	17	14	3.0	3.6	20	17	16	2.7	2.9	7	BEH	SAME	NO
Douwe	15	14	3.5	3.6	3	15	14	2.4	2.6	5			
Nesc Coll	6	6	3.7	3.4	9	13	12	2.2	2.3	4			
Carte Noi	6	6	3.4	3.4	0	12	12	2.2	2.2	2			
Kenco Pu	5	4	2.5	3.3	33	14	13	2.2	2.4	8	BEH	SAME	NO
Tesco Fin	5	3	2.2	3.3	54	13	13	2.2	2.3	5	BEH	SAME	NO

Finally, the instant coffee category (Table 30) also showed similar results: out of the five deviations from the Double Jeopardy pattern that were identifiable in behavioural metrics, there was no consistent deviation in brand salience metrics. This was because there was no deviation in brand salience metrics for this product category. However, for four of the five brands that deviated in behavioural metrics, the valence of the deviation in brand salience metrics was the same. This alone was not enough to determine any consistency across the two sets of metrics analysed.

Therefore, results across these three product-categories showed that there were only two instances of complete consistency from the 20 deviations from the Double Jeopardy pattern. Both were for change-of-pace brands. In eight instances the deviations showed the same valence (all change-of-pace brands), but there was no consistency given the established benchmark (APE equal to or greater than 15%).

Even stronger evidence of the inconsistency of deviations was found in the US data (brands are ranked according to purchase Penetration in Year 1), which are presented in Table 31, Table 32 and Table 33.

Table 31 – Comparing deviations from DJ pattern in US data (Year 1)

	Behavioral metrics					***Brand salience metrics***							
	Pen %		**APF**		**APEs**	**Sal Pen %**		**Ass Rate**		**APEs**	**Actual deviations**	**Valence**	**Consistent deviation**
	O	**T**	**O**	**T**		**O**	**T**	**O**	**T**				
COLG T. PR	25	26	1.9	1.8	6	67	69	5.4	5.2	5			
C-Crest + Sc	14	13	1.5	1.6	8	61	61	4.3	4.3	0			
AQ-F BASE	9	9	1.7	1.6	6	45	45	3.4	3.3	1			
CREST PRO-H	7	6	1.3	1.5	14	56	59	4.4	4.2	7			
COL MAX FR	7	7	1.5	1.6	3	50	50	3.5	3.5	1			
SENSODYNE	6	7	2.1	1.6	32	31	30	2.6	2.8	4	BEH	OPP	NO
A&H	5	8	2.2	1.6	41	35	36	3.1	3.0	4	BEH	SAME	NO
CREST WHIT	3	3	1.4	1.5	4	56	56	3.9	3.9	0			
TOMS	2	2	2.1	1.5	37	n.a.	n.a.	n.a.	n.a.	n.a	n.a.	n.a.	n.a.
CREST V. WH	2	2	1.6	1.5	5	47	40	2.6	1.4	13			
COLG SENS	2	2	1.8	1.5	18	n.a.	n.a.	n.a.	n.a.	n.a	n.a.	n.a.	n.a.
COLG 2 IN 1	2	1	0.9	1.5	38	45	48	3.7	1.9	7	BEH	OPP	NO

Table 32 – Comparing deviations from DJ pattern in US data (Year 2)

	Behavioral metrics					***Brand salience metrics***							
	Pen %		**APF**		**APEs**	**Sal Pen %**		**Ass Rate**		**APEs**	**Actual deviations**	**Valence**	**Consistent deviation**
	O	**T**	**O**	**T**		**O**	**T**	**O**	**T**				
COLG T. PR	22	22	1.8	1.7	2	64	67	5.5	5.2	7			
C-Crest + Sc	14	13	1.5	1.6	9	54	56	4.3	4.2	4			
AQ-F BASE	8	8	1.6	1.6	3	40	43	3.7	3.4	6			
CREST PRO-H	14	15	1.8	1.7	10	57	62	5.1	4.6	11			
COL MAX FR	8	8	1.5	1.6	4	51	48	3.5	3.7	6			
SENSODYNE	5	7	2.0	1.6	27	35	30	2.5	3.0	12	BEH	OPP	NO
A&H	6	8	2.1	1.6	29	39	37	3.1	3.2	4	BEH	OPP	NO
CREST WHIT	3	3	1.5	1.5	4	51	52	4.0	3.9	2			
TOMS	2	3	1.9	1.5	22	23	22	2.7	2.8	3	BEH	OPP	NO
CREST V. WH	2	2	1.9	1.5	21	43	37	2.8	3.2	13	BEH	OPP	NO
COLG SENS	2	2	1.8	1.5	15	n.a	n.a	n.a	n.a	n.a	n.a.	n.a.	n.a.

Table 33 – Comparing deviations from the DJ pattern in US data (Year 3)

	Behavioral metrics					*Brand salience metrics*							
	Pen %		**APF**		**APEs**	**Sal Pen %**		**Ass Rate**		**APEs**	**Actual deviations**	**Valence**	**Consistent deviation**
	O	**T**	**O**	**T**		**O**	**T**	**O**	**T**				
COLG T. PR	19	18	1.6	1.7	2	63	66	5.3	5.1	6			
C-Crest + Sc	13	13	1.5	1.6	6	55	57	4.3	4.2	4			
AQ-F BASE	7	7	1.5	1.6	1	52	47	3.3	3.6	8			
CREST PRO-H	15	17	1.9	1.7	12	58	62	4.9	4.6	9			
COL MAX FR	n.a	n.	n.a.	n.a.	n.a.	46	47	3.6	3.6	0			
SENSODYNE	5	6	1.9	1.6	21	35	31	2.7	3.0	9	BEH	OPP	NO
A&H	6	7	2.0	1.6	27	41	39	3.1	3.3	5	BEH	OPP	NO
CREST WHIT	2	2	1.4	1.5	4	51	51	3.8	3.8	1			
TOMS	2	2	1.9	1.5	23	24	22	2.6	2.8	5	BEH	OPP	NO
CREST V. WH	1	1	1.6	1.5	7	42	36	2.7	3.2	12			
COLG SENS	2	3	1.7	1.5	12	10	12	3.3	2.5	21	SAL	SAME	NO
COLG 2 IN 1	n.a	n.	n.a.	n.a.	n.a.	30	34	3.6	3.1	13			

Three brands represented systematic deviations from the Double Jeopardy pattern in behavioural metrics: Sensodyne, Arm and Hammer and Tom's of Main. These were all niche brands, with higher than expected levels of purchase frequency. For none of these brands was there a consistency in brand salience metrics and there these brands showed even a slightly opposite valence in brand salience metrics. The same pattern replicated for all instances of deviations from Double Jeopardy pattern in behavioural metrics: out of the 13 instances observed across the three years of data, there was no consistency in brand salience metrics. It is important to note that out of these 13 instances, 12 were niche brands and only one was change-of-pace brand. Therefore, the tendency observed in the other data set to indentify consistency between behavioural and brand salience metrics for change-of-pace brands did not replicate in the US data. Lastly, the only instance of deviation from Double Jeopardy pattern in brand salience metrics (Colgate Sensitive, showing a higher than expected association rate, with a APE of 21%) was not a deviation in behavioural metrics (it did, however, hold same valence in behavioural metrics).

These results complete this further comparison of behavioural and brand salience metrics and the comprehensive research outcome of the third level of analysis is the following:

> *Behavioural and brand salience metrics showed hardly any instance of consistent deviations from a common underlying pattern, Double Jeopardy (only 2 instances of consistent deviations out of 33 brands deviating from the Double Jeopardy pattern in behavioural metrics).*

In regards to shedding light on the existence and interpretation of the deviations from the Double Jeopardy pattern in brand salience metrics, this level of analysis has provided the following insight:

> *There are deviations from the Double Jeopardy pattern in brand salience metrics and these are configured as: (i) 'niche' brands, showing a higher than expected Association Rate for their level of Salience Penetration; (ii) 'change-of-pace' brands, showing a lower than expected Association Rate for their level of Salience Penetration.*

7.7 Results of LEVEL 4 of the analysis

The last level of analysis included a combination of the various research outcomes of the first three levels of analysis.

The key research outcomes obtained in the previous levels of analysis can be summarised as follows.

i. Given the differences observed in the Dirichlet parameters (both in terms of the values and level of temporal stability) it appears that the set of latent variables shaping purchase propensities is most likely *different* to those shaping retrieval propensities in memory;

ii. The existence of two different sets of latent variables suggests that when measured with past purchases and brand associations respectively, purchase and retrieval propensities are two separate components of consumer choice; as such, they must be also shaped by distinct stochastic processes;

iii. The difference at latent level causes marked differences in the description of the market and individual brand performance provided by the two sets of metrics analysed, hence different biases in purchases and brand associations.

Table 34 highlights the link between these conclusions and the various research outcomes for each level of analysis.

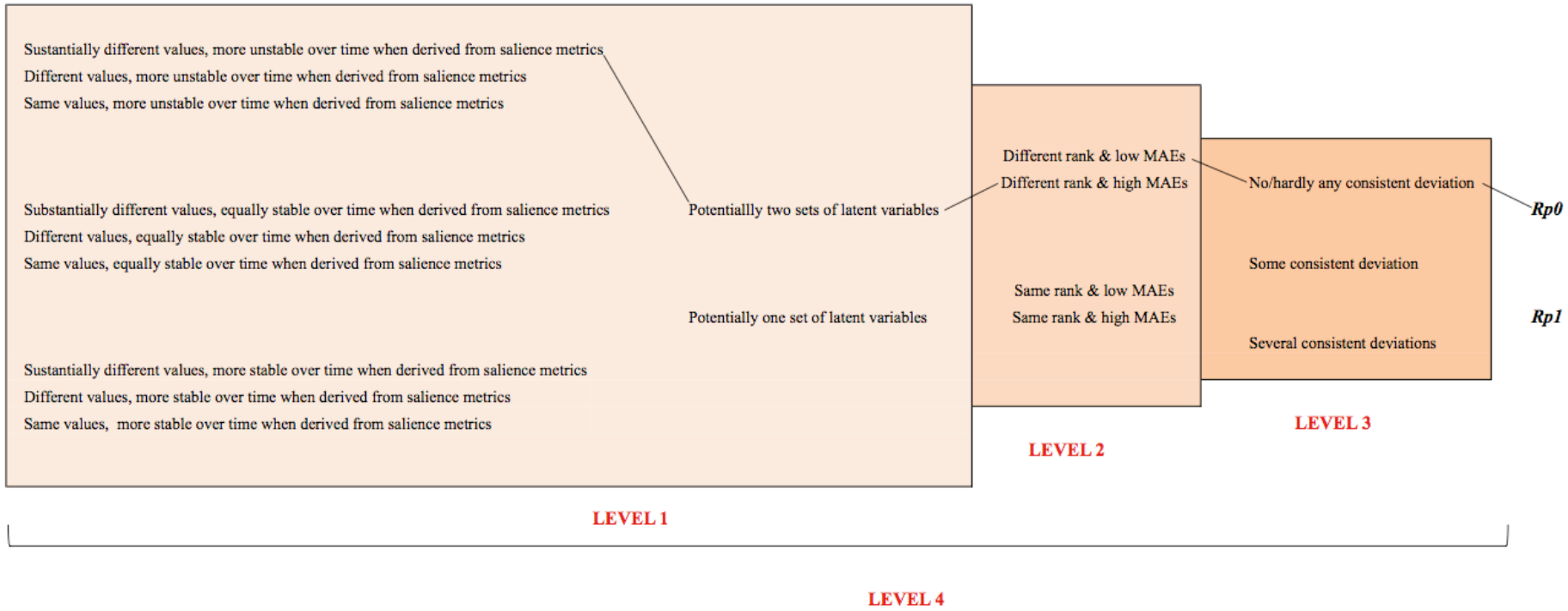
Table 34 – Outcome of the various levels of analysis

<table>
<tr><th colspan="2"></th><th>Competing view 1 (Rp0)</th><th>Competing view 2 (Rp1 partially)</th><th>Competing view 3 (Rp1)</th></tr>
<tr><td rowspan="2">LEVEL 1: Parameters</td><td>Values</td><td>Substantially different values</td><td>Different values</td><td>Same values</td></tr>
<tr><td>Temporal stability</td><td>Higher coefficient of variation when derived from salience metrics</td><td>Same coefficient of variation when derived from salience metrics</td><td>Lower coefficient of variation when derived from salience metrics</td></tr>
<tr><td colspan="5">• Different sets of latent variables shaping purchase and retrieval propensities.
• Distinct stochastic processes.</td></tr>
<tr><td rowspan="2">LEVEL 2: Metrics</td><td>Spearman’s correlation coefficients</td><td>Sig. correlation ≠ +/-1 for all analogous metrics</td><td>Non - Sig. correlation for all analogous metrics</td><td>Sig. correlation = +/- 1 for all analogous metrics</td></tr>
<tr><td>MAEs values</td><td>Greater than 5% for all analogous metrics</td><td>Around 5% for all analogous metrics</td><td>Smaller than 5% for all analogous metrics</td></tr>
<tr><td colspan="5">Marked differences in the description of the market provided by behavioural and brand salience metrics.</td></tr>
<tr><td>LEVEL 3: Deviations</td><td>Consistency in the deviations</td><td>No consistency / hardly any consistency</td><td>Some instances of consistency</td><td>Several instances of consistency</td></tr>
<tr><td colspan="5">• Marked differences in the description of the market provided by behavioural and brand salience metrics.
• Different biases.</td></tr>
</table>

This evidence is in line with the theoretical discussion provided at the end of Chapter 5, which described the competing views tested. Particularly, the outcomes described suggest that there was a systematic validation of Rp0, in support of Competing View 1 (i.e. no detectable similarity between behavioural metrics and brand salience metrics), as per the above table (validated research outcomes in bold and italic):

The resulting decision-tree is showed in Figure 24:

Figure 24 – The resulting decision-tree



7.8 Chapter summary

This chapter presented the results for the four different levels of analysis performed, preceded by the results of the research preamble (i.e. values obtained for the two sets of metrics analysed).

The first level of analysis compared the key theoretical benchmarks provided by the Dirichlet model, the model's parameters. Comparison of the values of the parameters *M*, *K* and *Phi* (obtained when modelling purchases versus brand associations) and the stability of these parameter values over time for both data sets suggest that there are two separate sets of latent variables shaping purchase propensities and brand salience. Despite meeting the condition of stationarity, the parameters estimated from brand salience metrics are, in fact, substantially different to those obtained from behavioural metrics.

The second level of analysis directly compared the two sets of metrics analysed, focusing on correlations in the ranks of brand performance provided by these metrics and the Mean Absolute Errors (MAEs) between metrics. The results highlighted marked discrepancies between behavioural and brand salience metrics.

The third level of analysis compared the deviations from the Double Jeopardy pattern in both sets of metrics. The deviations from Dirichlet benchmarks were not consistent across the two sets of metrics. There was hardly any instance of consistent deviation.

Finally, the combination of these research outcomes into a decision-tree validated Rp0 that behavioural metrics and brand salience metrics show no detectable similarity. The discrepancy is imputable to the existence of two distinct stochastic processes underpinning two different sets of latent variables, which shape purchase and retrieval propensities as two separate components of consumer choice, if measured with past purchases and brand associations respectively. However, the degree of separation between purchase and retrieval propensities can be quantified by looking at the differences detected between metrics representative of these propensities. How to approach this quantification and its relative implications is discussed in the next chapter.

Chapter 8 – Discussion and conclusions

8.1 Chapter overview

'All truths are easy to understand when discovered; the point is to discover them.'

Galileo Galilei – Physicist and philosopher (1564-1642)

This chapter discusses the empirical and theoretical contribution of this thesis. First, it presents a summary of the key research outcomes and interprets, at both aggregate and individual brand level, the differences found between the two sets of metrics analysed. Second, it includes a discussion of the most important managerial and academic implications of these outcomes. Lastly, it covers an overview of the potential limitations and some directions for future research.

§ 8.2 clarifies that the empirical analysis supports what was hypothesised at theoretical level, namely the existence of: (i) two distinct stochastic processes underlying purchases and memory; (ii) two different sets of latent variables shaping purchase and retrieval propensities; and thus (iii) purchase and retrieval propensities being two separate components of consumer choice when measured with past purchases and brand associations respectively.

§ 8.3 quantifies the degree of separation between purchase and retrieval propensities by looking at the differences between behavioural and brand salience metrics at *aggregate* and *individual brand level.* It also includes a discussion of whether brand salience metrics should be *leading versus lagging* indicators.

§ 8.4 includes an overview of the key managerial implications identified, especially in terms of clarifying the use of brand image data (hence brand salience metrics) as a *supplement* and not substitute for behavioural data.

§ 8.5 presents a summary of the theoretical and empirical contribution of this thesis.

§ 8.6 covers a discussion of two key sets of limitations: (i) limitations linked with the nature of the data sets analysed; and (ii) limitations linked with the interpretative approach used. It also covers a discussion of some potential future research directions, i.e. replication and extension of this study.

8.2 Two separate components of consumer choice

One of the key claims of Customer Based Brand Equity (CBBE) research is that brand memory structures are crucial to purchase decisions (Keller, 1993, Keller, 2003). More specifically, brand associations are assumed:

- To shape the initial cognitive processing of brand information (brand retrieval) and the subsequent steps leading towards choice (brand consideration and evaluation)(Nedungadi, 1990);
- To be influential of brand performance, since they are assumed to lead into behavioural outcomes (Krishnan, 1996, Keller, 2003).

Whilst the first point is broadly acceptable and theoretically robust when assuming a specific paradigm of consumer choice and memory (see Chapter 2), this thesis has questioned whether the second point can be supported empirically. To support the claim that brand associations would lead into behavioural outcomes, there should be some evidence of:

(i) *Very similar (if not identical) underlying structures* in purchases and brand associations, which would imply a common stochastic process underpinning a single set of latent variables shaping both purchase and retrieval propensities;

(ii) *Very similar (if not identical) empirical patterns* in purchases and brand associations, hence in their representative metrics (i.e. possibly a very similar description of brand performance at aggregate and individual level);

(iii)Most importantly, *brand associations and/or a brand's cognitive prominence (salience) leading to purchases.* To date, there is only some evidence of a link with purchase likelihood (Srull, 1989, Vieceli and Shaw, 2010), but not with actual purchases. Moreover, recent research by Viecieli (2010) found no relationship between brand salience and brand purchases for a typical FMCG category (shampoo).

The outcome of this thesis has provided empirical and theoretical evidence relevant to all three conditions above.

With regards to the first two conditions, the comparison of behavioural and brand salience metrics presented in this dissertation has highlighted: (i) different underlying structures in purchases and brand associations; and (ii) a different description of brand performance at aggregate and individual brand level. The two sets of metrics analysed showed:

- Different values and degree of stability over time of the underlying parameters, which suggested the existence of two separate sets of latent variables;
- Different values and description of the market;
- Different biases (appraised by looking at the deviations from a common robust underlying pattern).

