What happens when brands stop advertising?

Documenting long-term sales trends

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This thesis presents work carried out by myself and does not incorporate without acknowledgment any material previously submitted for a degree or diploma in any university; 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 in the text; and all substantive contributions by others to the work presented, including jointly authored publications, is clearly acknowledged.

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Abstract

Maintaining an advertising presence is expensive and it can be difficult to link advertising investments with financial returns to justify continued spending. Hence at times, some brands stop advertising, sometimes for long periods. This thesis addresses the question that follows: What happens to sales when a brand stops advertising?

Advertising literature currently offers limited knowledge on the potential sales outcomes of stopping a brand's advertising. Some evidence comes from advertising weight tests (e.g. Hu, Lodish & Krieger 2007; Hu et al. 2009; Lodish et al. 1995) or isolated case studies (e.g. Millward Brown 2012; Neff 2009; Sutherland & Sylvester 2009), but few studies explicitly and thoroughly address the sales outcomes of a long-term advertising hiatus.

There is an apparent gap in knowledge concerning the sales outcomes of stopping a brand's advertising. Without some understanding of the consequences of their actions, marketers risk making poor decisions, potentially misallocating resources and jeopardising the health of their brands. An important step in addressing this knowledge gap is documenting cases where brands stopped advertising and providing descriptive accounts of what happened. This thesis takes that step by systematically and empirically describing how sales evolved in over 50 cases of brands that stopped advertising for at least one year.

Data from the Australian alcohol market

The data used for this study comes from the Australian alcohol market, spanning more than twenty years (1993-2016) of advertising media spend and volume sales of 72 beer, cider, wine, spirits, ready-to-drink, and mixer brands. The dataset was mined to find cases where brands went unadvertised for at least one year. In total, 57 cases of advertising stops lasting from one to 10 years were identified. Sales in the year/s when brands were not advertised were compared to sales in the most recent advertised year. Sales changes in unadvertised years were then compared across all cases to reveal the average change following the cessation of advertising. Cases were also organised into subgroups based on brand size (big, medium or small) and prior sales trends (growing, stable or declining) to document sales outcomes related to these factors.

Sales most often decline after advertising stops

Sales declined for most brands in each unadvertised year. Across all cases, sales were 16% lower on average after one unadvertised year, 25% lower after two unadvertised years, and 36% lower after three. Individual cases varied around these averages, but decline over time was the norm. Sales decline became more common and larger in magnitude across cases as the number of unadvertised years increased.

Some sub-patterns are observed when the sample of cases is divided into previously growing, stable or declining brands. Every brand that was on a *declining* sales trend before stopping advertising continued to decline when unadvertised, and at a faster rate on average than other subgroups. Previously *stable* brands fared better on average, showing continued stability in the first two to three years without advertising. The cases that continued unadvertised beyond this point saw decline in sales. Brands that were *growing* before stopping advertising showed the greatest likelihood of sales growth after stopping. Although several cases showed decline, about half of previously growing brands continued growing in the first two unadvertised years, at which point most of these brands began advertising again.

Sales declines were observed across brands of all sizes, however, the rate of decline was slower on average for bigger brands and faster for smaller brands. This finding indicates a possible 'size advantage' for bigger brands, although there is extreme variation around the averages. The size advantage for bigger brands is clearer when prior sales trend is also accounted for. Amongst brands that were growing before stopping advertising, big and medium sized brands all continued to grow, while small brands mostly ceased growing.

Contributions and future research

This thesis provides new empirical evidence on how sales are likely to trend over time after a brand stops advertising. The study observes many cases where brands went unadvertised for multiple years, of which the current literature is particularly lacking. As such, this thesis provides new findings where there was little but conjecture before. The findings show that some regularity exists in sales changes after advertising stops.

Empirical evidence that sales most commonly declined after brands stopped advertising (even for previously growing brands and after periods as short as one year) may assist marketers to defend their advertising budgets when facing cuts. Inversely, understanding the conditions where little change in sales trends followed a stop may help combat over-advertising (i.e. wasteful over spending of resources better used elsewhere). This research may also support budget allocation decisions between brands when companies are forced to stop *some* advertising. Depending on the company's objectives for each brand and the portfolio as a whole, funds could be shifted between brands based on the likely outcomes of stopping their advertising (e.g. if cutting advertising is likely to damage one brand more than another).

This research is descriptive in nature and examines only aggregated data on advertising media spend and brand sales. More granular data and information on other internal and external influences on sales were not available and therefore not controlled for, which would be enlightening additions for future studies. Presently the extent to which stopping advertising *caused* or *contributed* to sales changes cannot be inferred. The results also pertain to a single product category in one country, which means the generalisability of findings are for now unknown. Hence, replications of this study are encouraged to reveal if the patterns extend to other conditions.

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Chapter 1
Introduction

This chapter commences this thesis and briefly summarises its core sections. The chapter outlines the background to the research, the main research problem, and the approach taken to address the problem. Key findings are provided, and the contributions of this research are briefly discussed.

1.1 Background

Mass media advertising allows companies to communicate efficiently with large numbers of prospective customers. Companies advertise their products and services for a number of reasons, but ultimately to influence the buying behaviour of consumers and increase brand sales (Sharp 2010). Much evidence exists to show the positive effects that advertising can have for a brand, and marketers' faith in advertising is reflected by the significant global expenditure devoted to it each year (Tellis 2009; Warc 2016b). However, despite the substantial value of advertising to business and brand management, there are times when companies require cuts to the advertising budget (including all spending on creative development and media placements). There are a number of possible reasons for this.

Creating ads and buying media space can consume a major portion of company marketing expenditure, and accountability of various marketing activities is a growing concern (Stewart 2008, 2009). Because of the challenges in linking advertising with business returns (Lewis & Rao 2013), and the confusion surrounding effective spending levels (Cheong, De Gregorio & Kim 2014), advertising is a common target for budget cuts.

Taking money from advertising budgets, as opposed to other areas, can be attractive for several reasons. The advertising budget has an element of flexibility to it, in that it is not committed until it is spent. It can be halted at short notice, effectively enlarging profits or liquid cash in that period (Lamey et al. 2007). Advertising is one of the few large budgets that can be cut and leave the business still functional, unlike wages or other inputs to produce a product or service. It can also be restarted easily after being paused. Altogether, if faced with financial pressures, stopping advertising is seen as a less radical measure than alternate actions, such as cutting operating expenses or reducing staff numbers. For these reasons advertising can seem discretionary or appear to be a 'dispensable luxury' (Wharton 2008), and its budget is commonly seen as a temporary reserve fund when needed.

Sometimes stopping a brand's advertising can be a strategic decision. In times of financial pressure, advertising budgets may be cut and the savings used to inflate profit levels. This financial manipulation can be used to fill shortcomings in profit targets, and may give the impression of superior brand performance to stakeholders. Cutting advertising also affords companies the option to invest in other activities. The previously committed funds may be channelled into different marketing tasks (e.g. increasing distribution), or it may be a portfolio-based decision, whereby one brand's advertising is down-weighted so another can receive support. These trade-offs may be well justified in reaction to seasonality, competitive factors, or differences in expected efficiency and/or effectiveness.

Other times, advertising cuts may occur for more incidental reasons or be forced onto a brand out of corporate interests. Large investments early in the budgeting period (e.g. a widely run seasonal campaign, or extra expenditure during certain high reaching events) may run the budget dry prematurely. The brand would then go unadvertised until its next budget allocation.

Increasingly popular budgeting techniques like ‘zero-based budgeting’ (ZBB) may also be responsible for reduced advertising spending (Papworth 2016; Roderick 2017). ZBB is designed to optimise spending and improve efficiency by re-evaluating and re-justifying the budgets of all business functions from a base of $0 in each budget cycle. Advertising may be disadvantaged in this situation, compared to other tactics like trade promotions which can be more accurately linked with financial returns. An over-reliance on marketing mix modelling and business culture that rewards short-term wins have also been blamed for advertising budgets being shifted into trade promotions (Hoo & Von Gonten 2013; Lodish & Mela 2007).

1.2 The Research Problem

For whatever reason, marketers can and do stop advertising their brands from time to time. It is a decision sometimes made strategically, other times reluctantly. Irrespective of the intent, it is important to document the consequences of this decision. Unlike many other marketing actions, the consequences of stopping advertising have not been thoroughly investigated, and the advertising literature provides insufficient evidence on the likelihood of different sales outcomes when brands stop advertising.

Without some understanding of the consequences of their actions, marketers risk making poor decisions. Poor judgement may result in misallocated resources, or worse, jeopardised brand health and lost sales. Marketing practice improves when marketers use evidence to support their decisions (e.g. Kennedy & Mccoll 2012). Systematically studying what happens when brands stop advertising, and identifying the most likely outcomes will provide much-needed support for managerial decisions. Marketers can use such knowledge to decide whether stopping advertising will help or hinder their progress towards objectives.

A major weakness of the literature, as it currently stands, is the lack of consistently documented cases of brands that stopped advertising for long periods. Collecting numerous cases and describing what happened is a sensible approach to address the issue. This thesis takes a step in this direction, by examining 57 cases of brands stopping advertising to identify more or less consistent outcomes. Results are compared across subgroups within the total sample, to investigate the influence of two factors on sales outcomes, which are *brand size* and *sales trend* prior to stopping advertising. The thesis provides answers to the following research questions:

> What happens to brand sales after a brand stops advertising for a year or more?

> How do aggregate sales differ after stopping advertising for:

>> Different size brands?

>> Brands on different prior sales trends?

1.3 Research Approach

Measuring the relationship between advertising and sales can be extremely difficult (Lewis & Rao 2013), especially in the current cross-media world where there are many confounds to deal with (Taylor et al. 2013). This research takes a descriptive approach and seeks to describe what happens to sales following a stop, and identify similarities and differences across a number of cases. Like navigation in the past improved with knowledge of the predictable “movement” in the stars, so too does marketing performance with an understanding of regular marketplace patterns (Sharp & Wind 2009). Depicting marketing phenomena through descriptive research such as this is an important step in advancing knowledge and providing support for marketing decisions (Ehrenberg, Barnard & Sharp 2000).

The dataset used in this thesis spans over 22 years (July 1993–April 2016). Advertising media spend and aggregate sales volume are studied from many alcoholic beverage brands that advertised on-and-off in the Australian market. Within this dataset, 57 cases are identified where brands stopped advertising for one year or longer.

To document what happened when brands stopped advertising, sales in unadvertised years were compared to the most recent previous year when they were advertised, and changes over time were calculated. Sales in each case were indexed (so all cases are on the same scale and directly comparable) and plotted together to identify similarities and differences in sales changes after advertising stops.

To explore how sales outcomes differed for different brands the sample was divided into subgroups, and cases separated by brand size (big, medium or small) and the trend in sales before stopping advertising (growing, stable or declining). Literature suggests that brand size is important to consider, as advertising effectiveness and elasticity have been found to vary with brand size (Assmus, Farley & Lehmann 1984; Aurier & Broz-Giroux 2014; Danenberg et al. 2016; Riskey 1997; Sethuraman, Tellis & Briesch 2011). Prior sales trend is also important, as it provides some context for investigating sales trends occurring after advertising stops, and possibly alludes to the motive for stopping advertising at that time. Similarities and differences in sales changes are identified between these subgroups. Finally, to quantify the relationships between brand size, prior sales trend and sales after stopping advertising, and to ensure the descriptive interpretations are consistent with statistical estimates, a post-test is conducted using correlation and regression analysis - see Appendix B for detail.

1.4 Main Findings and Contributions

On average, brands that stopped advertising reported decreasing yearly sales in unadvertised years relative to previous years when there was advertising. Across all cases, sales were 16% lower on average after one unadvertised year, 25% lower after two unadvertised years, and

36% lower after three. Results for individual cases varied around the average in each year, but sales decline became more common and larger in magnitude as the number of unadvertised years increased.

Organising the sample into subgroups based on brand size and sales trend prior to stopping advertising highlighted some systematic differences. It is important to note, however, that splitting the cases creates smaller sample sizes, which affects the reliability of these results. After stopping advertising, sales declined more rapidly on average for smaller brands than for bigger brands. This size-related difference aligns with prior findings, but there is extreme variation around the averages. There are also differences in sales outcomes for brands that were growing, stable or declining before advertising stopped. All previously declining brands continued to decline after stopping advertising, while some stability is observed amongst previously stable brands, and previously growing brands were the most likely to continue growing. Overall, sales decline was particularly marked amongst smaller brands and brands that were already in decline. A consistent exception to the broad decline was found for big and medium sized brands that were growing before stopping advertising ($n = 8$), which all continued growing for two years after stopping advertising (at which point these brands received renewed advertising support).

The data used in this study cannot reveal the extent to which stopping advertising caused or contributed to the observed changes in sales. The marketplace is not controlled like a laboratory, and other factors known to influence sales are not accounted for. However, stopping advertising coincides with decline in most of the observed cases. This thesis contributes to academia by discovering evidence of regularity in the sales of brands that stop advertising. This thesis also identifies what are likely to be important conditions (prior sales trend and brand size) that affect sales outcomes when brands stop advertising, which should be accounted for in future research. The results offer some support for marketing practitioners to help justify their advertising budgets, and to decide how to allocate scarce resources between a portfolio of brands.

The findings pertain only to one product category in one country, and draw on a modest sample size. Replication is necessary to reveal the extent to which patterns are common to other conditions. Further research into the sales outcomes of stopping advertising is strongly encouraged, to refine the patterns found and seek generalisability. Controlled experiments are also encouraged.

Chapter Summary

This chapter provides a brief background to this research and an extended summary of the thesis. The following chapter begins the main body of this thesis, discussing the background to this research in more detail.

Chapter 2
Background

Chapter two addresses the relevant background information that underpins this thesis study in terms of advertising measurement and practice. The chapter is divided into three subsections. The first section discusses advertising's issues with accountability. The second section builds on the first to discuss common motivations for brands to stop advertising. The final section describes the various ways that advertising's effect can be measured and comments on the utility of different measures.

2.1 Advertising Accountability

'Marketers are always asking for more money, but can rarely explain how much incremental business this money will generate'.

(The Fournaise Marketing Group 2011)

Accountability in a business forum typically refers to demonstrating the link between actions (or expenses) and financial outcomes, e.g. return on investment. It is an area where marketing is arguably found lacking relative to other business functions that more easily demonstrate their contribution to firm performance (Lehmann 2004). Concerns over the perceived lack of marketing accountability have increased in recent times (Stewart 2008, 2009), with alarming discussion in the literature of how marketers' inability to demonstrate the worth of their activities has undermined the influence of marketing in corporate strategy (Malter, Webster & Ganesan 2005; O'sullivan & Abela 2007; Verhoef & Leeflang 2009).

Advertising, in particular, faces several issues with accountability. The first issue is the cost of advertising. Each year, billions of dollars are spent developing ad content and buying media space (Warc 2016a). Advertising can be a major cost for many organisations, and a significant drain on profits. Since advertising competes for budget allocations against other potentially lucrative marketing activities (e.g. trade promotions, product innovation, increasing distribution), managers need to know that spending money on advertising is worthwhile (and/or under what conditions it is most valuable). To confidently allocate money to advertising, it needs to be accurately budgeted-for and linked with financial returns like any other activity. However, difficulties exist in current advertising budgeting and measurement practices, which are now discussed.

A second factor causing concern for advertising's accountability is budgeting malpractice. Deciding how much to spend on advertising is a challenging task. A balance must be struck where ad spending is sufficient to reach objectives without becoming an inefficient or wasteful use of resources better used elsewhere. Evidence-based approaches have been developed to inform the budgeting process (e.g. Binet & Field 2007; Danenberg et al. 2016; Wright 2009), however simple heuristics or "rules-of-thumb" for determining expenditure remain common in practice, such as setting the advertising budget to a fixed proportion of sales (Hung & West 1991; Prendergast, West & Shi 2006; West & Crouch 2007; West & Prendergast 2009). Heuristic methods like this, which have been criticised for being overly simplistic and non-scientific (Dean 1951; Low & Mohr 1999; Riordan & Morgan 1979), may result in misallocation of resources, which leaves managers less confident in their advertising investments. It was suggested over 30 years ago that many brands might be overspending on advertising (Aaker & Carman 1982), and recent evidence indicates continued inefficiencies (Cheong, De Gregorio & Kim 2014).

Advertising's effects must be measured to understand its contribution to firm performance. A third factor in advertising accountability is the difficulty in measuring advertising's financial returns (Lewis & Rao 2013). Measures of advertising's effects fit broadly into two classifications: intermediate measures and behavioural measures (Vakratsas & Ambler 1999). Intermediate measures typically capture the effect that advertising has on consumers' feelings or attitudes, using metrics like awareness or purchase intentions. These metrics may be useful in some situations (discussed further in section 2.3.1), but they measure intangible returns, and have a dubious relationship with actual in-market or behavioural metrics like sales (Lodish et al. 1995; Webb & Sheeran 2006; Wright & Klÿn 1998). Above all, changes in intermediate measures are difficult to evaluate in financial terms (e.g. *what is a 2% increase in awareness worth?*), and so provide limited support to justify investment in advertising.

Unlike intermediate measures, behavioural measures focus directly on the effect of advertising on consumers' purchasing behaviour, such as brand choices or sales. Behavioural measures offer more quantifiable evidence of advertising's financial contributions. For example, a sales uplift attributed to advertising can be expressed in terms of revenue gained and evaluated relative to the initial investment. A disadvantage of behavioural measures is the inherent challenge of separating the incremental effect of advertising from the numerous other influences on consumer behaviour. Attempts to isolate the sales that advertising is responsible for over and above those that would have happened anyway require data that is rare at the present time. Furthermore, advertising's sales effects are spread out over time because ads often reach people when they are not in a situation to immediately act (Mcdonald 2004). This means the sales outcomes of advertising are not always realised in the advertised period. A consumer's brand purchase, stimulated by advertising, may result in a preference being formed and additional repeat purchasing over time. This is a longer-term behavioural effect of exposure to advertising that cannot be easily measured. The issue was described well by Aaker and Carman (1982, p.68), who wrote '*looking for the relationship between advertising and sales is somewhat worse than looking for a needle in a haystack.*' Academic research has taken steps in recent years to more-accurately measure advertising's sales effect, for example using individual-level single-source data. However, the data is difficult and expensive to generate, and studies using it are uncommon (See section 2.3 of this chapter for more discussion on advertising measurement).

Another factor that could reduce senior management's faith in advertising may be the subjectivity of what makes "good" creative content in advertising. A number of studies have shown that creative content accounts for more variation in campaign effectiveness than media weight (Larguinat & Harvey 2011; Lodish et al. 1995; Wood 2009). However opinions on what makes good copy often differ, and predicting the success of creative content is challenging. No execution tactic is guaranteed to work every time (Hartnett et al. 2016). This means that large amounts of money could be invested to develop a campaign that ultimately fails to deliver. Advertising "pre-tests" may help, but their ability to predict in-market sales effective ads is questionable. This ambiguity may disadvantage advertising compared to other marketing efforts or investments that offer clearer pathways to increased sales (e.g. expanding distribution to a new location, or investing in new production equipment).

This discussion of accountability intends to demonstrate why advertising is often considered discretionary, and a common target for budget cuts. The next section elaborates on why companies may decide to stop advertising.

2.2 Stopping Advertising

Advertising is expensive and suffers from issues with accountability. For many brands it is deemed a discretionary activity or a ‘dispensable luxury’ (Wharton 2008), meaning that money can be taken out of advertising allocations when necessary. The advertising budget is flexible in that it is not committed until it is spent. Expenditure can be paused at short notice and restarted easily. It is also one of the few large pools that can be cut while still leaving the business functional, unlike wages or production expenses. So ultimately, when companies need to cut costs or need an immediate boost in liquid cash for other priorities, stopping advertising is perceived as a less radical and less risky measure than many other actions.

Stopping advertising can be a strategic decision. A common motivation to cut advertising budgets is to boost or sustain profit levels (sometimes referred to as “milking” brands for financial gain) (Jones 1990). Advertising is an expense that drains gross profits, which means companies can reduce or remove advertising spending to artificially inflate their publicised profit levels. Such financial manipulation may be done to fill shortcomings and meet profit targets, or to exaggerate company performance to stakeholders. Cutting advertising also affords companies resources to invest in other activities. The previously committed funds may be channelled into different marketing tasks (e.g. trade promotions, product innovation, increasing distribution, etc.), or it may be a portfolio-based decision, whereby one brand’s advertising is down-weighted so another can receive support. Trade-offs like this can be useful, for example, in reaction to seasonality, competitive factors, or differences in expected efficiency, and are perhaps more likely in companies with extensive portfolios of brands and/or SKUs (e.g. where an even split of expenditure between all brands would mean far less-than-effective levels for any one brand).

In addition to the deliberate manipulation of advertising budgets, there are other incidental reasons why brands may go unadvertised for some time. Depending on the budgeting cycle used by brands (e.g. quarterly, yearly, etc.), there is a risk of simply running out of money. Large investments early on in each period (e.g. a widely run seasonal campaign, or extra expenditure during high reaching events) may leave the brand without advertising support for some time until its next budget period. There may also be cases where efforts to increase the size of a brand are wasteful due to economic restrictions. Consider, for example, a product that sells close to its maximum production level, but cannot be granted increased production due to manufacturing scaling (i.e. it is impossible to produce just a *little* more, only to build additional plant and produce a *lot* more). Assuming sales of the brand always stay close to this maximum level, it is understandable that advertising would be a wasteful effort and expenditure is therefore removed.

For whatever reason, periods without advertising do occur for brands – either strategically or fortuitously, for different lengths of time. Like any marketing decision, it is important to understand how stopping advertising affects the brand in question. The next section discusses the different ways the effect of stopping advertising could be measured.

2.3 Measuring Advertising's Effects

The result of stopping advertising can be measured in many different ways, with a number of different metrics. To discuss advertising measurement, and the utility of different methods, metrics are often arranged into two broad categories: intermediate measures and behavioural measures (Vakratsas & Ambler 1999).

2.3.1 Intermediate Measures

The term "intermediate" is used to describe effects of advertising that are ancillary to sales. Intermediate measures (sometimes called "soft measures" or "mindset metrics") are concerned with consumers' cognitive, affective or emotional responses to advertising (Vakratsas & Ambler 1999). Examples of intermediate measures include advertising or brand recall, awareness, attitude, and purchase intention. Intermediate measures are widely used in both academic and industry research (Bergkvist & Langner 2017), partly because collecting and analysing the data is typically more straightforward than for behavioural measures. Surveys can attempt to measure the effect of advertising changes by tracking, for example, how many people recall the brand when prompted. Experiments (with intermediate measures as the target variables) can also be conducted in controlled lab environments, to minimise the effect of confounding factors (Broadbent 1999; Wright 2016).

Intermediate measures are intimately linked with the hierarchy-of-effects models of how advertising works (Lavidge & Steiner 1961; Palda 1966; Vakratsas & Ambler 1999). These models propose that advertising moves consumers through a sequence of stages, commonly beginning with cognition (e.g. awareness or preference) and ending in behaviour (e.g. purchase). The implication that consumers' cognitive responses to advertising precede and influence their behaviour, suggests that mindsets can be measured as a proxy for behaviour. For example, it suggests that measuring consumers' attitudes towards a brand may indicate their likelihood of purchasing the brand. However, other research has found that consumers' attitudes and purchase intentions correlate weakly with actual behaviour change (Kraus 1995; Webb & Sheeran 2006; Wright & Klÿn 1998), and are poor predictors of in-market sales (Bogart, Tolley & Orenstein 1970; Kuse 1991; Lodish et al. 1995). In addition, although lab experiments can be controlled to reduce the influence of confounding factors, it is not always clear whether the artificial advertising-viewing environment can produce findings that reflect in the real world. As such, intermediate measures can be poor substitutes for measuring actual behaviour, and knowledge related to advertising's intermediate effects may fail to apply in real market settings.

Intermediate measures *can* tell researchers how well advertising is remembered or whether it is improving consumers' attitudes toward a brand, and improvement in these areas can indicate that an ad campaign is performing well (Wright 2016), but they do not explicitly measure any behavioural change (e.g. nudging a consumer from not-buying to buying) or the sales that the advertising is responsible for. Recent work suggests that intermediate metrics may improve the predictive ability of marketing mix sales response models (Srinivasan, Vanhuele & Pauwels 2010). However, it remains unclear how research findings based solely on intermediate measures apply to sales effects in the marketplace and the company bottom-line.

2.3.2 Behavioural Measures

Behavioural measures are concerned with what people do in response to advertising rather than how they think or feel. Behavioural measures bypass consumers' intermediate responses, instead capturing *actions* that result from advertising exposure. The behaviour of interest for brands is typically purchasing (often measured in sales), but other behaviours like store visits or website hits can also fit into this category.

Linking advertising with in-market sales is typically more challenging than intermediate measures. Not only can sales data be scarce and expensive, but also it is mainly generated from consumers' normal buying behaviour, rather than collected in an experimental way. This means that confounding factors are far more difficult to control, or not controlled at all. Brand sales are affected by many factors other than advertising, including other marketing activities undertaken by the brand (e.g. price promotions) and external forces (e.g. competitor activity). These factors have different effects on sales (in direction and magnitude) and often occur simultaneously. Since the marketplace is not controlled like a laboratory, it is extremely difficult to disentangle all of the influences on sales and isolate the effect of advertising.

Despite the difficulty, efforts to link advertising with behaviour are worthwhile and important, because the ultimate goal of advertising is to influence consumer behaviour (Sharp 2010). Measuring sales shows whether advertising efforts have a real, tangible effect on the company bottom line, as opposed to an intermediate effect that may not actually manifest in the market. As such, research findings supported by sales evidence are more practical than intermediate measures, and therefore more managerially useful and meaningful. It means that marketers can make decisions with greater confidence in their knowledge of the outcomes. Findings from behavioural measures are also expressed in terms that are relevant to other business functions. A dollar value can be placed more easily on advertising's sales effects than its influence on consumer awareness. Measuring advertising's influence on behaviour is thus important to ensure advertising is financially accountable.

A key purpose of this thesis is to provide marketers with useful evidence regarding what happens when a brand stops advertising. Observing how sales evolve over time when advertising stops will provide more managerially useful knowledge than tracking intermediate responses – especially if findings are derived from analysing numerous cases. Accordingly, this thesis focuses on sales-based results.

Chapter Summary

This chapter broadly outlines the background information and research context for this thesis. The issue of advertising accountability is discussed, as well as common motivations for stopping advertising.

This chapter also outlines the two major categories of advertising measures, intermediate and behavioural, and concludes that behavioural or sales-based measures are preferable for the purposes of this thesis.