These results allow concluding that, when measured with past purchases and brand associations respectively, purchase propensities and retrieval propensities are most likely **two separate components of consumer choice**. Consumer choice would therefore include two independent streams (see Figure 25):

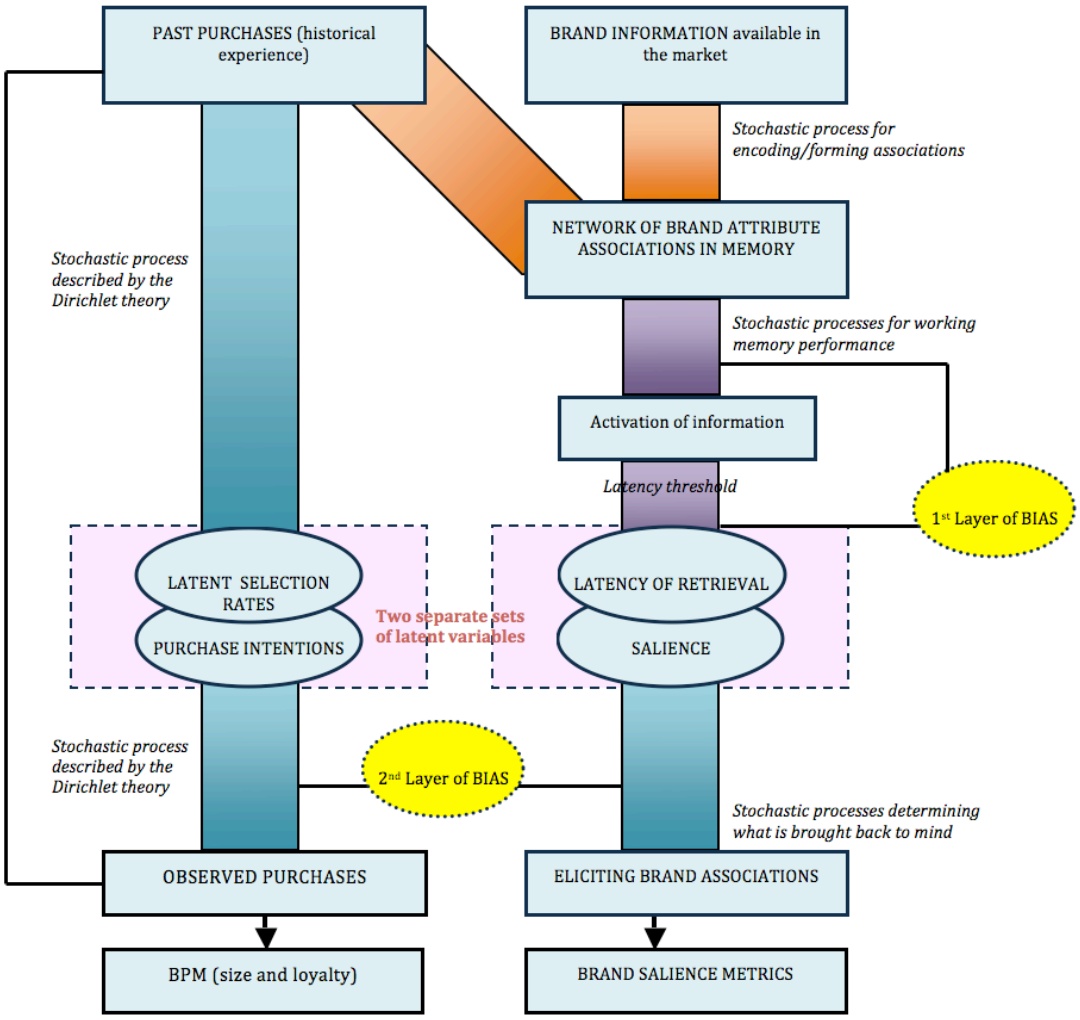
(i) A stochastic process shaping latent selection rates on the basis of past purchases, which underpin purchase intentions and ultimately actual purchases (left side of the diagram);

(ii) Various layers of stochastic processes affecting brand information underpinning latent variables in memory, which would shape retrieval propensities and a brand's cognitive prominence (salience) (right side of the diagram).

The existence of these two streams would justify the differences observed between metrics representative of purchase and retrieval propensities. It would also exclude the possibility that brand associations and/or a brand's cognitive prominence (salience) can lead to purchases, which would be relevant to the third condition needed to support CBBE's claim. Such a finding is largely in line with what was hypothesised on a theoretical level in Chapter 5. As pointed out by Gerald Goodhardt in a private conversation, the theoretical discussion presented in this thesis provides a very strong overarching argument that retrieval and purchase propensities *must* be distinct phenomena, although they are improperly assumed as inseparable components of consumer choice by CBBE research.

The existence of these two streams, however, does not exclude the possibility of a potential interaction occurring at *latent level* between the two components of consumer choice identified. This will be the key objective of any future research development following this thesis.

Figure 25 – Two separate components of consumer choice



Nevertheless, by examining the differences between purchase and memory patterns apparent in behavioural and brand salience metrics it was possible to determine when the difference between purchase and retrieval propensity was 'large' and when it was 'small'. This is an important quantification, since the differences between the two sets of metrics allow appraising: (i) instances in which, despite being determined by different sets of underlying variables, purchase and retrieval propensities are *nearly inseparable*, hence purchase decisions are largely reflective of cognitive processing of brand information; and conversely (ii) instances in which purchase and retrieval propensities are *very much separable*, hence purchase decisions are largely reflective of other unknown factors.

8.3 Interpreting the differences identified

There are two ways to quantify the degree of the difference between purchase and retrieval propensities that can be inferred from the data analysis presented in this thesis:

(i) Looking at aggregate patterns or *differences between behavioural and brand salience metrics in describing a certain market* (e.g. values of the metrics and ranking of brands).

Alternatively, (ii) looking at the *description of individual brand performance* provided by the two sets of metrics (e.g. deviations from expected benchmarks).

8.3.1 Differences at aggregate level

The key findings of the analysis comparing behavioural and brand salience metrics at aggregate level were that the metrics assumed substantially different values and that they provided different rankings of brand performance from market leader down. Therefore, largest the difference between the two sets of metrics in values and rank, the more pronounced the discrepancy between retrieval and purchase propensities at product category level (i.e. the largest the discrepancy between which brands consumers know better, know more about and think of, and the brands they finally purchase). Conversely, for markets where behavioural and brand salience metrics are more similar in values and rank, consumer choice should be more closely related to the cognitive processing and prominence of brand information, perhaps due to potential interaction occurring at latent level.

This conclusion can be better understood by considering the following hypothetical scenario. At the supermarket, assuming a consumer is interested in purchasing chocolate (see Figure 26), he/she might be looking for a prominent brand in memory, for example Cadbury chocolate. Hence, this person might be drawing upon a simple network of brand associations such as '*Cadbury-chocolate-purple*'.

Figure 26 – Difference between purchase and retrieval propensities (aggregate)



If this person ends up purchasing Cadbury by locating, for example, the colour purple in the isle, this would be an instance of a purchase and retrieval propensities being nearly inseparable, perhaps due to some interaction at latent level. However, if regardless of thinking of Cadbury this consumer ends up purchasing another brand (perhaps because this other brand is on special or because Cadbury is not available), this would be an example of high separation between purchase and retrieval propensities, most likely due to a lack of interaction at latent level.

Clearly, as a reflection of the degree of separation between purchase and retrieval propensities, these two instances would result in differences between behavioural and brand salience metrics at aggregate market level.

A possible explanation for the differences between the way brands compete for purchases and for activation and processing in memory may be the following. While purchase propensities for each brand are somewhat constrained by the propensity to purchase the category (see Chapter 4 in the section describing latent selection rates), it is unclear whether retrieval propensities measured with brand associations are subject to an analogous constraint. Hence, a further clue that the difference between purchases and brand associations may be established at latent level. In the literature, there are numerous attempts to address this issue with quantitative models on 'decision constraints' and consideration sets (Punj and Brookes, 2002). However, this

thesis does not provide empirical evidence explicitly addressing this issue, and so this remains a matter for future research.

8.3.2 Differences at individual brand level

Comparing behavioural and brand salience metrics at individual brand level highlighted no common consistent biases in purchases and brand associations, i.e. no consistent deviations from a common underlying pattern, the Double Jeopardy.

To interpret this finding with regards to quantifying the difference between purchase and retrieval propensities, two important aspects must be considered. First, given common drivers of deviations from Double Jeopardy in purchases, if it is reasonable *at all* to expect to observe any deviation from Double Jeopardy in brand image data. Second, if it is reasonable to assume that the drivers of excess/deficit cognitive prominence may be different.

As regards the first aspect, if one were to consider the typical causes of deviations discussed for behavioural data, i.e. *physical* and *cognitive availability*[8] (see Fader and Schmittlein (1993) and Bhattacharya (1997) respectively), it would seem reasonable not to expect any systematic deviation from the Double Jeopardy in brand associations due to the following reasons:

(i) Since in brand image data respondents are usually prompted with a number of brands and attributes, 'choice' options should be more limited than when facing purchase decisions. This should somewhat reduce the effects of a deficit in physical availability for low market share brands, but also cancel any advantage for high market share brands.

(ii) Since brand options are actually provided in brand image surveys, it is also reasonable to expect a greatly reduced effect of cognitive availability (in excess, as well as deficit).

Therefore, deviations from Double Jeopardy pattern in brand image data would be hard to observe, as by definition those brands included in the survey are present 'physically' and prompted cognitively. Nevertheless, the results obtained demonstrate

[8] The key studies on the causes of deviations from the Double Jeopardy pattern in behavioural data are Fader and Schmittlein (1993) and Bhattacharya (1997). Fader and Schmittlein (1993) identified the causes of deviations from the Double Jeopardy pattern in behavioural data as: segmentation, distribution strategies, advertising and communications, as well as price promotions. Among the factors analysed, the authors highlighted how these drivers were mostly external 'constraints' or 'advantages' in the *physical availability* of brands during purchase occasions. The same conclusions were drawn by Bhattacharya (1997) who, with cross-category regression modelling, additionally identified *cognitive availability* of brands during purchase occasions as a further source of deviations.

that even if the effect of physical availability might be negated (brands are prompted in the survey), brand image data and related measures are capturing more explicitly the effects of cognitive availability and perhaps other drivers of excess (or deficit) cognitive prominence. In fact, the instances of deviations from the Double Jeopardy pattern were:

- *'Niche'* brands in memory, that is brands showing low Salience Penetration (a low number of respondents provided at least one association to the brand), but higher than expected Association Rate. Therefore, for these brands, even though only a small cohort of respondents were able to provide at least one association, those who did mention that brand provided, on average, more associations than expected;
- *'Change-of-pace'* brands in memory, that is brands showing high Salience Penetration (a high number of respondents provided at least one association to the brand) and lower than expected Association Rate. Therefore, brands many people can think of, but those who can do not provide, on average, as many associations as expected.

As regards clarifying whether the drivers of excess/deficit cognitive prominence may be different than the drivers of excess/deficit loyalty, the instances of deviations listed above made it quite clear that causes of deviations from Double Jeopardy pattern in brand image data should be more directly imputable to memory theory. As discussed in Chapter 2, given the architectural assumptions about memory (i.e., ANT model), the *level* (total number of activated concepts) and *strength* (number of times concepts have been activated or simply the frequency of memory association) of activation determine cognitive prominence (salience) of information and retrieval chances (Reder, 1988). Therefore, brands that are not highly salient (linked with few concepts) might be harder to retrieve (low Salience Penetration), because only few concepts are held in memory (few pathways to retrieval and low frequency of associations). However, if the network is reinforced with strong marketing strategy it may result in a 'niche' brand in memory. Conversely, brands that are highly salient (linked with more concepts) should be easier to retrieve (high salience penetration), because the large number of concepts held in memory provides numerous pathways to retrieval and results in a higher frequency of association. However, if the network is not reinforced enough with marketing strategies, the strength of associations would decrease and result in a 'change-of-pace' brand in memory.

Given these considerations, it is possible to conclude that the discrepancy between purchase and retrieval propensities becomes even more obvious and quantifiable at individual brand level, as described with the following examples.

At the supermarket, assuming a consumer wants to purchase a specific brand of chocolate, e.g. Toblerone (Figure 27), he/she will be browsing alternatives by drawing

upon a simple network of brand associations such as '*Toblerone-Triangular shape-gold*'.

Figure 27 – Difference between purchase and retrieval propensities (brand level)



If the consumer successfully identifies and purchases Toblerone, this would be an instance of a match between purchase and retrieval propensities at individual brand level, since brand choice was entirely based on the cognitive prominence of Toblerone and the information linked to that brand in this consumer's memory.

However, such a simple correspondence would not take place in the following instance. Assuming the consumer is after the brand Rice Bubbles, he/she may draw upon a simple network of brand associations based on well-known visual element of the packaging to look for the brand. If presented with a home brand with a similar pack as per Figure 28, he/she may purchase this other brand. In this second scenario, regardless the cognitive prominence of the brand Rice Bubbles and the information linked to the brand in memory (the packaging features), consumer choice is allocated to another brand.

Figure 28 – Difference between purchase and retrieval propensities (brand level)



Clearly, both scenarios, if projected for a large sample of consumers, imply that the performance of these brands would be depicted quite differently by behavioural metrics, based on purchases and representative of purchase propensities, and brand salience metrics, based on brand associations and representative of retrieval propensities. For Toblerone, hypothetically, there would be a reasonable correspondence between the cognitive prominence of this brand and its level of purchases, thus most likely a consistency between behavioural and brand salience metrics. For Rice Bubbles, instead, there would be a substantial discrepancy between how prominent the brand is in consumer memory and the purchases allocated to the brand, thus a lower chance of consistency between behavioural and brand salience metrics.

Given the fact that the empirical analysis presented in this thesis showed, across all brands analysed, very few instances of consistent deviations, it appears that the example of Rice Bubbles is a more realistic scenario (regardless the fact that the discrepancy between purchase and retrieval propensities could be caused by other factor than confusing pack features). This would also imply that the more separate purchase and retrieval propensities in underpinning individual brand choice, the largest the difference in latencies and the drivers of bias between the two streams of consumer choice: purchases and brand associations. Another possible explanation, however, could be also linked to the way brand salience metrics are computed and the fact that they are representative of retrieval propensities based on the network of brand associations at the point in time of the survey, rather than the 'historic' network. This could have implications in determining whether brand salience metrics are leading or lagging indicators of brand performance, as it is now discussed.

8.3.3 Leading versus lagging

According to Bird, Channon and Ehrenberg, (1970), monitoring brand image data should allow explaining and detecting changes in buying behaviour, since brand associations follow purchase patterns and confirm them. Therefore, they suggested a possible *lagging* role of brand image data and related measures. This thesis has offered some interesting insights into this matter.

First, it seems reasonable to conclude that brand salience metrics cannot be lagging indicators. Lagging indicators are typically characterized by historical performance or trends. For example, behavioural metrics are lagging indicators, since they are based on the string of past purchases. Clearly, brand image data and thus brand salience metrics do not seem to be 'historical', since they are fully representative of retrieval propensities elicited by a set of brand associations at the time of the survey. That is, they provide '*cognitive snapshots*' of a brand's prominence in memory at the time of

the survey, but not a full representation of how this would change over time. Indeed, the values of the Dirichlet parameters for brand salience metrics were extremely stable over time, as any degree of variation would originate from respondents' heterogeneity (and most likely heterogeneity in memory performance), rather than time related trends.

Second, brand salience metrics also cannot be leading indicators. For brand salience metrics to be leading indicators, purchase and retrieval propensities should have been shaped by a single set of latent variables underpinned by the same stochastic process. This condition would have also resulted in a broad consistency across metrics representative of purchase and retrieval propensities. The results of this thesis showed that this is not the case and that any potential interaction would occur at latent level. Therefore, retrieval propensities determined by brand associations can, at best, occasionally 'feed' into the processes underlying purchases, most likely along with many other contextual factors. This would still not establish a direct lead into purchase behaviour, hence assuming that metrics representative of retrieval propensities are leading indicators would be conceptually and empirically misleading.

The impossibility to classify brand salience as lagging nor leading indicators of brand performance and the discrepancy at individual brand performance level has several managerial implications for the use of brand salience metrics, which are now discussed.

8.4 Managerial implications

Brand equity research has proliferated among academia and practitioners with multiple meanings and measurements. This has occurred with no general consensus on the actual use of this rather loose construct, other than the hope to link it to evaluating the effectiveness of marketing strategies.

Even when limiting the debate to the array of studies conceptualising and measuring brand equity from a consumer perspective, issues remain. Particularly, there seem to be very limited empirical evidence supporting the claim that a well-established network of brand associations will lead into the effectiveness of marketing actions and a solid market share. As a consequence, it is very difficult to generate reliable benchmarks for managers and to develop clear guidelines for marketing actions.

Nevertheless, there are numerous complex models that aim to explore and quantify the link between consumer knowledge and behavioural outcomes. For example, the one proposed by Ersch et al. (2006) (Figure 29) or Aaker (1992) (Figure 30). These are models typically used to develop measures of brand equity components, given the assumption that sales measures would lack of assessing correctly the 'value' of a

brand (its equity) and fail to capture a brand's most intangible aspects (Krishnan, 1996).

Figure 29 – Esch et al. (2006) framework (p.101)

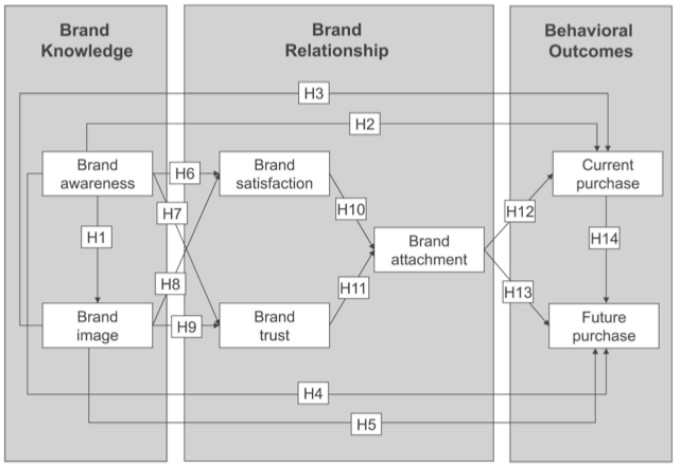
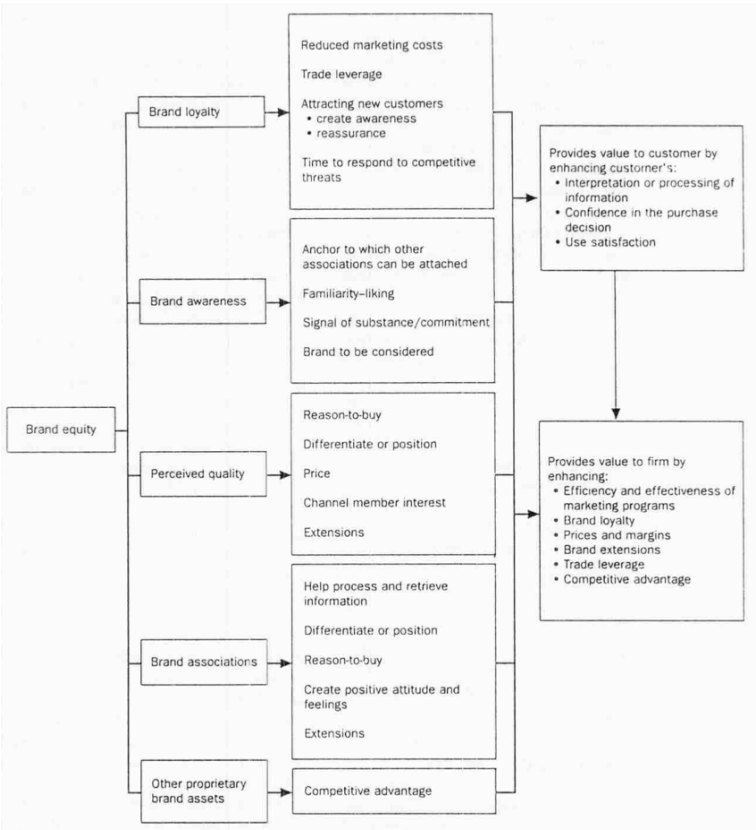


Figure 30 – Aaker (1992) framework (p.29)



Moreover, in a private conversation with the marketing science manager of a key multinational company, it emerged that the key claim of commercial research tracking brand equity components is that the resulting brand performance indicators should:

- Anticipate and ultimately predict Market Share;
- Explain changes in Market Share and in the overall performance of a brand;
- Allow direct appraisal of advertising and positioning strategies.

In contrast, the empirical evidence provided by this thesis leads to the following conclusions. When computed according to Romaniuk's (Forthcoming) guidelines, brand salience metrics are measures representative of brand retrieval propensities elicited by the network of brand associations held in memory at the time of the survey. As such, they provide a cognitive snapshot of the brand information. However, since retrieval propensities are quite separate from purchase propensities and show different underlying structures, brand salience metrics are unlikely to anticipate brand sales or explaining changes in sales. Moreover, despite the potential existence of some interaction between purchase and retrieval propensities at latent level, brand salience metrics show marked discrepancies with behavioural metrics and provide very a different description of brand performance. Therefore, although being a robust measure of a key brand equity component (brand associations), brand salience metrics cannot deliver at least the first two expectations listed above. This implies that metrics based on brand equity components such as brand salience metrics should be best used as a *supplement* and not a substitute for behavioural metrics, since they provide different insights and are not indicators of purchase behaviour or brand sales. As regards the last point, however, it is reasonable to hope that brand salience metrics may be valuable for appraising the direct effects of branding activities (e.g. advertising and deliberate positioning strategies) on brand memory structures. The type of insight that should be possible to obtain would be: (i) direct appraisal of the effectiveness of communication and branding strategies on the number and frequency of brand associations; (ii) if tracked over time, monitoring the 'life cycle' of brand memory structures; and (iii) benchmarking against competitors.

8.5 Contribution to academia

In this dissertation, there are two key types of academic contributions: one has been largely developed in the literature review provided (*theoretical contribution*); and one has originated analytically (*methodological* and *empirical contribution*).

The theoretical contribution originated by the literature review includes the following aspects (see Figure 31):

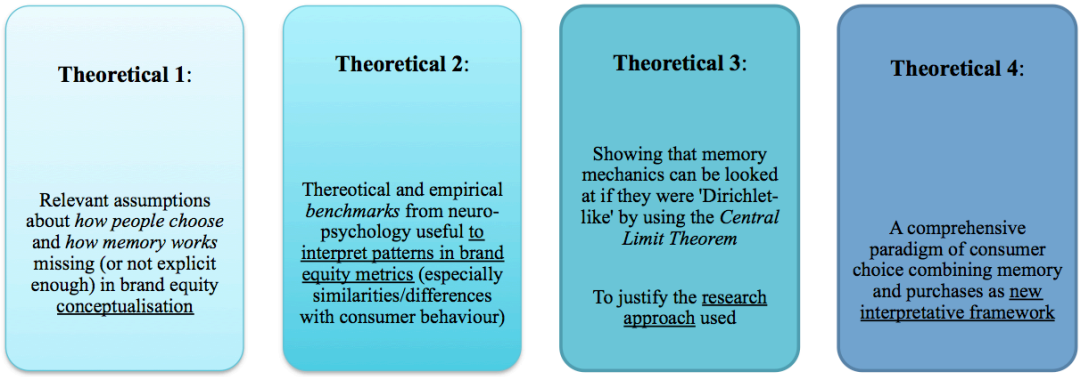
(i) A comprehensive clarification of the key underlying assumptions about how people choose and how memory works necessary to improve the conceptualisation of brand equity and related measures;

(ii) Consideration of the stochastic nature of memory and memory patterns/mechanics all the way through the theoretical, as well as empirical interpretation of results; this has provided a very powerful set of benchmarks to validate and interpret research outcomes; it also clearly provides insight for managerial interpretation and it will constitute direction for future research;

(iii) Theoretical considerations on the suitability of a Dirichlet-like stochastic process for describing memory patterns, given the analysis of literature on the layers of the stochastic processes affecting memory (in particularly, the use of the Central Limit Theorem);

(iv) The presentation and validation of a compounded consumer decision-making paradigm (combining memory and purchases) as an interpretative framework.

Figure 31 – Overview of the theoretical contribution



These contributions are important for *theory-building* purposes, as they have provided a very strong overarching argument that retrieval and purchase propensities *must* be distinct phenomena, improperly assumed as inseparable by brand equity research.

As regards the academic contribution originated analytically, it can be summarised as follows. In terms of the *methodological* contribution, the differences between the two aspects of consumer choice analysed have been tested explicitly, without using any complex technique, but using the theoretical and empirical benchmarks from purchase behaviour literature. In terms of the *empirical* contribution, the analysis has generated original empirical evidence as follows (see Table 35):

Table 35 – Overview of the theoretical contribution

Output	Empirical evidence
Values and temporal stability of the Dirichlet parameters	Different underlying structures: • Distinct stochastic processes; • Two sets of latent variables; • Different biases.
	Different degree of temporal stability and different parameters' meaning.
Values of the metrics and analysis of consistency of deviations from the Double Jeopardy pattern	Different empirical patterns: • Different description of the aggregate market; • Different description of individual brand performance; • Different deviations from the Double Jeopardy pattern.
	Different degree of separation between purchase and retrieval propensities: • The largest the difference between the two sets of metrics representative of these propensities at aggregate level, the less likely any interaction at latent level and the more separate the two propensities; • The largest the difference between the two sets of metrics representative of these propensities at aggregate level, the less likely any interaction at latent level and the more separate the two propensities.

This evidence has major implications in the validation of brand equity conceptualisation and measurement, thus it is likely to establish scope for an academic debate of some interest.

8.6 Limitations and future research directions

Despite the number of empirical and theoretical contributions discussed so far, as per any research, some potential limitations are present.

First, it would have been possible to draw further conclusions from the data analysis if other data had been available. Particularly, data that included both purchases and brand associations collected from the same sample across multiple time periods would have represented the 'ideal' scenario for the analysis. This set of limitations could be exploited as future research direction, mostly in terms of replication of this study.

Second, some limitations may have arisen from the interpretative approach used in this dissertation. The research approach adopted in this thesis included a constant triangulation of results obtained in memory patterns with those obtained in purchase patterns. This approach provided an array of empirical evidence and prior knowledge on which to draw. However, to understand patterns in memory-based metrics such as salience metrics, it seems desirable to also consider benchmarks from memory theory. This represents further scope for future research.

Finally, other possible future research directions are indicated by the key research outcome of this thesis. More specifically, to further investigate the possible relationship and interaction between purchase and retrieval propensities at the latent level.

These limitations and the future research directions are now discussed separately.

8.6.1 Limitations linked with the nature of the data

As it often happens in market research, these data sets were not the 'perfect' scenario for explicitly investigating the similarities and differences between purchase and memory patterns, as expressed by the two sets of metrics calculated and compared. Ideally, the 'perfect' condition would have been exhibiting both the following characteristics simultaneously, rather than singly:

- *Longitudinal*, that is data encompassing multiple time periods and possibly including not only yearly values, but also shorter time fractions, such as quarterly values. This characteristic would have allowed a more rigorous appraisal of the values of the Dirichlet parameters, hence replicating the first level of analysis in a more homogeneous way. In this thesis, it was possible to compare the values of the parameters for both data sets, but the analysis of the

temporal stability of the parameters has been performed on the data that were collected from different samples.

- *Same sample*, this being data that includes a record of both purchases and brand associations by the same consumers. This is an important condition for any future replication of this research, as well as expansion of this research. In fact, in order to compare further purchase and retrieval propensities or eventually assess the potential interactions between these two constructs found to be separate, it is necessary to analyse purchase and memory patterns by the same sample.

Nonetheless, despite the limitations of the data sets analysed, this thesis has been successful in controlling for the following conditions: single and multiple time periods, same and different sample, within and between chain. This analytical approach has increased the robustness of findings, since only results consistent across both data sets (hence across all conditions) were considered. Moreover, the data sets analysed were always large samples and covered US and UK markets, as well as multiple product categories.

Therefore, future replication of this analysis could be expanded across more data sets that meet the two 'ideal' conditions described above.

8.6.2 Limitations caused by the interpretative approach

Due to the broad research approach adopted in this dissertation (i.e. the use of the Dirichlet theory as a research method to investigate similarities and differences between behavioural and brand salience metrics), the only interpretative benchmarks used were well-known patterns in consumer behaviour.

However, to more comprehensively appraise the differences between behavioural and brand salience metrics (especially at individual brand level) it seems necessary to integrate the interpretative benchmarks from consumer behaviour with those provided by memory theory. For example, as discussed in relation to the interpretation of deviations from the Double Jeopardy pattern in brand salience metrics, looking at empirical patterns affecting memory described in neuropsychology literature would provide solid foundations to reinforce the explanations for the differences between purchases and brand associations. For example, it should be possible to identify and quantify the impact of: (i) factors driving the degree of separation between purchase and retrieval propensities and the differences in their underlying structures; (ii) factors causing any potential interaction between purchase and retrieval propensities at latent level; and (iii) origins and causes of discrepancy in bias between purchases and memory.

This approach would be suitably in line with the theoretical recommendation to account for the relevant assumptions of human memory indicated as crucial to measuring brand equity components. Moreover, this approach would help to further validate any potential research finding and it would also favour the linking of two strongly related disciplines: marketing and neuropsychology.

Simple 'tests' to appraise whether expanding the benchmarks used for the comparison between purchases and brand associations would lead to different conclusions include:

- Quantifying underlying patterns consistent across both phenomena with different models, i.e. some typical from consumer behaviour and some typical from memory theory. If these are simultaneously valid in explaining the same pattern, then there would be a value in embracing benchmarks from another discipline (neuropsychology) to explore the link between consumer behaviour and brand associations;
- Modifying existing models of consumer behaviour in order to account for typical memory-related patterns (e.g. working memory heterogeneity) and use the newly generated benchmarks to interpret results between purchases and brand associations.

8.6.3 The relationship between purchase and retrieval propensities

A future research direction that naturally follows the outcomes produced by this dissertation is assessing potential interactions and ultimately the relationship between purchase and salience propensities.

The analysis of stochastic theories of memory has highlighted the existence of multiple layers of stochastic processes characterising cognitive processes. It also highlighted that, despite the fact that a common mathematical abstraction, the Dirichlet model, is suitable to anticipate the patterns in memory, this theory may be failing to pick up some characteristics of memory (e.g. heterogeneity is assumed *endogenous* in memory theory, whereas in purchases it is considered *exogenous*). Therefore, ideally, given the fact that the use of stochastic models is suitable for both purchase and memory patterns, it could be possible to formulate a comprehensive model that could anticipate simultaneously purchase and memory patterns. By doing so, the challenges would be:

- Modification of the Dirichlet theory in order to account for the existence of two separate sets of latent variables;

- Modification of the Dirichlet theory in order to account for the existence of two levels of consumers' heterogeneity (not only in their purchase patterns, but also in their memory patterns, as per the differences highlighted in memory theory in terms of working memory performance);
- Introduction of covariates, accounting, for example, for positioning strategies, in order to reduce the impact of the larger differences that are apparent at individual brand performance.

8.7 Chapter and thesis summary

The most relevant finding of this thesis was that purchase and retrieval propensities are two separate components of consumer choice, i.e. they do not always jointly determine purchase decisions, as they originate from different sets of latent variables underpinned by distinct stochastic processes. To appraise the degree of separability, it is necessary to look at the difference between metrics representative of purchase and retrieval propensities, such as behavioural and brand salience metrics. The greater the difference in the description of the market provided by the two sets of metrics, the more distinct are purchase and retrieval propensities (and vice versa) at aggregate or product category level. The greater the difference at individual brand performance level (e.g. inconsistent biases), the largest the separation between purchase and retrieval propensities in underlying individual brand choice.

Such a finding did not exclude the possibility of an interaction between purchase and retrieval propensities, nor disconfirmed the fact that brand salience metrics can be looked at as meaningful cognitive 'snapshots' of brand memory structures (although unlikely to be informative of future brand performance). It did, however, challenge a famous and implied claim of brand equity research. That is, consumer choice being straightforwardly underpinned by cognitive components and processes (Keller, 1993).

The most relevant direction for future research that follows this finding is a research program aimed to appraise at latent level the two aspects of consumer choice identified and their potential interaction. This would possibly result in developing an empirically grounded paradigm of consumer choice combining behaviour and memory. In other words…making the dream of brand equity researchers becoming true! However, this thesis has demonstrated that achieving this dream will not be a simple, or straightforward, exercise.

Appendix A: Correlations between brand attributes

Table 36 – Attributes legend for Kendall Taub's correlations

	Tea - UK	Instant coffee - UK	Roast coffee - UK	Toothpaste - US
A	Satisfy Thirst	**Helps me to wake up**	**Helps me to wake up**	**Provides the best protection against cavities**
B	**Would warm me up inside**	Would help me stay awake	Would help me stay awake	**Keeps my teeth strong and healthy**
C	**Calm me down**	To have with friends	**To have with friends**	**Prevents gum problems**
D	**After dinner**	After dinner	After dinner	**Works all day**
E	**When I want to indulge myself**	**When I want to indulge myself**	**When I want to indulge myself**	Eliminates germs on teeth and gums
F	**Good first thing in the morning**	Good first thing in the morning	Good first thing in the morning	Recommended by dentists/hygienists
G	When I want to relax	**When I want to relax**	**When I want to relax**	**Is the best brand at whitening teeth**
H	Good value for money	Good value for money	**Good value for money**	**Leaves my breath fresh**
I	**Would taste good**	**Would taste good**	**Would taste good**	Leaves my mouth feeling clean
J	Would have a strong flavour	Would have a strong flavour	Would have a strong flavour	**Meets all my daily toothpaste needs**
K	A brand I can trust	A brand I can trust	A brand I can trust	Has a taste I like
L	High quality ingredients	High quality ingredients	**High quality ingredients**	**Is suitable for the whole family**
M	**Natural**	**Natural**	Natural	Is a brand for someone like me
N	Always doing new things	Always doing new things	Always doing new things	Is worth paying more for
O	**Great aroma**	Great aroma	Great aroma	**Is an innovative brand**
P	Down to earth	**Smooth**	Smooth	
Q	Up-to-date	Mild taste	Mild taste	
R	Traditional	Full-bodied	**Full-bodied**	
S	-	**Down to earth**	Down to earth	
T	-	**Wholesome**	Wholesome	
U	-	Daring	Daring	
V	-	Up-to-date	Up-to-date	
W	-	Successful	Successful	
X	-	Upper Class	Upper Class	
Y	-	Traditional	Traditional	

Table 37 – Kendall Taub's correlations – TEA (average of all brands)

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
A		**0.23**	0.12	0.12	0.02	**0.20**	**0.15**	0.13	0.08	0.02	0.07	0.01	0.03	-0.03	0.02	0.04	0.02	0.03
B	**0.20**		0.09	0.08	0.00	0.14	0.10	0.08	0.05	0.00	0.03	0.00	0.03	-0.05	0.00	0.03	0.01	0.02
C	0.07	0.06		0.10	0.12	0.06	**0.20**	0.02	-0.04	-0.06	-0.04	-0.06	-0.02	0.03	-0.01	-0.02	0.01	-0.04
D	0.09	0.07	0.12		0.12	0.12	0.12	0.06	0.01	-0.02	-0.01	-0.01	-0.01	0.01	0.01	-0.02	-0.01	-0.02
E	-0.09	-0.08	0.06	0.05		-0.08	0.01	-0.09	-0.09	-0.05	-0.13	-0.03	-0.05	0.06	0.00	-0.10	-0.02	-0.07
F	**0.20**	**0.17**	0.11	**0.16**	0.04		**0.18**	**0.16**	0.09	0.01	0.09	0.01	0.02	-0.03	0.03	0.05	0.02	0.05
G	**0.15**	0.13	**0.25**	**0.16**	0.12	**0.17**		0.11	0.05	-0.01	0.04	0.00	0.02	0.01	0.04	0.01	0.03	0.01
H	0.06	0.04	0.00	0.03	-0.05	0.09	0.04		-0.01	-0.04	0.02	-0.05	-0.04	-0.03	-0.04	0.08	-0.02	0.00
I	0.08	0.08	0.01	0.04	0.02	0.08	0.05	0.06		0.09	**0.23**	**0.17**	0.09	0.01	0.11	0.04	0.05	0.07
J	-0.13	-0.12	**-0.15**	-0.13	-0.08	-0.14	-0.16	-0.12	-0.06		-0.07	0.01	-0.05	-0.02	0.00	-0.06	-0.09	-0.03
K	0.06	0.04	-0.01	0.02	-0.03	0.08	0.02	0.07	**0.22**	0.06		**0.16**	0.08	0.00	0.08	0.06	0.05	0.09
L	-0.04	-0.02	-0.06	-0.02	0.03	-0.04	-0.05	-0.03	0.12	0.12	0.12		0.10	0.04	0.10	-0.02	0.06	0.03
M	-0.05	-0.02	-0.05	-0.06	-0.03	-0.07	-0.06	-0.05	0.01	0.02	0.01	0.07		0.03	0.04	0.00	0.03	0.00
N	**-0.25**	**-0.24**	-0.14	**-0.18**	-0.05	**-0.25**	**-0.21**	**-0.18**	**-0.21**	-0.09	**-0.21**	-0.14	-0.11		-0.11	-0.14	-0.04	**-0.17**
O	-0.03	-0.02	0.00	0.00	0.06	-0.02	-0.01	-0.02	0.07	0.10	0.05	0.10	0.07	0.07		-0.02	0.02	0.00
P	-0.13	-0.11	-0.13	-0.15	**-0.15**	-0.12	**-0.15**	-0.02	-0.13	-0.07	-0.10	-0.14	-0.09	-0.08	-0.14		-0.05	0.06
Q	-0.09	-0.07	-0.05	-0.08	-0.02	-0.10	-0.08	-0.07	-0.06	-0.06	-0.05	-0.01	0.00	0.07	-0.04	0.01		-0.02
R	-0.11	-0.10	-0.14	-0.13	-0.11	-0.10	-0.14	-0.08	-0.08	-0.03	-0.05	-0.07	-0.07	-0.09	-0.10	0.08	-0.06	

Table 38 – Kendall Taub's correlations – INSTANT COFFEE (average of all brands)

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y
A		0.29	0.09	0.08	0.04	0.28	0.12	0.08	0.00	-0.03	0.01	-0.05	-0.02	-0.01	-0.02	-0.01	0.00	-0.02	0.02	-0.02	-0.02	-0.03	-0.01	-0.05	-0.01
B	0.27		0.04	0.05	0.04	0.10	0.00	0.01	-0.03	0.02	-0.02	-0.04	-0.03	-0.01	-0.03	-0.06	-0.04	-0.01	-0.03	-0.04	0.00	-0.04	-0.02	-0.02	-0.03
C	0.13	0.10		0.21	0.13	0.17	0.19	0.12	0.09	-0.01	0.09	0.03	0.03	0.01	0.06	0.08	0.02	0.03	0.02	0.02	-0.02	0.03	0.04	0.00	0.02
D	0.09	0.09	0.19		0.16	0.09	0.14	0.06	0.06	0.02	0.02	0.02	0.01	-0.02	0.05	0.02	-0.02	0.05	-0.02	0.00	0.01	0.02	0.00	0.04	-0.01
E	0.00	0.03	0.06	0.11		-0.03	0.04	-0.06	-0.03	0.00	-0.08	-0.02	-0.05	0.02	-0.02	-0.04	-0.03	0.00	-0.07	-0.04	0.06	-0.02	-0.07	0.08	-0.07
F	0.30	0.14	0.15	0.10	0.03		0.20	0.17	0.05	-0.04	0.06	-0.02	0.01	-0.02	0.00	0.07	0.04	-0.01	0.06	0.02	-0.04	-0.01	0.01	-0.06	0.01
G	0.13	0.03	0.16	0.13	0.09	0.19		0.14	0.03	-0.06	0.03	-0.03	0.01	0.01	0.01	0.07	0.04	-0.02	0.04	0.03	-0.02	0.00	0.00	-0.04	0.00
H	0.07	0.02	0.07	0.03	-0.03	0.14	0.12		0.01	-0.08	0.05	-0.05	0.01	-0.03	-0.03	0.06	0.07	-0.06	0.12	0.01	-0.07	-0.02	0.01	-0.10	0.05
I	0.06	0.05	0.11	0.10	0.06	0.09	0.08	0.08		0.09	0.23	0.21	0.10	0.02	0.20	0.17	0.02	0.13	0.02	0.06	-0.01	0.07	0.12	0.02	0.04
J	-0.09	-0.02	-0.11	-0.06	-0.03	-0.13	-0.13	-0.13	-0.03		-0.05	0.06	-0.03	0.02	0.05	-0.09	-0.13	0.19	-0.11	-0.05	0.05	-0.03	-0.05	0.08	-0.07
K	0.06	0.06	0.11	0.06	0.01	0.09	0.07	0.11	0.23	0.06		0.19	0.11	0.00	0.16	0.14	0.05	0.10	0.05	0.07	-0.05	0.07	0.15	0.00	0.08
L	-0.02	0.02	0.03	0.04	0.04	-0.01	-0.01	0.00	0.18	0.16	0.17		0.11	0.04	0.19	0.09	-0.02	0.17	-0.03	0.05	0.01	0.08	0.09	0.10	0.01
M	-0.04	-0.02	-0.02	-0.03	-0.03	-0.03	-0.02	0.00	0.03	0.01	0.04	0.06		0.03	0.04	0.05	0.04	0.04	0.01	0.05	-0.01	0.01	0.00	-0.02	0.01
N	-0.14	-0.12	-0.16	-0.16	-0.07	-0.17	-0.13	-0.15	-0.16	-0.04	-0.18	-0.12	-0.08		-0.12	-0.13	0.00	-0.09	-0.11	-0.10	0.08	-0.04	-0.14	-0.01	-0.12
O	0.02	0.04	0.06	0.07	0.06	0.02	0.03	0.02	0.18	0.15	0.15	0.19	0.10	0.04		0.11	-0.01	0.19	-0.02	0.03	0.01	0.07	0.08	0.05	0.01
P	-0.01	-0.03	0.05	0.01	0.00	0.05	0.06	0.08	0.12	-0.02	0.10	0.07	0.08	0.00	0.08		0.11	0.03	0.03	0.03	-0.05	0.00	0.03	-0.03	0.04
Q	-0.18	-0.19	-0.19	-0.21	-0.17	-0.16	-0.15	-0.09	-0.21	-0.25	-0.18	-0.22	-0.12	-0.05	-0.22	-0.07		-0.27	-0.02	-0.13	-0.10	-0.18	-0.17	-0.15	-0.05
R	-0.01	0.02	0.00	0.05	0.04	-0.03	-0.02	-0.04	0.08	0.26	0.06	0.15	0.07	0.04	0.16	0.03	-0.09		-0.05	0.02	0.04	0.04	0.02	0.08	-0.02
S	-0.08	-0.10	-0.11	-0.13	-0.13	-0.05	-0.07	0.04	-0.13	-0.14	-0.09	-0.15	-0.06	-0.07	-0.15	-0.07	0.07	-0.15		0.04	-0.04	-0.05	-0.01	-0.12	0.12
T	-0.06	-0.05	-0.05	-0.05	-0.04	-0.03	-0.01	-0.01	-0.03	-0.02	-0.02	-0.02	0.03	-0.01	-0.04	-0.01	0.01	-0.02	0.10		0.03	0.05	0.05	0.00	0.07
U	-0.18	-0.13	-0.21	-0.16	-0.06	-0.21	-0.19	-0.21	-0.23	-0.04	-0.26	-0.18	-0.15	0.05	-0.19	-0.21	-0.08	-0.12	-0.10	-0.10		-0.05	-0.18	0.10	-0.12
V	-0.05	-0.03	-0.03	-0.01	0.00	-0.05	-0.02	-0.03	0.00	0.02	0.00	0.03	0.01	0.07	0.02	-0.02	-0.02	0.02	0.03	0.06	0.09		0.10	0.08	0.00
W	-0.01	0.00	0.00	-0.02	-0.03	-0.01	-0.01	0.02	0.06	0.01	0.10	0.06	0.02	-0.01	0.04	0.03	0.01	0.01	0.09	0.08	-0.02	0.12		0.02	0.13
X	-0.17	-0.12	-0.16	-0.10	0.00	-0.21	-0.18	-0.21	-0.16	0.02	-0.18	-0.06	-0.12	-0.01	-0.11	-0.16	-0.09	-0.05	-0.15	-0.09	0.13	-0.03	-0.10		-0.11
Y	-0.10	-0.09	-0.10	-0.11	-0.12	-0.09	-0.10	-0.02	-0.11	-0.10	-0.06	-0.10	-0.05	-0.08	-0.11	-0.05	0.04	-0.11	0.13	0.02	-0.05	-0.06	0.04	-0.07	