The next chapter discusses the existing research into stopping advertising, focusing particularly on the sales-based literature.

Chapter 3
Literature Review

Chapter three discusses existing research into the sales effects of stopping advertising. The chapter is divided into sub-sections based on the different focuses of research that contribute knowledge to the topic of stopping advertising (for example, setting advertising budgets, the effect of different spending levels, and advertising decay). Each research stream is outlined and the relevant studies are reviewed. The literature and knowledge gaps discussed in this chapter provide a foundation for the research questions, developed in chapter four.

There are very few academic studies that *specifically* focus on brands that stop advertising, let alone for long periods (i.e. more than one year) and where the outcome is brand sales (i.e. the specific topic of interest for this thesis). In a recent study, Aravindakshan and Naik (2011) did focus on the cessation of advertising, however they empirically analyse a stop in advertising of only 32 weeks, and they estimate the effect of stopping using only the intermediate measure: advertising awareness. Fortunately, robust evidence has been developed in other sales-based advertising research (i.e. with different specific research aims), which can help inform this study. For example, stopping advertising and tracking subsequent sales is essentially an extreme example of an advertising weight test (e.g. where advertising spend is controlled and varied across markets to study the effects of different spending levels). Therefore, results from prior weight tests (both aggregate and individual level studies) can help establish expectations. Advertising budgeting literature is also relevant, such as how different adspend levels impact brand performance. It is also useful to consider the advertising decay literature, which investigates the duration of advertising's effects in the market. The following literature review outlines these fields of study, describes how they relate to this particular thesis, and discusses the important findings on which this research builds.

3.1 In-Market Experiments

In-market advertising experiments share some common traits with experiments conducted in a laboratory. Advertising experiments involve holding some variables constant while manipulating others to more accurately discern the effects of advertising on sales or other performance metrics. Most experiments follow a typical "treatment versus control" method, where one sample group receives some advertising manipulation, and the result of this is compared against a matched control group exposed to normal advertising (Hu, Lodish & Krieger 2007). A strong stream of research in this field was developed in the 1980s using a form of in-market experiment called the "Split Cable" method (Abraham & Lodish 1990; Blair 1987; Litzenroth 1991; Lodish et al. 1995). Split Cable experiments are so called because they involve dividing a panel of households into two groups or "cells" and adjusting the television advertising that is broadcast to each group (splitting the broadcast of cable television). Before the test, two cells are matched based on consumer demographics, initial advertising exposure and purchase behaviour, and the initial baseline sales in each are noted. Then during the test period, the advertising delivered to each cell is controlled so that one receives a different treatment (weight tests will adjust the *amount* of advertising aired using the same creative content; whilst copy tests will adjust the *content* but keep the amount of advertising constant). Several potential confounding factors (e.g. price promotions and in-store marketing) are balanced across the cells during the experiment, in order to isolate the advertising variable. The subsequent purchase behaviour of each cell is tracked and any differences indicate the effect of the experimental treatment. By strictly controlling confounds, split cable tests provide a relatively clear view of the effect of advertising changes on sales.

The most relevant experiments to the current research are those where a brand's advertising weight is reduced to zero for one cell of households, in comparison to a matched cell with normal levels of advertising (referred to here as a "zero-weight" test). This essentially creates a case study of stopping television advertising and allows researchers to explore the effects on brand sales. Though studies including such tests are uncommon, there have been notable examples.

The largest in-market split cable study in the public domain was reported by Lodish and colleagues (1995), which included 389 weight and copy tests of television advertising. The most relevant tests are the 62 in which one cell received zero advertising weight compared to a control. Brand sales were tracked each week and analysed over one year, and tests were considered significant if the higher weight cell bettered the lower in either share or sales volume at the 80% confidence level. Of the 62 established product zero-weight tests, 64% showed no significant difference between the cells. In other words, in around two-thirds of the tests, stopping TV advertising for one year resulted in no clear difference in sales – a reasonably high figure considering the generous 80% confidence level. Of the tests that did result in significant sales differences, the advertised cells increased on average by 23% in sales volume and 19% in share over the unadvertised cells.

A further 23 zero-weight tests were reported by Riskey (1997) for Frito-Lay snack chip brands in the US, using the same BehaviorScan platform as Lodish et al. (1995). There is no mention of significance tests on sales differences; the article merely reports whether there was a 'sizeable increase in sales' in the advertised cell. After the 12-month test period, 57% of tests (n=12) showed greater sales volume in the cells with television advertising compared to the unadvertised control cells. To extend the main finding, the tests were also categorised by brand size (big or small). Tests involving bigger brands were less likely to report large differences between cells compared to smaller brands. This is similar to the finding in Lodish et al. (1995) that 'new' products were more likely to report a significant effect than 'established' products. Riskey (1997, p.293) reports 'smaller brands represented in the study had a higher likelihood of showing sizable volume increases from advertising,' which can be interpreted inversely to mean *stopping advertising* showed a higher likelihood of sales volume *deficits* for the smaller brands than bigger brands.

The 1995 study by Lodish and colleagues was updated in 2007 with 46 zero-weight tests added (Hu, Lodish & Krieger 2007), of which 37% yielded no significant difference at $p<0.05$* (an increase in significant results). And another update in 2009 (Hu et al. 2009) added 27 zero-weight tests and found 59% of them non-significant at $p<0.05$* (See Table 1). The exact sales difference between cells in the significant zero-weight tests is not reported in either update, but volume was higher on average in the advertised cells. The authors also observed a greater

* This statistic was not reported in the published article, however the author was able to provide it on request.

average difference in sales in the tests involving ‘new’ products, compared to ‘established’ products.

Table 1 – Proportion of zero-weight split cable tests with significant sales effects.

Study	Type	Tests (n)	% Significant	Sales diff.
(Lodish et al. 1995)	Split cable	62	36% (p<0.2)	23% (Vol.)
(Riskey 1997)	Split cable	23	57%	15% (Vol.)
(Hu et al. 2007)	Split cable / Matched markets	46	63% (p<0.05)	-
(Hu et al. 2009)	Split cable / Matched markets	27	41% (p<0.05)	-

Across the four studies and 158 zero-weight tests, a near equal number of tests show no change in sales, as those showing a significant effect of stopping TV advertising for 12 months. When there was a significant sales effect observed, average sales volume was lower in the unadvertised cell. This suggests that stopping TV advertising for 12 months may not always have an observable effect on sales, but if it does, it is likely to be a decrease. In general, the likelihood and magnitude of sales impact after stopping advertising is higher for small/new brands compared to big/established brands.

A famous in-market study into stopping advertising was conducted by Ackoff and Emshoff (1975) in the 1960s for American brewing company Anheuser-Busch. In testing the effects of several different advertising weight levels on the sales of Budweiser beer, they noticed that test areas completely deprived of advertising (zero weight) experienced no significant differences in sales from the control areas. The advertising hiatus and associated sales stability continued for over 18 months before slight declines appeared in each monthly check. After reapplying the normal weight of advertising from before the experiment, sales were restored to normal within six months. Based on these results, the researchers actioned several changes in advertising expenditure at Anheuser-Busch. Over time, spending cuts were introduced into more markets at deeper levels until the “adspend per barrel” was less than half the initial figure (Ackoff & Emshoff 1975). During this time, both sales and market share actually increased! The authors concede that advertising changes could not be solely responsible for the organisation’s growth in this period, and that other company actions or market conditions (which were not specified) also contributed, however they assert that ‘the changes induced by the research described here [such as complete cessation of advertising] did not *hurt* Anheuser-Busch’ (Ackoff & Emshoff 1975, p.12). Though this is an interesting finding, the tests relate to one brand in one market over 40 years ago, and no published replications could be found.

Other authors have examined the effect of *reduced* advertising spending on sales; that is, a partial decrease in adspend, and the results tend to align with the previous discussion. Aaker and Carman (1982) conducted a historic review of in-market studies to examine the incidence of “over-advertising” (brands spending more than necessary on advertising). They argue that only tests involving reduced adspend can really identify these effects. Over-advertising or ‘saturation’ is evident in cases where no significant sales decline is experienced following a reduction in advertising weight. Aaker and Carman (1982) summarised 11 tests involving reduced advertising weight, most running for one or two years. Of these 11 tests, 10 resulted in stable or non-decreasing sales. The authors interpreted this as evidence of overadvertising but caution the integrity of their results. The analysed studies are a non-random sample and thus are subject to several biases. Similar results are presented by Eastlack and Rao (1989), following a series of in-market advertising experiments by the Campbell’s soup company. Of those experiments, the few that involved reduced advertising weight showed little (or inconclusive) effect on sales over an 8-10 month period. None of the tests on Campbell’s soup brands involved a complete cessation of advertising.

Much has been learned about advertising’s effects from in-market experiments, particularly split-cable tests, but they are not without limitations. First is that the split cable weight tests reviewed above only vary the amount of advertising on *television*. Brands may still be advertised in other media, so the tests are not a complete simulation of stopping all media spending (the situation of interest in this thesis). Furthermore, researchers vary the amount of advertising that is broadcast, but do not typically track what is actually seen by consumers. Although it is reasonable to assume that the zero-weight cell will see no television advertising for the brand, researchers can’t be sure that the control households see appropriately “normal” levels of advertising, only that it was broadcast. The results typically also report average changes in sales across the entire cell of households, rather than at the individual or household level. Together, these limitations reduce the precision of the tool, as it cannot be known whether sales differences between cells are the result of consumers who actually see advertising and subsequently purchase, or from other random variation. In addition, it is difficult to conduct controlled in-market experiments and split cable tests, requiring vast resources to set them up and see them through (e.g. cost, commitment, time before and after). As a result, most have been conducted under similar conditions, for example within IRI’s BehaviorScan ecosystem and in the US. Almost all published tests are also 12 months or shorter. Without sufficient variability in the conditions of tests, the generalizability of findings is limited. Fortunately, advances in digital and passive data collection are making these experiments more practicable (e.g. with advertising split tests now possible on platforms such as Facebook).

To summarise, in-market experiments are a powerful way to observe real market responses to advertising changes. Prior experiments offer knowledge into what happens when a brand stops advertising. Tests have shown that sales stability is common when a brand goes unadvertised for one year, but if there is some statistically significant change (which tends to be more common and greater in magnitude for smaller brands than bigger brands), it is typically decline. These findings are extremely useful, however their generalisability is largely unknown and evidence regarding advertising cessation longer than 12 months is severely limited.

3.2 Individual Level Single-Source Data

Individual level single-source data is another robust method of measuring the in-market sales effects of advertising. Unlike the split cable method, which typically uses aggregate level data (i.e. total sales over groups of households), the single-source approach examines the advertising viewing and brand purchasing behaviour of individual consumers or households. The data is typically generated using a panel of households whose media exposure (e.g. TV viewing data from a set-top box, or online activity tracking) is matched with purchasing data (e.g. from scanners, loyalty cards or credit card payments) (Shimp & Andrews 2013). Researchers are given a disaggregated view of the advertising that individuals see and the brands that they buy and how this changes over time. This disaggregation is a major strength of the method, as it can identify sales effects of advertising even if there is no change in total aggregate sales (Eskin 1985).

Single-source data allows researchers to identify consumers who were exposed to advertising and see if their purchasing is different to unexposed consumers. If a brand's market share is higher amongst exposed consumers than non-exposed, the advertising is considered effective at stimulating purchases (assuming biases and confounds are controlled for, e.g. the purchase-viewing bias, Taylor et al. 2013). Consumers can also be grouped based on the amount of advertising they were exposed to for the target brand (e.g. heavy or light exposure), or the timing of their exposure (e.g. exposed recently or not), to see whether these factors affect their purchase decisions. Because of these strengths, the use of single-source data has received considerable support in advertising literature and is widely considered a gold standard in advertising effectiveness research (Broadbent 1997; Kennedy, Mcdonald & Sharp 2008; Mcdonald 1992; Taylor 2010).

Single source research was pioneered by Colin McDonald (1970) who examined advertising's influence on brand switching behaviour by asking consumers to record their exposure to different media and their brand purchases in a diary. In this study, he discovered that advertising had a measurable effect on consumers' choices when switching brands (Mcdonald 1970).

Most single-source studies examine how exposure to advertising for a brand is related to consumers' subsequent purchases of that brand. Put simply, do households that receive advertising buy more than those that do not? Across multiple single-source studies, researchers have found that advertising does positively influence consumers' purchasing behaviour and brand sales. In most cases, a brand's market share is higher amongst households exposed to advertising compared to those without exposure, all other things equal (Jones 1995, 2002; Kennedy et al. 2008; Reichel & Wood 1997; Roberts 1998). Furthermore, it has been found that the effect of advertising can be observed in individual-level sales for some time after the exposure, though the strength of the sales effect declines over time (Reichel & Wood 1994; Roberts 1999).

Single source research has not yet been strictly applied to exploring the effects of stopping advertising. The "non-exposed" group in any period could be considered the test sample, but in most studies the test window for analysis has been shorter than three months. Nonetheless, some implicit conclusions can be drawn from the existing research. Evidence suggests that, all other variables considered equal, the group of consumers exposed to a brand's advertising are more likely to purchase the brand over other competing brands than the non-exposed group. The exposed group's likelihood of purchase is nudged somewhat higher above the baseline of the non-exposed group. This means that for consumers in a category purchase situation, the advertising they have been exposed to recently is one factor that influences their choice. If a brand stops advertising, it essentially denies the chance for anyone to receive advertising exposure and moves all consumers into the non-exposed group. An unadvertised brand therefore holds one less tool than advertised brands in the fight for consumer choice.

Individual-level single-source data has also shown that the magnitude of advertising's sales effect depends on the relative recency of the exposure and provided evidence for the magnitude of decay over time (Wood 2009). For example, households exposed to advertising five days before a category purchase show a greater increase in sales than those exposed 28 days before purchase. The decay in effectiveness has been reported in single source studies by a small number of authors, predominantly over short time frames (e.g. Jones 1995; Reichel & Wood 1994; Roberts 1999; Wood 2009). The evidence suggests that in the short-term, a brand's purchase propensity decreases as the time without advertising support increases, all other things being equal (see further discussion of advertising decay in section 3.4).

The strengths of single source data are great and numerous, and its use has been responsible for several advances in advertising knowledge, yet the method is not without its weaknesses. Like all in-market advertising effectiveness research, care must be taken to address confounding factors that clutter the relationship between advertising and sales. Confounds such as price promotions and purchase-viewing bias have been controlled using contingency table methods (Roberts 1996), where the data is divided into subsets based on whether a confound is present or not. But the effects of other potential contaminants such as advertising creative content, share of voice, physical availability, brand loyalty and competitor promotional and advertising activity are less often considered (one exception is Taylor et al. 2013). Single source data makes it possible to know whether people who see advertising buy more than people who don't. But exposed people might also have seen little or no competitor advertising and visited the store on a day when the target brand was on promotion – factors which may have a stronger effect on purchase than the advertising exposure.

Single-source panels have usually required huge resources to establish and maintain, with one large-scale attempt (Project Apollo) failing due to insufficient support (Neff 2008). It can also take a long time to gather enough data to establish clear patterns (Mcdonald 2003). A consequence of these difficulties is that the adoption of the method has been slow since its inception (Mcdonald 1992). Fortunately, thanks largely to technological advances, more (and more sophisticated) systems are currently being developed (Taneja & Mamoria 2012). Improvements to the data collection processes are continually reducing the burden on participating households and making it easier to passively measure large samples of people (e.g. Wood & Poltrack 2015). Given the resources required to set up and manage single-source panels, long-term observation of individual-level sales after stopping advertising remains a topic for future research.

3.3 Advertising Budgeting

Advertising budgeting research is concerned with how much brands spend on advertising, and how different levels of advertising spend contribute to brand performance – including when the advertising budget is drastically reduced. Stopping advertising (i.e. removing expenditure from all major media platforms, or all “above the line” expenditure) is a budget decision, thus the budgeting literature can offer insights into brand performance after stopping advertising.

Within the budgeting literature, the most relevant area for this thesis is the body of research on how advertising spending relates to brand size. Within a market, bigger brands tend to spend more on advertising than their smaller competitors, which means advertising budgets typically rank in the same order as brand size (i.e. the bigger the brand, the bigger the budget) (Binet & Field 2007; Danaher, Bonfrer & Dhar 2008; Jones 1990; Schroer 1990). Relatively speaking, a brand’s advertising spending can be expressed as a share of the total market spending or it’s “share-of-voice”. A brand that accounts for $1M of a total $10M of advertising spending would have a share-of-voice (SoV) of 10%, and competing brands would account for the remaining $9M or 90%. Much like market share, SoV shows advertising weight relative to competition. Given that bigger brands tend to spend more, a pattern appears across brands where SoV is similar or equal to share-of-market (SoM).

For budget planners, patterns like SoV=SoM have served as benchmarks for setting advertising spending levels. The pattern has been described as an ‘equilibrium’ level of advertising spending, which some researchers have suggested is sufficient for brands to maintain their market share level (Binet & Field 2007). A refinement to the SoV=SoM benchmark was first proposed by Jones (1990) who documented a systematic deviation from the pattern. Bigger brands tend to slightly underspend on advertising relative to their size (SoV<SoM), and smaller brands tend to overspend (SoV>SoM). Jones formalised this pattern as the Advertising Intensiveness curve (AI) and AI relationships have since been consistently documented across a wide range of conditions (e.g. Binet & Field 2013; Buck 2001; Danenberg et al. 2016; Field 2009; Hansen & Bech Christensen 2005). Jones suggested that the AI curve serves as a more accurate benchmark than SoV=SoM for maintenance spending, and this was confirmed by Danenberg et al. (2016). The ability of large brands to spend proportionately less without losing market share may be a result of the various economies of scale they enjoy. Bigger brands can leverage advantages in pricing, innovation and market-based assets such as physical and mental availability (Sharp 2010), which have the combined effect of assisting in share maintenance (meaning bigger brands have a lower reliance on advertising) and improving the effectiveness of any advertising they do.

Beyond brand size *maintenance,* the share-of-voice adspend benchmarks have also been linked to brand growth and decline (both SoV=SoM and AI). A number of studies have reported that brands spending at non-equilibrium levels (over or underspending their benchmark) often experience changes in market share (Binet & Field 2007; Danenberg et al. 2016; Field 2009; Hansen & Bech Christensen 2005; Schroer 1990). In other words, a brand spending consistently less than its suggested maintenance level is likely to lose market share over time. This has implications for stopping advertising, as *no advertising* could universally be considered underspending. Schroer (1990) asserts, without empirical evidence, that share changes tend to appear 18 months after spending changes (this aligns with Ackoff & Emshoff 1975). That said, Binet and Field (2007) found that the lower a brand's SoV is below the maintenance benchmark (i.e. deeper levels of underspending), the faster market share will shrink.

Several brand and category factors have been suggested to influence the relationship between SoV and changes in market share. Bigger brands tend to be less affected by underspending than smaller brands (Hansen & Bech Christensen 2005; Jones 1990), which was also observed by Riskey (1997). Category factors such as the weight of category advertising, competitive makeup of the category (number and size of brands), and disruptive innovations can also distort the relationship (Hansen & Bech Christensen 2005). It has therefore been suggested that precise AI curves and the derived levels of maintenance spending are likely to be industry-specific (Danenberg et al. 2016).

The relationships observed between SoV and SoM contribute important knowledge for this thesis. Evidence suggests that market share decline can be expected when brands underspend relative to their size on advertising, and deeper levels of underspending are likely to bring the decline more rapidly. Although several brand and category factors influence the spend and share relationship, such that "underspending" may be defined differently across markets, stopping advertising could be universally considered underspending and a precursor of future decreases in market share.

3.4 Advertising Decay

Advertising decay occurs where the effectiveness of an advertisement declines over time (East, Wright & Vanhuele 2013). Research into decay seeks to answer questions such as "how long does advertising's effect last?" and "at what rate does the effect diminish over time?" Such knowledge is valuable for this thesis, as any lingering effects of advertising may continue to influence brand performance after it is stopped.

The decay of advertising's effect over time is typically best fit by a downward exponential curve, which recognises an initial effect that diminishes toward zero over time (East, Wright & Vanhuele 2013; Roberts 1999). The rate of decay is commonly measured through advertising "half-life", a term borrowed from measurement of radioactive decay. Half-life reports the time taken for the immediate short-term effect of advertising to diminish to 50% of its initial level (Naik 1999). Another common measure used across studies is the "90% duration interval," which is similar to half-life, but reports the point at which 90% of advertising's effect has occurred (Clarke 1976).

Much research into advertising decay utilises econometric modelling, where advertising's effect on sales is established statistically, often through regression models. Advertising is one independent variable, tracked over time in line with the dependent variable, sales, in order to estimate the relationship between the two. The duration of advertising's effect, or "carryover" (and the decay over time), is gleaned from this time-series data using lagged parameters of advertising effect.

A large review of econometric research was conducted by Clarke (1976), who summarised the differences and consistencies of 70 studies of the duration of advertising's effect on sales. Within the literature, Clarke found somewhat consistent agreement that for mature, frequently purchased goods, 90% of advertising's influence on sales occurs within three to nine months of the advertising. There is strong support for the conclusion that 'advertising's effect on sales lasts for months rather than years' (Clarke 1976, p.355). In an empirical generalisation study, Leone (1995) refined Clarke's generalisation by adjusting the figures for a statistical bias; higher levels of sales data aggregation (weekly, monthly, yearly, etc.) tend to systematically increase the estimates of advertising carryover (Assmus, Farley & Lehmann 1984; Clarke 1976). With this correction, the data suggests that 90% of advertising's effect occurs within six to nine months from the advertised period (Leone 1995). However, these estimates of the duration of advertising's effect rest on assumptions about the appropriate interval for data aggregation. These assumptions and the interval used by these studies have been challenged, suggesting that the estimates may in fact be too high (Tellis & Franses 2006).

The validity of econometrics for analysing advertising effectiveness is debated. Proponents of econometric modelling claim that the method can quantify the relative impact of different marketing actions on sales, and thus predict the success of future campaigns (Cook & Holmes 2004). However it has been argued that econometric modelling is inappropriate for measuring advertising's effect because of the nature of advertising's influence (Dawes, Green & Kennedy, Unpublished). Advertising works through consumers' memories and its sales effects play out over time (Ehrenberg 1974; Mcdonald & Sharp 2005). Advertising rarely causes distinct "blips" in aggregate sales, and without these marked changes, econometric models cannot quantify its effect. In addition, when modelling software is fit to a set of sales and advertising data, it will generate an equation that most accurately fits the given dataset. This "best fit" will include any unique or random variation in sales specific to that dataset. So while the model may find statistical relationships between advertising and sales, the model parameters are unlikely to generalise to different time periods or data sets (Dawes, Green & Kennedy, Unpublished).

Beyond econometrics, studies using individual level-single source data also consistently report a decline in advertising's effect over time (Jones 1995; Reichel & Wood 1994; Roberts 1999; Wood 2009). Few, however, quantify this decline in terms of half-life or 90% duration interval. One exception is Roberts (1999), who investigated the duration of ad effects using a contingency table method. Individuals' purchases are organised into cells based on the interval prior to purchase that advertising was seen and their brand choice. The data indicate that the greatest uplifts in brand sales occurred when advertising for the brand was seen one day prior to purchase, with the sales uplift decaying over longer periods at a rate of 4.4% per day. Roberts' analysis was limited to 28-day periods between exposure and purchase, but suggested a half-life of 16 days (90% duration interval of just over 7 weeks). This is shorter than the econometric estimates. As important as Roberts' findings are, it must be noted that the analysis considered television advertising only, and the data was collected in the UK between 1996 and 1998 (when the volume of advertising and clutter was far lower than today's levels).

To summarise, short-term sales effects from advertising (e.g. uplifts over baseline) have been observed to carry over beyond the immediate period of the advertising. However, evidence suggests sales uplifts tend to decay back to the baseline level over a period of months. This may help explain why sales have often been observed to stay stable when advertising is stopped for one year (Lodish et al. 1995), but decline has appeared after longer unadvertised periods (e.g. Ackoff & Emshoff 1975).

3.5 Reacting to Recession

Many examples of brands stopping advertising come from firms acting during times of market recession. Recessions are a weakening of economic activity, and typically bring decline in consumer confidence and spending (Ang 2001). For businesses, reduced consumption means lower sales and cash flow. Under these heightened pressures to survive, firms' most frequent response is to cut costs and conserve resources (Deleersnyder et al. 2009; O'malley, Story & O'sullivan 2011). Advertising is among the areas most at risk of cuts during economic downturns.

The frequency of recession-driven advertising cuts has led to a number of studies of its effect on brand performance (see reviews by O'malley, Story & O'sullivan 2011; Tellis & Tellis 2009). Evidence is offered from academic research, practitioner studies, and theoretical discussions. In general, there is consensus that reducing adspend in a recession is associated with declining sales and weakened company performance. Conversely, firms that invest in advertising during a recession often improve in performance, partially because of the share-of-voice they win from competitors who reduce advertising spending (Field 2008). The evidence suggests that firms that cut advertising also experience worse decline in subsequent years (beyond the period of recession) than firms that maintained or increased advertising spending. Interestingly, Tellis and Tellis (2009) also note that cutting advertising during a recession is not associated with any increase in profits – though preserving profit is likely one motivation for stopping advertising in the first place.

For this thesis, the literature on advertising during a recession provides another view of what happens when brands cut advertising spending. There is agreement across many studies that advertising cuts generally lead to declining sales and profitability, both during and after a recession (O'malley, Story & O'sullivan 2011; Tellis & Tellis 2009). However, the integrity of certain findings has been questioned, as market downturn creates even more confounding factors than normal, and many studies fail to control for other possible reasons for firm performance. Results from practitioner and industry-funded studies have also been questioned for conflicts of interest, as the supporters or sponsors of the study may have vested interests in brands continuing to advertise (for example, if studies were sponsored by media owners). Nonetheless, the economic climate may be one condition that matters when brands stop advertising (specifically, how different product categories are affected and what it means for brands within).

Chapter Summary

This chapter has introduced, outlined and reviewed the prior sales-based research into what happens when advertising stops. Knowledge is contributed from several areas of advertising research; split cable experiments, individual level single-source data, advertising budgeting, decay and case histories from market recession. Together, the different fields provide broad but disjointed clues towards the issue. There are clear gaps in knowledge and a lack of documentation of the sales outcomes when brands stop advertising.

This thesis undertakes to address one gap by documenting what happens to aggregate brand sales when advertising is stopped for long periods. The next chapter builds on this review of the literature to formulate the specific research questions of this thesis.