Table 39 – Kendall Taub's correlations – ROAST COFFEE (average of all brands)

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y
A		0.28	0.05	0.04	0.02	**0.23**	0.06	0.03	-0.04	-0.02	-0.02	-0.06	-0.03	-0.02	-0.04	-0.05	-0.01	-0.04	-0.02	-0.02	-0.01	-0.02	-0.04	-0.04	-0.05
B	0.24		-0.01	0.00	-0.01	0.05	-0.03	-0.05	-0.08	-0.03	-0.08	-0.10	-0.06	-0.06	-0.07	-0.10	-0.06	-0.06	-0.07	-0.07	-0.03	-0.06	-0.07	-0.04	-0.07
C	0.11	0.10		**0.21**	0.14	**0.15**	**0.18**	0.11	0.12	0.03	0.10	0.07	0.03	0.01	0.10	0.07	0.00	0.07	0.02	0.04	-0.02	0.04	0.07	0.01	0.04
D	0.07	0.08	**0.18**		0.13	0.09	0.13	0.07	0.07	0.04	0.05	0.06	0.01	-0.02	0.08	0.03	-0.01	0.06	-0.02	0.00	-0.03	-0.01	0.01	0.02	0.02
E	0.01	0.02	0.07	0.08		-0.01	0.07	-0.04	-0.01	0.00	-0.04	0.00	-0.06	0.01	-0.01	-0.03	-0.03	-0.01	-0.06	-0.03	0.01	-0.01	-0.03	0.08	-0.04
F	**0.26**	0.12	0.11	0.08	0.02		0.12	0.11	0.03	0.00	0.04	-0.03	0.00	-0.02	0.01	0.02	0.00	-0.01	0.02	0.00	-0.03	-0.02	0.00	-0.06	0.00
G	0.08	0.04	0.13	0.11	0.10	0.12		0.10	0.01	-0.03	0.03	-0.01	0.00	0.00	0.00	0.04	0.04	-0.02	0.02	0.02	-0.01	0.02	0.01	-0.03	0.00
H	0.04	0.00	0.05	0.04	-0.03	0.09	0.08		0.00	-0.06	0.04	-0.03	0.01	-0.01	-0.02	0.03	0.05	-0.03	0.11	0.02	-0.04	0.00	0.00	-0.08	0.02
I	0.05	0.05	0.14	0.12	0.08	0.09	0.07	0.08		0.14	**0.24**	**0.23**	0.12	0.02	**0.24**	**0.18**	0.02	**0.18**	0.03	0.04	-0.03	0.04	0.10	0.04	0.05
J	-0.03	0.01	-0.04	0.00	0.00	-0.03	-0.07	-0.07	0.05		0.01	0.08	0.01	0.00	0.08	0.00	-0.09	**0.19**	-0.07	-0.03	0.02	-0.03	-0.02	0.03	-0.03
K	0.07	0.05	0.13	0.11	0.06	0.11	0.10	0.13	**0.25**	0.10		**0.22**	0.13	0.03	**0.20**	**0.18**	0.04	**0.17**	0.05	0.07	-0.03	0.05	0.12	0.02	0.08
L	0.00	0.02	0.07	0.09	0.08	0.01	0.03	0.03	**0.21**	**0.15**	**0.20**		0.13	0.03	**0.20**	0.13	-0.02	**0.19**	0.00	0.04	-0.02	0.04	0.09	0.07	0.04
M	-0.03	-0.02	-0.03	-0.03	-0.04	-0.02	-0.02	0.01	0.04	0.02	0.04	0.07		0.03	0.04	0.07	0.07	0.03	0.04	0.04	-0.01	0.00	-0.01	-0.02	0.01
N	-0.13	-0.13	**-0.16**	**-0.17**	-0.10	**-0.15**	-0.14	-0.12	**-0.17**	-0.10	**-0.16**	-0.14	-0.09		**-0.17**	-0.13	0.00	-0.15	-0.05	-0.10	0.09	-0.03	-0.11	-0.05	-0.13
O	0.04	0.06	0.12	0.12	0.08	0.07	0.05	0.06	**0.23**	**0.17**	**0.19**	**0.21**	0.11	0.02		**0.16**	0.00	**0.22**	0.01	0.03	-0.02	0.05	0.09	0.04	0.05
P	0.00	-0.01	0.06	0.05	0.03	0.04	0.07	0.07	0.14	0.06	0.14	0.12	0.11	0.03	0.13		0.10	0.11	0.02	0.06	-0.02	0.03	0.05	0.00	0.05
Q	**-0.20**	**-0.21**	**-0.25**	**-0.23**	**-0.21**	**-0.20**	**-0.17**	-0.14	**-0.25**	**-0.26**	**-0.23**	**-0.27**	-0.12	-0.07	**-0.26**	-0.13		**-0.28**	-0.06	**-0.16**	-0.08	**-0.19**	**-0.20**	-0.15	-0.10
R	0.01	0.04	0.05	0.08	0.05	0.02	0.01	0.02	0.15	0.25	0.13	0.17	0.08	0.02	**0.19**	0.11	-0.05		-0.02	0.03	-0.01	0.02	0.05	0.04	0.03
S	-0.11	-0.11	-0.13	-0.14	-0.14	-0.09	-0.09	0.02	-0.14	-0.14	-0.12	-0.15	-0.05	-0.02	**-0.15**	-0.11	0.04	**-0.16**		0.03	0.02	-0.01	-0.05	-0.09	0.01
T	-0.03	-0.03	-0.03	-0.04	-0.03	-0.04	-0.01	0.01	-0.06	-0.03	-0.03	-0.04	0.03	0.00	-0.05	0.00	0.01	-0.03	0.10		0.04	0.07	0.04	0.03	0.08
U	**-0.17**	-0.14	**-0.25**	**-0.22**	-0.13	**-0.21**	**-0.19**	**-0.20**	**-0.27**	-0.13	**-0.28**	**-0.24**	**-0.17**	0.04	**-0.25**	-0.23	-0.06	**-0.22**	-0.06	-0.10		-0.04	**-0.15**	0.06	-0.14
V	-0.03	-0.02	-0.02	-0.05	0.00	-0.04	-0.01	-0.01	-0.04	-0.02	-0.04	-0.03	0.00	0.08	-0.03	-0.03	-0.01	-0.03	0.07	0.07	0.11		0.12	0.06	0.01
W	-0.02	-0.01	0.03	-0.01	0.00	0.00	0.00	0.01	0.03	0.01	0.05	0.05	0.01	0.02	0.03	0.02	0.00	0.02	0.05	0.06	0.02	0.14		0.06	0.09
X	**-0.16**	-0.11	**-0.17**	-0.13	-0.02	**-0.20**	**-0.17**	**-0.20**	**-0.16**	-0.08	**-0.19**	-0.11	-0.14	-0.05	**-0.15**	**-0.17**	-0.08	-0.13	-0.12	-0.08	0.11	-0.05	-0.07		-0.04
Y	-0.10	-0.08	-0.08	-0.07	-0.08	-0.08	-0.08	-0.04	-0.08	-0.07	-0.07	-0.08	-0.04	-0.07	-0.08	-0.06	0.03	-0.07	0.04	0.03	-0.04	-0.04	0.01	0.02	

Table 40 – Kendall Taub's correlations – TOOTHPASTE (average of all brand, example of Year 1)

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
A		0.08	0.10	0.06	0.04	0.05	-0.03	-0.01	-0.03	0.01	-0.01	0.05	-0.04	-0.03	-0.03	
B	0.12		0.11	0.06	0.10	0.07	-0.02	0.08	0.06	0.05	0.02	0.04	0.01	-0.01	0.00	0.12
C	0.10	0.08		0.04	0.14	0.06	-0.07	0.02	-0.02	-0.01	-0.05	0.03	-0.06	-0.05	-0.03	0.10
D	0.06	0.03	0.04		0.01	0.02	-0.02	0.01	0.01	0.05	0.02	0.05	-0.02	-0.01	-0.02	0.06
E	0.04	0.06	0.13	0.00		0.01	-0.04	0.05	0.03	0.00	-0.03	-0.01	-0.05	-0.07	0.00	0.04
F	0.01	0.00	0.02	-0.02	-0.02		-0.01	-0.07	-0.08	-0.05	-0.06	-0.01	-0.06	-0.03	0.00	0.01
G	**-0.18**	**-0.20**	**-0.21**	**-0.17**	**-0.18**	-0.12		**-0.22**	**-0.16**	**-0.19**	**-0.18**	**-0.20**	-0.10	0.04	0.07	-0.18
H	0.02	0.09	0.06	0.04	0.09	0.01	-0.03		**0.18**	0.09	0.11	0.05	0.04	0.01	-0.01	0.02
I	0.00	0.05	0.01	0.03	0.07	-0.01	0.01	**0.17**		0.07	0.10	0.04	0.07	0.01	0.02	0.00
J	0.05	0.06	0.03	0.10	0.04	0.04	0.00	0.10	0.08		0.12	0.10	0.11	0.02	-0.01	0.05
K	0.00	0.00	-0.03	0.03	-0.01	0.00	-0.02	0.09	0.08	0.09		0.06	0.11	0.03	-0.02	0.00
L	0.02	-0.02	0.00	0.01	-0.03	0.00	-0.08	-0.01	-0.02	0.03	0.02		-0.03	-0.07	-0.07	0.02
M	-0.03	-0.01	-0.04	-0.01	-0.03	-0.01	0.06	0.01	0.05	0.08	0.10	0.02		0.12	0.06	-0.03
N	-0.10	-0.11	-0.12	-0.08	-0.13	-0.07	0.11	-0.10	-0.09	-0.09	-0.05	-0.11	0.04		0.05	-0.10
O	-0.12	-0.11	-0.11	-0.11	-0.08	-0.04	0.14	-0.13	-0.09	-0.14	-0.12	-0.12	-0.03	0.04		-0.12
P		0.08	0.10	0.06	0.04	0.05	-0.03	-0.01	-0.03	0.01	-0.01	0.05	-0.04	-0.03	-0.03	

Appendix B: Results of usage-image regression

Table 41 – Usage-Image regression analysis – TEA (average of all brands)

	% of brand associations by brand users	% of brand associations by non-users of the brand	Expected % of brand associations by non-users (b-value of 0.4257)	Deviations
Satisfy thirst	44	16	19	-2.9
Would warm me up inside	42	18	18	0.0
Calm me down	26	8	11	-3.0
After dinner	30	10	13	-3.1
When I want to indulge myself	21	8	9	-1.3
Good first thing in the morning	40	13	17	-4.2
When I want to relax	35	11	15	-4.1
Good value for money	36	12	15	-3.2
Would taste good	52	24	22	1.4
Would have a strong flavour	30	16	13	3.5
A brand I can trust	54	25	23	1.8
High quality ingredients	44	21	19	2.7
Natural	34	16	15	1.6
Always doing new things	12	6	5	0.8
Great aroma	33	13	14	-0.7
Down to earth	30	18	13	**5.2**
Up-to-date	28	13	12	1.1
Traditional	38	24	16	**7.8**

Figure 32 - Usage-Image regression analysis – TEA (average of all brands)

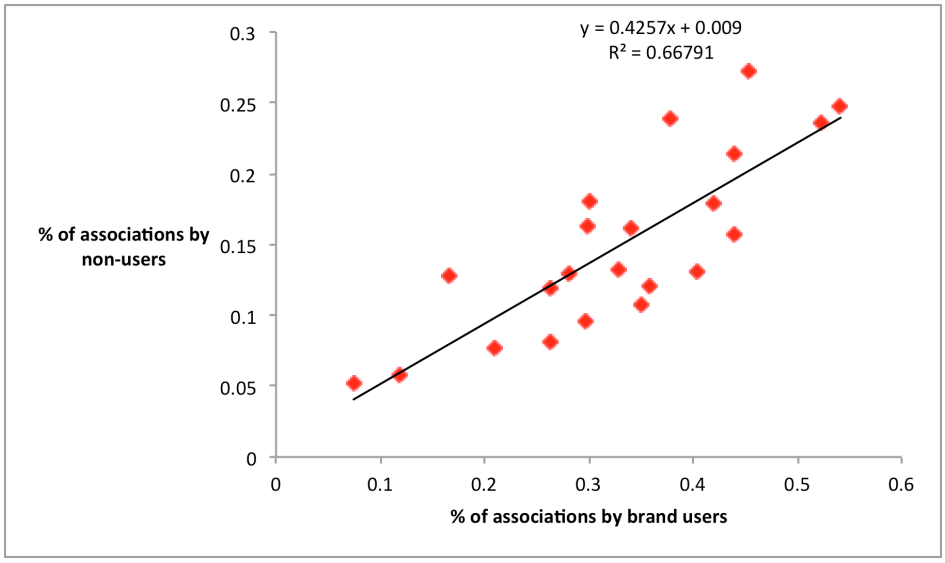


Table 42 – Usage-Image regression analysis – INSTANT COFFEE (average of all brands)

	% of brand associations by brand users	% of brand associations by non-users of the brand	Expected % of brand associations by non-users (b-value of 0.4257)	Deviations
Helps me to wake up	15	5	6	-1.4
Would help me stay awake	14	7	6	1.0
To have with friends	19	7	8	-1.2
After dinner	17	7	7	-0.6
When I want to indulge myself	12	5	5	0.1
Good first thing in the morning	18	5	8	-2.6
When I want to relax	16	4	7	-2.4
Good value for money	18	5	8	-2.3
Would taste good	27	13	11	1.5
Would have a strong flavour	16	12	7	5.0
A brand I can trust	28	14	12	1.4
High quality ingredients	25	15	11	4.3
Natural	15	7	6	1.0
Always doing new things	6	4	3	1.3
Great aroma	23	12	10	1.9
Smooth	19	8	8	-0.4
Mild taste	9	6	4	1.9
Full bodied	20	11	8	2.2
Down to earth	13	7	6	1.2
Wholesome	13	6	6	0.3
Daring	5	4	2	2.2
Up-to-date	16	8	7	1.5
Successful	23	13	10	3.3
Upper class	10	9	4	**5.1**
Traditional	15	9	6	2.4

Figure 33 - Usage-Image regression analysis – INSTANT COFFE (average of all brands)

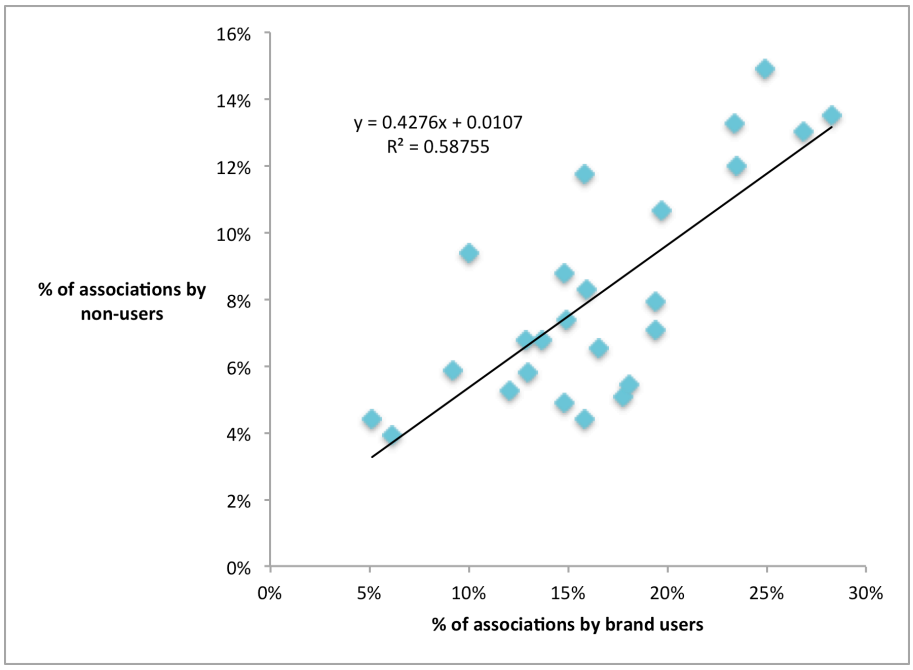


Table 43 – Usage-Image regression analysis – ROAST COFFEE (average of all brands)

	% of brand associations by brand users	% of brand associations by non-users of the brand	Expected % of brand associations by non-users (b-value of 0.4257)	Deviations
Helps me to wake up	23	11	10	0.5
Would help me stay awake	26	14	12	2.2
To have with friends	35	16	16	-0.2
After dinner	31	15	14	0.5
When I want to indulge myself	24	11	11	0.6
Good first thing in the morning	28	12	13	-1.1
When I want to relax	24	10	11	-0.4
Good value for money	30	14	13	0.5
Would taste good	46	24	21	3.1
Would have a strong flavour	32	18	14	3.3
A brand I can trust	47	23	21	2.1
High quality ingredients	40	22	18	4.5
Natural	26	13	12	0.9
Always doing new things	10	7	5	2.3
Great aroma	44	22	20	2.1
Smooth	33	16	15	1.4
Mild taste	12	9	5	3.4
Full bodied	37	18	17	1.6
Down to earth	17	11	8	3.4
Wholesome	20	11	9	1.3
Daring	7	5	3	1.9
Up-to-date	25	14	11	2.9
Successful	36	22	16	**5.3**
Upper class	17	12	8	4.8
Traditional	24	14	11	3.5

Figure 34 - Usage-Image regression analysis – ROAST COFFE (average of all brands)