Chapter 4
Research Questions

Chapter four develops the questions that guide this research. Two major questions are formed to understand broadly what happens when a brand stops advertising, and how the outcomes of stopping advertising differ for different brands. Relevant literature is provided to support the pertinence of these questions.

4.1 Documenting Brand Sales

Stopping a brand's advertising is a quick and easy way to save money. But what are the risks? In-market advertising weight tests support the generalisation that changes in advertising weight typically make little difference to short- or medium-term brand sales (Aaker & Carman 1982; Blair & Rosenberg 1994; Eastlack & Rao 1989; Lodish et al. 1995; Tellis 2009). When television advertising is stopped for one year, it is equally likely that sales will remain stable as decrease (Hu, Lodish & Krieger 2007; Hu et al. 2009; Lodish et al. 1995; Riskey 1997). Even when *all* spending on advertising is cut, sales can continue undisturbed for one year (Ackoff & Emshoff 1975). For marketers, these results imply that stopping advertising for brief periods may be a safe way of increasing liquid cash.

In-market reduced advertising weight tests lasting longer than one year are rare (no published tests could be found from within in the last 35 years). Of five multi-year reduced weight tests conducted before 1980, four showed no effect of reducing advertising spending (Aaker & Carman 1982). This finding implies that the "safe" length of time a brand can go without advertising may be longer than one year. Research into advertising decay suggests that within twelve months, advertising's effect on sales decays to only a small fraction of its initial effect (Leone 1995; Roberts 1999), implying that longer periods without advertising would see decline in the baseline level of sales. Budgeting studies also suggest that consistent underspending on advertising (relative to brand size) over multiple years leads to decline in market share (Binet & Field 2007; Danenberg et al. 2016; Field 2009; Hansen & Bech Christensen 2005). Findings from single source data tell us that advertising exposure nudges consumers' propensity to purchase, so an unadvertised brand holds one less weapon in the fight for consumer choice (Jones 1995, 2002; Kennedy et al. 2008; Reichel & Wood 1997; Roberts 1998; Wood 2009).

Presently, there exists no systematic, contemporary study specifically focused on what happens to brand sales when advertising support is entirely removed. Moreover, evidence concerning the sales effect of reducing or stopping advertising for longer than one year is extremely limited. Increasing knowledge in this area is important, as the risks and rewards of stopping advertising are potentially profound, but currently not well known. Observing numerous past cases of brands that stopped advertising for long periods and documenting how their sales evolved over time will help address this gap in knowledge. Thus, the following research question is proposed:

> What happens to brand sales after a brand stops advertising for a year or more?

4.2 Documenting Differences in Sales

Stopping advertising may affect different brands in different ways. Outcomes may vary based on different qualities of the brands themselves and the circumstances surrounding an advertising hiatus. Understanding what contributes to variation in results is important, as it helps explain *why* a particular result occurs, and improves prediction.

One factor that prior literature identifies as relevant is brand size (or brand *competitive position*, e.g. category leader vs. challengers) (Aurier & Broz-Giroux 2014). Advertising weight tests report that the likelihood and magnitude of sales changes following a reduction in advertising weight are greater for smaller/newer brands than bigger/established brands (Hu et al. 2009; Lodish et al. 1995; Riskey 1997). Advertising budget research shows how maintenance-spending levels are different for brands of different sizes. Bigger brands can afford to underspend on advertising (relative to their size) without consequence, while smaller brands often have to overspend to maintain their position (Binet & Field 2007; Danenberg et al. 2016; Hansen & Bech Christensen 2005; Jones 1990). Bigger, more mature brands also tend to have smaller advertising elasticity, meaning sales are less reactive to changes, (Assmus, Farley & Lehmann 1984; Danenberg et al. 2016; Sethuraman, Tellis & Briesch 2011) and greater mental availability to leverage when advertising (Sharp 2010). This evidence suggests brand size will be an important moderating factor in sales outcomes when advertising stops.

Another factor worth considering is the sales trajectory a brand is on before it stops advertising. Documenting sales tends *prior* to stopping advertising will provide important context to sales *after* the stop. For example, a brand observed to stop advertising and experience subsequent decline in sales might have already been in steep decline, which would qualify the result. Documenting the sales trend that brands are on before an advertising hiatus will also reveal if there are any differences in sales outcomes for previously growing, stable or declining brands. This is important for companies with a portfolio of brands, as brand performance can be a key determinant of advertising budget allocations (Low & Mohr 1999) and a reason why some brands go unadvertised. For example, money may be taken from non-growing brands and invested in other brands that are expected to provide greater returns on advertising investment. Knowledge of how differently performing brands (i.e. growing, stable or declining) are affected by an advertising cut would allow marketers to make evidence-based budget allocations.

Therefore, to extend the findings of the first research question, this study investigates how brand results differ across key conditions. Specifically, brands are categorised on the basis of their size and their trend in sales prior to stopping advertising.

> How do aggregate sales differ after stopping advertising for:

>> Different size brands?

>> Brands on different prior sales trends?

Chapter Summary

This chapter has outlined the research questions of this thesis, drawing from the preceding literature review. These questions will guide the focus of this thesis in documenting what happens to brands when advertising stops. The next chapter describes the data used to answer these questions and the method of analysis.

Chapter 5
Data and Method

Chapter Five begins with an outline of the Empirical Generalisation research philosophy employed by this thesis. This is followed by a recount of how data was acquired and a description of the data used for analysis. The chapter describes the steps taken to prepare the data, the method of analysis, and the strengths and weaknesses of the approach taken.

5.1 The Empirical Generalisation Approach

The empirical generalisation philosophy adopted by this thesis was popularised in marketing research by Andrew Ehrenberg and his colleagues over many years (Barwise 1995; Ehrenberg 1968, 1984, 1995). Ehrenberg advanced the use of classical scientific methods of replication and generalisation between datasets in marketing research to document law-like relationships that have broad application (Lindsay & Ehrenberg 1993; Scriven & Goodhardt 2012). This is achieved by observing the extent that a relationship between variables holds subject to various moderating conditions. For example, does a relationship hold in different countries, with measurements taken by different instruments at different times? Law-like empirical generalisations emerge where results hold despite such differences, and are replicated and extended to more and more varied circumstances.

Ehrenberg contrasts the empirical generalisation approach to the traditional statistical methods of line fitting through least-squares regression (Ehrenberg 1984). Regression aims to quantify a relationship between variables by identifying an equation that best fits the data points. Outputs include precise measures of the slope and direction of correlation between the variables, the closeness of the fit and the statistical significance of the result. However, the statistical significance and fit of a regression equation to a single dataset tells us nothing about where and when the result might generalise (Ehrenberg 1968; Lindsay & Ehrenberg 1993). In fact, since the equation is so precisely fit to the conditions in the single dataset, it is unlikely to generalise due to the natural variation across datasets. If the result cannot be replicated or applied to other conditions, it is isolated and of little practical use.

According to Ehrenberg's approach, rather than looking for statistical significance in a single dataset, researchers should look for significant "sameness" across many sets of data (MSOD) (Bound & Ehrenberg 1989; Ehrenberg 1984, 1995). As more and more data sets are used to study a relationship, the specific conditions of each will either not affect the relationship, thus increasing its generalizability, or impose boundaries where the relationship does not hold. In either case the relationship is refined and findings become more 'law-like and predictable' (Ehrenberg 1990).

Lindsay and Ehrenberg (1993) suggest that even separating the total sample of one dataset into multiple subgroups is better than nothing, as it introduces some degree of internal replication. For example, rather than treating an entire sample of brands as an undifferentiated whole, they may be categorised into big, medium and small brands. If the results replicate to a close degree of approximation for these within-sample subgroups it can be said that the results generalise across this condition. Otherwise, systematic variation between subgroups may suggest the presence of a confounding or moderating variable. Of course, testing relationships in more differentiated conditions is preferable, but even a successful within-sample replication tells researchers whether or not a result generalises at all and whether wider generalisation may be possible.

5.2 Acquiring Data

The aim of this thesis is to document what happens to brand sales when advertising stops, noting the effects of brand size and prior sales trend. Two types of data are necessary for this objective; brand level advertising media expenditure and sales. Data was required from real market conditions where brands had stopped advertising at some point. The data needed to span the full time the brands stopped advertising, as well as sufficient time before stopping to capture the prior sales trend.

To acquire the necessary data, a brief summary of the project and call for collaborators was circulated amongst the network of 70+ sponsor companies of the Ehrenberg-Bass Institute – as well as the personal networks of Institute staff. The document requested help from any companies with brands and data that fit the description, and offered early access to the findings in return. Some background information on the project and the research questions were provided, followed by a detailed description of the data we sought (see Appendix C). A "stop" was specified as at least 12 months without any spending on advertising, to ensure that the data include actual cessation in advertising, rather than merely short gaps in a media scheduling. Data requirements were separated into "must haves" and "nice to have" so that extra detail or the circumstances surrounding a stop in advertising would be included if possible.

The initial response to the data request was good, which suggested a broad interest in the questions from practitioners. Specifically, 10 companies indicated an interest in the project. With the finer details of the project clarified, some, it turned out, did not have the data necessary to answer the research questions. After numerous emails and calls, and weeks of discussion, one consumer packaged goods (CPG) corporation shared their data.

Data was provided by a large alcoholic beverages corporation. The dataset included two decades of advertising media spend and aggregate sales volume for several beer, cider, wine, spirits, premixed ready-to-drink (RTD) beverages, and non-alcoholic or mixer brands in the Australian market.

The advertising data comprised of brand and variant-level AU$ dollar media expenditure estimates, reported yearly for 20 years (1996-2015). Expenditure was rounded to the nearest $1000 across 10 media types (metro TV, regional TV, metro press, regional press, magazines, radio, online, cinema, out of home, and direct mail).

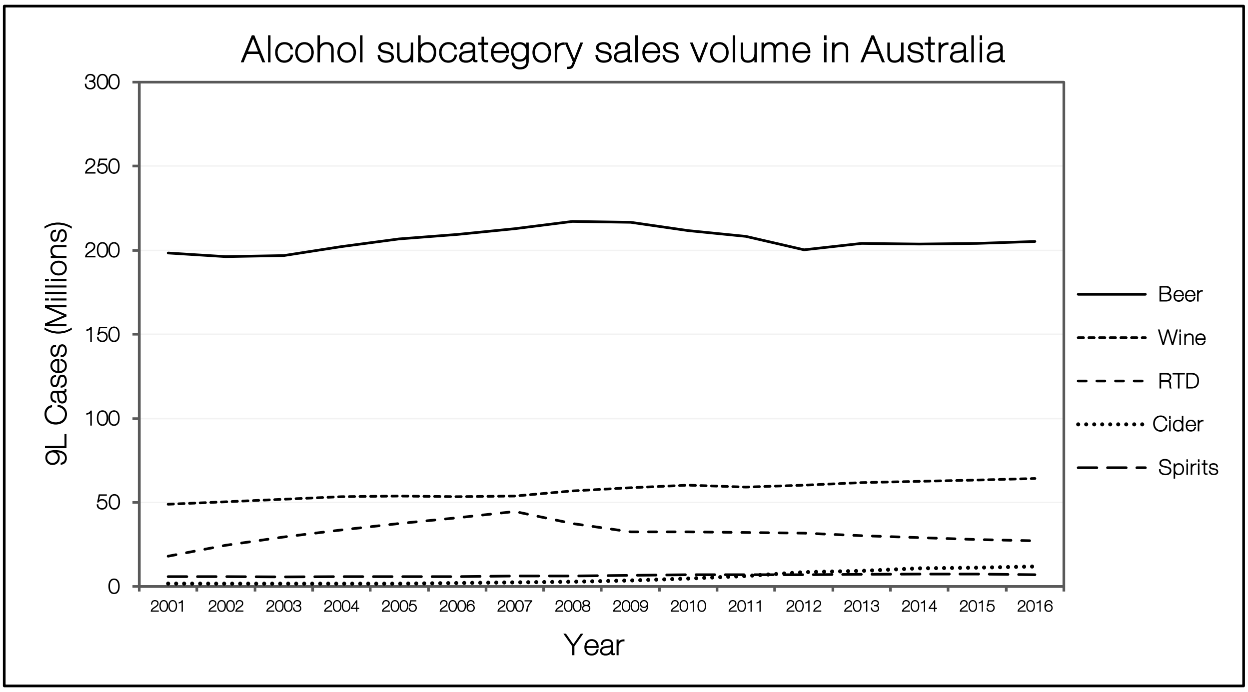
The sales data comprised of brand and variant-level sales volume reported monthly for over 22 years (July 1993 – April 2016). The data was normalised to 9 litre case equivalents and included both on- and off-premise sales (i.e. bulk keg sales as well as retail packs). Brand-level market share information was not present in the dataset, so the main analysis in this thesis considers the brands' aggregate sales figures only. Post-hoc testing was conducted with additional category-level data after the main analysis – see Appendix B for details.

5.3 The Australian Alcohol Market

Alcohol advertising is a widely regulated and sometimes controversial form of marketing. In Australia, alcohol brands are permitted to advertise on mass media, and are subject to the same legislation and codes of ethics of all advertising, with several additional guidelines set out in the Australian Beverages Advertising Code (ABAC). The ABAC scheme regulates the content that is permissible in alcohol advertising, in particular the creative elements used in the portrayal of alcohol (for example, to reduce its appeal to minors). The scheme came into effect in 1998 – during the period of this data set – and could have had some influence on the creative choices made by the subject firm. However, few restrictions are placed on the media weight and scheduling of alcohol advertising, so it is unlikely to have had any major consequence for this study.

Total alcohol consumption in Australia grew in the mid 2000s before plateauing and remaining stable in last five years (Euromonitor International 2016). Over time there have been broad changes in the types of alcohol preferred by Australians. Chart 1 plots the total sales volume of different alcohol categories in Australia from 2001 to 2016. At its highest point, consumption of beer rose to 217 million 9L case equivalents in 2009. Total beer sales have since fallen and stabilised since 2012. There has been steady long-term growth in both wine and cider consumption. RTD consumption was growing rapidly up until 2008, a year when the Australian Government introduced increased taxes on premixed spirit-based RTD beverages (Chikritzhs et al. 2009).

Chart 1 – Sales volume of alcohol subcategories in Australia.



Source: Passport (2017), Euromonitor International.

5.4 Preparing the Data

The dataset required extensive cleaning and organisation before analysis could begin. The data was provided in Microsoft Excel spreadsheets, so wherever possible, every step taken to clean, organise and prepare the data for analysis was done using automated Excel formulas to minimise the potential for error. Any action that required human input was crosschecked in multiple ways with Excel formulas to ensure accuracy.

Both the advertising and sales data were arranged in tall formats (i.e. years arranged vertically with each row containing one sales or advertising observation). The media spend sheet was 1323 rows tall, made up of many different types of advertising activity over the 20 years, including:

- Brewery/distillery/winery-level corporate advertising
- Brand-level advertising
- Specific brew/spirit/wine type/variant/flavour-level advertising
- Separate lines for brand related competitions/promotions/website spending.
- Various types of sponsorship

There were 446 unique advertising lines, many of them one-offs for various promotional or online activities. Likewise, the sales data was 44,234 rows tall (much larger due to monthly observations), with 478 unique product lines.

The analysis was to be conducted at brand-level, so it was necessary to decide how a brand was defined in this dataset. This is particularly challenging in the alcohol category, as often a brewery/distillery/winery brand or title is given to various brews/spirits/wine type variants. Decisions needed to be made whether a brand’s variants would be analysed individually or aggregated up as one brand. In some cases, it was appropriate to analyse a brand’s variants individually – for example, where they had high sales volume and their own specific advertising media spending lines. Yet in other cases the line between brand and variant was less clear and it was more appropriate to aggregate them – for example, where only the umbrella title was advertised (or all variants together), rather than the individual variants. No perfect rule could be applied across the entire dataset to separate brands and variants, so the classification proceeded according to the way the advertising and sales data was structured for different brands and the best judgement of the researcher (who is familiar with the product category).

For the sales data, the 478 unique product lines were aggregated and reduced into 253 brands. For the advertising data, all forms of corporate advertising and sponsorship were removed (leaving only the brand-specific mass advertising expenditure), and the remaining brand-level advertising aggregated into 120 brands.

To be considered in the final sample, brands needed to meet several criteria. Since this thesis is about *stopping* advertising, included brands must have advertised at some point in the dataset. Many brands appeared in the sales data but were never advertised, so they were therefore removed. There were also many brands (mostly wine) that were advertised but did not appear in the sales data, which were removed. This left a shortlist of 72 brands that had both advertising and sales at some point in the dataset.

To be included in the final sample there must have been a period of at least one year where the brand did not advertise. In typical market conditions, it is unlikely that any competitive brand ever completely stops all forms of advertising (depending on the chosen definition of "advertising", e.g. in-store activations and brand websites probably remain active even when mass media spending is reduced). The term "stop advertising" is used as shorthand here to indicate a massive reduction in mass reach advertising. A stop in advertising was defined as any year when a brand's total media expenditure was less than 1% of its average yearly expenditure. This definition captured years with zero media spend, and also allowed us to include several larger brands that typically spent multiple millions of dollars each year, and then reduced media spending in some years to only a few thousand dollars in low reaching media. Including such years as a "stop" in advertising increased the number of cases to analyse and is a close approximation to a complete cessation in a brand's communication with customers.

Finally, the analysis approach required that brands, at some point in the 20 years, had a period of at least two consecutive advertised years before the stop, and sales data for entirety of that period. Of the 72 shortlisted brands, 29 did not meet these criteria, either having too few years of advertising, no consecutive advertised years, or no stop in advertising. Thus the final sample included 43 brands (30 beer, 4 cider, 4 spirits, 3 RTD, 1 wine, and 1 mixer).

Before moving on to the analysis, brand sales were aggregated from months to calendar years. Alcohol is a highly seasonal category, so this aggregation not only converted sales into the same temporal format as the media spend data, but also smoothed the seasonal variation. Sales in 1993 and 2016 were removed, as they were not full calendar years.

5.5 Method of Analysis

Brands stopped and started advertising at different times during the period of the dataset – some stopped only once; others had bursts of spending with gaps in between. To reconcile these differences, each year was coded as either having *some advertising* or *no advertising* ("advertised" or "unadvertised" years). For each brand, years with advertising spend were coded as 1, and unadvertised periods were coded -1 in the first year, -2 in the second, and so on (see example in Table 2).

Table 2 – Example of media spend coding.

Brand / Year	2000	2001	2002	2003	2004	2005	2006
Brand A	1	1	1	-1	-2	-3	-4
Brand B	1	1	-1	1	1	1	-1

Years with spending = ‘1’. Periods with no spending = ‘-1’ in the first year, ‘-2’ in the second, and so on.

As mentioned, useable cases were those where a brand had two consecutive years of advertising followed by at least one year without advertising. The two advertised years are required to document the brand’s sales trend prior to stopping advertising. The continued example in Table 3 highlights three such cases across the two brands, which are ringed by thick borders.

Table 3 – Example of useable cases of stopping advertising.

Brand / Year	2000	2001	2002	2003	2004	2005	2006
Brand A	1	1	1	-1	-2	-3	-4
Brand B	1	1	-1	1	1	1	-1

Across all 43 brands there were 59 such cases – that is, 59 times when a brand stopped advertising for at least one year. Each of the 59 cases comprised of two advertised years termed the “prior” year (the first of the two advertised years) and “base” year (the last of the two advertised years before stopping), followed by one or more unadvertised years. Once identified, cases were tabulated with the base years aligned (see continued example in Table 4).

Table 4 – Example of tabulated cases.

Case	Brand	Prior	Base (Index year)	-1	-2	-3	-4
1	Brand A	2001	2002	2003	2004	2005	2006
2	Brand B	2000	2001	2002			
3	Brand B	2004	2005	2006			

Once the useable cases were aligned as in Table 4, sales of each brand in these years were plugged into the table. Each case was then a record of a brand’s sales in the two years before it stopped advertising and the unadvertised year/s after.

Comparing sales in the prior year to the base year shows whether a brand's sales had grown, declined or remained stable in the year before stopping advertising. Then, comparing sales in unadvertised years to the base shows how sales evolved without advertising support, relative to the last advertised year.

The sample of brands included some very large brands and some quite small brands, with average yearly sales volume ranging from tens of millions to tens of thousands. These differences meant absolute sales changes could not be easily compared across cases (e.g. after one year without advertising, then two years, and so on). In order to compare what happened to these vastly different brands, a relative measure of change was required. For each case, sales in every year were divided by the base year (i.e. the final advertised year before stopping) then multiplied by 100. This means that the sales in the base year are indexed at 100, with all other years converted to reflect this. An index higher than 100 represents higher-than-base-year sales, and lower than 100 represents lower-than-base sales.

With the data presented in this way, sales indexes can be observed across cases at one year without advertising, then two years, and so on, and the average sales index can be calculated at each stop length. Cases can also be organised into subgroups based on brand size and prior sales trend, to address the second research question.

The two factors of interest in this study are brand size and sales trend prior to stopping advertising. Cases were divided into these factors at three levels, to ensure the top group (e.g. big brands) was considerably different from the bottom (e.g. small brands). To classify size, brands were tagged as big, medium or small based on their average yearly sales. Thresholds were chosen to split the cases into three groups of roughly equal numbers. Brands with average yearly sales greater than 1 million units were tagged as big, between 1 million and 250 thousand tagged as medium, and fewer than 250 thousand as small. For prior sales trend, brands were tagged as previously growing, stable or declining based on the percentage change in sales between the prior and base years. The threshold for sales stability was chosen as +/- 10% difference in sales, with brands labelled growing or declining if sales had changed by more than 10% from the prior to base year – which also split the cases into three roughly equal groups. The next chapter discusses the sample in more detail, including how cases are apportioned into brand size and prior sales trend subgroups.

5.6 Strengths and Weaknesses

The approach to analysis described above offers several benefits. First, it is relatively straightforward and produces unambiguous results. Parsimony is considered a characteristic of good empirical generalisations (Barwise 1995), and simplicity has been hailed as a virtue of impactful research (Tellis 2017). Ehrenberg (1969) stated that 'no deep principles or elaborate statistical techniques are required to uncover law like relationships.' He believed that well presented data would communicate information on its own, without needing complex statistical manipulation (Ehrenberg 1975; Scriven & Goodhardt 2012). With this in mind, extensive cleaning and arrangement of data was undertaken to produce simple graphics and easily absorbed results (reported in Chapter Six). Second, looking broadly *across* multiple cases (rather than *within* cases) advances the search for “significant sameness” and regularity under different conditions. This is also in line with the empirical generalisation philosophy. The sample includes different sized brands, in different alcohol categories, that stopped advertising at different times, so regularity in the outcomes in spite of these varying conditions would be interesting. The method also recognises brand’s prior sales trend before stopping advertising, rather than simply observing sales in unadvertised years. Documenting existing trends provides additional context to the results and the conditions that relate to different outcomes when advertising is stopped.

There are, however, several limitations to the data and method used here. First, the media spend was provided only as a yearly figure for each brand and media platform. The exact point when a brand’s last ad was run before stopping (down to the month or day) could not be extracted from this data. The precision of each case is reduced by this aggregation. If the last burst of media spending happened to be in January of any calendar year, the entire year would have been considered ‘advertised,’ and the stop, for the purposes of analysis, would begin from the following year (11 months later).

To identify cases of stopping advertising across all brands, each year was binary coded as either advertised or unadvertised. Cases were chosen on the condition that the brand had advertised for at least two years prior to stopping, but the *amount* of advertising spending in those prior years was overlooked by this coding method. Some brands may have been spending multiple millions of dollars, while others maybe only a few thousand, or there could have been a large increase or reduction in spending before stopping completely. It is plausible that the weight of prior media spending influenced sales after stopping advertising, but this was not accounted for in this analysis. There was also no information available on the creative content or effectiveness of brands’ prior advertising. Stopping *good quality* (i.e. sales effective) advertising may have a different effect to stopping *poor quality* advertising, as there is evidence from single-source data that ‘powerful’ advertising content can be 10 or 20 times more sales effective than ‘mediocre’ advertising (Wood 2009). These questions remain for future research.

Another potential influence that was not accounted for was the potential for “halo effects” of advertising for some brands. Since some brands in the sample are variants produced under the same overarching parent brand (though differently branded, for example: Miller Lite and Miller Chill), it is plausible that consumers could confuse advertising for one brand as that of another. If one such brand stops advertising while another continues and focuses on the few elements that are consistent between them, it could work also for the unadvertised brand (Carter & Curry 2013). To account for this effect would require specific detail on the creative content of each brand’s advertising and knowledge of the common distinctive assets they share, which was not available. There is also disparity in the literature on advertising halo effects, so exactly how to operationalize the phenomenon for consideration in this analysis is beyond the scope of this thesis. It is also possible that advertising by other members of the alcohol supply chain (e.g. distributors, retailers, etc.) supported brands while they were classified as unadvertised in this dataset. The cost of this advertising may be borne by the manufacturer though (like trade promotions), so it may already be captured in the dataset.

Finally, once cases had been identified, the sales trend of each brand before it stopped advertising was calculated using only two prior years of sales. The difference in sales between the two prior years indicated whether the brand's sales had grown, remained stable or declined year-to-year before advertising stopped. These two years may not have accurately reflected the brands' long-term sales trends. Aggregate yearly sales can fluctuate randomly within a longer-term trend, so some brands may have been misclassified as previously growing, stable or declining. A remedy for this would be to observe sales for longer than two years prior to when advertising stopped. However, this was not possible in every case, and the additional selection criteria would mean fewer cases in the final sample.

5.7 Post-hoc regression analysis

Once the descriptive analysis was complete, it was decided that further post-hoc analysis be undertaken using regression modelling. The purpose of this post-test was to check whether or not the conclusions from the descriptive analysis were consistent with estimates from statistical analysis. This regression modelling also made it possible to include further data and to take into account the influence of category sales change. Please see Appendix B for a description of the analysis undertaken and the results of this post-test (page 84).

Chapter Summary

Chapter five described the dataset examined in this thesis and the approach to analysis. The total sales of brands in years when they went unadvertised are compared to the last year when they were advertised (the base or index year). The year before the last advertised year is also compared to this base year. This information reveals the sales trajectory that a brand was on before stopping advertising and its relative sales in the years after. This process is repeated for every possible case of stopping advertising across the numerous brands in the dataset. Relative sales in unadvertised years can then be observed across cases and any consistencies or differences over time noted.

To further explore the findings from this descriptive analysis, post-hoc statistical tests were undertaken (see Appendix B for discussion and results).

The following chapter details the results of this analysis.

Chapter 6
Results

This chapter details the results of the analysis described in Chapter Five. The chapter begins by describing the nature of the sample. Results are initially presented with all cases combined, then divided into subgroups. Each section of this chapter builds on the section before it, adding detail to the discussion by slicing the results in different ways.

6.1 The Sample

The 43 brands included in the final sample provided 59 useable cases of stopping advertising. However, as the analysis commenced, it became apparent that two cases were extremely different from the rest. One case was a very small brand whose sales increased tenfold over seven unadvertised years. This growth was not enormous in absolute terms (e.g. the brand is considered a "small" brand by the definition adopted in this thesis over the duration of the dataset), yet the relative change, exaggerated by the brand's small base figure, was far greater than all other cases. Investigation revealed that this brand was extremely large in other international markets, but newly licensed to this Australian corporation for local distribution. The Australian company spent a little on advertising media in the early years of its launch before stopping, hence why it is included in the sample, but it is plausible that additional support was provided by its holding company and not reported in this dataset. This outlier was excluded from analysis.[†] The other abnormal case was an aggregation of many small variants of a larger parent brand. Some of these variants were newly introduced or delisted during the unadvertised period. This churn of brands created erratic variation in sales and made the aggregated case unsuitable for further analysis, so it too was removed.

The 57 remaining cases came from brands from a range of alcohol subcategories (43 beer, 5 cider, 4 spirits, 3 RTD, 1 wine, and 1 mixer). Subcategories other than beer had too few cases to examine subcategories separately, so the following results include all cases.

Each of the 57 cases naturally included at least one year without advertising. Of those 57 single-year stops, 34 persisted for a further year to become a two-year stop in advertising, and so forth (see Table 5). Fewer cases remain at each stop length due to brands either restarting advertising, being delisted, or reaching the last year of the dataset. There are more than ten cases at each stop length up to five years, and one brand went unadvertised for ten years.

Table 5 – Number of cases at each length of advertising stop.

Length of advertising stop (years)	1	2	3	4	5	6	7	8	9	10
Number of cases	57	34	17	12	11	6	6	4	2	1

To briefly reiterate the method, each case comprises of two advertised years, termed the *prior* and *base* years, and at least one year without advertising. The base year of each case is the last year before advertising was stopped, thus sales in that year are indexed at 100 with all other years converted to reflect this. Indexes higher than 100 represent higher-than-base-year sales, and lower than 100 represent lower-than-base sales. Comparing the prior year with the

[†] Although this outlying case was excluded from analysis, it is an interesting observation. Stopping advertising may prove to be an insignificant decision for a large, global brand entering a new market.

base in each case reveals whether yearly sales of the brand were increasing or decreasing before it's advertising was stopped. Once all cases are tabulated, sales indexes can be observed across cases at one year without advertising, then two years, and so on.

Cases are also arranged into subgroups, determined by their sales trend prior to stopping advertising and brand size. Brands were labelled previously stable if the difference between prior and base sales was less than 10%. Cases with change greater than 10% (increase or decrease) were labelled growing or declining. Brands with average yearly sales less than 250k units were labelled small brands, between 250k and 1M labelled medium, and greater than 1M labelled large. These cut off values were chosen to split the sample into three roughly equal groups for each factor. Table 6 shows how the 57 cases are apportioned into these subgroups.

Table 6 – Distribution of cases into brand size and prior sales trend subgroups.

Trend / Size	Growing	Stable	Declining	Total
Big	4	7	6	17
Medium	4	5	8	17
Small	10	7	6	23
Total	18	19	20	57

A near equal number of cases are classified as previously growing brands (18), as stable (19) and declining brands (20). Most of those growing cases are small brands. More cases in general come from small brands (23) than medium (17) or big brands (17). Importantly, brands did not change their size classifications throughout the duration of the dataset. Small brands were not reclassified as medium, or medium as large when growing, nor the reverse when brands declined.

Enough cases exist in each subgroup of the two main factors for perceptible differences between groups to emerge (e.g. large versus medium versus small brands), but applying both size and trend variables in a two-factorial design leaves few cases in each subgroup – as low as four in some groups.

6.2 Results – All Cases

Table 7 below summarises the sales indexes of all cases in each year. Central tendency and dispersion are reported through the mean of all sales indexes (MSI) and the standard deviation from the mean. The largest sample sizes are for brands stopping advertising for one and two years, so the results from these samples are the most reliable. There are fewer longer-term advertising stops, and beyond five years there are less than ten cases to report on. In spite of these small samples, all observations are reported on.

Table 7 – Mean indexed sales: All cases.

	Year	Prior	Base	1	2	3	4	5	6	7	8	9	10
	Number of cases	57	57	57	34	17	12	11	6	6	4	2	1
All Cases	Mean Sales Index (MSI)	113	100	84	75	64	46	42	37	32	28	29	34
	Standard Deviation	53	0	33	50	42	30	24	25	23	18	7	-

The MSI across all cases after twelve months without advertising is 84. Put simply, sales after one year without advertising are 16% lower on average than the previous advertised year. The MSI falls further below the base year in each additional unadvertised year. On average, sales are 25% lower than the base year after two years without advertising and 58% lower after five years.

The base year is indexed at 100 in every case, giving a standard deviation of zero in that year. Sales indexes varied considerably in most other years. For example, amongst only the one-year advertising stops, indexes ranged from 175 to 3. The dispersion of cases at each stop length is presented visually in Chart 2 below. Each case is plotted as a series of dots over time, with the MSI displayed by the solid line.

Chart 2 – Aggregate annual sales, all cases of brands stopping advertising, indexed on last advertised (base) year.

Note: Chart omits one prior-year value that is greater than the Y-Axis maximum (374).

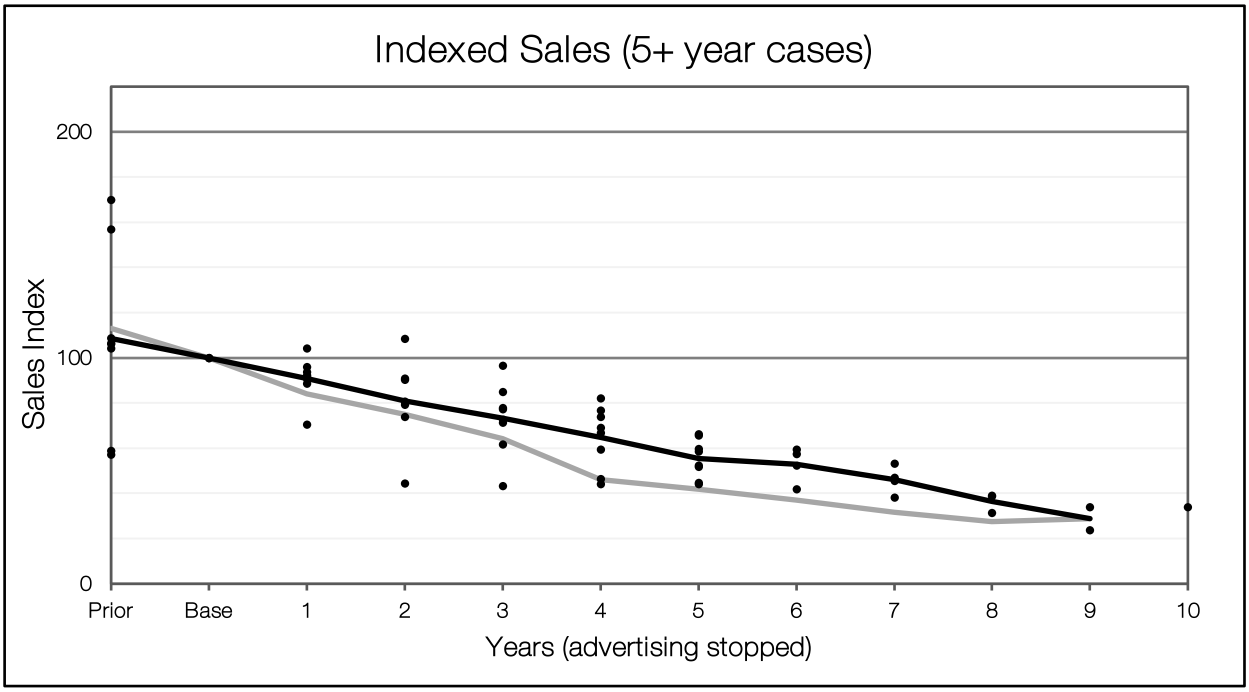
Chart 2 shows a clear downward trend across cases in sales index over time. Of all cases, 54% reported a sales index of 90 or less after one year without advertising (-10% difference in sales). This proportion increases to 68% after two years and 71% after three. 32% of all cases were previously growing brands that stopped advertising, yet only 12% of cases reported growth after stopping advertising for one year. All brands that stopped advertising for four years or more saw sales fall and stay below their base year level, although this seems partly because almost every case where a brand indexed higher than the base year in the first unadvertised year is shorter than four unadvertised years (i.e. brands that grew while unadvertised did not stay unadvertised for long).

From year four onwards, the MSI sits between two broad groupings of cases – one group with sales indexes between 40-60, and another below 10. The multi-modal distribution of indexes in those years may be related to differences between those brands, as the higher group are mostly big, previously stable brands, while the lower group are all small or medium sized brands (these factors are discussed further in sections 6.3 to 6.5).

The MSI plotted across all cases in each year is subject to the issue of a selection bias of sorts, or a “survivor effect.” Because fewer cases remain at each stop length (see Table 5), the MSI in each successive unadvertised year is calculated from a smaller sample of brands. This means that changes in the mean over time are partially a result of cases dropping out of the sample, rather than sales changes within cases in each year. For example, in Chart 2 a steeper drop in the MSI occurs between years three and four. The cases that persist from year three to four do mostly experience a decrease in sales there, but the main driver of the falling mean is the last growth case leaving the sample (that brand restarted advertising after three unadvertised years). Similarly, brands that are delisted after some years without advertising leave the sample and the MSI in the following year is calculated without them.

To address this selection bias, Chart 3 plots only the cases where brands were unadvertised for 5+ years, and were not ultimately delisted (the continuous reporters). The change in the MSI up to year 5 across these cases is entirely a result of the within-case sales changes, rather than sample differences. The MSI of all cases (from Chart 2) is also plotted in grey for comparison.

Chart 3 – Indexed sales: brands that stopped advertising for 5+ years and were not ultimately delisted.



Removing the effect of sample differences reduces the variability, and reveals some regularity in sales indexes in each year. The MSI is 91 after one year (-9% difference in sales), and it declines almost linearly over time. After five years without advertising, the eight cases plotted in Chart 3 all report sales indexes between 66 and 44. It is also noteworthy that despite being a reduced sample, some variation in case conditions is preserved. Cases are mostly beer brands (6/8) and mostly big brands (5/8), but there are small and medium brands, spirits brands, and a split of previously growing, stable and declining brands. The similarity in sales outcomes in spite of this variation is notable.

6.3 Results – Split by Prior Sales Trend

In this section, the sample of 57 cases is split into three subgroups based on the sales trend of each brand prior to stopping advertising. Table 8 shows the sample size of each subgroup.

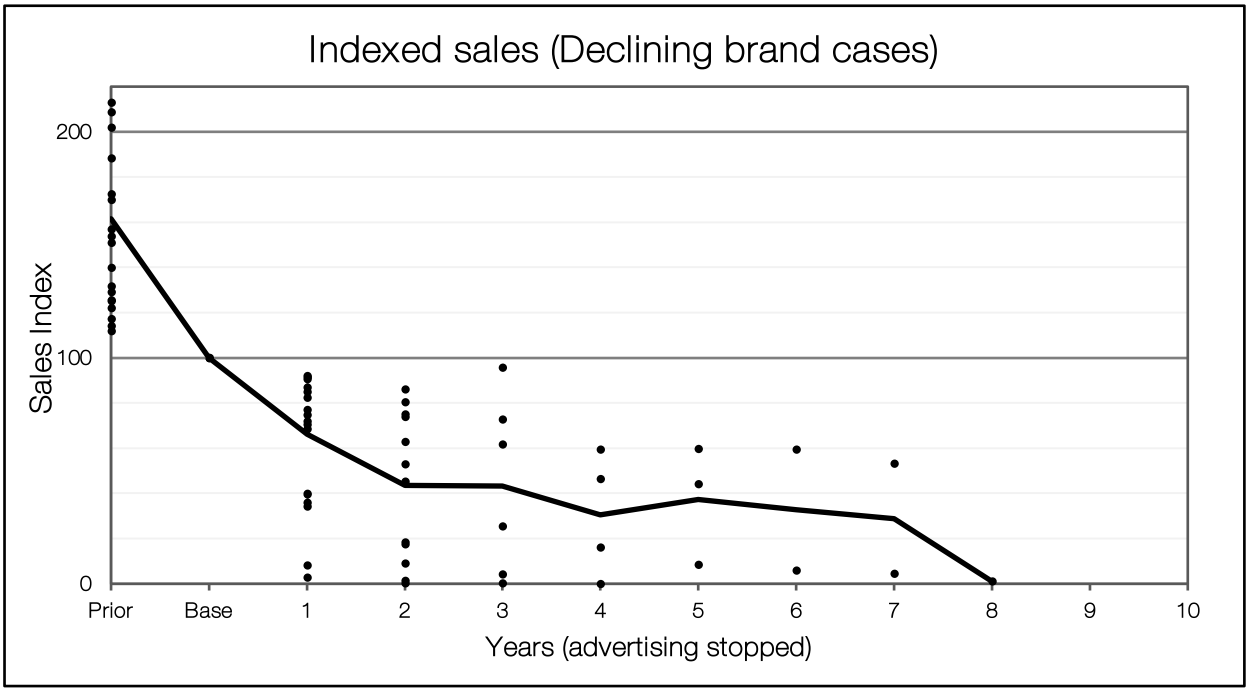
Table 8 – Sample sizes of prior sales trend subgroups at each length of advertising stop.

Years	Prior	Base	1	2	3	4	5	6	7	8	9	10
Previously growing	18	18	18	11	3	3	3	0	0	0	0	0
Previously stable	19	19	19	11	8	5	5	4	4	3	2	1
Previously declining	20	20	20	12	6	4	3	2	2	1	0	0

Each subgroup contains over ten cases of brands stopping advertising for one and two years, but the samples are small for 3+ year advertising stops. Regardless of small sample sizes, all observations are reported and qualitatively explored.

Charts 4, 5 and 6 below plot the cases of each subgroup. The MSI is again shown as a solid line in each chart, and the mean and standard deviation figures are provided in Appendix A.

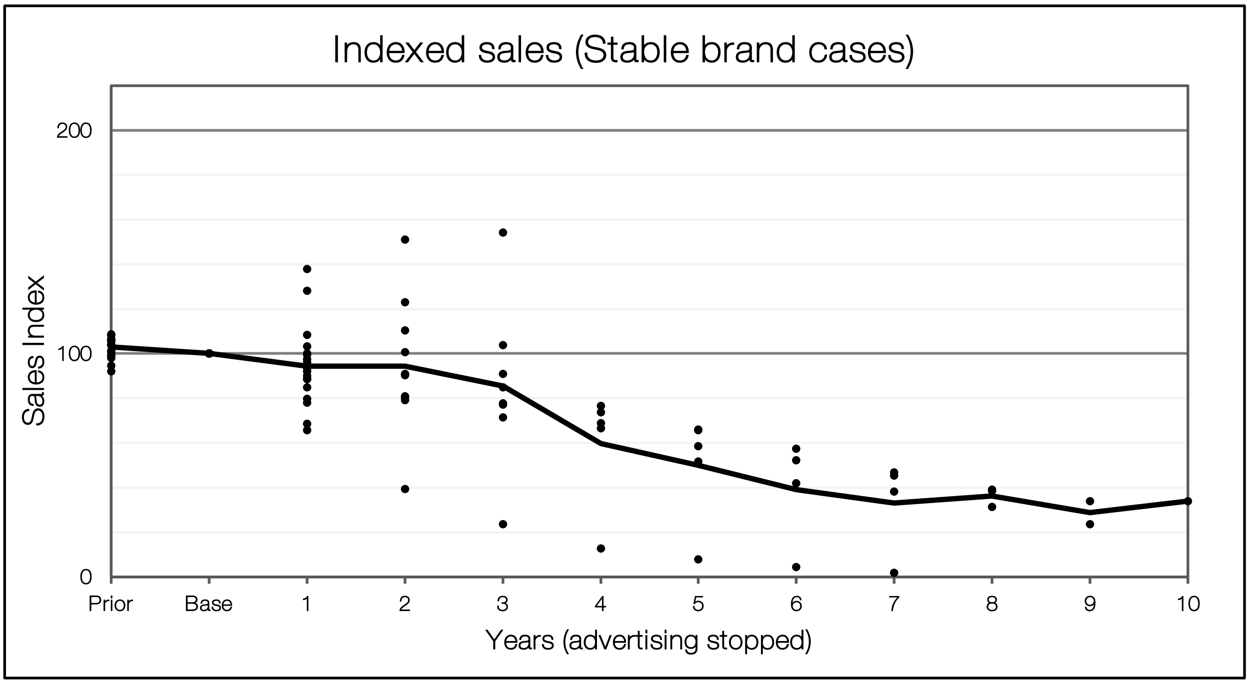
Chart 4 – Indexed sales: Previously declining brands that stopped advertising.



Note: Chart omits one prior-year value that is greater than the Y-Axis maximum (374).

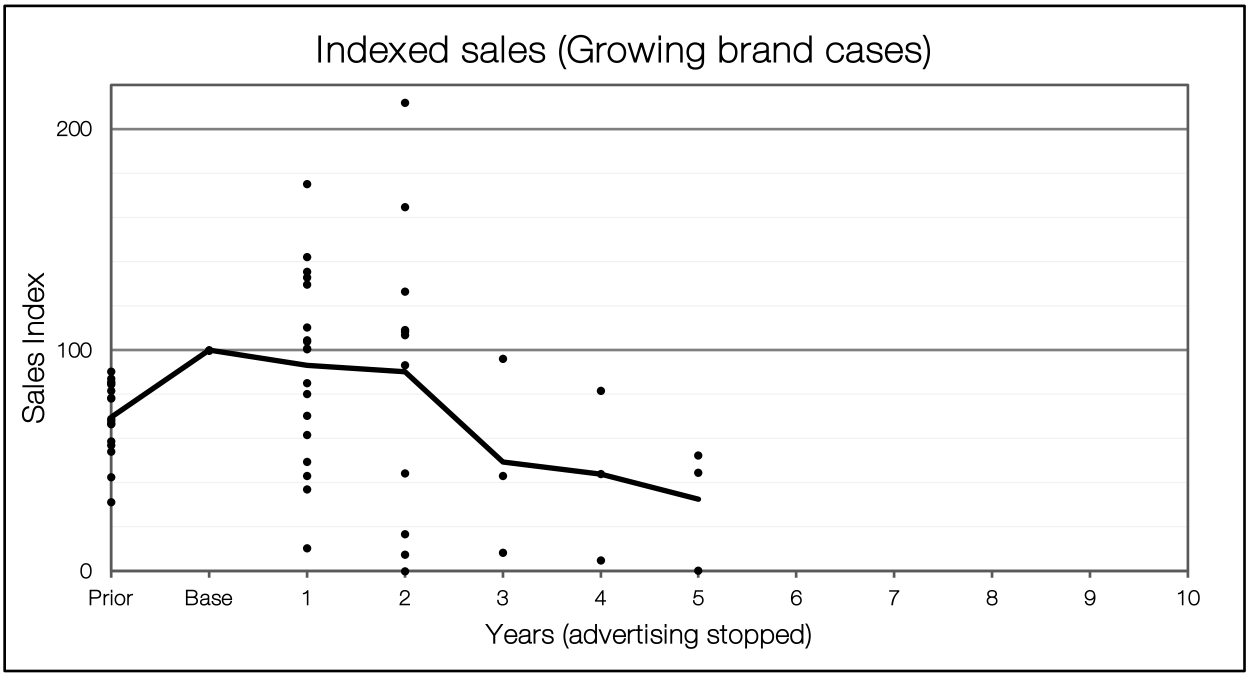
The MSI in unadvertised years is the lowest amongst brands that were already in decline (Chart 4). The MSI is 66 after one unadvertised year and 44 after two, but individual cases varied considerably around this average. Most strikingly, no previously declining cases indexed above 100 in any year after stopping advertising. Every brand that was declining by 10% or more before stopping advertising posted sales below the base year during unadvertised years. One case arrested its decline and increased sales slightly but still did not reach its base year level.

Chart 5 – Indexed sales: Previously stable brands that stopped advertising.



Previously stable brands (Chart 5) converged around an average index of 94 after one year without advertising. The average index remained at 94 after two unadvertised years, before declining further below the base. Previously stable brands stayed somewhat stable on average for two years without advertising. Unlike the previously declining brands, some previously stable brands did experience growth relative to the base after stopping advertising, even after two and three unadvertised years. However decline was more common, with more cases indexing below 100 than above in every year.

Chart 6 – Indexed sales: Previously growing brands that stopped advertising.



Previously growing brands (Chart 6) show a wider dispersion of sales indexes after stopping advertising than previously stable or declining brands. There is little apparent consistency in Chart 6. However, an almost equal number of cases indexed above the base year as below, after one and two years without advertising. This means proportionally more *growing* cases indexed above 100 after stopping advertising than previously stable or declining cases.

Although there is extreme variation across cases in Chart 6, the dispersion seems to be related to brand size. Section 6.5 discusses brand size and sales trend interaction in more detail.

6.4 Results – Split by Brand Size

In this section, the sample of 57 cases are separated by their average yearly sales into big (1M+ per year), medium (1M – 250k) and small brands (< 250k). Table 9 shows the sample size of each brand size subgroup.

Table 9 – Sample sizes of brand size subgroups at each length of advertising stop.

Years	Prior	Base	1	2	3	4	5	6	7	8	9	10
Big brands	17	17	17	12	6	5	5	3	3	3	2	1
Medium brands	17	17	17	11	6	3	3	3	3	1	0	0
Small brands	23	23	23	11	5	4	3	0	0	0	0	0

Like the prior trend subgroups, each brand size group contains over ten cases of brands stopping advertising for one and two years, but the samples are small for 3+ year advertising stops. Again, all observations are reported.

Charts 7, 8 and 9 below plot the cases in each brand size group. Discussion of these groups is provided below all three charts, and the mean and standard deviation figures are provided in Appendix A.

Chart 7 – Indexed sales: Big brands that stopped advertising.

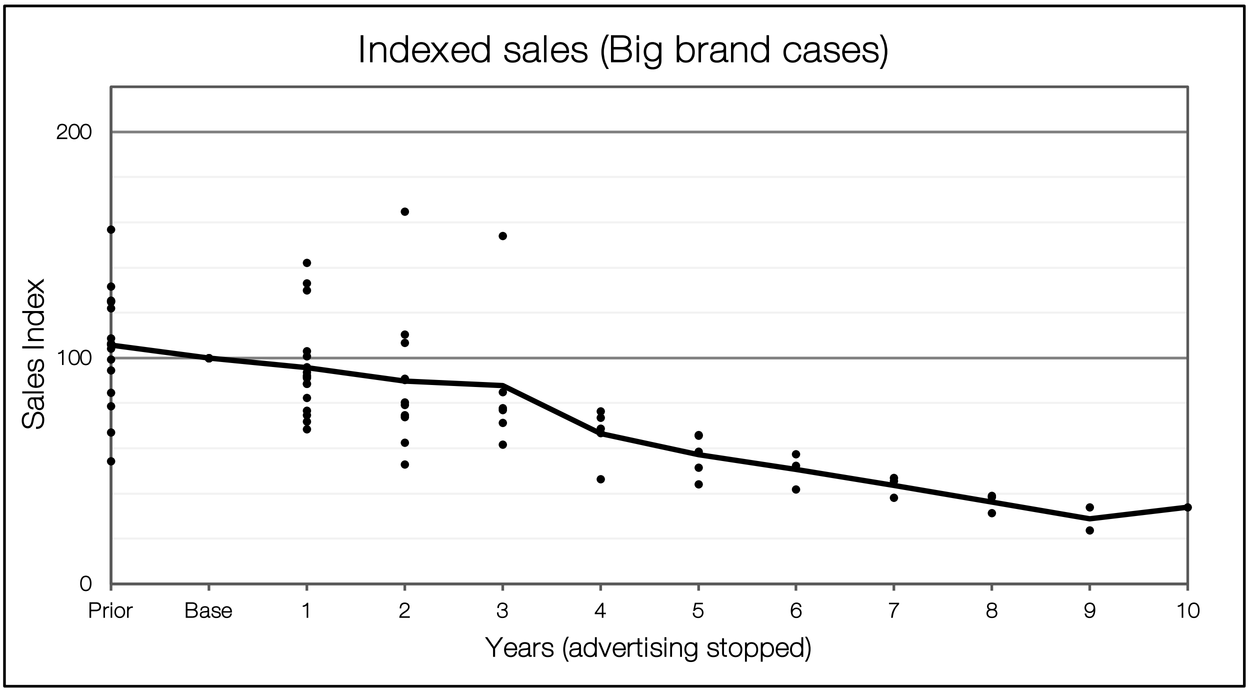


Chart 8 – Indexed sales: Medium brands that stopped advertising.