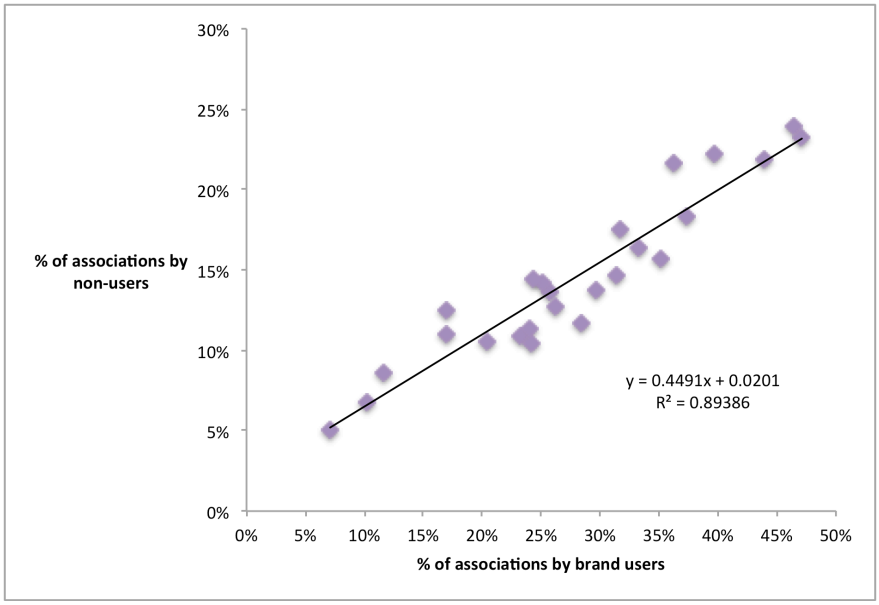
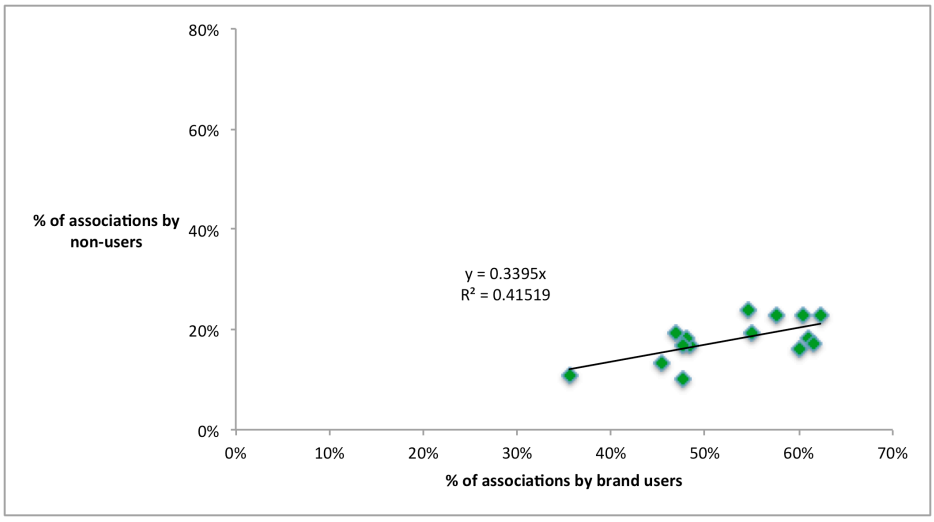


Table 44 – Usage-Image regression analysis – TOOTHPASTE (average of all brands, Year 1)

	% of brand associations by brand users	% of brand associations by non-users of the brand	Expected % of brand associations by non-users (b-value of 0.4257)	Deviations
Provides the best protection against cavities	48	17	16	1.0
Keeps my teeth strong and healthy	55	19	18	1.1
Prevents gum problems	48	18	16	2.3
Works all day	45	13	15	-1.6
Eliminates germs on teeth and gums	55	24	18	**6.0**
Recommended by dentists/hygienists	47	19	15	3.9
Is the best brand at whitening teeth	36	11	12	-0.9
Leaves my breath fresh	60	23	20	2.9
Leaves my mouth feeling clean	62	23	21	2.1
Meets all my daily toothpaste needs	61	18	20	-1.8
Has a taste I like	60	16	20	-3.7
Is suitable for the whole family	58	23	19	4.0
Is a brand for someone like me	62	17	20	-3.3
Is worth paying more for	48	10	16	**-5.7**
Is an innovative brand	48	17	16	1.1
Provides the best protection against cavities	48	17	16	1.0
Keeps my teeth strong and healthy	55	19	18	1.1
Prevents gum problems	48	18	16	2.3

Figure 35 - Usage-Image regression analysis – TOOTHPASTE (average of all brands, Year 1)



Appendix C: Example of NBD fitting (TEA – UK data)

Table 45 – NBD fitting for the brand Clipper

	Frequency	Total associations	Observed (%)	Theoretical (%)	MADs (%)
0	6348	0	78	78	0
1	817	817	10	11	1
2	351	702	4	5	0
3	219	657	3	3	0
4	135	540	2	1	0
5	99	495	1	1	0
6	59	354	1	1	0
7	45	315	1	0	0
8	31	248	0	0	0
Tot.	**8104**	**4128**			
	1756				
22% Proportion of people providing at least one association **2.4** Average number of associations					

Figure 36 - NBD fitting for the brand Clipper

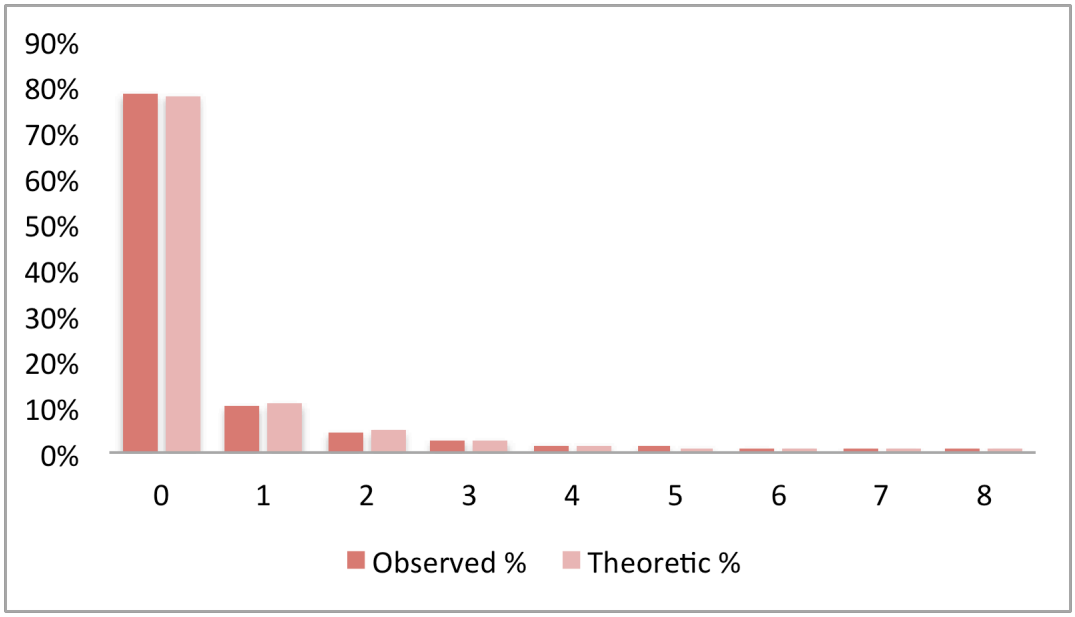


Table 46 – NBD fitting for the brand PG Tips

	Frequency	Total associations	Observed (%)	Theoretical (%)	MADs (%)
0	2805	0	35	35	0
1	932	932	12	19	7
2	786	1572	10	12	3
3	772	2316	10	9	1
4	715	2860	9	6	3
5	685	3425	8	5	4
6	544	3264	7	3	3
7	429	3003	5	3	3
8	436	3488	5	2	3
Tot.	**8104**	**20860**			
	5299				

65% Proportion of people providing at least one association
3.9 Average number of associations

Figure 37 - NBD fitting for the brand PG Tips

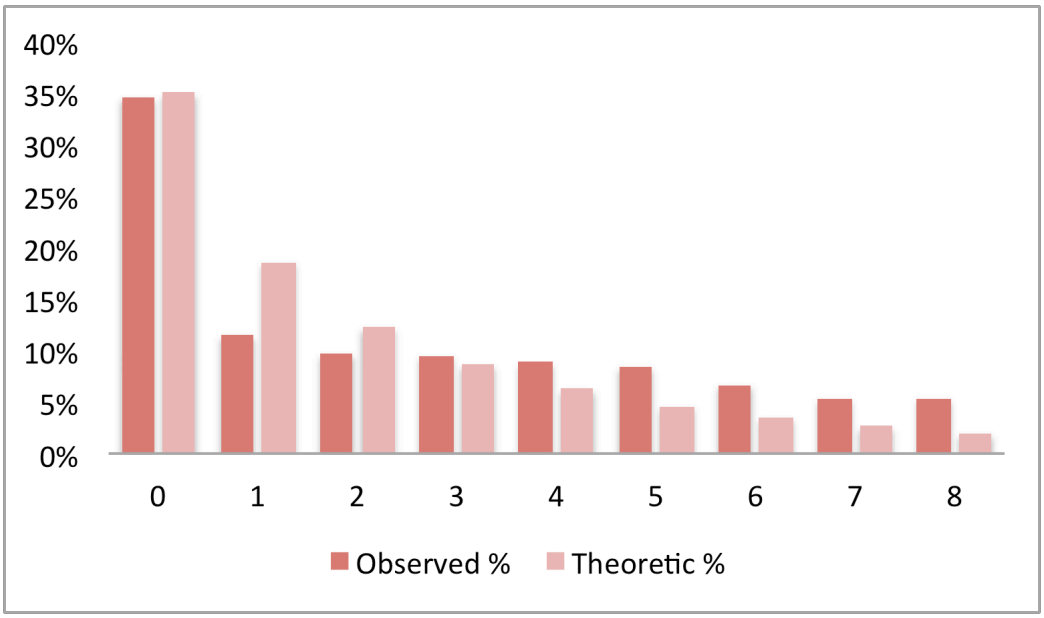


Table 47 – NBD fitting for the brand Tesco Finest

	Frequency	Total associations	Observed (%)	Theoretical (%)	MADs (%)
0	4746	0	59	59	0
1	1175	1175	14	17	2
2	729	1458	9	9	0
3	503	1509	6	5	1
4	332	1328	4	3	1
5	238	1190	3	2	1
6	181	1086	2	1	1
7	110	770	1	1	0
8	90	720	1	1	0
Tot.	**8104**	**9236**			
	3358				

41% Proportion of people providing at least one association
2.8 Average number of associations

Figure 38 - NBD fitting for the brand Tesco Finest

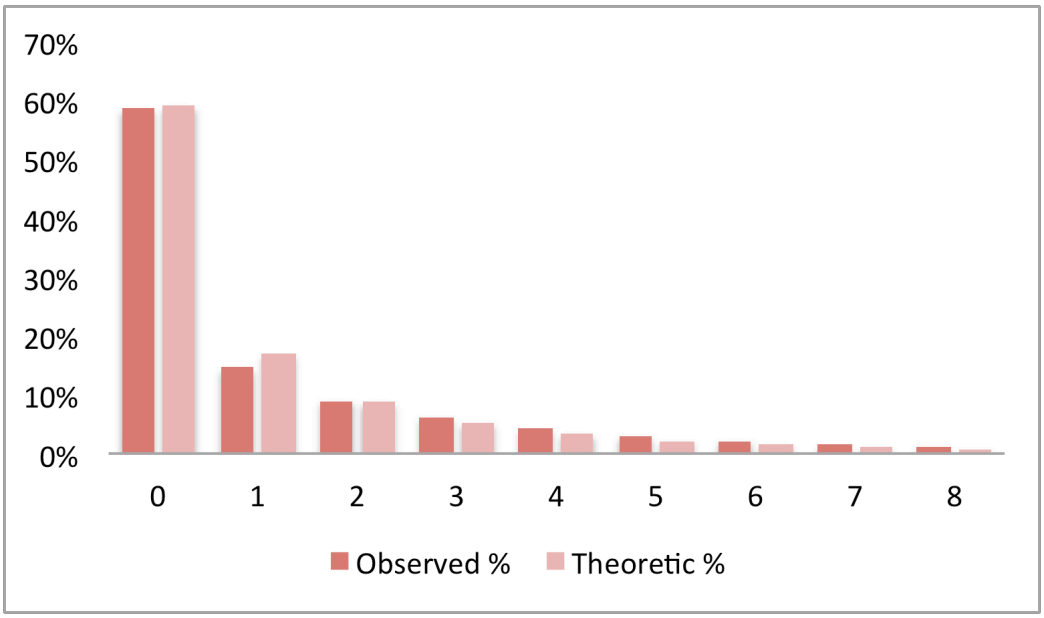


Table 48 – NBD fitting for the brand Tesco Standard

	Frequency	Total associations	Observed (%)	Theoretical (%)	MADs (%)
0	5738	0	71	71	0
1	766	766	9	12	2
2	406	812	5	6	1
3	301	903	4	3	0
4	251	1004	3	2	1
5	234	1170	3	2	1
6	186	1116	2	1	1
7	125	875	2	1	1
8	97	776	1	1	1
Tot.	**8104**	**7422**			
	2366				

29% Proportion of people providing at least one association
3.1 Average number of associations

Figure 39 - NBD fitting for the brand Tesco Standard

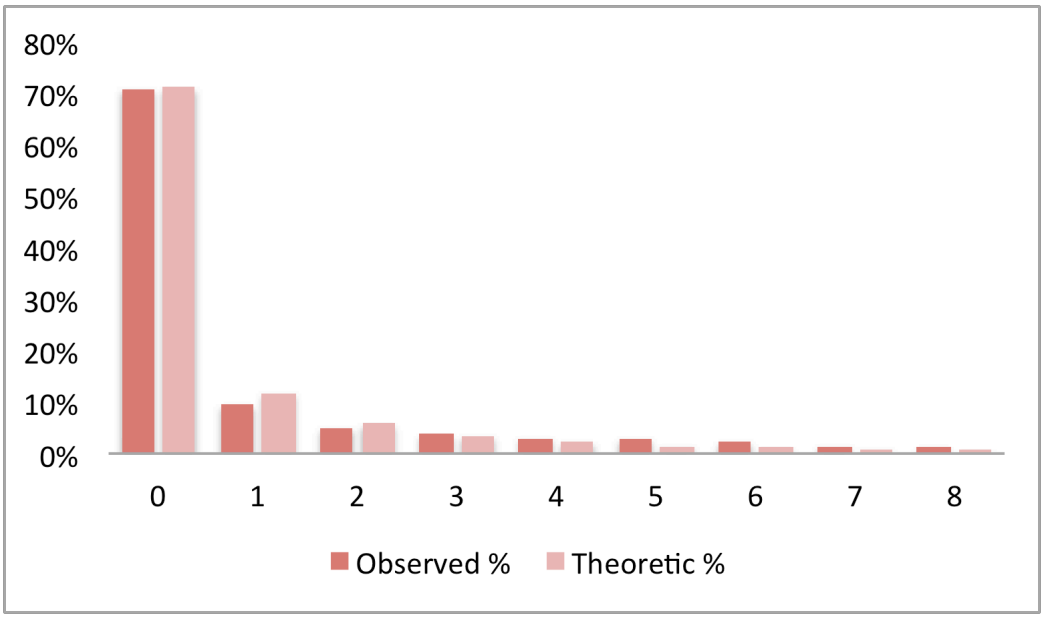


Table 49 – NBD fitting for the brand Tetley

	Frequency	Total associations	Observed (%)	Theoretical (%)	MADs (%)
0	3093	0	38	38	0
1	971	971	12	19	7
2	754	1508	9	12	3
3	714	2142	9	8	1
4	674	2696	8	6	2
5	623	3115	8	4	3
6	502	3012	6	3	3
7	407	2849	5	2	3
8	366	2928	5	2	3
Tot.	**8104**	**19221**			
	5011				

62% Proportion of people providing at least one association
3.8 Average number of associations

Figure 40 - NBD fitting for the brand Tetley

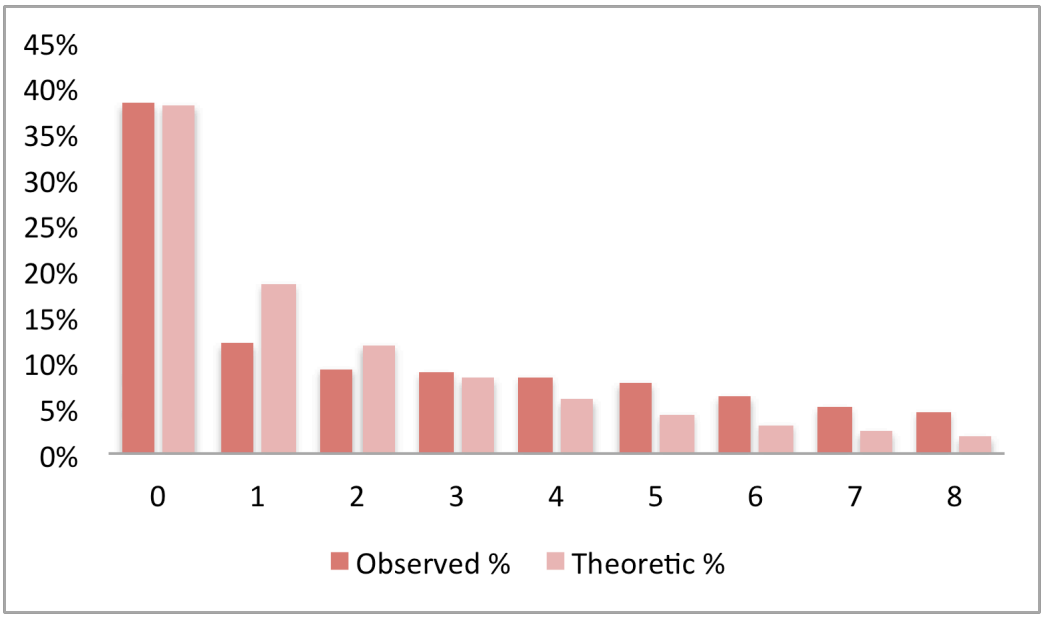


Table 50 – NBD fitting for the brand Twinings

	Frequency	Total associations	Observed (%)	Theoretical (%)	MADs (%)
0	3531	0	44	44	0
1	1076	1076	13	19	5
2	837	1674	10	11	1
3	721	2163	9	7	1
4	546	2184	7	5	2
5	487	2435	6	4	2
6	362	2172	4	3	2
7	292	2044	4	2	2
8	252	2016	3	1	2
Tot.	**8104**	**15764**			
	4573				

56% Proportion of people providing at least one association
3.4 Average number of associations

Figure 41 - NBD fitting for the brand Twinings

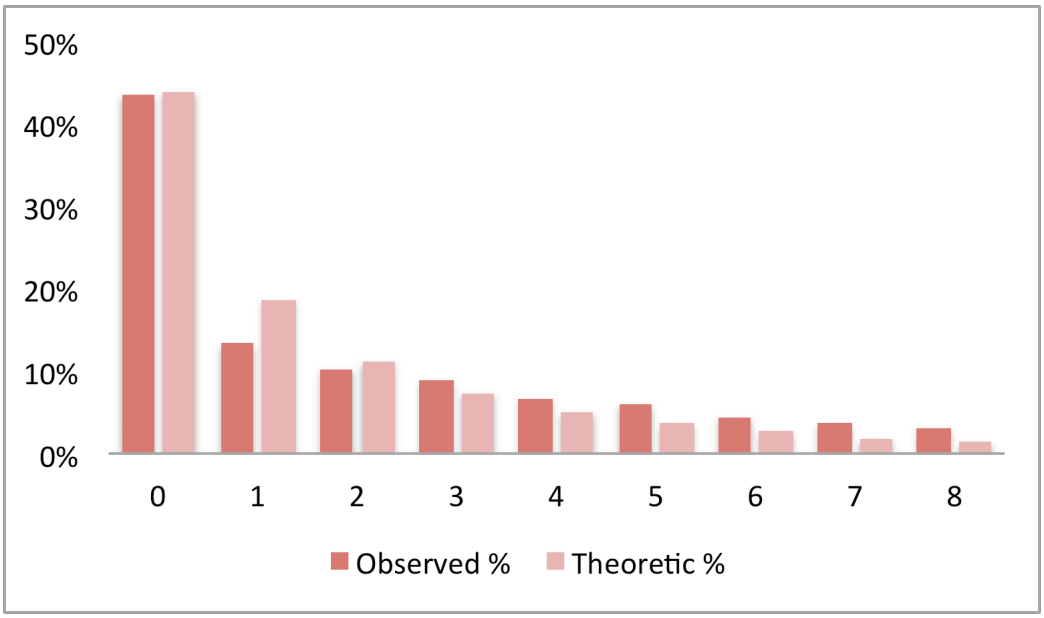


Table 51 – NBD fitting for the brand Typhoo

	Frequency	Total associations	Observed (%)	Theoretical (%)	MADs (%)
0	4222	0	52	52	0
1	1148	1148	14	18	4
2	730	1460	9	10	1
3	583	1749	7	6	1
4	473	1892	6	4	2
5	363	1815	4	3	2
6	266	1596	3	2	1
7	176	1232	2	1	1
8	143	1144	2	1	1
Tot.	**8104**	**12036**			
	3882				