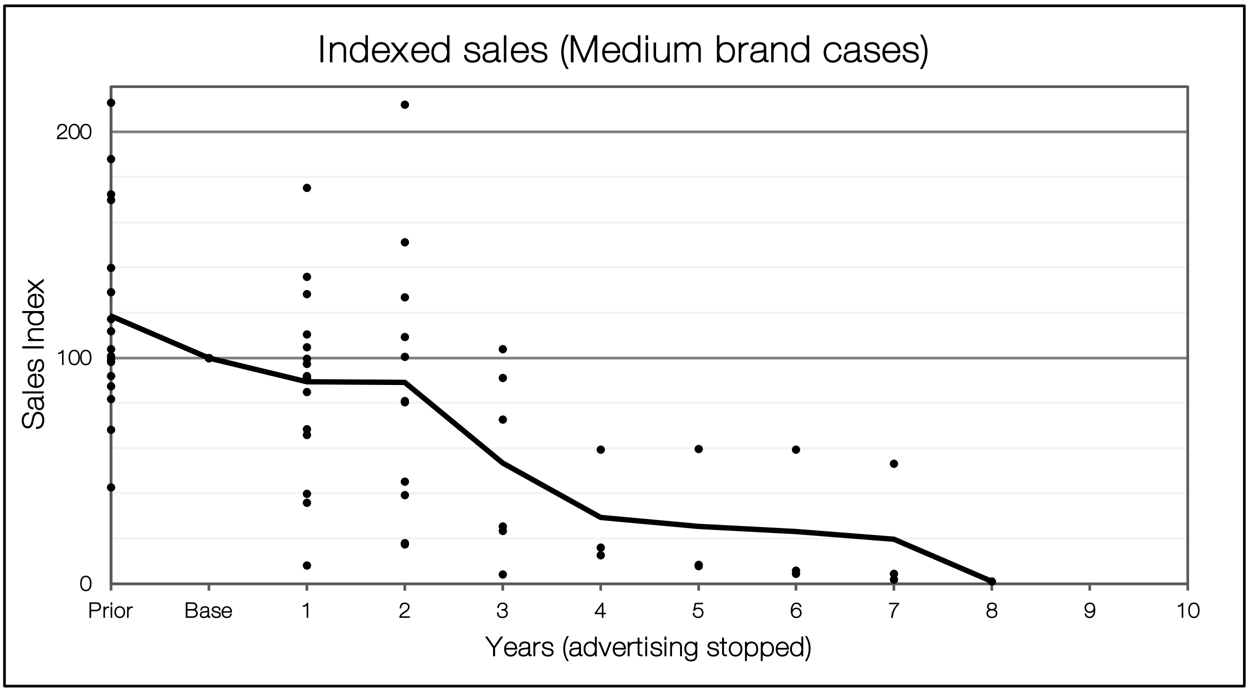
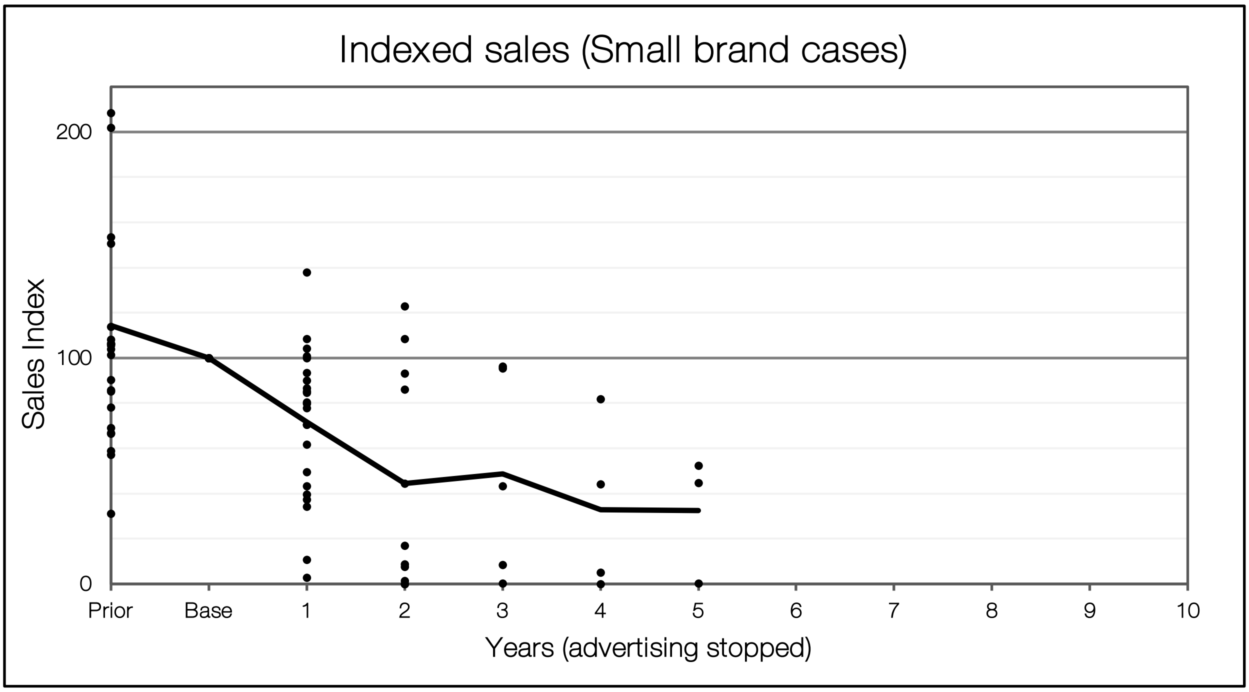


Chart 9 – Indexed sales: Small brands that stopped advertising.



Note: Chart omits one prior-year value that is greater than the Y-Axis maximum (374).

All brand size groups show declines in the average index over time. But all groups also include brands that grew after stopping advertising. The most notable difference between groups is that average decline across cases is slower for the biggest brands (Chart 7) compared to the medium (Chart 8) or small brands (Chart 9). However the dispersion of sales indexes amongst the medium and small cases is extreme and there is little consistency over time. The medium and small subgroups both feature cases where a brand's sales index declined to near zero and was ultimately delisted, but no large brands reached a sales index less than 20 after stopping advertising (even after 10 unadvertised years).

Another difference between brand size groups is the length of time brands stopped advertising for (see Table 9 above). Bigger brands include some cases where advertising was stopped for 9 and 10 years, while the longest case amongst medium brands is 8 years, and small brands went unadvertised for no longer than 5 years. This may be related to the increased speed of decline of small and medium brands and their greater likelihood of being delisted.

In sum, splitting cases by brand size alone does little to clarify the variation in sales trends over time. The slower average decline for big brands is interesting but expected, as relative sales change will appear less extreme from their larger base figure. Brand size does provide additional insight when jointly considered with prior sales trend, as discussed in Section 6.5.

6.5 Results – Split by Prior Sales Trend and Brand Size

Using the definitions for prior sales trend and brand size outlined in Chapter Five, there are nine combinations of the two factors. Splitting the 57 cases into these nine groups means there are few examples in some groups (see Table 6, reproduced below). So while these two-factor subgroups make some patterns clearer, it comes at the cost of sample size and reliability.

Table 6 – Distribution of cases into brand size and prior sales trend subgroups.

Size \ Trend	Growing	Stable	Declining	Total
Big	4	7	6	17
Medium	4	5	8	17
Small	10	7	6	23
Total	18	19	20	57

Some of these two-factor subgroups produce more interesting results than others. For example, as discussed in Section 6.3, all brands whose sales were declining prior to stopping advertising continued to decline after stopping, irrespective of their size. Little additional insight is gained when declining brands are further separated by brand size.

The most interesting difference appears when previously growing brands are split by size. Charts 10, 11 and 12 display these results. The full set of charts is also provided in Appendix A.

Chart 10 – Indexed sales: Growing + Big brands that stopped advertising.

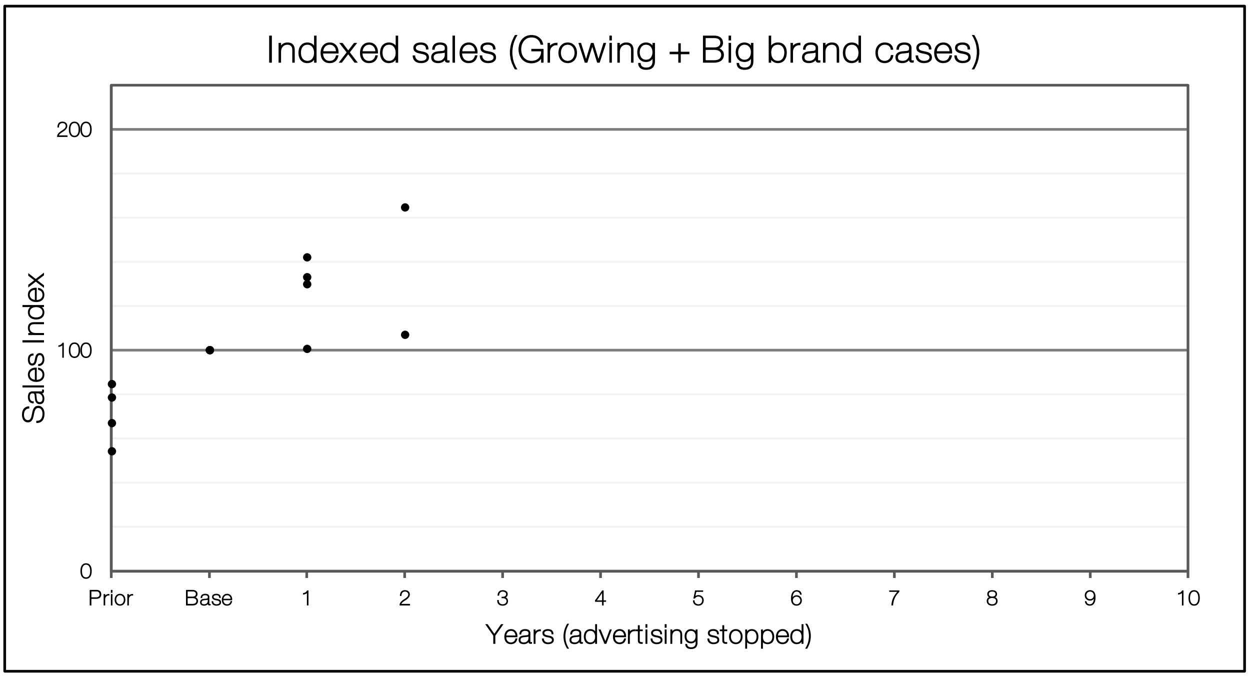


Chart 11 – Indexed sales: Growing + Medium brands that stopped advertising.

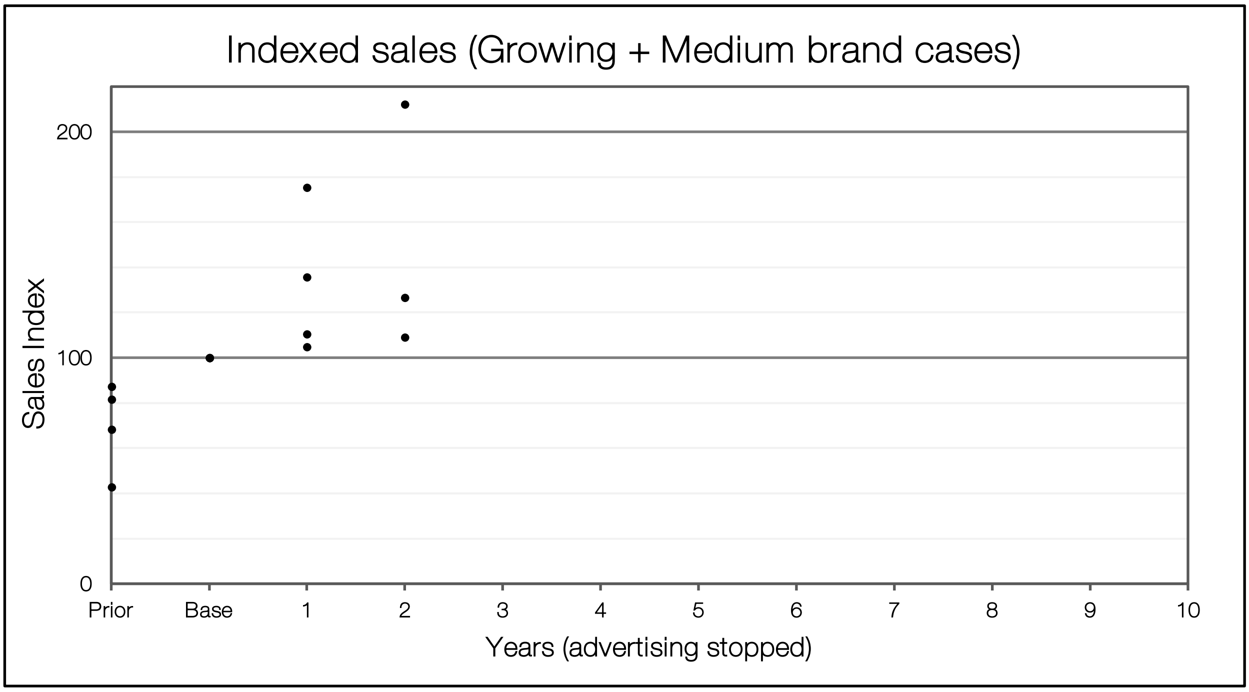
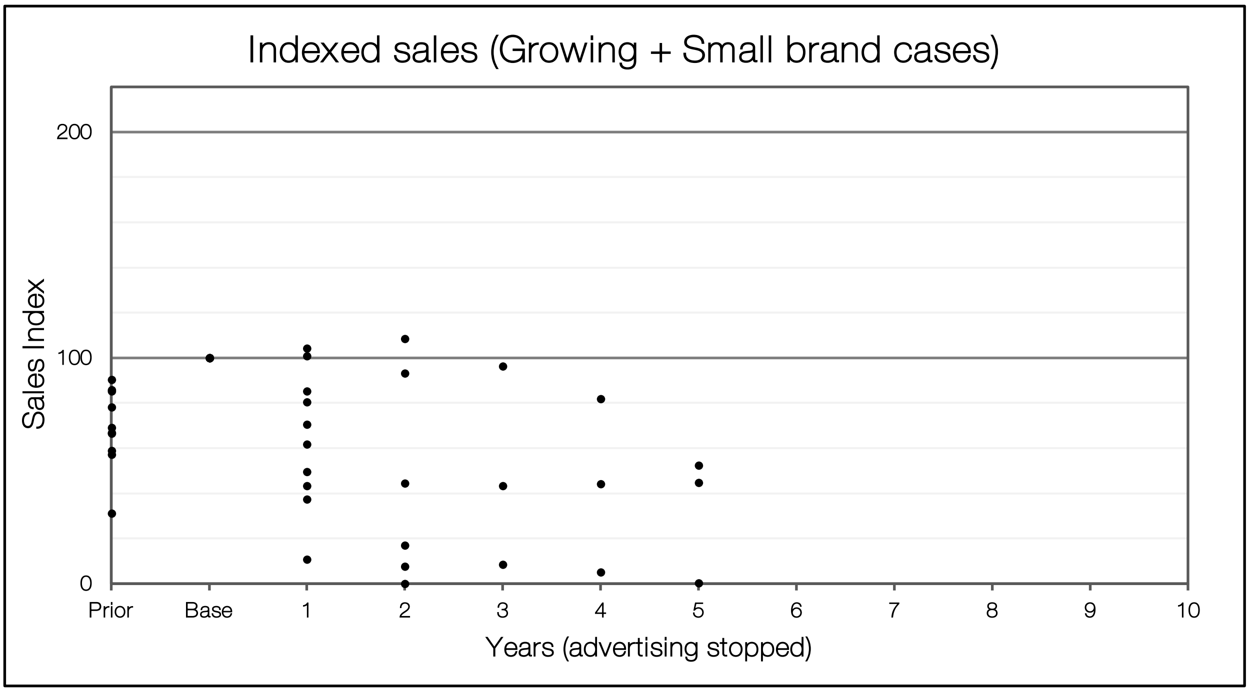


Chart 12 – Indexed sales: Growing + Small brands that stopped advertising.



Amongst brands with a previously growing sales trend, there is a clear difference in sales after stopping advertising between bigger and smaller brands. All big and medium brands (Charts 10 and 11) (n = 8) continued on a growth trend after stopping advertising, with sales indexes greater than the base year in the first unadvertised years. In stark contrast, all small brands (Chart 12) (n = 10) declined below the base year after stopping advertising, after only one year in most cases. The three brand size groups contain cases that were growing by similar relative magnitudes before stopping advertising, and all include brands from multiple alcohol subcategories (e.g. beer, cider, spirits, etc.). The difference is remarkably clear, and provides evidence for differences in the outcomes of stopping advertising related to brand size.

Another interesting sub-pattern is visible when the biggest brands in the dataset are separated by their sales trend prior to stopping advertising. Charts 13 and 14 below show the big + previously declining, and big + previously stable brands respectively, and can be compared with Chart 10 which shows the big + previously growing brands.

Chart 13 – Indexed sales: Declining + Big brands that stopped advertising.

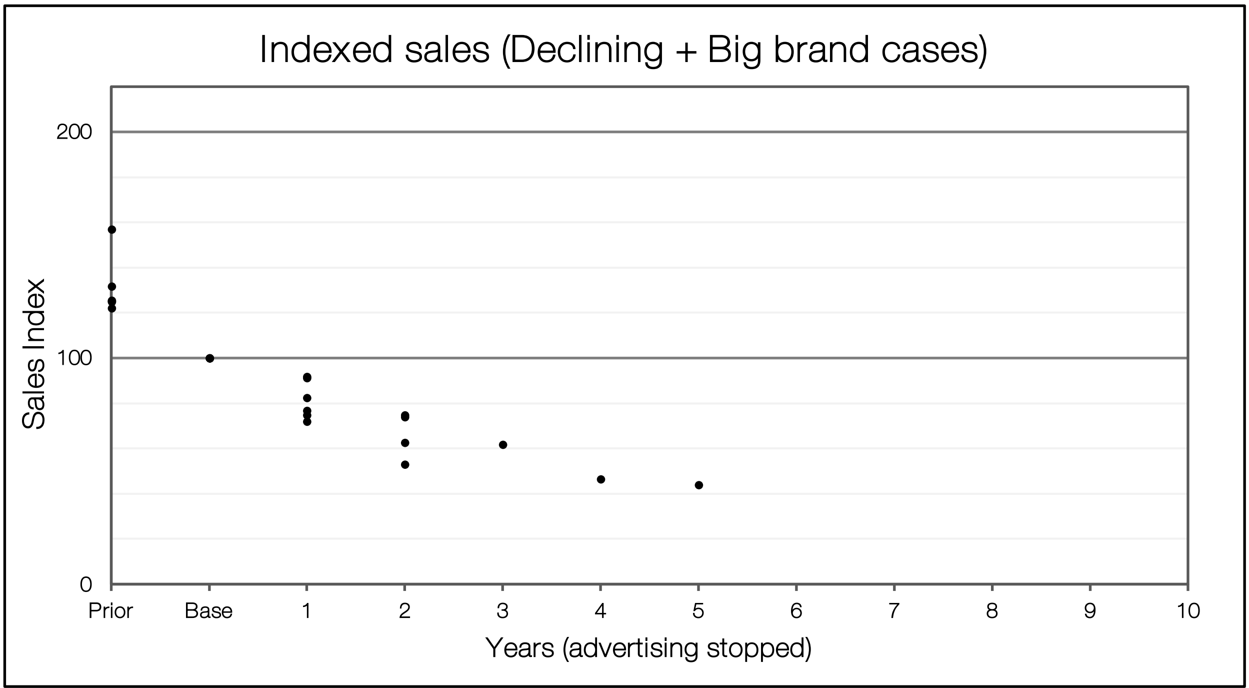
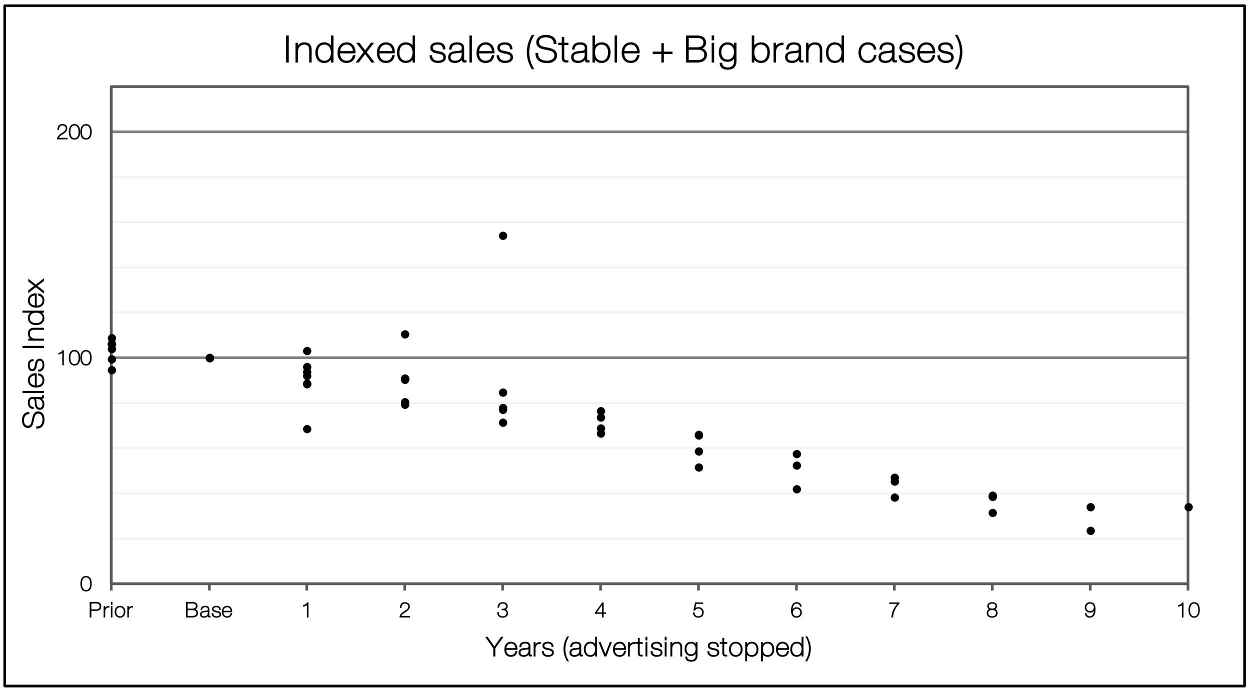


Chart 13 shows the six cases of big brands with declining sales trends prior to stopping advertising. When jointly considered with Chart 10 (big + previously growing), it suggests that stopping advertising had little effect on the trend in aggregate sales of the biggest brands when in growth or decline greater than 10%. All big brands growing by 10% or more before stopping advertising continued to grow after stopping, and all big brands declining by 10% or more continued to decline. The big brands on a stable trajectory, however, showed some initial stability after stopping advertising, but suffered more decline than growth as time without advertising increased (see Chart 14) (n = 7).

Chart 14 – Indexed sales: Stable + Big brands that stopped advertising.



Sales changes of big brands that were stable before stopping advertising (Chart 14) are remarkably alike across time. When advertising stopped for these brands, one case grew over three unadvertised years, and one case declined quickly after one year, but the rest (n = 5) all show a similar declining trend – even up to nine years. While this consistency is noteworthy, a factor of these cases being quite long (i.e. several years without advertising) is that some cases occurred in the same years as others (or there are some overlapping years where brands were not advertised at the same time). This means they may be victims of similar confounding circumstances that explain why their sales follow similar trends. For example, a restructure in the brand portfolio, particularly strong competitor activity, or any other forces that could have dampened sales for all of these brands simultaneously.

Unlike the big brands, the continued trajectory of strong growth or decline after stopping advertising was not observed in the smallest brands. Not only did all previously declining small brands index below 100 in every unadvertised year, but all previously growing small brands declined below the base year as well. Small brands tended to suffer more regardless of their prior sales trend.

Chapter Summary

This chapter presented the results of this thesis study, first in aggregate, then broken down by the size of the brands and their sales trend prior to stopping advertising.

The majority of cases experienced decline in yearly sales in unadvertised years, relative to their last advertised year. Of all cases, 54% reported a sales index of 90 or less after one year without advertising (-10% difference in sales). This proportion increases to 68% after two years and 71% after three. Decline was especially common amongst previously declining brands, and more severe on average for smaller brands in the dataset.

There were cases where brands' sales increased relative to the base year after they stopped advertising. All large and medium sized brands that were on a growth trajectory before stopping advertising continued to grow afterwards. There were also some previously stable brands that grew in unadvertised years, but these were the minority.

The next chapter discusses the results in reference to existing literature and theory, provides implications for marketing practice and research, and addresses the limitations of this study.

Chapter 7
Discussion and Conclusion

Chapter seven concludes this thesis. The chapter returns to the research questions of this study, and details the key findings with reference to existing research and literature. Implications are drawn, and the contributions to marketing theory and practice are discussed. The chapter also addresses the limitations of the results and comments on the future of research investigating stopping advertising.

7.1 What happens to brand sales after a brand stops advertising for a year or more?

A) On average, brands that stopped advertising reported decreasing yearly sales in unadvertised years relative to previous years when they were advertising.

Relative to the last year *with* advertising, sales were -16% lower on average after one unadvertised year, -25% lower after two unadvertised years, and -36% lower after three. Individual cases varied around the average in each year, but decline over time was the norm. Decline became more common and more pronounced across cases as the number of years without advertising increased.

Looking at only cases where brands went unadvertised for five or more years, and were not ultimately delisted addresses a selection effect where the mean over time is altered by cases dropping out of the sample. The eight cases observed all follow a similar trend in sales after stopping advertising, declining at a rate of around -11% per year.

Because of differences in research design and method, the results from this study are not strictly comparable with the earlier reviewed literature. For example, the split cable experiments discussed in chapter three report the average difference in sales between groups of households that see different amounts of TV advertising (Hu, Lodish & Krieger 2007; Hu et al. 2009; Lodish et al. 1995). Similarly, Ackoff and Emshoff (1975) report the difference in sales between test markets and matched control markets. The present study instead observes longitudinal change over time, relative to the previous advertised years' sales, which means the sales change figures are not equivalent. Quantifying sales changes relative to matched control conditions (e.g. a test market where the same brands remain advertised) was not possible in this study.

A broad conclusion reached in Chapter three, regarding evidence from the split-cable studies, is that stopping TV advertising for 12 months may not always have an observable effect on sales, but if it does, it is likely to be a decrease. This is qualitatively similar to the conclusion from the present research. My results suggest that when brands stop advertising for one year, sales outcomes can vary greatly, yet the most likely outcome for sales is decline (relative to the previous advertised year). Lodish et al. (1995) report that for established products, after one year of reduced TV advertising, the average difference in sales volume amongst significant tests was -23%. This average difference is calculated from only the tests that showed a significant effect (only 33% of the established product weight tests conducted), which means that average change would likely be closer to zero (perhaps closer to the -16% change observed in this study) if the other non-significant tests were included.

B) Not all cases declined after stopping advertising. There is much variation around the average. Some brands grew after stopping advertising, while others declined rapidly.

After one year without advertising, sales indexes across all cases ranged from 175 to 3. The spread in sales indexes widened after two years without advertising (212 to 0.1).

Although the majority of cases declined over time, 8 out of 57 cases reported a 10% or greater increase in sales after one year without advertising. There were 6 such cases out of 34 after two unadvertised years and one case showed continued growth after three unadvertised years. Many of these growth examples came from brands that were already on an increasing sales trend when their advertising stopped, however some had previously stable sales. There are also cases in which sales remained stable after three years without advertising.