48% Proportion of people providing at least one association
3.1 Average number of associations

Figure 42 - NBD fitting for the brand Typhoo

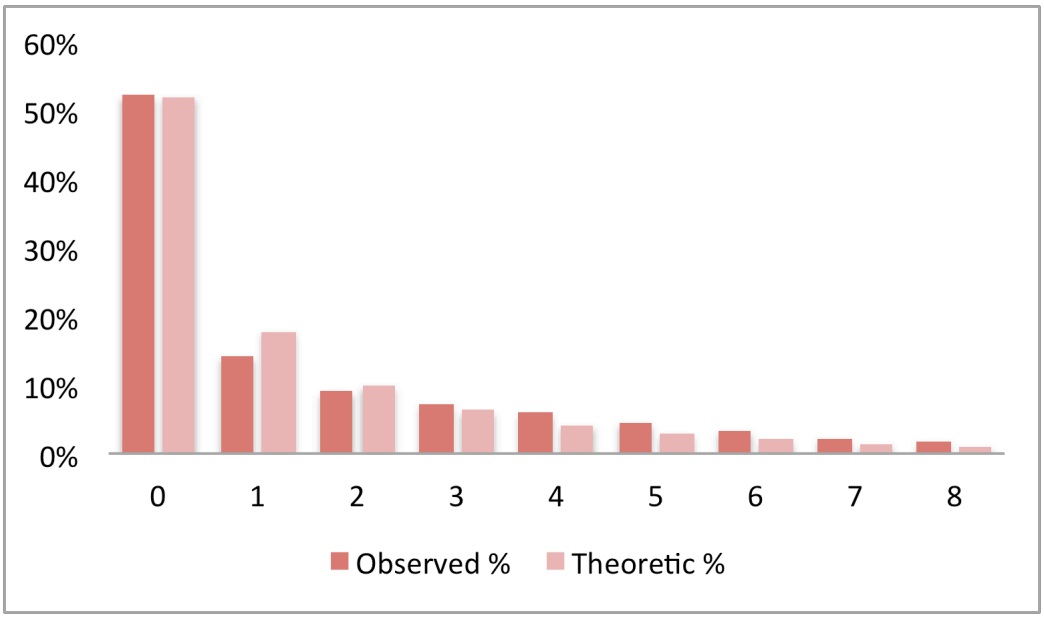


Table 52 – NBD fitting for the brand Yorkshire

	Frequency	Total associations	Observed (%)	Theoretical (%)	MADs (%)
0	4745	0	59	59	0
1	1066	1066	13	16	3
2	645	1290	8	8	0
3	502	1506	6	5	1
4	335	1340	4	3	1
5	290	1450	4	2	1
6	234	1404	3	2	1
7	141	987	2	1	1
8	146	1168	2	1	1
Tot.	**8104**	**10211**			
	3359				

41% Proportion of people providing at least one association
3.0 Average number of associations

Figure 43 - NBD fitting for the brand Yorkshire

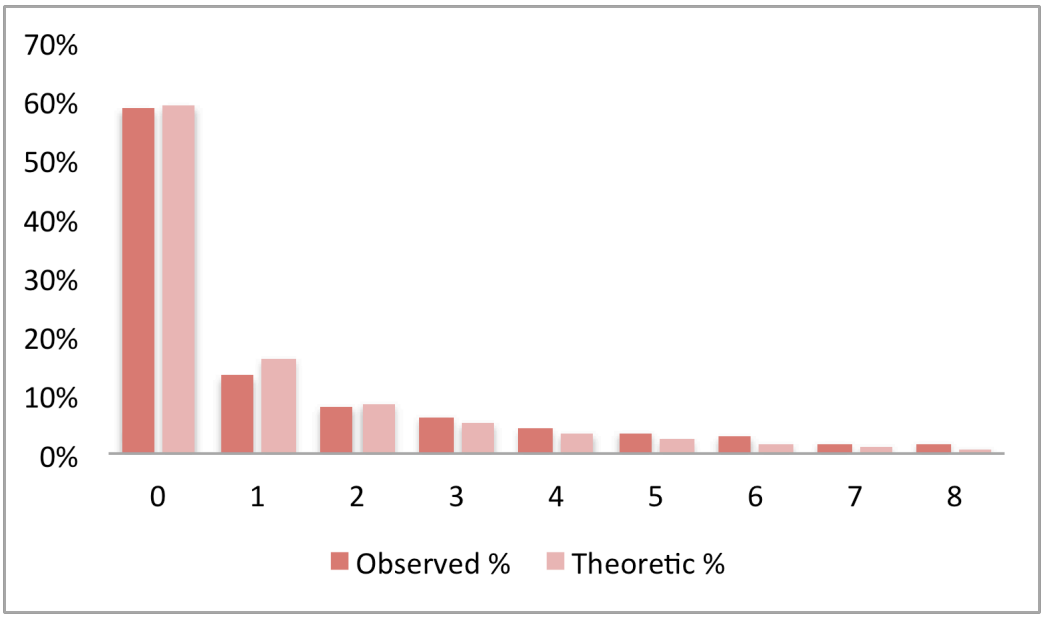
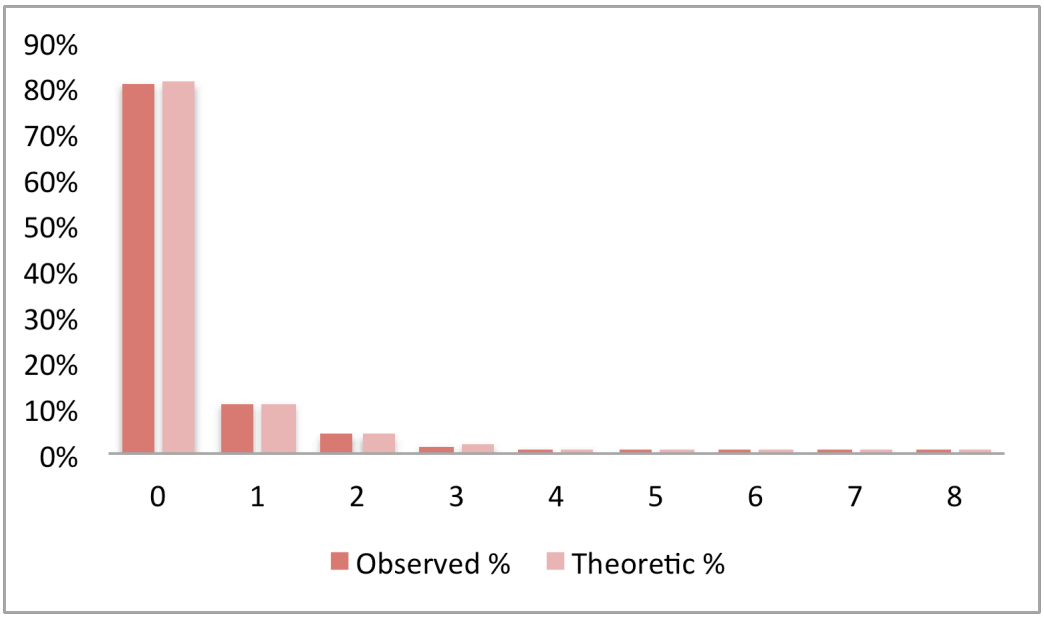


Table 53 – NBD fitting for the brand Punjana

	Frequency	Total associations	Observed (%)	Theoretical (%)	MADs (%)
0	6552	0	81	81	0
1	882	882	11	11	0
2	336	672	4	4	0
3	134	402	2	2	0
4	72	288	1	1	0
5	55	275	1	1	0
6	31	186	0	0	0
7	26	182	0	0	0
8	16	128	0	0	0
Tot.	**8104**	**3015**			
	1552				

19% Proportion of people providing at least one association
1.9 Average number of associations

Figure 44 - NBD fitting for the brand Punjana



Appendix C: Behavioural metrics

Table 54 – Observed and theoretical behavioural metrics – TEA (UK data)

	Market share %	Penetration %		Purchase Freq.		SCR %	
		O	T	O	T	O	T
Tesco Stand	29	38	48	5.8	4.5	9	46
PGTips	21	37	37	4.2	4.1	8	41
Tetley	19	40	35	3.5	4.1	8	40
Twinings	13	26	27	4.0	3.8	10	37
Typhoo	5	17	12	2.5	3.5	9	33
Yorkshire	5	9	11	4.4	3.5	10	33
Clipper	4	10	9	3.3	3.5	13	32
TescoFinest	3	8	8	3.5	3.4	12	32
Punjana	0	3	2	2.1	3.3	10	31
Average	**11**	**21**	**21**	**3.7**	**3.7**	**10**	**36**

Table 55 – Observed and theoretical behavioural metrics – INSTANT COFFEE (UK data)

	Market share %	Penetration %		Purchase Freq.		SCR %	
		O	T	O	T	O	T
Tesco Stand	32	32	38	5.2	4.4	30	50
Nesc Origin	22	27	28	4.2	4.0	63	44
Nesc Gold	13	20	18	3.2	3.7	50	39
Kenco	10	17	14	3.0	3.6	44	37
Douwe	10	15	14	3.5	3.6	46	37
Nesc Coll	4	6	6	3.7	3.4	42	35
Carte Noire	4	6	6	3.4	3.4	42	35
Kenco Pure	2	5	4	2.5	3.3	35	34
Tesco Fin	2	5	3	2.2	3.3	30	34
Average	**11**	**15**	**15**	**3.4**	**3.6**	**42**	**38**

Table 56 – Observed and theoretical behavioural metrics – ROAST COFFEE (UK data)

	Market share %	Penetration %		Purchase Freq.		SCR %	
		O	T	O	T	O	T
Tesco Stand	30	8	9	3.2	2.8	6	49
Tesco Coll	21	6	7	3.3	2.6	8	43
Tesco Fin	17	6	6	2.5	2.5	6	41
Taylors	15	5	5	2.6	2.5	7	40
Percol	6	2	2	2.5	2.3	8	35
Douwe	4	2	1	1.5	2.3	7	34
Starbucks	4	2	1	1.6	2.3	6	34
Carte Noire	3	2	1	1.8	2.2	7	33
Average	**13**	**4**	**4**	**2.4**	**2.4**	**7**	**39**

Table 57 – Observed and theoretical behavioural metrics – Toothpaste Year 1 (US data)

	Market share %	Penetration %		Purchase Freq.		SCR %	
		O	T	O	T	O	T
COLGATE TOT PR	14	25	26	1.9	1.8	39	34
Others	12	21	20	1.7	1.7	36	32
CREST BASE AD	8	18	19	1.7	1.7	36	32
CREST WHITE EX	6	13	13	1.6	1.6	27	30
C-Crest + Scope	6	14	13	1.5	1.6	26	30
SENSODYNE	6	6	7	2.1	1.6	28	29
AQ-F PREMIUM	6	12	13	1.8	1.6	28	30
A&H	4	5	8	2.2	1.6	32	29
MENTADENT	3	3	5	2.1	1.5	48	28
CREST EXTR WHIT	3	6	5	1.3	1.5	30	28
CREST PRO-HEAL	3	7	6	1.3	1.5	21	28
COLG MAX FRESH	3	7	7	1.5	1.6	19	29
AQ-F BASE ADULT	3	9	9	1.7	1.6	30	29
COLGATE ORIG	3	7	7	1.6	1.6	31	29
COLGATE LUMI	3	8	7	1.4	1.6	19	29
COLG SPARK WHI	2	7	6	1.3	1.5	21	29
COLGATE BSPW	2	6	6	1.4	1.5	24	28
CREST SENS	2	3	3	1.7	1.5	21	28
TOMS	2	2	2	2.1	1.5	38	28
AIM	1	6	7	1.8	1.6	36	29
CREST MC WHIT	1	3	3	1.4	1.5	23	28
CREST VIVID WH	1	2	2	1.6	1.5	19	28
ULTRA BRITE	1	5	6	1.8	1.5	32	28
COLGATE TCW	1	4	3	1.3	1.5	23	28
COLGATE SENS	1	2	2	1.8	1.5	26	28
COLGATE 2 IN 1	1	2	1	0.9	1.5	20	27
PEPSODENT	1	4	5	1.8	1.5	35	28
REMBRANDT	1	1	1	1.6	1.5	15	27
CLOSE-UP	1	3	3	1.8	1.5	32	28
Average	**3**	**7**	**7**	**1.6**	**1.6**	**28**	**29**

Table 58 – Observed and theoretical behavioural metrics – Toothpaste Year 2 (US data)

	Market share %	Penetration %		Purchase Freq.		SCR %	
		O	T	O	T	O	T
Others	12	21	20	1.7	1.7	34	32
COLG TOT PREM	11	22	22	1.8	1.7	3	33
CREST PRO-HEAL	8	14	15	1.8	1.7	30	31
CREST BASE	7	17	18	1.7	1.7	36	32
C-Crest + Scope	6	14	13	1.5	1.6	28	30
AQ-F PREMIUM	6	13	14	1.8	1.6	28	31
SENSODYNE	5	5	7	2.0	1.6	30	29
CREST WHITE EX	4	9	9	1.6	1.6	26	29
A&H	4	6	8	2.1	1.6	30	29
COLG TOT PREM	4	8	7	1.5	1.6	20	29
COLG MAX FRESH	4	8	8	1.5	1.6	21	29
MENTADENT	3	3	4	2.1	1.5	49	28
COLGATE ORIG	2	7	7	1.6	1.6	30	29
CREST EX WHIT	2	5	5	1.3	1.5	28	28
AQ-F BASE ADULT	2	8	8	1.6	1.6	28	29
COLGATE BSPW	2	6	6	1.4	1.6	25	28
CREST SENS TP	2	3	3	1.8	1.5	21	28
TOMS TP	2	2	3	1.9	1.5	34	28
COLG SPARK WH	2	6	5	1.3	1.5	23	28
COLGATE LUMIN	2	5	4	1.3	1.5	18	28
AIM TP	1	6	7	1.8	1.6	39	29
CREST M-C WHIT	1	3	3	1.5	1.5	23	28
CREST VIVID WH	1	2	2	1.9	1.5	22	28
COLGATE SENSIT	1	2	2	1.8	1.5	28	28
ULTRA BRITE	1	4	5	1.9	1.5	35	28
COLGATE TCW	1	4	3	1.3	1.5	23	28
SENSOD PRO NAM	1	2	1	1.3	1.5	13	27
REMBRANDT	1	1	1	1.6	1.5	13	27
CLOSE-UP	1	3	3	1.7	1.5	33	28
Average	**3**	**7**	**7**	**1.7**	**1.6**	**27**	**29**

Table 59 – Observed and theoretical behavioural metrics – Toothpaste Year 3 (US data)

	Market share %	Penetration %		Purchase Freq.		SCR %	
		O	T	O	T	O	T
Others	12	21	21	1.7	1.7	34	33
CREST PRO-HEAL	10	15	17	1.9	1.7	34	32
COLG TOT PREM	10	19	18	1.6	1.7	36	32
CREST BASE	7	18	19	1.7	1.7	35	32
C-Crest + Scope	6	13	13	1.5	1.6	28	31
COL T SUP PREM	6	13	13	1.6	1.6	22	31
AQ-F PREMIUM	6	12	13	1.8	1.6	30	31
SENSODYNE	5	5	6	1.9	1.6	28	29
A&H TP	4	6	7	2.0	1.6	31	29
COLG MAX FRESH	4	9	9	1.5	1.6	20	29
CREST WHITE EX	3	7	8	1.6	1.6	26	29
COLGATE ORIGIN	3	8	8	1.6	1.6	28	29
CREST EX WHIT	2	5	4	1.3	1.5	28	28
AQ-F BASE ADULT	2	7	7	1.5	1.6	29	29
MENTADENT	2	2	3	2.0	1.5	54	28
COLGATE BSPW	2	7	6	1.3	1.5	25	29
SENSOD PRO NAM	2	2	2	1.6	1.5	19	28
TOMS	2	2	2	1.9	1.5	36	28
AIM	2	7	8	1.7	1.6	35	29
CREST SENS	1	2	2	1.8	1.5	21	28
COLGATE SENSIT	1	2	3	1.7	1.5	25	28
COLG SPARK WH	1	5	4	1.3	1.5	21	28
ULTRA BRITE	1	4	5	1.9	1.5	36	29
COLGATE TCW	1	4	3	1.3	1.5	21	28
COLGATE LUMIN	1	4	3	1.2	1.5	18	28
CREST M-C WHIT	1	2	2	1.4	1.5	21	28
CLOSE-UP	1	3	3	1.6	1.5	32	28
CREST VIVID WH	1	1	1	1.6	1.5	19	28
PEPSODENT	1	3	3	1.8	1.5	32	28
REMBRANDT	1	1	1	1.6	1.5	17	28
Average	**3**	**7**	**7**	**1.6**	**1.6**	**28**	**29**

Appendix D: Brand salience metrics

Table 60 – Observed and theoretical brand salience metrics – TEA (UK data)

	Salience %	Sal. penetr. %		Association Rate		Share of Mind %	
		O	T	O	T	O	T
PGTips	20	65	66	3.9	3.9	35	26
Tetley	19	62	63	3.8	3.8	32	25
Twinings	15	56	56	3.4	3.5	27	22
Yorkshire	15	41	42	3.0	3.0	22	19
Typhoo	12	48	47	3.1	3.1	21	20
Tesco Fin	9	41	39	2.8	2.9	18	18
Tesco St	7	29	33	3.1	2.8	24	17
Clipper	4	22	20	2.4	2.5	16	15
Punjana	3	19	15	1.9	2.4	12	14
Average	**12**	**43**	**42**	**3.1**	**3.1**	**23**	**20**

Table 61 – Observed and theoretical brand salience metrics – INSTANT COFFEE (UK data)

	Salience %	Sal. penetr. %		Association Rate		Share of Mind %	
		O	T	O	T	O	T
Nescafe Orig	19	22	19	3.1	3.6	33	21
Nescafe Gold	18	21	19	3.1	3.4	30	20
Kenco	13	17	16	2.7	2.9	22	15
Douwe	10	15	14	2.4	2.6	20	13
Tesco	9	14	13	2.2	2.4	20	11
Kenco Pure	8	14	13	2.2	2.4	16	11
Nescafe Coll	8	13	13	2.2	2.3	17	11
Tesco Finest	8	13	12	2.2	2.3	16	11
Carte Noire	7	12	12	2.2	2.2	17	10
Average	**11**	**16**	**15**	**2.5**	**2.7**	**21**	**14**

Table 62 – Observed and theoretical brand salience metrics – ROAST COFFEE (UK data)

	Salience %	Sal. penetr. %		Association Rate		Share of Mind %	
		O	T	O	T	O	T
Douwe	22	19	15	2.8	3.7	34	18
Tesco Fin	16	16	14	3.0	3.5	25	16
Carte Noire	13	14	15	3.9	3.7	23	18
Tesco Coll	12	12	9	1.9	2.5	25	10
Starbucks	10	11	13	3.8	3.2	24	15
Taylor	10	10	12	3.4	2.9	26	13
Café Direct	7	8	8	2.4	2.3	20	9
Tesco St	6	10	11	3.1	2.8	17	12
Percol	4	4	6	3.1	2.1	17	7
Average	**11**	**12**	**11**	**3.0**	**3.0**	**24**	**13**