Jones (1990) and others have shown how a brand's relative sales (i.e. market share) can decline if the brand consistently spends less than its relative maintenance level of advertising spending (derived from SoV=SoM or AI benchmarks). However, while not strictly observed here, it seems implicit that a brand could see continued growth in *absolute* sales while not advertising for longer than three years. Some cases were growing extremely rapidly after one and two years without advertising and looked to continue growing even if they remained unadvertised. It appears that under certain conditions (e.g. if brands can support sales in other ways, or if its product category is expanding as a whole), advertising is not vital for maintaining a growing sales trend (see Kennedy 2016, for a discussion of brands that grew without advertising). Similarly, "Global brands" that are taken to a new market may find stopping advertising to be less of a barrier to growth (one such case was observed but removed from the final sample because it was extremely outlying). Due to their global status they may already be well known by potential consumers (e.g. from news and television, or from people travelling, etc.). In addition, they may have established marketing programs and other economic advantages to grow in new markets (e.g. distribution networks or power with retailers).

In this dataset, most cases where a brand grew in the first year without advertising are only one or two unadvertised years long. There were no cases where a growing brand went unadvertised for longer than three years. Advertising was paused for some growing brands but restarted perhaps when they showed continued growth. In a discussion with the data provider they disclosed that their media decisions often consider the broader portfolio of brands, and advertising support is typically invested in brands that are likely to provide strong returns – 'we've been known to back the winning horses' (Personal communication, 9 Dec 2016). This strategy could explain why brands that continued growing after stopping advertising did not stay unadvertised for long. However, this statement was made in retrospect, and may simply be a post-hoc rationalisation of earlier decisions. Regardless, the sample of cases is not random, and likely subject to some selection bias (e.g. poorly performing brands may be less likely to receive advertising support).

Variation in sales outcomes across cases is to be expected, as brand sales are often influenced by many and varied forces other than advertising. For example, brands could have spent the money saved by not advertising on other activities that either supported or impaired sales. There could have been changes in pricing tactics or distribution, or changes in competitors' marketing strategy or infinite other unpredictable marketplace factors that combined to produce the sales changes observed in each case. However, a reasonably large number of cases were examined in this study, and every case is subject to unique variation from confounding market forces. Not every case will have reinvested the savings from not spending on advertising, or been subject to fierce competitor advertising while unadvertised. So the confounding influences on sales in each case are controlled to some extent by the volume of cases examined.

To illustrate, consider one potentially major confound on brand sales: company performance. A failing company may be more likely to cut costs and stop advertising, and is simultaneously more likely to see decline in sales. These conditions would bias results; making decline more likely to be observed when advertising stops. In the present research, the market share of the holding company grew and declined at times during the 20 years studied. The cases analysed included brands that stopped advertising at different times over the years (e.g. there is at least one case beginning in every year from 1998–2015). So although some brands stopped advertising when the company was in broader decline, the overall results are offset by other brands that stopped during times of company prosperity.

The cases observed in this study involve:

- Different sized brands,
- With different prior sales trends,
- In different alcohol subcategories,
- That spent different amounts on advertising before stopping,
- And stopped advertising at different times.

Each case was undoubtedly subject to other market forces that influenced sales as well. There is little wonder then that results varied across cases. Nonetheless, it is compelling that there is some regularity across cases in sales changes over time. Future research with tighter controls may find even more uniformity in what happens when brands stop advertising.

7.2 How do aggregate sales differ after stopping advertising for different brands?

Splitting cases into subgroups based on brand size and prior sales trend helped to explain some of the variation across cases. There is some evidence of consistent differences in sales outcomes based on whether a brand was growing, stable or declining prior to stopping advertising, and whether it was a big, medium or small brand. These factors serve, to some extent, as boundary conditions of the broad findings discussed above. They reveal where a pattern is found not to hold, or to be different from the norm. It must be noted, however, that arranging cases into smaller groups means fewer cases in each group. The sample sizes are small, so the findings discussed here are tentative.

C) Considering only brand size, there is some evidence of a 'size advantage' for bigger brands when stopping advertising.

Splitting cases by brand size alone did little to clarify the variation across cases in sales trends. Decline is observed in the average sales index in unadvertised years for all brand size groups. However on average, the smallest brands declined more rapidly than the medium brands, and the medium brands declined more rapidly than the big brands. No big brands reported a sales index below 20, even after ten years without advertising, while the medium and small subgroups both contain cases where brands declined to near zero and were ultimately delisted.

The less severe declines reported by bigger brands suggest they have an advantage over the smaller brands when stopping advertising. This 'size advantage' is consistent with prior advertising research. Evidence from in-market split cable weight tests suggests that big, established brands are less likely to report large differences in sales after 12 months without advertising (Hu et al. 2009; Riskey 1997). Bigger, more mature brands typically have smaller advertising elasticity than smaller brands, and are thus less affected by changes in spend (Assmus, Farley & Lehmann 1984; Danenberg et al. 2016; Sethuraman, Tellis & Briesch 2011). Bigger brands also enjoy several scale advantages over smaller brands, such as more other marketing activities, greater mental and physical availability, and a larger base of potential users with some propensity to buy them (Sharp 2010), which perhaps better insulates their sales when cutting mass media spending. This finding also aligns with research into the relationship between brand size and advertising budgets. Evidence suggests that bigger brands can afford to slightly underspend on advertising (relative to their size) without consequence, while smaller brands often have to overspend to maintain their position (Binet & Field 2007; Danenberg et al. 2016; Hansen & Bech Christensen 2005; Jones 1990). This predicts that smaller brands would suffer more after stopping advertising, which is observed in the current research.

The size advantage sub-pattern is apparent when comparing average sales indexes across the three brand size groups, but there is extreme variation in individual cases amongst the small and medium-sized brands. The mean index in these subgroups does not describe a *typical* case particularly well. One reason for this variation is the base level that sales changes are measured from. Smaller brands have a smaller base level of sales, which exaggerates relative changes. There is little consistency in the variation in sales indexes among the small and medium sized brands, and cases generally appear scattered. The large variation within groups suggests that more factors contribute to the outcomes of stopping advertising than brand size alone. The scatter in each group may be partly because they include cases of brands on vastly different sales trends before they stopped advertising. Differences between the prior sales trend subgroups were more prominent.

D) A brand's sales trend prior to stopping advertising seems related to its sales trend after stopping advertising.

On average, sales indexes declined after stopping advertising in all three prior sales trend subgroups. However, there are differences in outcomes across the subgroups.

Every brand that was on a *declining* sales trend before stopping advertising reported below base level sales in unadvertised years. This continued decline was irrespective of brand size (i.e. same for bigger and smaller brands).

Previously *stable* brands fared better on average, showing continued stability in the first two to three years without advertising. Unlike the previously declining brands, there were examples of previously stable brands growing after stopping advertising. The sales stability without advertising support possibly occurred due to investment in other marketing activities, but likely also because consumers' choices in repeat purchase situations are largely habitual. Evidence suggests that in repeat purchase situations, when consumers make choices between alternatives, habitual repetition of behaviour (manifesting as a bias or preference, e.g. brand loyalty) is the norm (Livaditis 2013). For stable brands that stopped advertising, this 'inertia' in purchase propensity may contribute to the continued stability.

Brands that were *growing* before stopping advertising showed the greatest proportion of growing cases after stopping. Nearly half of previously growing cases indexed above base level sales (i.e. continued growing) in the first two unadvertised years.

Despite the fact that decline was the most common outcome in all three sales trend subgroups, there is more stability amongst previously stable brands and more growth amongst previously growing brands. These differences in sales outcomes suggest that a brand's sales trajectory *before* it stops advertising is somewhat indicative of its trend *after*. For these cases, it may be that whatever drove sales growth or decline before advertising stopped continued to do so in unadvertised years. In other words, if other forces are responsible for a brand's sales trend, stopping advertising may have little consequence on the trend.

Splitting cases into subgroups based on their prior sales trend helped explain the variation in sales outcomes after stopping advertising better than brand size. However, brand size does prove important when jointly considered with sales trend. The results of analysing the two-factor (size and trend) subgroups are now discussed. The findings must be cautioned, as the sample size of these subgroups is very small (e.g. some have as few as four cases).

E) Bigger brands on a growing trend continued growing after stopping advertising – the trend continued relatively uninterrupted by stopping advertising. Small brands on a growing trend stopped growing after stopping advertising.

The sales of previously growing brands after stopping advertising showed a clear difference based on brand size. Large and medium brands that were growing when advertising stopped continued to grow. Small brands that were growing all stopped growing and declined below base level sales – most after one year without advertising. This makes clearer the size advantage for bigger brands, discussed above.

The pattern observed suggests an advantage for bigger brands akin to greater momentum in sales growth. An already-large and growing brand may continue to grow despite its advertising being cut, because of advantages in other marketing functions and market-based mental and physical availability. While smaller or younger brands, which are less mentally and physically available and also typically have higher advertising elasticity (Sethuraman, Tellis & Briesch 2011), may rely more heavily on their advertising to continue growing.

This study is especially fortunate to observe four examples of big brands on a growing trajectory that stopped advertising, as it seems like it would be an uncommon situation. It seems unlikely that managers would declare a large and growing brand as not worthy of advertising support. That they all continued to grow (and mostly on the same trajectory as prior advertised years) is especially interesting, and may have useful implications for budgeting planning.

F) Bigger brands' sales trends appear generally uninterrupted by stopping advertising for one to two years.

Big brands that were growing by 10% or more before stopping advertising kept on a relatively unchanged growing trend after stopping advertising. Likewise, the previously declining big brands kept declining after advertising stopped. In general, big brands on a marked trend in yearly sales typically remained on the same trend after stopping advertising for the first year or two. This may be another example of habitual purchasing or 'inertia' more strongly influencing sales trends than advertising changes. Most cases in these subgroups last only one or two unadvertised years so longer-term outcomes could not be explored.

The subgroup of big brands that were stable before stopping advertising contains several cases of longer-term advertising stops. Like the growing and declining brands, the pre-stop trend (stability in this case) is maintained by most cases after stopping advertising for one or two years. Amongst cases that went unadvertised for four years or longer, there is gradual decline in yearly sales over time. A continued sales trajectory after stopping advertising for one to two years seems common amongst the biggest brands, but longer periods without advertising make decline more likely. This notion can be put simply with an analogy:

'The sales of a brand are like the height at which an airplane flies. Advertising spend is like its engines: while the engines are running, everything is fine, but, when the engines stop, the descent eventually starts.'

(Broadbent 1989)

Theories of how advertising works offer some rationalisation for what was observed here. One of the most empirically grounded theories is that advertising works as Creative Publicity (Ehrenberg 1974; Ehrenberg et al. 2002). The theory proffers that advertising is rarely a persuasive or demand-inducing force for brands, but rather a mild "nudging" tool (Barnard & Ehrenberg 1997). Advertising serves mainly to publicise brands and remind consumers of its availability as an option in its product category (Weilbacher 2003). Advertising refreshes consumers' existing memories of the brand (and sometimes creates new memories), making the brand more likely to be thought of and chosen when consumers enter a purchase situation (Sharp 2010). Thus, advertising improves the likelihood (or propensity) of the brand to be purchased. Advertising is also a defensive tool to combat competitors' advertising and their efforts to nudge their purchase propensity (Ehrenberg 1974).

The Creative Publicity theory fits with many of the predictable patterns identified in consumer behaviour and brand performance (Barnard & Ehrenberg 1997; Ehrenberg 1974; Sharp 2010). It also explains why advertising is rarely responsible for large or immediate changes in sales (compared to other marketing actions, e.g. expanded distribution) (Lodish & Mela 2007; Tellis 2009). The theory implies that stopping advertising would also be unlikely to cause immediate or dramatic changes in sales. But stopping advertising does remove the gentle reminding influence and allow competitors to nudge consumers unchallenged. As mental availability is eroded over time, so may sales be in the longer-term. The outcomes observed for big, previously stable brands that stopped advertising for many years support this notion. Their sales trend is not immediately affected by stopping advertising (first one to two years), but decline occurs when brands remain unadvertised for longer.

7.3 Implications and Contributions

7.3.1 For marketing knowledge and theory

The process of discovering and using empirical generalisations takes a long time (Ehrenberg 1969; Tellis 2017). To develop an empirical generalisation or scientific law you need to observe an event or relationship, confirm that it repeats, and document (through replication) conditions that do and do not affect the event (Sharp & Wind 2009). Much additional research is required to refine what has been investigated in this research. But 'if one studies the things which are regular, one will find regularities' (Ehrenberg 1969, p.15). This thesis contributes to marketing academia by finding evidence of regularity in the sales of brands that stop advertising. Yearly sales in many cases appear to move together over several unadvertised years despite vast differences in the conditions of each. Two factors are also confirmed to be useful to explain variability in sales outcomes when brands stop advertising (brand size and prior sales trend). The findings of this thesis compel further research into the sales outcomes of stopping advertising, to refine the patterns found and possibly reveal further generalizability and or conditions where this knowledge varies.

This thesis contributes broadly to the area of behavioural or sales-based advertising research. Chapter Two discussed the distinction between intermediate and behavioural measures of advertising's effect. Despite being generally considered superior to intermediate measures (Jones 2006), behavioural or sales-based research remains comparatively rare in the advertising literature. The present research observes the sales of real brands in a competitive marketplace, and develops findings related to in-market performance. Through its behavioural measure, this research offers more practical knowledge to the literature.

More specifically, this research adds new empirical evidence to two areas of advertising research scarcely explored with sales data: what happens when advertising stops and long-term changes in spend. It may seem intuitive or uninteresting that sales declined on average after advertising stopped. There is much research showing the positive effect of advertising, so it is fitting that a negative outcome was common where there was *no* advertising. However, published empirical evidence of what occurs when brands stop advertising is lacking. In-market, sales-based research into *stopping* advertising is understandably rare, as it entails some element of risk for the focus brand. Published examples of brands stopping advertising for multiple years are rarer still, presumably because the perceived risk of more serious damage escalates over time. As such, most in-market studies of stopping advertising evaluate results after only one or two unadvertised years. In many cases one year is not long enough for significant changes in sales to appear (Lodish et al. 1995). The present study contributes to this matter by analysing several cases where brands went unadvertised for multiple years, which also means the findings may serve as a benchmark for future research.

Finally, this thesis responds to calls in the literature for simpler analytical methods and data presentation. Andrew Ehrenberg – a pioneer of empirical generalisation in marketing research – believed that well presented data would communicate information on its own, without needing complex statistical manipulation (Ehrenberg 1975; Scriven & Goodhardt 2012). Science often seeks to simplify the complexities of our world (Sharp & Wind 2009), so simplicity and brevity are virtuous qualities of interesting and impactful research (Tellis 2017). With this in mind, much data was extensively cleaned and arranged as part this thesis, in order to produce simple graphics. The way cases are presented, along the same timeline and indexed for comparison, allows us to easily absorb the results.

7.3.2 For marketing industry practice

Marketing practice improves when marketers use evidence to support their decisions (e.g. Kennedy & Mccoll 2012). Knowledge of the outcomes of alternative tactics gives marketers a window into what-if scenarios for their brands. The findings of this research apply to companies thinking of stopping a brand's advertising, which is a common scenario that lacks specific empirical attention.

Faced with financial pressure, a natural reaction for companies is to cut seemingly nonessential expenses and free up cash. Advertising is commonly abandoned here. The findings of the present research, chiefly that sales most commonly declined after brands stopped advertising (even for previously growing brands and after only one year), may assist marketers to defend their advertising budgets when facing cuts. More research is required to understand the causal effect of stopping advertising, but since advertising (and marketing in general) has been perceived to lack accountability, research into how sales trends evolve when it stops may help justify its role.

Inversely, understanding the conditions where little change in sales trends followed a stop may help combat over-advertising, and therefore save brands money. It has been suggested that many brands may be spending more than necessary on advertising (Aaker & Carman 1982; Cheong, De Gregorio & Kim 2014), and wasting precious resources that could be better used elsewhere. In the present research, large and growing brands continued to grow for two years after stopping advertising. This may be a condition where brands can effectively withstand an advertising hiatus, however we can't be sure if they wouldn't have grown by *more* had they kept advertising. Stopping advertising entirely is an extreme approach to combat overspending, but this study forms part of the wider research into efficiency in advertising spending. An evidence-based answer to how long a brand can safely stop advertising for (and which brands, under what conditions), would allow managers to improve efficiency in their spending. More research and replication of these results are required to get to this point, however.

Finally, if budget cuts cannot be avoided, and the advertising purse strings are tightened, research such as this can help marketers make informed decisions when distributing the remaining allowance between brands in a company's portfolio. Given a limited advertising budget, an even split of expenditure between all brands may mean far less-than-effective levels for any one brand. In this case advertising may be cut for some to focus on others. The present research found some consistent variation in the sales of unadvertised brands based on whether they were big, medium or small, and previously growing, stable or declining. The sales trend of previously growing big brands seemed relatively unaffected by stopping advertising, but previously growing small brands all stopped growing and declined below base level sales. Understanding differences such as these may be useful to support managers' budget allocation decisions. Depending on the company's objectives for each brand and the portfolio as a whole, funds could be shifted between brands based on the likely outcomes of stopping their advertising (e.g. if cutting advertising is likely to damage one brand more than another).

7.4 Limitations

This thesis is a step towards better understanding the outcomes of stopping advertising. The results however are qualified by several limitations, which are now discussed.

A major limitation of this study, but one that affects most in-market, sales-based natural experiments is the lack of controls on confounding variables. The analysis examined only advertising media spend in relation to aggregate sales, but many other internal and external forces are known to influence sales as well. Changes in pricing and promotions, distribution, competitor activity, consumer buying behaviours and other marketplace forces likely contributed to the changes observed here. The period of the dataset also saw several disruptive changes in the Australian alcohol market, such as large mergers between alcohol companies and corporate takeovers, new competitor entrants, a notable trend toward premium "craft" brands, changes in physical and online distribution, changes in category sizes and trends, and more. The sole effect of stopping advertising on sales cannot be revealed without removing or controlling the myriad of other influences. The issue was described well by Aaker and Carman (1982, p.68), who wrote '*looking for the relationship between advertising and sales is somewhat worse than looking for a needle in a haystack.*' Controls were not possible in this study, as the data comes from the normal operation of real brands in real competitive markets, and information on other variables was limited.

The sample of brands analysed is also non-random, and is likely subject to several biases. Surveys have revealed that it is common for advertising budgets to be set as a percentage of sales (West & Crouch 2007; West, Ford & Farris 2014), so advertising spend for many brands may in fact be a function of performance, rather than a determinant of it. Brands whose advertising is stopped may be otherwise additionally neglected across various other marketing activities. Even if all major marketplace events were noted, the direction of influence may still be unclear (in other words, sales decline might lead to advertising cessation, rather than cessation leading to decline). Another issue is that the brands analysed are managed by a single company, but compete with each other in the market to some extent. The savings from not advertising one brand may be reinvested to support another (competing) brand. This means that decline observed in the unadvertised brand could be due to the success of a further-supported competitor brand, on top of the stop in advertising.

The generalisability of the findings is as yet unknown, as the results pertain only to one product category in one country (alcohol in Australia). Replication of this study is necessary to reveal the extent that patterns are common to other conditions.

7.5 Future Research

This thesis has identified several interesting threads that invite additional research. There are rich areas to pursue.

A great leap in understanding what happens when brands stop advertising will come from repeating this study using additional new data, as the generalizability of results is currently unknown. Replication(s) will determine the extent that these results can be reproduced under different conditions (Lindsay & Ehrenberg 1993). An ideal extension would involve different product categories, additional countries and/or additional measures of performance (e.g. market share, value sales, etc.). Results become more robust, predictable, and managerially useful if they are found to be similar, or even different in some consistent way, under known conditions.

Future behavioural research into brands stopping advertising – and replications of the present study – would benefit from clarifying the relationship between advertising and sales. Advertising is only one small factor in a myriad of forces that influence sales. Removing, controlling or documenting confounding variables on the relationship will make the sales effect of stopping advertising clearer. To that end, future research should utilise more granular data than aggregate sales. It is extremely difficult to attribute changes in aggregate sales to advertising alone. Revealing causal links between stopping advertising and sales will require data generated in other ways, such as controlled in-market experiments ideally with individual level single-source tracking (which are becoming more possible in today's changing technological environment). These methods make it possible to control and remove other influences on sales, and have been used to address several questions about advertising. As of yet, there are no published examples of these methods being used to specifically study brands stopping advertising for long periods.

This thesis split cases by brand size and their prior sales trend, to see whether any clear differences in sales outcomes appeared. Future research is encouraged to consider other influences that may contribute to differences in outcomes when brands stop advertising, including:

- Weight of prior advertising / share of voice
- Weight of category advertising
- Creative content and effectiveness of prior advertising
- Longer-term brand and category sales trends (i.e. expanding / contracting)
- Halo effect of advertising other brands
- What is done with the savings from not advertising
- Interactions with changes to other marketing activations especially relationship to changes in distribution and promotion levels.

Another related question that currently lacks an evidence-based answer is what happens when previously unadvertised brands *start* advertising? Research in this field could investigate both brands that have never advertised and those that have paused advertising for some time before restarting. Some discussion suggests it can take a long time and be quite challenging for brands to reverse sales decline after stopping advertising (e.g. Millward Brown 2012; Sutherland & Sylvester 2009). Additional empirical research to clarify this phenomenon and document outcomes across conditions would be enlightening, and have important implications for brands that stop advertising.

Advances in data collection (mainly from new technologies) look to make sales-based or behavioural advertising research more practical in the future. However, continuing research into what happens to real brands' in-market performance when they stop advertising for long periods may be challenging. The data requirements are quite specific, so useable cases are not easy to come by. Perhaps one reason why little research exists into stopping advertising is the scarcity of examples of brands stopping advertising for long periods. Managers might make small cuts or experiments, but panic if there is decline or some other event (e.g. change of management) and quickly restart. To generate new primary data may require convincing companies to stop advertising their brands (potentially putting them at risk) and waiting long enough for useful data. This requires discipline and patience, but has the benefits of allowing researchers to enact controls or track other marketing mix activities, and explore the impact across a broader range of brands (rather than a skewed sample). On the other hand, it may be unwise to gamble with the health of real brands (and shareholders' investments) for the sake of research. The other option is to mine historic sales and advertising datasets that include brands that stopped advertising (such as the one examined in this thesis). Natural experiments where brands stopped advertising may be more readily available for analysis and do not impose any additional risks to brands, but similar problems related to lack of controls would apply.

Chapter Summary

This chapter concludes this thesis. The key findings have been discussed with reference to existing literature, the contributions of this research to academia and industry practice have been outlined, and the limitations of this study addressed, providing directions for future research.

The results of this study find that most brands that stopped advertising experienced decline in sales in unadvertised years, relative to previous years when they were advertising. Sales decline was most severe among smaller brands and previously declining brands. A consistent exception was found amongst bigger, previously growing brands, which all continued growing after stopping advertising.

There are few benchmarks in the existing literature to compare these findings to. This thesis is thus a first step towards documenting what happens when brands stop advertising for many years. The results are limited in scope, as the findings currently pertain to one product category in one country, and the study lacks the controls of split cable experiments and the like, meaning that the causal effect of stopping advertising on sales cannot be inferred. Nonetheless, the findings hint that some regularity exists in brand sales changes after stopping advertising, and that further generalisation may be possible.

Though it may be challenging, future research into stopping advertising is encouraged to extend the scope of the current findings.

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Appendix A
Additional Charts and Figures

The figures behind charts 4 through 9 are provided below. Also included in this appendix are the full set of two-factor subgroup charts, of cases split by both brand size and prior sales trend.

Table A1 – Mean indexed sales, cases split by prior sales trend.

Years	Prior	Base	1	2	3	4	5	6	7	8	9	10
Previously declining brands (n)	20	20	20	12	6	4	3	2	2	1	0	0
MSI	162	100	66	44	43	31	37	33	29	1	-	-
Standard deviation	60	0	29	33	39	27	26	38	34	-	-	-
Previously stable brands (n)	19	19	19	11	8	5	5	4	4	3	2	1
MSI	103	100	94	94	86	60	50	39	33	36	29	34
Standard deviation	5	0	18	28	36	27	24	24	21	4	7	-
Previously growing brands (n)	18	18	18	11	3	3	3	0	0	0	0	0
MSI	70	100	93	90	49	44	32	-	-	-	-	-
Standard deviation	16	0	42	67	44	38	28	-	-	-	-	-

Table A2 – Mean indexed sales, cases split by brand size.

Years	Prior	Base	1	2	3	4	5	6	7	8	9	10
Big brands (n)	17	17	17	12	6	5	5	3	3	3	2	1
MSI	106	100	96	90	88	66	57	51	44	36	29	34
Standard deviation	25	0	21	29	33	12	9	8	5	4	7	-
Medium brands (n)	17	17	17	11	6	3	3	3	3	1	0	0
MSI	119	100	89	89	53	29	25	23	20	1	-	-
Standard deviation	45	0	39	60	41	26	30	31	29	-	-	-
Small brands (n)	23	23	23	11	5	4	3	0	0	0	0	0
MSI	114	100	72	45	49	33	32	-	-	-	-	-
Standard deviation	71	0	33	49	46	38	28	-	-	-	-	-

Chart A1 – Indexed sales: Growing + Big brands.

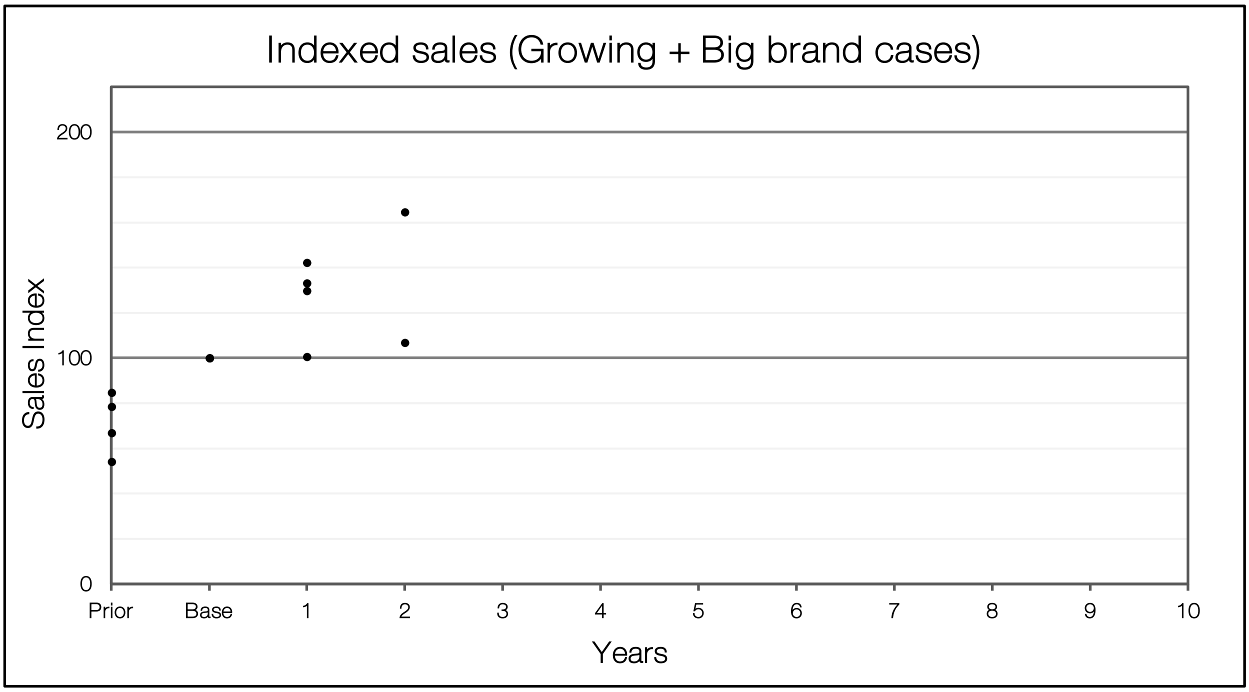


Chart A2 – Indexed sales: Growing + Medium brands.