Table 63 – Brand salience metrics – Toothpaste Year 1 (US data)

	Salience %	Sal. penetr. %		Association Rate		Share of Mind %	
		O	T	O	T	O	T
Colgate Total	19	67	69	5.4	5.2	32	21
C-Crest Plus	14	61	61	4.3	4.3	22	16
Crest Pro Health	13	56	59	4.4	4.2	19	16
Crest Whitening	12	56	56	3.9	3.9	19	15
Colgate Max Fr	9	50	50	3.5	3.5	14	13
Colgate 2 in 1	9	45	48	3.7	3.5	14	12
Aquafresh	8	45	45	3.4	3.3	19	12
Crest Vivid	6	47	40	2.6	3.1	11	11
Arm & Hammer	6	35	36	3.1	3.0	16	10
Sensodyne	4	31	30	2.6	2.8	12	9
Average	**10**	**49**	**49**	**3.7**	**3.7**	**18**	**13**

Table 64 – Brand salience metrics – Toothpaste Year 2 (US data)

	Salience %	Sal. penetr. %		Association Rate		Share of Mind %	
		O	T	O	T	O	T
Colgate Total	18	64	67	5.5	5.2	31	20
Crest Plus	12	54	56	4.3	4.2	20	15
Crest Pro Health	15	57	62	5.1	4.6	24	17
Crest Whitening	10	51	52	4.0	3.9	18	14
Colgate Max Fr	9	51	48	3.5	3.7	19	13
Colgate 2 in 1	8	45	46	3.6	3.6	14	12
Aquafresh	8	40	43	3.7	3.4	13	12
Crest Vivid	6	43	37	2.8	3.2	11	11
Arm&Hammer	6	39	37	3.1	3.2	14	11
Sensodyne	5	35	30	2.5	3.0	13	10
Tom's of Main	3	23	22	2.7	2.8	15	9
Average	**9**	**45**	**45**	**3.7**	**3.7**	**17**	**13**

Table 65 – Brand salience metrics – Toothpaste Year 3 (US data)

	Salience %	Sal. penetr. %		Association Rate		Share of Mind %	
		O	T	O	T	O	T
Colgate Total	17	63	66	5.3	5.1	29	19
Crest Pro Health	14	58	62	4.9	4.6	23	17
Crest Plus	12	55	57	4.3	4.2	20	15
Crest Whitening	10	51	51	3.8	3.8	17	13
Aquafresh	9	52	47	3.3	3.6	18	13
Colgate Max Fr	8	46	47	3.6	3.6	14	12
Crest Vivid	6	42	36	2.7	3.2	10	11
Arm&Hammer	6	41	39	3.1	3.3	15	11
Colgate 2 in 1	5	30	34	3.6	3.1	13	10
Sensodyne	5	35	31	2.7	3.0	13	10
Colgate Tot Adv	4	15	25	4.8	2.8	19	9
Tom's of Main	3	24	22	2.6	2.8	13	9
Colgate Sensit	2	10	12	3.3	2.5	10	8
Average	**8**	**40**	**41**	**3.7**	**3.5**	**16**	**12**

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Modeling mental market share

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ABSTRACT

Normative benchmarks for a brand's network of associations provide managers with guidelines to set brand strategy. Benchmarks also help marketers evaluate the impact of marketing activities. This paper outlines an approach to obtain benchmarks for the relative size and structure of a brand's associative network using the NBD–Dirichlet model (Goodhardt, Ehrenberg, & Chatfield, 1984). The results reveal an excellent fit, showing that the NBD-Dirchlet is able to obtain predictions for a brand's mental market share. This finding has implications for understanding of the structure of consumers' memory for brands and the dynamic nature of the associative network across brands and time.

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1. Introduction

Metrics pertaining to consumer-base brand equity (CBBE) are a critical part of most marketing or brand manager's portfolios. These metrics help formulate brand strategy and assess the performance of brand expenditure (Aaker, 1992; Lehmann, Keller, & Farley, 2008). An important dimension of CBBE is the brand's network of associations in consumer memory (Keller, 2003). This associative network (in line with Associate Network Theories of memory such as Anderson & Bower, 1979) is a store of knowledge that consumers draw upon to elicit and select between brands available in memory in choice situations. Marketers seek to influence consumer's associative networks for brands, through activities to build and refresh brand associations in consumer memory. Consequently, a considerable amount of research aims to understand how consumers encode, organise, store and use brand associations.

Keller (1993) proposes CBBE as an antecedent to consumer' brand buying behavior; therefore CBBE may be an attractive input for setting brand strategy. Understanding the CBBE of a successful brand can help marketers set appropriate objectives and devise tactics to achieve these objectives. Therefore, alongside research to identify and measure the different dimensions of CBBE, research efforts test the relationship between CBBE and future buying behavior.

The size of the brand's associative network, or the number of brand-attribute links in consumer memory is one dimension of CBBE. Both theoretical support and empirical evidence exist to link associative network size with future brand choice. Theoretical support comes from models of associative memory and the retrieval cue process (Anderson & Bower, 1979; Collins & Loftus, 1975). These models infer that a brand with more associations will have more pathways to retrieval, and therefore consumers are more likely to think of the brand. Empirical evidence shows that the more associations a brand has, the more likely the consumer will chose the brand (Alba & Marmorstein, 1987; Romaniuk, 2003), and the higher the brand's equity (Krishnan, 1996).

However all brands face competition, and the presence of competitor brands in consumer's memory inhibits the process of brand retrieval (Alba & Chattopadhyay, 1986; Burke & Srull, 1988; Heil, Rösler, & Hennighausen, 1994). Therefore, value of a brand's associative network is in the strength relative to competitors.

At the same time, retrieval from consumer memory is never certain (Mitchell, 1982), and neither are brand links to associations over time. The retrieval of the brand, when the attribute is the cue to access memory, is a probabilistic or stochastic process, prone to variation at individual level but predictable in aggregate (Dall'Olmo Riley, Ehrenberg, Castleberry, Barwise, & Barnard, 1997; Mitchell, 1982; Rungie, Laurent, Dall'Olmo Riley, Morrison, & Roy, 2005). Therefore, while a link between an attribute and a brand may be available in memory, a link may not be accessible at any point in time. Retrieval of a brand can happen for an attribute today, however future retrieval is not a certainty, and an underlying probability influences the possibility. This characterisation of consumer's retrieval of the brand via the associative network as a repeated, competitive, stochastic process provides a theoretical basis for drawing on the NBD–Dirichlet model.

The NBD–Dirichlet model is a stochastic mathematical model for competitive brands in repeat-purchase repertoire markets (Goodhardt et al., 1984). Drawing from the underlying frequency distributions of brand and category buying in a given time period, the NBD–Dirichlet provides benchmarks for brand sales metrics (Ehrenberg, Uncles, & Goodhardt, 2004). These benchmarks inform brand managers' expectations about brand performance metrics, and help identify deviations

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requiring action. A testimony to the robustness of the model is the successful application to hundreds of markets around the world (Ehrenberg et al., 2004). Many of the world's large packaged goods firms, such as Procter & Gamble, Unilever, Colgate-Palmolive and Kraft draw on the model.

In addition to benchmarks at a point in time, the model provides estimations for how brands grow or decline (Wright & Sharp, 2001), and gives expectations for new brands entering a category (Ehrenberg & Goodhardt, 2000). The model's theoretical values provide norms to assess the effectiveness of marketing interventions, such as loyalty programs (Sharp & Sharp, 1997) and marketers can use the model to investigate new markets (Uncles & Kwok, 2009). The NBD–Dirichlet model also informs the theoretical limits for brands on any metric, which is important for objective setting (Sharp, 2010; Sharp & Ehrenberg, 2000; Wright & Sharp, 2001). This ability makes the model very useful for those seeking to understand the buying patterns of a brand's customer base and/or to change a brands' market share.

These applications of the NBD–Dirichlet model are useful for researchers and marketers in a CBBE context. Currently little guidance exists on a brand's potential or ideal CBBE. Managers assess the performance of a brand on CBBE metrics by tracking changes in brand scores over time. However, most CBBE metrics suffer from a feedback mechanism where past consumer behavior strongly influences the scores for a brand. This feedback mechanism means that brands with more past users gain higher scores than brands with fewer past users, regardless of future trajectory (Barnard & Ehrenberg, 1990; Bird, Channon, & Ehrenberg, 1970; Brakus, Schmitt, & Zarantonello, 2009). This high correlation between a brand's CBBE and market share (for examples see Ehrenberg, Barnard, & Scriven, 1997) means that without accounting for a brand size/market share, CBBE metric risk measuring a brand's past performance, rather than the future potential.

When calculating theoretical values, the NBD–Dirichlet model considers the share of brands, which could help account for the feedback of the effect of past buying/using a brand on CBBE. The other benefits of the NBD–Dirichlet model are a greater theoretical understanding of the underlying structure of a brand's associative network, which can help when setting objectives and evaluating a brand's performance. However, a possibility exists that despite a widespread ability to provide estimations for buying behavior, the model might not be appropriate for modeling brand associations. Such outcome would also advance the understanding of the relationship between a brand's associative network and the behavior the associations possibly precede.

Therefore, this paper has four objectives. First, the paper presents the case for a brand's relative associative network size, and the corresponding mental market share, as a measure of CBBE. The second objective is to explain the theoretical rationale for the use of the NBD–Dirichlet model in this context. The third objective is to report on the performance of the model when modeling brand associations, and the associate errors. The final objective is to discuss the implications of the results for marketing practice and future research.

2. Background to the modeling approach

A theory, with considerable empirical support, is that human memory comprises a network of association links, or the associative network theories of memory (ANT) (Bower, 1998; Tulving & Craik, 2000). Under the ANT, the brand represents a node in memory. The concepts that the consumer encounters in conjunction with the brand and processes sufficiently to form a memory trace or association form links to this brand. A link's presence means that the concept is available for retrieval if the brand is a cue, and that the concept is a possible cue to retrieve the brand from long-term memory (Anderson & Bower, 1979; Tulving & Pearlstone, 1966). Keller (1993) refers to these concepts as brand associations.

Brand associations influence consumers' salience and evaluation of a brand (Keller, 2003; Romaniuk & Sharp, 2004). However, alternative theories about how consumers use these associations in the process of retrieving and deciding between brands are apparent. From an ANT perspective and drawing on the spreading activation theories of retrieval (Anderson, 1983; Collins & Loftus, 1975), these associations have two roles. The first role of brand associations is as cues for consumers to evoke brands from memory (Nedungadi, 1990). The product category is a common cue for brand retrieval (Assael & Day, 1968), however research points to consumers using a wide variety of cues to retrieve brands from memory (Desai & Hoyer, 2000; Nedungadi & Kanetkar, 1992; Shocker, Ben-Akiva, Boccara, & Nedungadi, 1991). The second role of brand associations is to help the consumer decide which of the subset of brands is suitable at that point is time (Nedungadi, 1990). At either an evocation or evaluation stage, a brand with links to more potentially relevant attributes has higher choice probabilities. Meyers-Levy (1989) refers to the number of brand associations as association set size.

A large associative network likely has a positive influence on brand choice. Alba and Marmorstein (1987) find a positive relationship between the frequency of associations and brand choice, as does Romaniuk (2003). In the service area, Romaniuk and Sharp (2003) show a positive relationship between the number of associations and customer loyalty across the three studies. Krishnan (1996) also links the size of the associative network to an external financial measure of brand equity.

However, just as brand links facilitate retrieval, competitor links inhibit retrieval (Burke & Srull, 1988; Heil et al., 1994). Past research into the size of the associative network neglects the impact of competitor brands links to the same attributes on retrieval and choice. While Keller (1993) highlights the value of uniqueness, which is the absence of competitor associations, Romaniuk and Gaillard (2007) show that often competitor brands also have links to relevant attributes. Q4

Therefore, any associative network size measures need to account for the strength of competitor brands. This combination of brand and competitor effects leads to a market of associations across brands in the category, with each brand having a share of the total associations, or a mental market share. This mental market share has theoretical and practical parallels with sales market share. The NBD–Dirichlet model calculates theoretical norms for sales market share. The next section explains this model and the argument for applying the NBD–Dirichlet to the modeling of mental market share.

2.1. Background to the NBD–Dirichlet model and the applicability to this context

Numerous approaches exist for modeling a brand's mental market share. The choice of the NBD–Dirichlet in this paper is for theoretical and practical reasons. An outline of the NBD–Dirichlet model precedes discussing these reasons.

The NBD–Dirichlet model provides predictions for a wide range of consumer buying metrics over time. A typical use of the NBD–Dirichlet model is to describe how consumers buy packaged goods brands, including how many people should buy the brand, how many times they should buy that brand, how much of their total spend in the category should be with that brand versus competitors. The estimates the model provides draw on a mix of distributions for brands and category purchase frequencies. At category level, the model draws on the Negative Binomial Distribution (as per Ehrenberg, 1959), while at brand level the model draws on the Dirichlet Multinomial Distribution (as per Goodhardt et al., 1984). The estimates for a specific brand vary according to the category purchase rate, the brand's market share and the timeframe of analysis.

The timeframe influences the number of purchase occasions the model includes, and so has an impact the specific brand metrics. For example, metric expectations for the purchase frequency for a brand adjust to be higher for longer timeframes and lower for shorter timeframes (for more details on the underlying distributions, model

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history and the use of the model to provide brand performance metrics, please see Ehrenberg et al., 2004; Goodhardt et al., 1984).

The first theoretical reason for drawing on this specific model is that the NBD–Dirichlet is a stochastic model (Goodhardt et al., 1984). This characteristic means that underlying propensities lead to consumer's buying some brands more than other brands. However, no certainty exists about which brand the consumer will buy at any one point in time, making the buying process as-if random. Consumers retrieving brands via cues follow a similar probabilistic process, where repeat linkage of a brand with an attribute is unstable, but with a predictability that suggests an underlying retrieval propensity (Castleberry, Barnard, Barwise, Ehrenberg, & Dall'Olmo Riley, 1994; Dall'Olmo Riley et al., 1997; Rungie et al., 2005; Sharp, 2002; Sharp & Romaniuk, 2000, 2002; Sharp & Winchester, 2002). Brand associations may enhance a consumer's choice probabilities. Consumer's use of brand can then positively influence brand associations. If these assumptions are valid, a reasonable postulate is that the underlying structure of brand associations may mimic the underlying structures of brand buying. Therefore, the NBD–Dirichlet model will be appropriate in this context.

The second theoretical reason is that both buying and retrieving a brand are competitive processes. When accessing memory, the consumer retrieves the brand and/or competitors. When buying, the consumer either buys a brand, and/or competitors. In both cases, the strength of the competitor negatively affects brand performance. In buying, if a consumer buys a competitor, the brand does not get the revenue. In retrieval, competitors can inhibit, and therefore prevent, brand retrieval and/or provide an alternative option to buy (Alba & Chattopadhyay, 1986; Burke & Srull, 1988). The NBD–Dirichlet model considers both brand and competitor strength when calculating theoretical values.

The third theoretical reason is that a binary variable capture both retrieving and buying. A consumer can buy a brand or not. When accessing brands from memory, a consumer can associate a brand with an attribute or not, which is also a binary variable. Therefore, both scenarios create a frequency of distribution of occurrences, either purchases or associations, whereby a consumer has zero, one, two, three counts and so on. This data quality is an essential requirement for using the Negative Binomial Distribution. For associations, only one questioning technique, a free choice pick any format, can produce such distributions (Barnard & Ehrenberg, 1990; Driesener & Romaniuk, 2006).

Practicality and parsimony are the final reasons for applying the NBD–Dirichlet model to brand association modeling. The NBD–Dirichlet needs few inputs and provides richness of outputs, which makes the model very efficient. Extensive evidence exists that the NBD–Dirichlet model is extremely useful for understanding what to expect from a brand's performance on buying behavior. Therefore trying to apply a related, robust, generalizable model is more practical than starting afresh.

2.2. Identifying an appropriate set of attributes to measure brand associations

Researchers assemble lists of attributes to measure brand associations. Lists vary in length, with up to 30 attributes in some studies. When compiling a list of attributes to assess brands' associative network size, two issues need addressing; removing attributes that (a) are repetitions of constructs and (b) that encourage the consumer to engage in evaluative or constructive processes. These two confounding factors have the potential to bias the associative network measure that the attribute set collects.

2.2.1. (a) Removing repetitive attributes

Lists can comprise of attributes that overlap in meaning to consumers. Overlapping attributes lead to duplicate counts of memory structures and so bias associative network size measures. For example, brands with positioning on lower prices/value for money will appear to have a wider associative network if the attribute set includes multiple good value pricing attributes, when in fact this wider network is just a measurement artifact. This process is similar to reducing items in a multi-item factor (e.g., Aaker, 1997). Non-parametric correlations are applicable to binary variables and allow the researcher to identify attributes that represent similar constructs to consumers. After identifying these overlaps, the researcher can select one attribute to represent the construct in the model attribute set.

2.2.2. (b) Removing strong evaluations or constructions

Strong evaluations take place when attributes include a superlative such as *best brand for whitening teeth* or invite judgements about superiority relative to competitors such as *more effective than other brands at freshening my breath*. These strongly worded attributes encourage additional processing from the consumer before responding and so are more likely to capture conscious evaluations rather than direct links in memory between the attributes and brands. Therefore, these attributes capture different responses to other attributes, and can skew the brand response distributions. Consumers are prone to construct associations when the attribute contains words that infer an associative link to brands. For example, the attribute *helps sensitive teeth* is likely to favor Sensodyne, Colgate Sensitive and Crest Sensitivity. Even if the respondent knows nothing of the brands, just wanting to be helpful can lead to a positive response. While this construction of associations may be apparent for other attributes, these attributes have different underlying empirical patterns that can also skew the brand distributions (e.g., Barwise & Ehrenberg, 1985). Researchers should therefore omit these attributes from the model set.

2.3. How many attributes?

A long time period for market share analysis allows people to engage in more than one purchase occasion, and gives them more opportunities to buy the brand or competitors, and reveal more accurately any split preferences (Ehrenberg, 2000). For brand associations, each attribute is like a choice occasion. The number of attributes is analogous to the timeframe in NBD–Dirichlet modeling. The more attributes, the more opportunities to pick any brand, and reveal more accurately the scope of brand and competitive memory structures. Attribute lists sometimes list up to 30 attributes. This number is equivalent to 30 possible choice occasions, which is an extremely long representation of time. However, at the other extreme, if the measure includes only one or two attributes, such measure will insufficiently capture customer heterogeneity in memory structures, and fail to get an adequate sample of memory structures for smaller share brands. This is analogous to trying to model toothpaste buying over one week, where most people will not buy at all and very few will buy more than one brand. Negative Binomial Distribution (NBD) becomes useful at this point. By fitting the NBD to the distributions of the largest and smallest brands in the set, a researcher can determine if the measure includes enough attributes to capture a representative mental market share.

2.4. Deriving the metrics: brand associations versus brand buying

A brand's market share calculation is how many times consumers buy the brand in a specific time period, as a percentage of the total universe of purchases made in that time frame, or in the case of consumer panel data records, a representative sample of consumers. These purchase counts are irrespective of the circumstances of each purchase, such as whether the purchase occurs in a supermarket or a convenience store or for what specific need a customer purchases the brand. Similarly, deriving a CBBE metric from brand associations requires the same process of adding up the number of associations given to a brand and dividing the sum by the total number of associations given by a representative sample of consumers in the market.

Table 1 displays brand buying and the analogous brand associative network metrics. These metrics are inputs to assess the fit of the

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NBD–Dirichlet model, to determine if a possibility exists to obtain figures from the NBD–Dirichlet model that correspond with the figures the survey data generates. Each of the buying metrics comes from a well-established, simple, mathematical calculation (for more details see Ehrenberg, 2000). The analogous measure for brand associations draws on the same approach, but substitutes brand association figures for sales. For example, Brand Penetration (b) is the number of people buying the brand at least once as a percentage of the total possible number of buyers. Associative Penetration (Ab) is the number of people giving at least one brand association divided by the total number of people who could give a brand association.

3. Results

The first results section draws on a data from a packaged goods market, and explains process of constructing an attribute set as well as the results of the NBD–Dirichlet modeling. The second results section extends this modeling to service markets, which is untraditional territory for the NBD–Dirichlet model (Sharp, Wright, & Goodhardt, 2002).