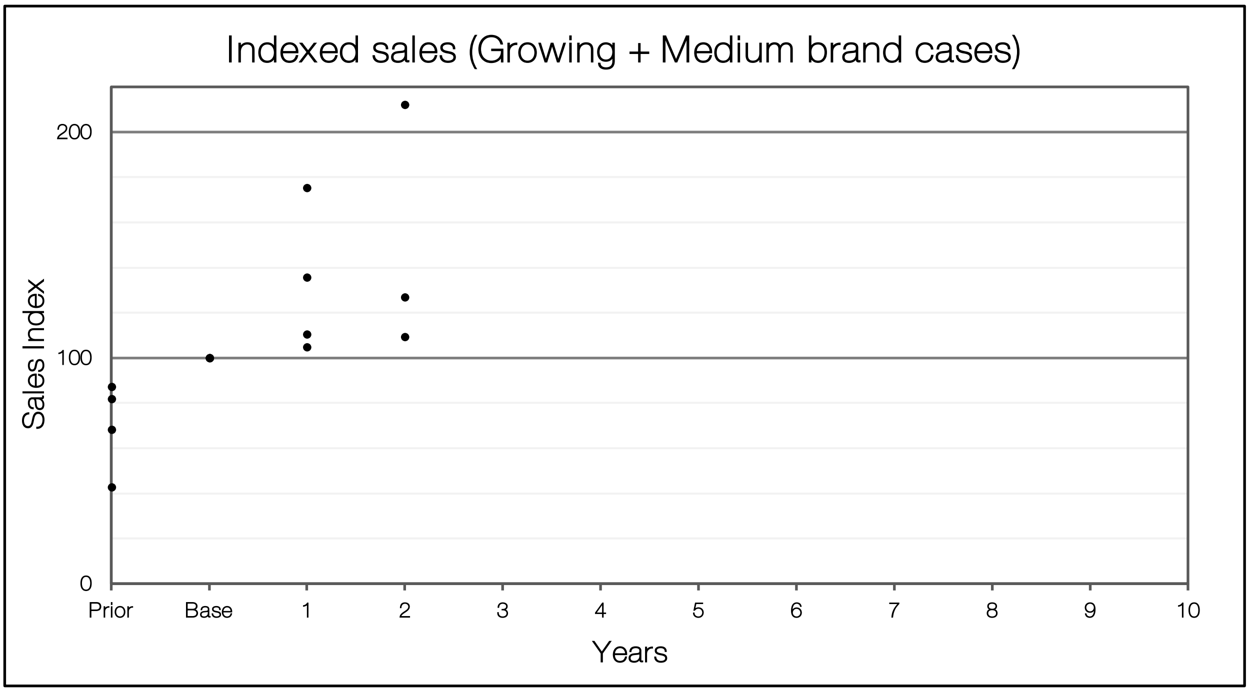


Chart A3 – Indexed sales: Growing + Small brands.

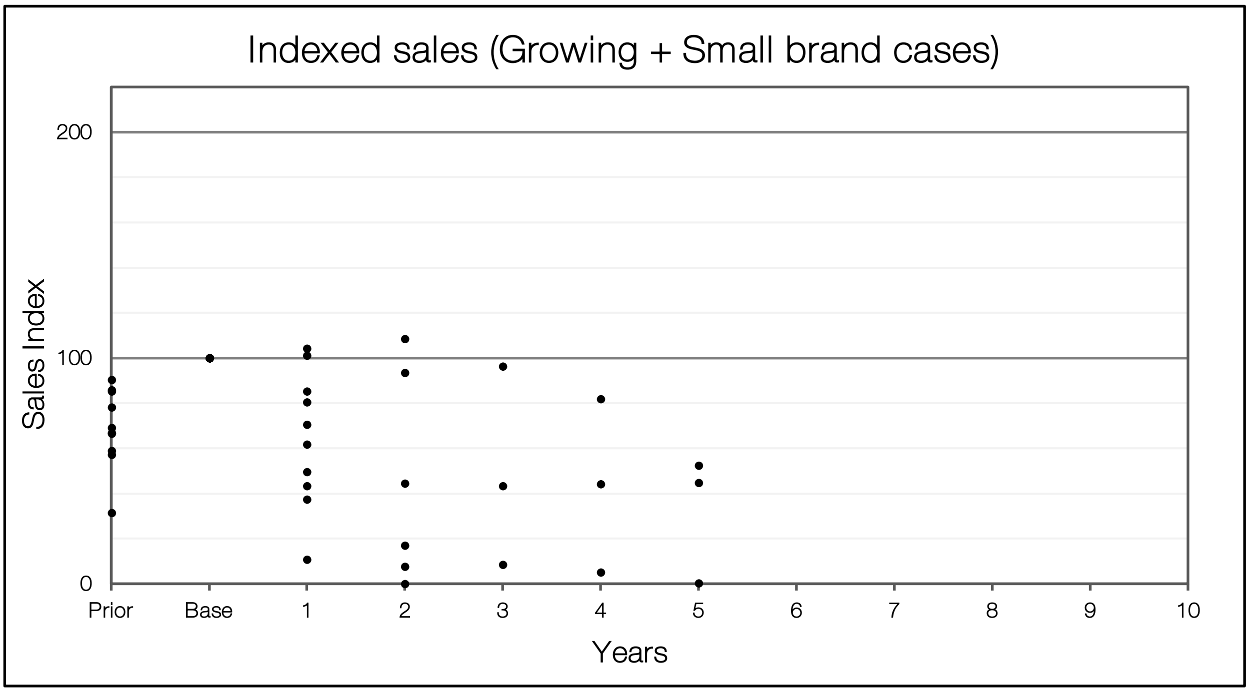


Chart A4 – Indexed sales: Stable + Big brands.

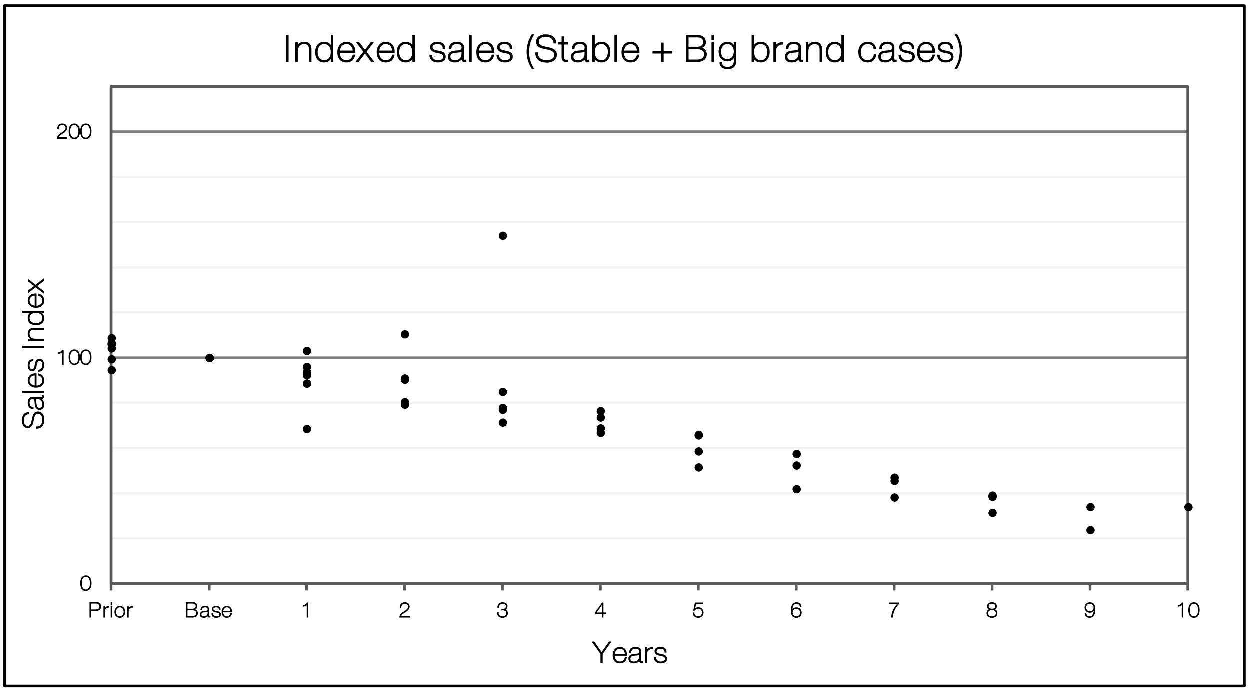


Chart A5 – Indexed sales: Stable + Medium brands.

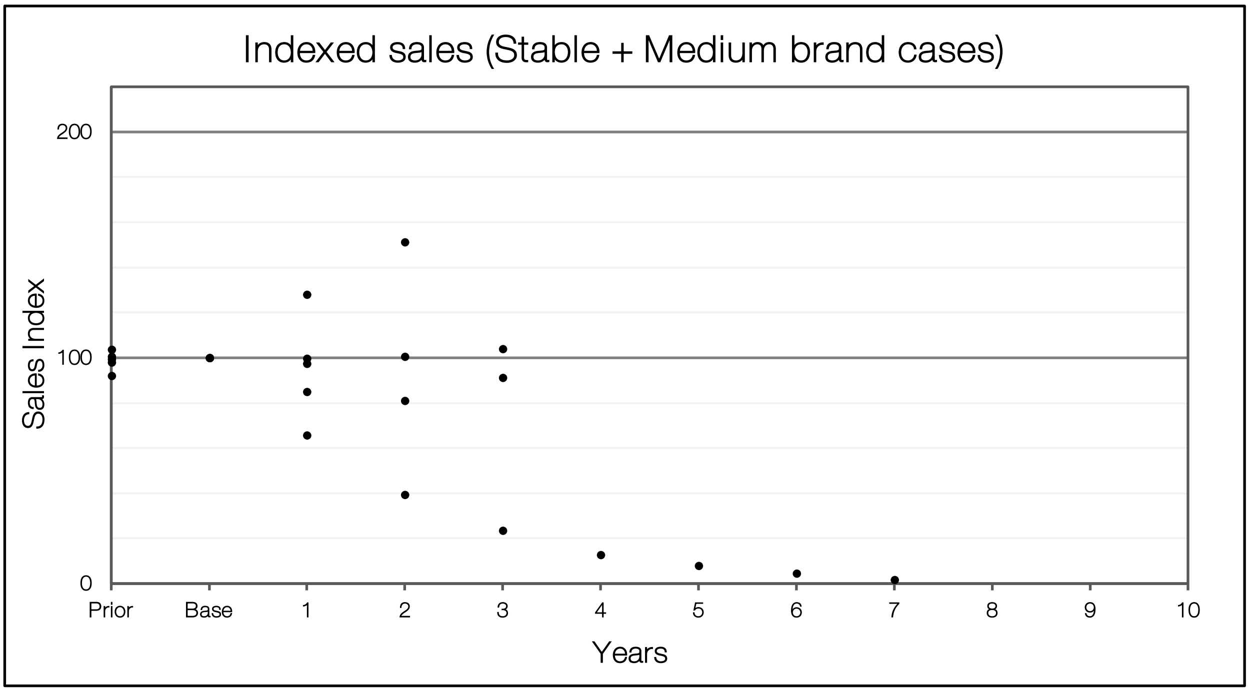


Chart A6 – Indexed sales: Stable + Small brands.

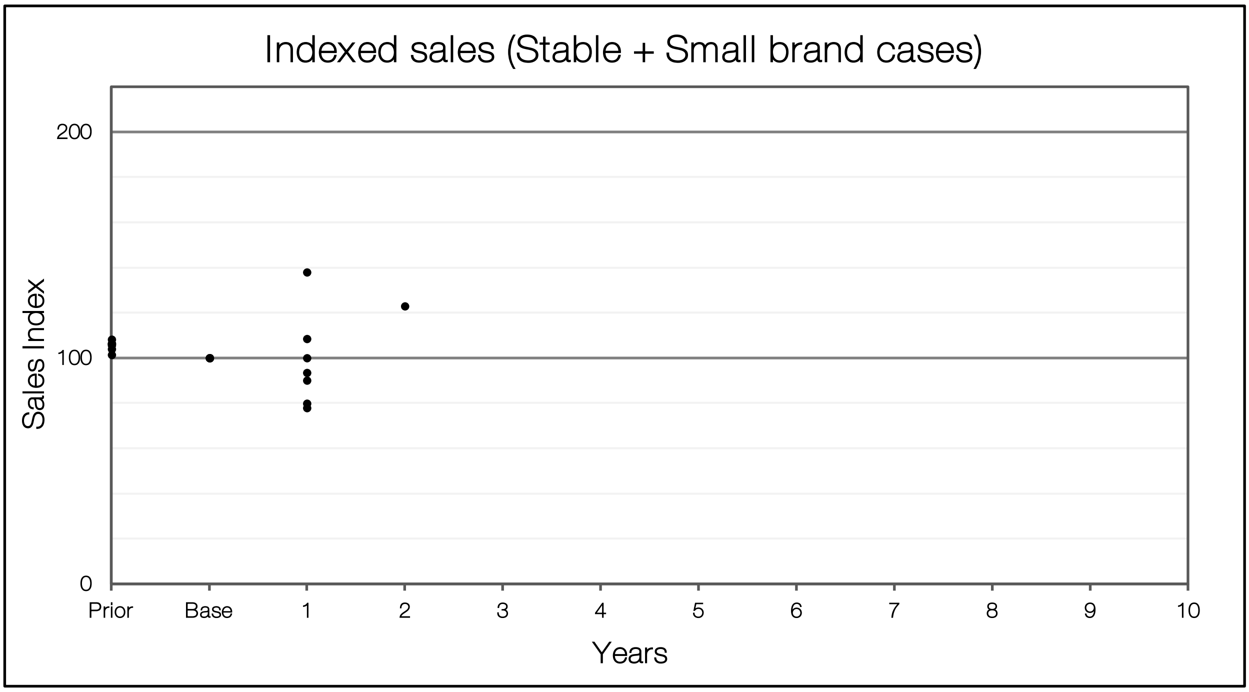


Chart A7 – Indexed sales: Declining + Big brands.

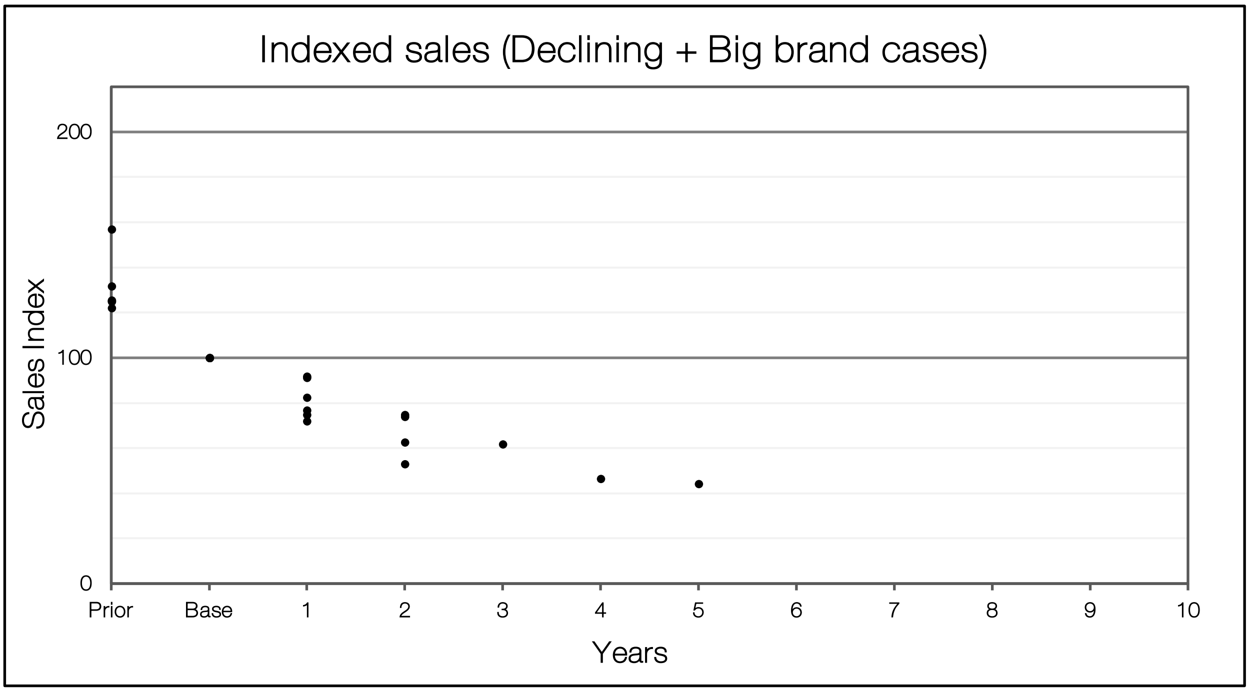


Chart A8 – Indexed sales: Declining + Medium brands.

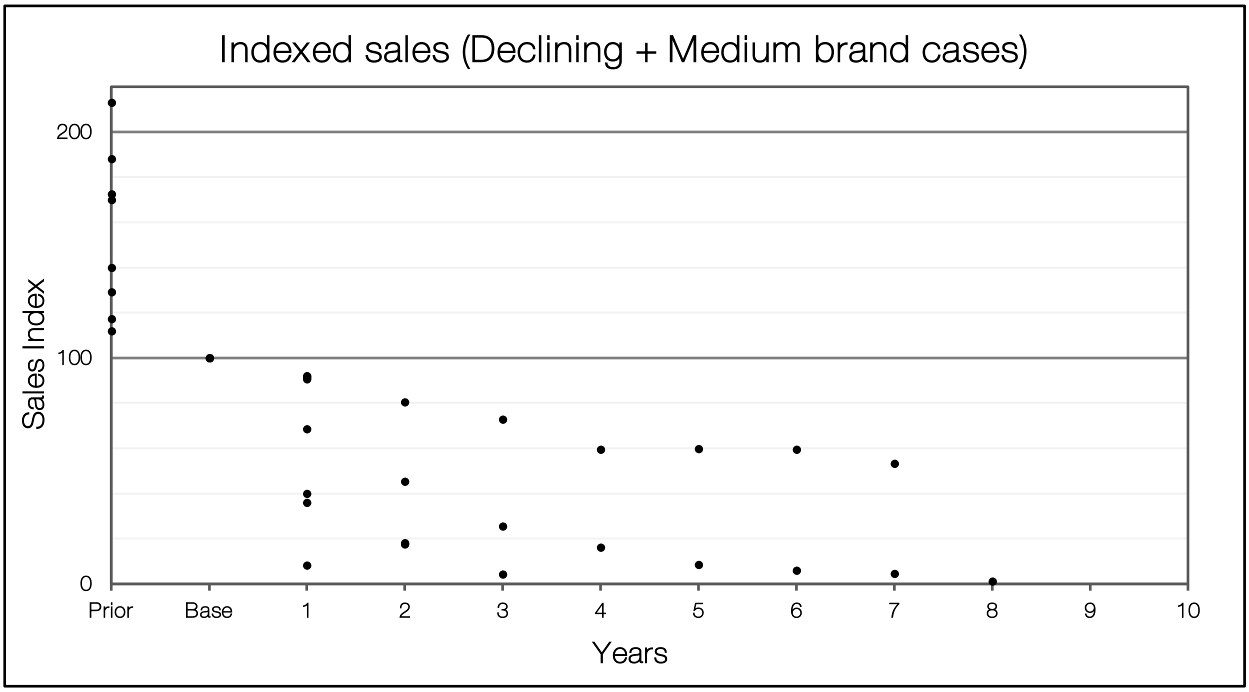
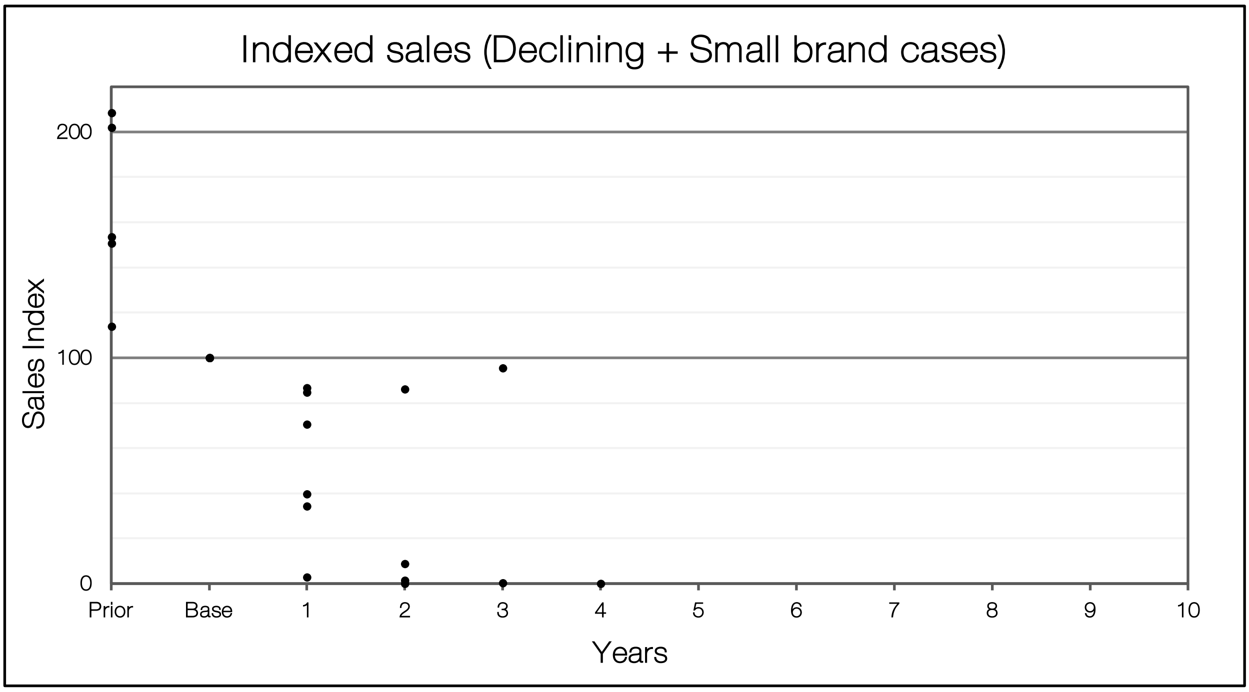


Chart A9 – Indexed sales: Declining + Small brands.



Note: Chart omits one prior-year value that is greater than the Y-Axis maximum (374).

Appendix B
Post-Hoc Statistical Tests

Appendix B reports the results of a series of statistical post-tests conducted after the descriptive analysis in the thesis. The purpose of these tests is to check whether or not the interpretations from the descriptive analysis are consistent with estimates from statistical analysis. Correlation, simple linear regression and multiple regression are used to quantify the relationships between brand size, prior sales trend, and change in sales after stopping advertising. Furthermore, the addition of new data makes it possible to explore the influence of category growth or decline on sales changes.

To understand the relationship between each independent variable and the dependent variable, correlations and simple linear regression are first conducted. Next, the combined explanatory input of the independent variables is estimated using multiple regression. The model estimates and coefficients are reported.

The results of these post-tests are included as an appendix to the thesis, as they add complexity but little new information on top of the descriptive analysis already presented.

Variables

The dependent variable for this post-test is sales change after stopping advertising. This is calculated in each of the 57 cases as the brand's year-to-year percentage change in sales after one year without advertising. One year without advertising was chosen as an appropriate interval, as all 57 cases include at least one unadvertised year. Increasing this interval to look at sales change after multiple unadvertised years would reduce the number of cases included in the sample.

The three independent variables are brand size, prior sales trend, and category growth/decline. In the main thesis analysis, brands were allotted into size groups (big, medium or small) based on their average yearly sales volume over the period of the dataset. This was preferable for the descriptive analysis as it simplified comparisons between broadly different brand size groups. For this statistical analysis however, the raw figure of average yearly sales is used instead. Similarly, the descriptive analysis in the thesis grouped brands into prior sales trend categories (previously growing, stable or declining) based on their year-to-year percentage change prior to stopping advertising. For this statistical analysis, the raw percentage change figure is used instead.

For this post-test, the effect of category growth and decline on brand sales after stopping advertising is also considered. This variable is potentially quite important, as a brand's sales may be influenced by the growing or declining trend of its entire product category. For example, a brand observed to decline after stopping advertising may be in a shrinking product category, meaning that the brand's decline was likely to have occurred regardless of advertising cessation. Since alcohol consumption trends evolved and category sales volumes grew and declined in Australia during the period of the dataset, exploring the effect of this potential confound could be enlightening.

The category sales data was reported by the corporation who supplied the brand-level data, and was supplemented with additional data from online statistics portal Euromonitor: Passport. Yearly sales volume (in 9L case equivalents) was available for cider and RTD beverages from 1996 – 2016, for spirits from 1997 – 2016, and for beer and wine from 2001 – 2015. Since category sales records for beer and wine were not available from 1996, nine out of the 57 cases where a brand stopped advertising could not be matched with category information. For the remaining 48 cases, category growth/decline was calculated as the year-to-year percentage change in category sales volume in the year the brand stopped advertising.