3.1. Results — packaged goods market

Carbonated beverages is the test category. Professional market research interviewers collect the data, recruit consumers as per standard industry practice and screen potential respondents to identify category consumers. Respondents receive the brand names and then a series of attributes and indicate the brands with links to each attribute. The order of presenting attributes and brands is random.

Sixteen attributes are in the dataset and so available for analysis. This dataset's purpose is commercial brand health tracking, and so the attributes represent concepts marketers consider important for consumers. The author has no influence on the attribute set.

Four attributes represent strong evaluations or ask respondents to make direct comparisons with competitors, thereby encouraging additional cognitive processing than simply giving an associative link. These attributes are *feel more indulgent*; *are for someone like you*; *are better for you than other brands*; *and are more enjoyable to drink*. A further two attributes duplicate other attributes. Higher than average non-parametric correlations (Kendall's Tau-b) are apparent for *appropriate for social situations* (0.46 versus average of 0.35 with *for having fun with friends*); and *you feel good about drinking* (0.53 versus average of 0.42 with *taste great*).

This analysis leaves ten attributes to measure the associative set size of brands in the soft drinks category: *refreshing*; *give energy*; *tastes great*; *to have with food*; *for times with your family*; *for having fun with friends*; *cool*; *are worth the cost*; *authentic*; *to drink at work, school or college*. While the list is not exhaustive, the list is representative of different relevant memory structures consumers can use to retrieve brands in the carbonated soft drinks category.

The NBD–Dirichlet model inputs are the Ab and Aw for brands and the category. Brand level statistics from the survey data assess fit along with the NBD–Dirichlet estimates for each brand. NBD–Dirichlet model has no single goodness-of-fit statistic. Therefore, as Ehrenberg et al. (2004) suggest, the correlations between survey and model theoretical metrics, and the mean absolute deviation (MAD) are the goodness-of-fit indicators.

The survey data metrics are very close to the NBD–Dirichlet model estimates (see Table 2). High correlations (0.90 and higher, $p<0.01$) and low MADs show that the NBD–Dirichlet model predicts mental market share and the underlying metrics. Results from other categories are in Appendix 1 to affirm the wide applicability of this approach.

The NBD–Dirichlet does not fit perfectly, with evidence of brand deviations. For example, *Diet Coke* has fewer people giving at least one association about the brand (Ab) (51% versus 68%) and a higher frequency of associations (Aw) than estimates from those that do (4.2 versus 3.1). *Sunny Delight* displays a similar pattern of deviations. These brands have a fewer people with more associations than estimates suggest is normal for a brand with their mental market share. Explaining the reasons for the deviations is beyond the scope of the paper, however, this illustrates that this approach can identify such deviations.

One can argue that the NBD–Dirichlet model's use in packaged goods markets is widespread, and since a consumer using a brand has an impact on that consumer's associative structure, the good fit of the model on brand associations may simply reflect the impact of past buying behavior in these associations. However, a correlate of the mental market share scores with sales market share from the same set of brands in the same year shows convergent validity, with a Pearson's co-efficient of 0.74 ($p=0.009$), but not a perfect match. This finding suggests that the mental market share is not an exact replica of sales market share. As this approach draws from consumer survey responses, the model has the potential for application to any market where one can collect such responses. Data from financial services tests this potential.

3.2. Results: non-packaged goods markets

NBD–Dirichlet modeling is popular in packaged goods markets, however the model is also applicable to other consumer and business-

Table 1
Comparing metrics from buying behavior with analogous metrics from brand associations.

Buying behavior metric		Brand associative network metric	
Label	Calculation	Label	Calculation
Sales market share (SMS)	Share of purchases as a % of total purchases	Mental market share (MMS)	Share of associations as a % of total associations
Penetration (b)	% people buying the brand at least once	Associative penetration (Ab)	% people giving at least one brand association
Buy rate (w)	Number of times the brand is bought by the customer base	Association rate (Aw)	Number of associations given by those who have at least one brand association
Share of category requirements (SCR)	Share of purchases the brand gets from the customer base	Share of mind (SOM)	Share of associations the brand gets from those who have at least one associative link to the brand

Table 2
NBD–Dirichlet fit of mental market share for carbonated drinks. Q2

	MMS %		Ab %		Aw (mean)		SOM %	
	Obs	Est.	Obs	Est.	Obs	Est.	Obs	Est.
Coca-cola	23	23	94	88	5.2	5.6	30	23
Fanta	12	12	68	73	3.7	3.4	16	13
Diet Coke	10	10	51	68	4.2	3.1	18	12
Pepsi Cola	9	9	66	67	3.1	3.0	13	11
Dr Pepper	9	9	59	66	3.3	2.9	13	11
Sprite	9	9	66	65	2.9	2.9	14	11
7 Up	7	7	56	59	2.8	2.6	11	10
Lilt	7	7	55	58	2.8	2.6	11	9
Sunny Delight	7	7	47	57	3.1	2.6	12	9
Schweppes	5	5	54	50	2.2	2.3	9	8
Virgin Cola	2	2	30	28	1.7	1.8	7	6
Average	9	9	59	62	3.2	3.0	14	11
Mean AbsEr	0.03		5		0.3		3	
Corr. Obs v Est	1.00*		0.90*		0.91*		0.98*	

Obs = data from survey; Est = NBD–Dirichlet estimations.
* $p<0.01$.

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to-business behavior, such as doctors' prescriptions (Stern & Ehrenberg, 1995), television viewing, (Goodhardt, Ehrenberg, & Collins, 1987), gambling behavior (Lam, 2009) and store choice (Uncles & Ehrenberg, 1988), see Ehrenberg et al. (2004) for further examples. These markets typically involve some form of repeat-interaction behavior that one can count across brands, providing the statistics necessary for NBD–Dirichlet modeling.

NBD–Dirichlet model is, however, less applicable to buyer behavior in subscription markets. Sharp et al. (2002) describe consumers solely loyal to one brand for a long period of time as a key characteristic that distinguishes subscription markets from repertoire markets. In this paper, the NBD–Dirichlet model describes buyer behavior in credit card and long distance telephone phone call markets. Sharp et al. (2002) note that subscription categories are where buyers use fewer brands for long tenure. In these categories, with no frequent repeat-purchase behavior, researchers cannot draw on the NBD–Dirichlet model. For example, the behavioral interaction buyers have with insurance brands is often at annual renewal time, with rare interactions to make claims.

However, despite the differences in subscription market buying behavior, Romaniuk and Sharp (2003) present evidence that a brand's association set size affects buyer behavior in these types of categories. Therefore, consumers may similarly draw on brand associations, even though the behavioral outcomes may differ. Most of the interaction a consumer has with a subscription brand is via the marketing activity the brand undertakes between renewals, something common for brands irrespective of category. Therefore, even in subscription markets, the NBD–Dirichlet may effectively model consumer's brand associations, despite the inability to model buyer behavior.

For financial services, where the customer can hold a variety of products with a company brand, this is particularly relevant. Consumers interact with each financial product differently. For example, interaction with a transaction account may be every week via an ATM, while a home loan, although a large financial commitment has few instances of ongoing buyer interaction. Financial service providers also often bundle products, linking consumer's purchase of one product to another. Therefore, attempting to model consumer's full behavioral relationship with a financial service brand with the NBD–Dirichlet would be theoretically unsound and computationally complex. However, consumers use the same memory and retrieval processes to access the brand via the associative network. Therefore modeling the associative network size using the NBD–Dirichlet may provide insights into consumer's relationship with the corporate brand, and the formation of memory structures.

Another commercial brand tracking survey provides the data in a consumer financial service market. Interviewers recruit respondents via telephone in line with industry standards. The adult population in an Australian capital city provides the sampling frame from which to draw the sample randomly. The sample has a composition similar to the local adult population.

The attributes in the set for modeling are: *Easy to get to a branch*; *Can easily talk to a person*; *Can get ongoing financial advice*; *Good for home loans*; *Low fees*; *Good option to invest money*; *Trustworthy*; *Professional*; *Local* and *Good when I need money in a hurry*. Qualitative research separate to this study is the source of attributes, with refinement from marketers in the industry. The attribute list to represents that relevant to consumers. The researcher conducts the same tests on the attributes to confirm they are appropriate, but does not include the full results due to space limitations.

The results (see Table 3) show high correlations and low errors between actual and theoretical values. Brand 6 (in Table 3) deviates, with a higher than estimate Ab, and a lower Aw. Therefore, more consumers have associations for Brand 6, but the breadth of the network is lower than for other brands. Brand 7, with a similar mental market share, provides a useful point of contrast. For this brand, the survey brand associations closely follow the theoretical distribution. Therefore, despite the difference in buying behavior for financial services, the memory structures for consumers follow a similar underlying structure as for carbonated soft drinks.

Table 3
NBD–Dirichlet model fit of brand associations for consumer financial services (10 attributes modeled, 2008).

Brand names	Mental market share		% giving at least one association.		Frequency of associations		Share of mind %	
	Obs	Est.	Obs	Est.	Obs	Est.	Obs	Est.
Brand 1	17	17	65	64	3.5	3.6	28	23
Brand 2	16	16	62	61	3.4	3.5	27	22
Brand 3	13	13	52	54	3.3	3.2	25	20
Brand 4	13	13	51	52	3.2	3.2	24	19
Brand 5	12	12	50	51	3.1	3.1	22	19
Brand 6	10	10	53	46	2.6	3.0	19	18
Brand 7	10	10	44	44	2.9	2.9	20	18
Brand 8	9	9	43	43	2.9	2.9	20	17
Average	13	13	53	52	3.1	3.2	23	19
MAD	0.1		2		0.1		4	
Pear. corr.	1.00*		0.94*		0.88*		0.96*	

Obs = data from survey; Est = NBD–Dirichlet estimations.
* $p<0.01$.

3.3. Exploring market dynamics

Modeling mental market share provides insights into CBBE dynamics, as the following example illustrates. Table 4 shows exploratory carbonated soft drinks data from two different years, 2003 and 2005. Four brands with changes in mental market share show how the underlying metrics change. In all cases, a substantive change in associative penetration (Ab) is apparent. This finding suggests that people with few associations drive changes in mental market share. Lilt also has a substantive drop in the association rate (Aw), more so than Diet Coke. Exploring the reason for differences in dynamic patterns across brands is a topic for future research.

4. Discussion

Building on evidence that having a broader associative network is beneficial for a brand (Alba & Marmorstein, 1987; Krishnan, 1996; Romaniuk, 2003), this paper shows how researchers can apply the NBD–Dirichlet model (Goodhardt et al., 1984) to provide benchmarks for the underlying structure of a brand's associative network. The paper further demonstrates that the NBD–Dirichlet model can provide benchmarks for the associative networks of corporate brands in service markets. This finding extends the applicability of the NBD–Dirichlet model in marketing to CBBE. This extension has implications for marketing research and marketing practice. Finally, the finding shows that the underlying structure of associative network does not

Table 4
Dynamics of mental market share over time.

Declining	Diet Coke			Lilt		
Year	2003	2005	Dev	2003	2005	Dev
Mental market share %	12	10	−2	11	8	−3
% at least one association	63	55	−8	66	58	−8
Frequency of associations	4.3	4.1	−0.2	3.7	2.9	−0.8
Share of mind %	21	20	−1	15	13	−2
Increasing	**Dr Pepper**			**Fanta**		
Year	2003	2005	Dev	2003	2005	Dev
Mental market share %	10	11	1	12	14	2
% at least one association	60	65	5	69	73	4
Frequency of associations	3.8	3.7	−0.1	3.8	4.1	0.3
Share of mind %	15	16	1	15	18	3

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differ when comparing very different categories, such as carbonated drinks and financial services.

This approach of using the NBD–Dirichlet model provides normative scores or expectations for the metrics of a brand of a particular size. The immediate benefit of such norms is that to allow marketers to assess if the brands' associative structure is as expected. These norms contribute to CBBE theory as they reveal a predictable structure, and the nature of this structure. A number of questions follow. The first is why is mental market share predictable? One could assume that that mental market share is simply a reflection of sales market share. Considerable support for this idea exists, with the many studies showing a relationship between past buying behavior and current brand associations (Barnard & Ehrenberg, 1990; Barwise & Ehrenberg, 1985; Bird et al., 1970; Bogomolova & Romaniuk, 2006; Winchester & Romaniuk, 2008). The correlation between mental and sales market share is high, and is possibly not perfect simply due to flaws when measuring brand associations.

If this is the case, then this approach could be a simple way to get market share, as well as other brand performance metrics. Panel data is costly (Lee, Hu, & Toh, 2000). A single survey is much easier and cheaper than collecting records of actual purchase behavior. Indeed, in markets such as alcoholic beverages with a considerable amount of out-of-home consumption or chocolate, with many difficult to remember impulse purchases, a brand health survey may provide a more accurate representation of the brand's share than panel data. Comparisons of mental market share and sales market share, at an overall level, and their respective underlying consumer metrics, will help the researchers understand this further. This approach has particular potential in emerging markets, where records of panel statistics are less available or less robust than in developed markets.

A possibility exists that mental market share is a related, but different construct to sales market share. Relative pricing, including price promotions, as well as distribution all affect a brand's sales market share. Mental market share may reflect a brand's potential for selection, and the brand's performance on other elements of the marketing mix moderates the relationship between mental market share and sales market share. This result would make modeling measure mental market share separately to sales, and to investigate any mismatches, a useful endeavor.

The similarity in the modeling results between financial services and carbonated soft drinks raises some interesting questions about the interaction between mental market share and sales market share. The different buyer behavior patterns for these two markets mean that simply consigning mental market share to be a reflection of sales market share, and a product of repeat usage of a repertoire of brands is difficult. Further research in other service markets would help understand this in more detail.

4.1. The meaning of the underlying metrics

For a given mental market share, the NBD–Dirichlet provides estimate for underlying brand level associative metrics. The metrics present a rich source of avenues for future research. The following discussion briefly covers this area.

Associative penetration (*Ab*) represents the proportion of consumers with the brand node sufficiently salient in memory for retrieval for at least one cue. This suggests that Ab is similar to an awareness measure, in line with conceptualisations of awareness that draw on the Associative network memory (Holden, 1993; Nedungadi, 1990; Nedungadi, Chattopadhyay, & Muthukrishnan, 2001). Therefore, the higher the brand achieves on this metric, the greater the number of consumers that have potential to retrieve the brand. Further research should test convergent validity between Ab and conventional awareness measures such as top-of-mind, unaided and aided awareness scores.

Association rate (*Aw*) is a comparative measure of the size of the associative network, and is a representation of the number of attributes linking to the brand. Given the attribute-to-brand links represent paths to brand retrieval, the wider the associative network, the more likely those who have potential to retrieve the brand will do so (Anderson, Collins, & Smith, 1988). This metric displays a classic Double Jeopardy pattern, where in this case, smaller brands have fewer people that are likely to think of them, and those that do have fewer pathways to retrieval (Bandyopadhyay, Gupta, & Dube, 2005; Ehrenberg, Goodhardt, & Barwise, 1990; McPhee, 1963). This network should grow if marketing activities are effective in communicating appropriate messages to consumers. Future research could examine the impact of advertising on broadening the size of the associative network, thereby increasing Aw.

Share of Mind (*SOM*) captures the relative competitiveness of the brand's associative network in consumer memory, of those with some propensity to think of the brand. Again, a Double Jeopardy pattern is apparent, as the NBD–Dirichlet would predict. In buyer behavior, Share of Category Requirements is a measure of loyalty to the brand, future research could examine if a link exists between SOM and consumer's attitudinal loyalty to the brand.

4.2. Finding explanations for deviations

Brands can deviate from the NBD–Dirichlet estimates. These deviations open up a new area of research to identify why consumers' underlying distribution for these brands differs. Do different patterns in buying behavior link to these distributions? Are deviations persistent or short-term?

Comparing the scores and deviations in mental market share with sales market share is an important avenue for future research. In buyer behavior, deviations for brands have links to characteristics such as selective distribution, as in the case of private labels (Uncles & Ellis, 1989). While a sensible rationale for how selective distribution impacts sales exists, a difficulty arises to see how selective distribution affects mental market share. However, a disproportionately lower share of voice in advertising could lead to a brand having a lower mental market share than estimates predict. Given retailers generally do not advertise their private labels, these brand could conceivably display the same deviation, but for a different reason. The more recent trend for the advertising of private labels (Lincoln & Thomassen, 2008), would lead them to look like normal brands. This analysis is a possible test for researchers to determine if the source of such deviations.

The example in Table 4 provides an illustration as to how this approach can aid in understanding market dynamics. Further investigating into the differences between brands could help identify the factors that affect brand decline. This research could lead to insights into how to arrest this decline or how to stimulate growth.

As a final implication, discovering how mental market share changes for brands at different levels can be useful to help with media planning. For example, for Lilt to have the mental market share of Pepsi Cola, the model estimates Lilt needs 11pp more people (66%–55%) to have at least one association salient, have frequency increase by +0.3 (3.1–2.8) and a slightly higher share of mind (13% versus 11%). This finding provides insights to help set media reach and frequency targets.

5. Future research

Modeling the cross-sectional and dynamic relationship between mental market share and sales market share is an important area for future research. The sources of any brand-specific disparities may help highlight deficiencies in the brand's marketing mix that may be hampering CBBE translating into sales. Understanding the dynamic relationship will help uncover if changes in mental market share precede sales market share, which will help disentangle the two constructs.

Further research should test and validate the use of the NBD–Dirichlet model and compare this result to the performance of alternative models.

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In particular, investigate the technical issues about the number and different types of associations on NBD–Dirichlet fit. Learning the implications of any brand attribute sets where the underlying structure does not follow NBD–Dirichlet patterns will help understand consumer memory structure and measuring brand associations.

Finally, the new metrics require more research to fully understand meaning and value. This situation is common, as researchers have many CBBE metrics that are the topics of considerable research without a full understanding of their value to marketing knowledge or marketing practice. For example, considerable research investigates the measurement and meaning of brand personality, (Aaker, 1997; Azoulay & Zapferer, 2003; Durgee, 1988; Geuens, Weijters, & De Wulf, 2009; van Rekom, Jacobs, & Verlegh, 2006), even in the absence of evidence of a link brand performance. Future investigations into mental market share over time, and the link to current and future brand performance will help ascertain the full value to brand theory and practice.

Appendix 1. Other examples of mental market share fit to NBD–Dirichlet model

Table A: US toothpaste, 2009 (10 attributes).

	Mental market share		% giving at least one association.		Frequency of associations		Share of mind %	
	Act	Est	Act	Est	Act	Est	Act	Est
Crest	36	36	79	79	5.3	5.3	48	39
Colgate	30	30	70	74	5.0	4.7	43	34
Aquafresh	14	14	50	49	3.2	3.2	24	21
Arm and Hammer	9	9	38	35	2.7	2.8	18	18
Sensodyne	7	7	31	28	2.4	2.7	17	17
Tom's Mayne	4	4	22	19	2.2	2.5	16	16
Average	17	17	48	47	3.5	3.6	28	24
Pear. corr.	1.00*		1.00*		1.00*		1.00*	

Table B: Portugal standard whisky 2011 (8 attributes).

	Mental Market share		% giving at least one association.		Frequency of associations		Share of mind %	
	O	T	O	T	O	T	O	T
Johnnie Walker	18	17	81	79	3.0	3.1	21	19
J&B	17	17	78	78	3.0	3.0	22	19
Jameson	15	15	75	75	2.8	2.8	21	17
TFG	13	13	71	72	2.6	2.6	18	16
Ballantine's	13	13	76	71	2.4	2.6	18	16
Cutty Sark	13	13	70	70	2.5	2.5	17	15
Grants	11	11	65	67	2.4	2.4	16	14
Average	14	14	74	73	2.7	2.7	19	17
Pear. corr.	1.00*		0.92*		0.96*		0.94*	

Table C: Taiwan premium whisky 2010 (8 attributes).

	Mental market share		% giving at least one association.		Frequency of associations		Share of mind %	
	O	T	O	T	O	T	O	T
The Macallan	25	23	76	81	3.4	3.2	36	26
Glenlivet	18	17	71	71	2.7	2.7	24	22
Glenfiddich	18	17	72	71	2.7	2.7	21	22
Glenmorangie	13	12	63	59	2.2	2.3	19	19
Singleton	12	11	59	57	2.2	2.3	17	18
The Balvenie	12	11	64	56	2.0	2.3	17	18
Average	17	15	68	66	2.5	2.6	22	21
Pear. corr.	1.00*		0.96*		0.99*		0.97*	

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