Part 1: Correlation and simple linear regression

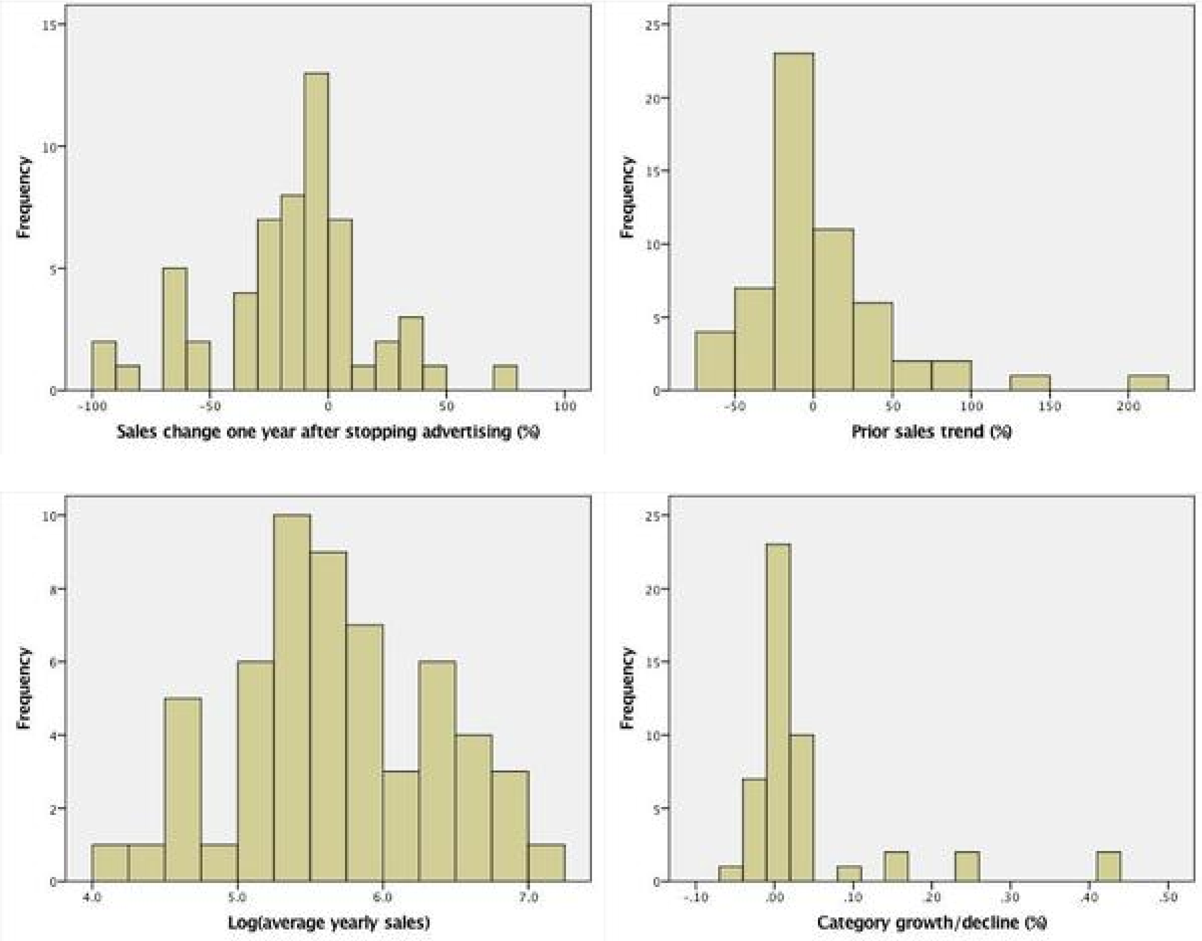
To first understand the relationships between brand size, prior sales trend, category growth/decline, and sales change after stopping advertising, correlations and simple linear regression are conducted. Analysis was conducted using IBM SPSS Statistics, and the strength of the correlation between each independent variable and the dependent variable is measured using Pearson's correlation coefficient (r).

Correctly assessing a relationship between two variables with Pearson's correlation coefficient requires that three assumptions be met by the data. First, there must be a linear relationship between the variables. The shape of the relationship is assessed for each variable individually below.

The second assumption of Pearson's correlation is that there are no *significant* outliers in the data, as outliers can have an exaggerated effect on the correlation coefficient. Using 1.5xIQR as a benchmark for detection, the software finds a small number of outliers present in each of the four variables in this analysis. Given the modest sample size, and the fact that none of these outliers are errors of data entry or measurement (i.e. they are all genuine values), the analysis proceeds with all values entered.

Finally, Person's correlation assumes that values of each variable are normally distributed. Figure B1 below displays histograms for the values of each variable.

Figure B1 – Distribution of values for all four variables.

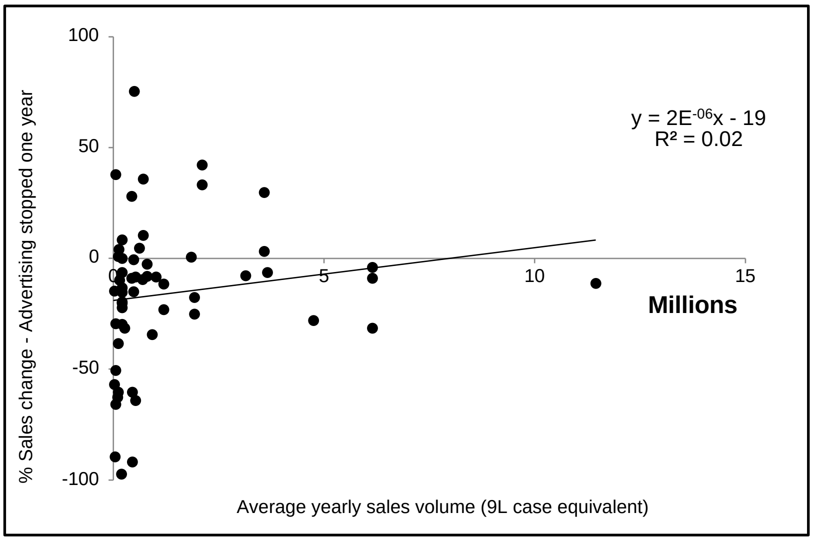


The assumption of normality is satisfied for log10 transformed brand size (discussed further below), prior sales trend, and sales change after stopping advertising. The values for category growth/decline are not normally distributed. The treatment of this violation is discussed below.

Brand Size

Figure B2 below plots the relationship between average yearly sales volume (i.e. brand size) and percentage change in sales one year after stopping advertising.

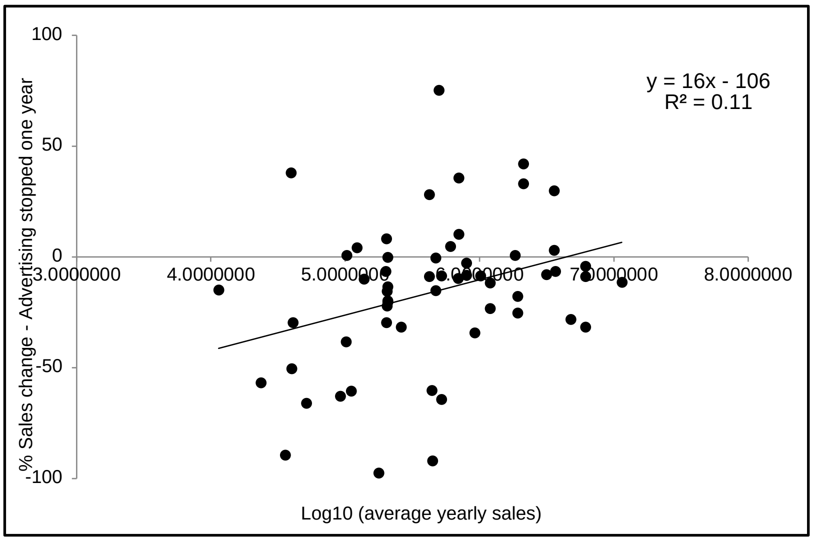
Figure B2 – Relationship between average yearly brand sales volume and sales change after stopping advertising for one year (%) (n=57).



Visual inspection of Figure B2 shows the relationship between the two variables is non-linear. There is a vast range and non-normal distribution of the raw values for average yearly sales, and the relationship appears "►" shaped. This suggests smaller brands were more likely to experience large percentage changes in sales (increase or decrease) compared to bigger brands. This makes sense, as absolute changes will appear relatively greater for the smaller brands.

To see whether a clearer relationship could be found, a log10 transformation was applied to the average yearly sales variable. This transformation normalises the shape of the variable's distribution. Figure B3 below plots the relationship between the transformed average yearly sales variable and sales change after stopping advertising.

Figure B3 – Relationship between log10(average yearly sales) and sales change after stopping advertising for one year (%) (n=57).



Although the relationship in Figure B3 is still widely scattered, it is an improvement on the raw values. Therefore, this analysis proceeds with the log10 transformed variable of average yearly sales. A Pearson's correlation, run using the transformed average yearly sales variable and percentage change in sales one year after stopping advertising, showed a positive and significant correlation, $r = .33$, p (two tailed) $< .05$. This correlation aligns with observations in Chapter Six, and indicates that smaller brands were broadly worse off after stopping advertising than bigger brands.

A simple linear regression was run to estimate the predictive ability of brand size regarding sales change one year after stopping advertising. The results are reported in Table B1.

Table B1 – Linear regression results for log10 transformed average yearly sales, and sales change after stopping advertising for one year (%).

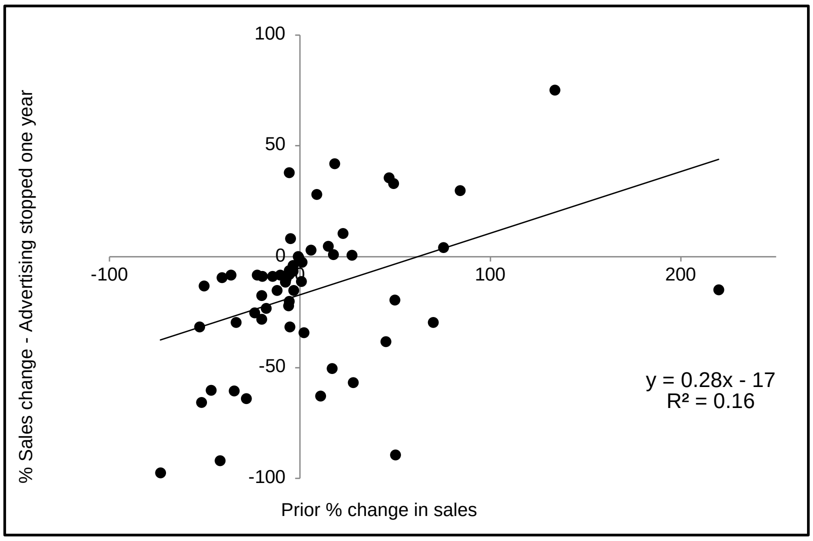
		Standardised Coefficients			
Model	B	Beta	t	Sig.	Adjusted R Square
Brand Size	16	.33	2.6	.01	.09

The result is significant, and returns a B value of 16 and adjusted R^2 of .09. Since the average yearly sales values are log10 transformed, the B value implies that as average yearly sales increase tenfold (i.e. if one brand is ten times bigger than another), sales change after stopping advertising is 16 percentage points higher (for example, -2% versus -18%). While the fit of the model is weak ($R^2 = 0.11$), the variable's positive correlation with sales change after stopping advertising supports its inclusion in the multiple regression model in part two of this appendix.

Prior sales trend

Figure B4 plots the relationship between percentage change in sales before stopping advertising (i.e. prior sales trend) and percentage change in sales one year after stopping.

Figure B4 – Relationship between prior change in sales (%) and sales change after stopping advertising for one year (%) (n=57).



Visual inspection of Figure B2 shows that the relationship between prior sales trend and sales change after stopping advertising for one year is somewhat linear (despite some outlying values). A Pearson's correlation was run to determine the relationship between these variables. The correlation shows a significant positive relationship, r = .39, p (two tailed) < .01. This is consistent with the conclusion from the descriptive analysis; brands that were declining before stopping advertising continued to decline, while brands that were growing beforehand were more likely to continue growing.

Next, linear regression was used to estimate the predictive ability of prior sales trend regarding sales change one year after stopping advertising. The results are reported in Table B2.

Table B2 – Linear regression results for prior change in sales (%) and sales change after stopping advertising for one year (%).

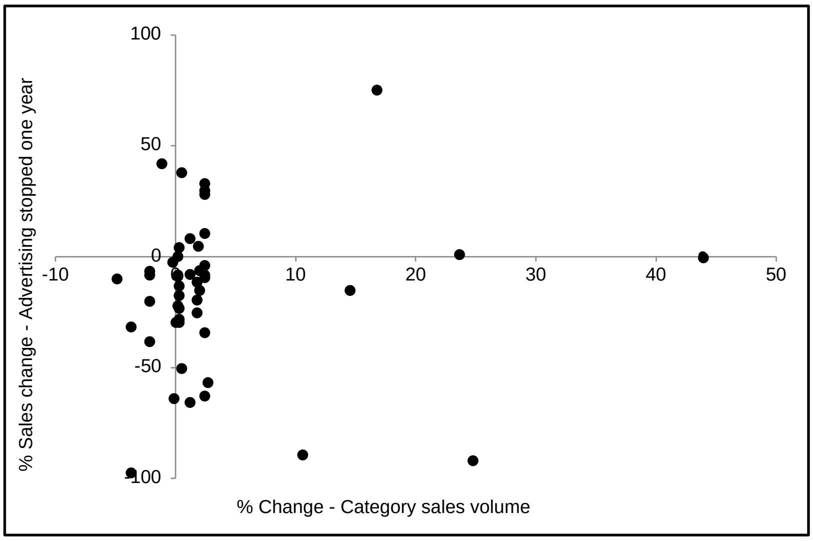
Model	B	Standardised Coefficients Beta	t	Sig.	Adjusted R Square
Prior sales trend	.28	.39	3.2	.00	.14

The model is significant and returns a B value of .28 and adjusted R^2 of .14. The clearer linear relationship and slightly stronger correlation and model fit between the two variables are consistent with the conclusion from the descriptive analysis, that prior sales trend explains the variation in sales outcomes more clearly than brand size.

Category growth/decline

Figure B5 below plots the percentage change in category sales volume against percentage change in brand sales after stopping advertising.

Figure B5 – Relationship between category growth/decline (%) and sales change after stopping advertising for one year (%) (n=48).



There is no clear relationship between the change in sales of each brand after stopping advertising for one year, and the growth or decline in sales volume of its product category in that year. Figure B3 shows there are seven cases of a brand being unadvertised for a year while its product category sales grew by 10% or more (all seven cases are cider or RTD brands; categories that evolved the most during the period of the dataset). In only one of those seven cases did the brand itself grow as well. Removing all cider and RTD brands from the sample did not improve the clarity of the relationship between these variables. No clearer relationship could be found by transforming the variables.

Since the variables are not linearly related, Pearson's correlation is inappropriate here. To assess the relationship between category growth/decline and percentage change in sales after stopping advertising, a Spearman's rank correlation was run. No significant relationship was found between the variables, $r_s = .18$, p (two tailed).

Despite lacking a clear relationship with sales change after stopping advertising, the category growth/decline variable is included in the multiple regression model in part two to explore whether the variable adds any incremental benefit to the model. The following section incorporates all three independent variables into a multiple regression model to assess their combined predictive ability of sales change after stopping advertising.

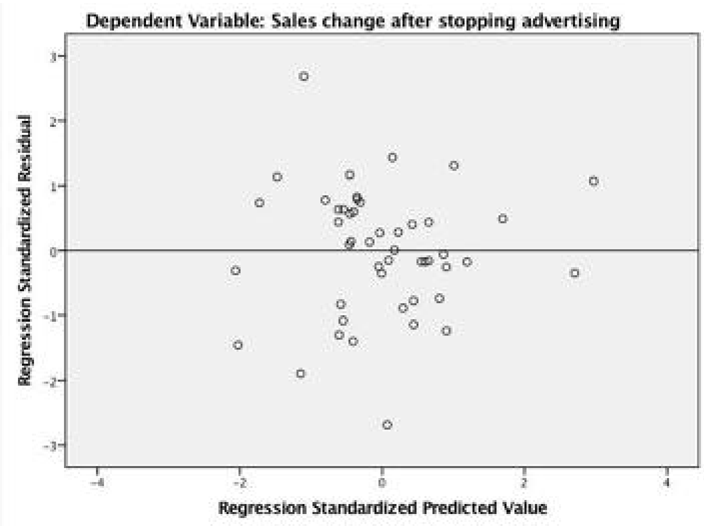
Part 2: Multiple regression

Multiple regression estimates the extent that a number of independent variables explain the variation in a single dependent variable. The method also quantifies the relative input of each independent variable out of the total model estimation. In this case, the independent variables are the log10 transformed average yearly sales (i.e. brand size), change in sales prior to stopping advertising (i.e. prior sales trend), and category growth/decline. The dependent variable is change in sales one year after stopping advertising.

Correctly using multiple regression requires that a number of assumptions be met by the data. Firstly, multiple regression assumes that each independent variable has a linear relationship with the dependent variable. From part one of this appendix, the brand size and prior sales trend variables meet this assumption. The category growth/decline variable is not linearly related to sales change after stopping advertising, which indicates a violation of the assumption. However, as mentioned above, the variable is included to see if it adds any incremental improvement.

To further assess linearity, Figure B6 plots the standardised residuals and standardised predicted values of the variables. The plot does not show any marked pattern or clustering, and aside from some slightly outlying values, does not suggest any violation.

Figure B6 – Plot of standardised residuals and standardised predicted values.

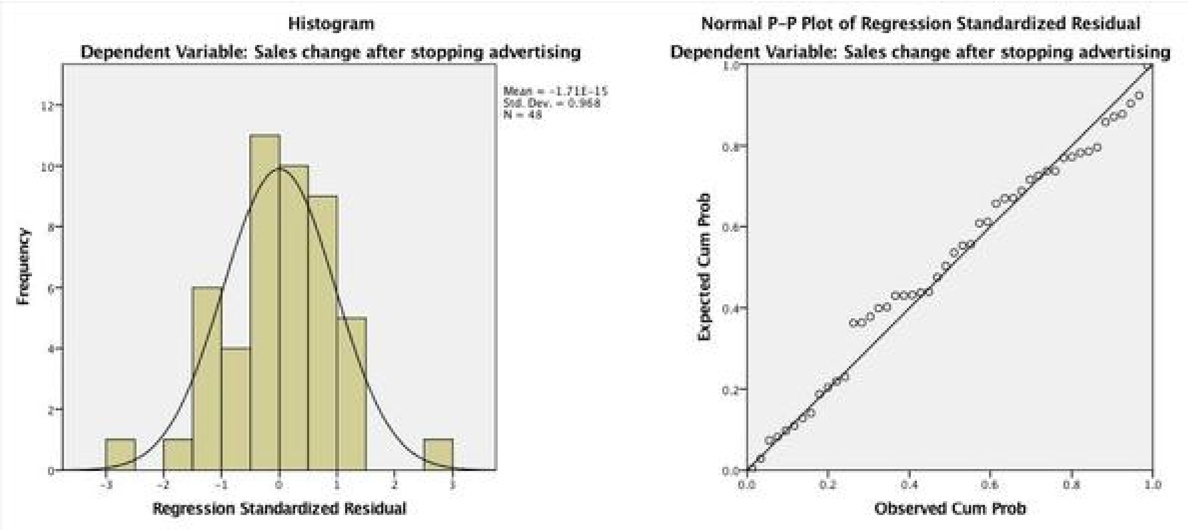


Visual inspection of Figure B6 also reveals whether the assumption of homoscedasticity is met. The spread of residuals appears approximately constant across all predicted values (i.e. no marked “fan” shaped pattern is visible), which suggests that there is homoscedasticity.

To detect outlying values, leverage points and influential points, variables were computed for studentized deleted residuals, leverage values and Cook’s distance. Only two points showed a studentized deleted residual greater than +/- 3 standard deviations, but these points had low leverage values (i.e. value < .1) and were not classified as influential as per Cook's distance (i.e. value < 1).

Finally, to test the assumption of normality of the residuals, a histogram and P-P plot were generated (see Figure B7). The residuals display an acceptable level of normality for the analysis to proceed.

Figure B7 – Histogram and normal P-P plot for regression standardised residuals.



To summarise, the data meets the assumptions of multiple regression at acceptable levels for this post-test. Since the purpose of this post-test was not to develop or test a precise predictive model, but rather to check whether the conclusions from the descriptive analysis were consistent with statistical estimates, the multiple regression method is suitable. The analysis proceeds with all cases entered into the model calculation. The model explores the effect of brand size, prior sales trend and category growth/decline on sales change one year after stopping advertising. The estimates and coefficients given by the model are reported in Tables B3 and B4.

Table B3 – Model for sales change after stopping advertising estimates.

Model	R	R^2	Adjusted R^2	Std. Error of Estimate	df	F	Sig.
1	.60	.36	.31	28	3	8.2	.00

The model is significant, as indicated by $F = 8.2$, $p<.01$ and returns an R^2 value of .36. In other words, the model estimates that brand size, prior sales trend and category growth/decline account for 36% of the variation in sales change after stopping advertising for one year. This is a strong improvement from the simple linear regressions for each variable individually. Removing category growth/decline from the model has only a minor effect on the result, $F = 13$, $p<.01$, $R^2 = .33$.

Table B4 – Model for sales change after stopping advertising coefficients.

Model	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
Constant	-119	36		-3.3	.00		
Prior sales trend	.47	.11	.50	4.1	.00	.96	1.0
Brand size	18	6.3	.35	2.9	.01	1.0	1.0
Category growth/decline	-14	41	-.04	-.33	.74	.96	1.0

The tolerance and VIF statistics suggest that no obvious collinearity is present.

The constant, prior sales trend and brand size are all significant, $p<.01$ but category growth/decline is not. Standardised beta-weights show that prior sales trend (B=.50) more strongly predicts the sales change after stopping advertising than brand size (B=.35), which is consistent with the correlations in part one and the conclusions drawn from the descriptive analysis. The model suggests that the effect of category growth/decline on sales change after stopping advertising (B=-.04) is relatively minor.

Appendix C
Call for Collaborators

WHAT HAPPENS WHEN ADVERTISING STOPS?

THE LONG-TERM EFFECTS OF CUTTING ADVERTISING

Faced with financial pressure, managers often look to the advertising budget as a low risk option to make savings. Advertising is large cost that offers few obvious returns. Cutting expenditure (even for a short time) could sharply increase net profit. But is it reasonable? How long is too long "off-air"? And what, if any, consequences should be expected?

Existing research hints towards the answers. Empirical evidence shows that, in the short to medium term, cutting advertising often causes no change in sales. It has been theorised then, that much expenditure may in fact be "overadvertising" and that many firms could benefit from brief periods off-air.

Short-term sales stability is to be expected, in line with the widely generalised patterns in buyer behaviour. Consumers are creatures of habit, buying from the same repertoire of brands over time. Advertising merely seeks to remind them of a brand and make it more mentally available – slightly increasing its chance of being chosen during their next category purchase. Removing advertising makes little difference to consumers' habitual behaviour, but it does remove the reminding and reinforcing influence.

We know from single-source data that advertising nudges sales at the individual level (even if aggregate sales are stable) and that competitive advertising reduces its effect. Ceasing advertising will allow competitors to strengthen their mental availability and nudge purchase propensities unchallenged.

So at some point, the savings from a cut in advertising will be outweighed by the losses in mental availability and sales. Advertising's effects decay and consumers forget. Yet the reasons to reduce spending persist, and questions remain concerning the rate of advertising decay and the effect of advertising cuts on sales and buyer behaviour, especially over the long term (e.g. a year or more).

This research seeks to describe and quantify the long-term sales effects of stopping advertising. Our questions include:

1. What happens to aggregate brand performance?
   a. Brand size
   b. Brand loyalty
2. What happens to individual-level brand buying?
   a. Repertoire size
   b. Repertoire composition
3. How do different conditions affect the results? (Brand size, category advertising, etc.)

Documenting the results of in-market examples (natural experiments) will provide some clarity amongst the myths and conjecture. The project is expected to provide further empirical support for advertising budget and schedule decisions.

INTERESTED IN EARLY ACCESS TO THE RESULTS? YOU CAN HELP!

Please see over the page.

ABOUT THE EHRENBERG-BASS INSTITUTE

www.MarketingScience.info

Based at the University of South Australia Business School, the Ehrenberg-Bass Institute is the world's largest centre for research into marketing. Our team of 50+ marketing scientists are advancing marketing knowledge, busting pseudo-science and marketing myths, and teaching marketers how marketing really works and how brands grow. We help companies all over the world to develop and benefit from a culture of evidence-based marketing.

For further details about the Institute, and how we can work with you, please contact our Commercial Director Elké Seretis - Elke.Seretis@MarketingScience.info

University of South Australia

Ehrenberg-Bass Institute for Marketing Science

EVIDENCE-BASED MARKETING

HOW CAN YOU HELP? GET INVOLVED!

CALL FOR DATA - ADVERTISING AND SALES

To explore the effects of stopping advertising on brand performance, we are looking for instances where brands have ceased advertising for at least one year (and preferably longer).

We want to examine both aggregate brand performance (through penetration, purchase frequency and share of category requirements) and household-level buyer behaviour (purchase weights, repertoire size and composition) over the long term.

This will require brand sales and consumer purchasing data in the year (or two) prior to the advertising cease and the year (or two) after. Longer-term data will be ideal however two to four years is sufficient for this project.

ADVERTISING

At best:

For the focus brand/s:

- Total week-by-week expenditure at brand level.
- Spend split across different media channels (i.e. television, online, etc.).
- Precise timing of stopping advertising across all above/below the line activity.
- Advertising reach information if possible.

For the category:

- Competitor advertising activity, owned brands or otherwise.
- Share of voice amongst competing brands.
- Additional below the line activities (e.g. POS activity, catalogue data).

At least:

Week by week expenditure (accumulated across all media channels) for any brands experiencing a cease in advertising, and the exact timing of the cessation.

SALES

At best:

- Longitudinal panel data at household level for the category/ies affected.
- In-store sales data at store level (including volume sold and prices paid).
- Data extends multiple years before and after stopping advertising.
- Information on new product introductions and/or delistings.

At least:

Aggregate sales data, or better yet household panel data, for any product category/ies affected, in the year before and after stopping advertising.

We are also interested in contacting anyone with relevant knowledge to stopping advertising.

For any enquiries or to get involved, please contact Adam.Gelzinis@marketingscience.info

EVIDENCE-BASED MARKETING