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Essay 1: How We Feel: The Role of Macro-Economic Sentiment in Advertising Spending-Sales Relationship; Essay 2: It Was the Best of Times; It Was the Worst of Times: The Effect of Emotional Uncertainty and Arousal on Healthy Food Choices

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HOW WE FEEL: THE ROLE OF MACRO-ECONOMIC SENTIMENT IN ADVERTISING SPENDING-SALES RELATIONSHIP

IT WAS THE BEST OF TIMES; IT WAS THE WORST OF TIMES: THE EFFECT OF EMOTIONAL UNCERTAINTY AND AROUSAL ON HEALTHY FOOD CHOICES

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ABSTRACT

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Leila Khoshghadam
Old Dominion University, 2020
Director: Dr. Yuping Liu-Thompkins

Essay 1: Controversies regarding the advertising spending-sales relationship have spawned many studies in marketing. Previous research on macroeconomic influencers of this relationship has focused mostly on objective macroeconomic indicators such as cyclical contraction and expansion. Extending these previous studies, the current research argues that sales response to advertising is also contingent upon the pervasive feelings present in the macroeconomic environment, above and beyond the influence from objective macroeconomic factors. Specifically, it argues that future outlook negativity and uncertainty in macroeconomic sentiment can affect the ad spending-sales relationship. Analyzing sales and advertising spending data for salty snacks in conjunction with macroeconomic sentiment data from Thomson Reuters Market-Psych Indices, I found that the effect of ad spending on sales is stronger when macroeconomic future outlook is negative than when it is positive, and when the sentiment is more uncertain than when it is certain. Furthermore, the moderating effects of future outlook negativity

and uncertainty on the ad spending-sales relationship are stronger for brands with a low market share in comparison with brands with a high market share.

Essay2: Although notable literature exists on individuals' mood valence and food consumption choices, the findings are somewhat mixed showing the possibility of unhealthy food choices in both highly positive and highly negative affective states. Furthermore, the effect of affective dimensions other than valence has been explored much less, and limited research in this stream has focused exclusively on positive emotions. Addressing these gaps, the current research investigates the effect of emotional arousal and uncertainty on individuals' food consumption choice in the negative emotional domain. Analyzing the sales data of 1,128 salty snack products over five years (2008-2012) from Information Resource Incorporated (IRI) and consumer well-being data from the weekly Gallup U.S. poll, along with two lab experiments, I find that, not all negative emotions have an equal impact on food choices. Among negative emotions, high-arousal, and uncertain emotions are more likely to lead to unhealthy food consumption choices than low-arousal and certain emotions. However, the process underlying the influence of arousal and uncertainty are different, which necessitate different interventions to counter their effects.

I dedicate this dissertation to my parents, as their constant love is the source of inspiration for me.

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ESSAY 1

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ABSTRACT

Controversies regarding the advertising spending and sales relationship have spawned many studies in marketing. Previous research on macroeconomic influencers of the ad spending-sales relationship has focused mostly on objective macroeconomic indicators such as cyclical contraction and expansion. Extending these previous studies, the current research argues that sales response to advertising is also contingent upon the pervasive feelings present in the macroeconomic environment, above and beyond the influence from objective macroeconomic factors. Specifically, it argues that future outlook negativity and uncertainty in macroeconomic sentiment can affect the ad spending-sales relationship. Analyzing sales and advertising spending data for salty snacks in conjunction with macroeconomic sentiment data from Thomson Reuters Market-Psych Indices, I found that the effect of ad spending on sales is stronger when macroeconomic future outlook is negative than when it is positive, and when the sentiment is more uncertain than when it is certain. Furthermore, the moderating effects of future outlook negativity and uncertainty on the ad spending-sales relationship are stronger for brands with a low market share in comparison with brands with a high market share.

INTRODUCTION

"*The ad addresses consumers as if they are basically frozen in place*"

- Orson Munn, chief executive at Munn Rabôt. [1]

Firms continue to allocate a large amount of money to advertising. Yet debate continues over whether firms are getting an adequate return on their spending or not (Sethuraman et al., 2011). One essential element in this debate is how much advertising spending is generating sales. For several decades, scholars have attempted to develop a better understanding of the ad spending-sales relationship and to explain the discrepancies in existing findings by introducing moderators of this relationship. Although an impressive body of research has identified influential moderators at the micro individual or firm level, much less is known about macro-level influencers of the ad spending-sales relationship. In practice, advertising spending is greatly affected by the general economic conditions. Every time the economy experiences a fluctuation, advertising budget seems to be among the first expenditures reconsidered (Heerde et al., 2013). Managers believe these reconsiderations are necessary because consumers show a different level of responsiveness to advertisements in different economic conditions (Lamey et al., 2012).

The varying responses consumers exhibit under different macroeconomic conditions point to the possibility that consumers' macroeconomic sentiment can shape their expectations about future financial well-being (van Giesen and Pieters, 2019) and subsequently their consumption decision and sensitivity to advertisements. Different from factual economic conditions, macroeconomic sentiment reflects how consumers actually perceive and feel about economic conditions. Indeed, there is research evidence indicating that consumers' economic sentiment can

[1] Elliott Stuart. (May 14th, 2009). Does Ranting Sell? Worth a Try. *The New York Times.* Page 1

significantly affect consumption at the aggregate level (Nguyen and Claus, 2013). If this pattern is systematic, it would be valuable to understand how advertising spending impacts sales under different macroeconomic sentiment conditions. Unlike the cyclic up and down patterns in the macroeconomy, sentiment can fluctuate much more frequently (e.g., day-to-day), not only reflecting hard economic facts but also absorbing influences from the content of news and social media (Nguyen and Claus, 2013). Understanding the effect of this more frequently changing variable is important in today's advertising environment, where spending decisions often need to be made at much shorter time intervals (e.g., how much to spend on Google search advertising today or tomorrow).

To this end, the current paper investigates the moderating influence of two macroeconomic sentiment factors – future outlook negativity and uncertainty – on the ad spending-sales relationship. In particular, it proposes that the effect of ad spending on sales is stronger when future outlook is negative than when it is positive and when there is a high level of uncertainty than when uncertainty is low. Furthermore, it assesses the role of market share and argues that the moderating effect of macroeconomic sentiments are stronger for brands with a low market share than brands with a high market share.

The current research provides several important contributions to marketing theory and practice. First, previous research has yielded contradictory findings about the ad spending-sales relationship. By considering macroeconomic sentiment as another influential factor in this relationship, the current research can shed some light on the complexity of advertising effects and help reconcile previous conflicting findings. Second, the existing literature on advertising spending has typically focused on factual macroeconomic factors, such as recession and business cycle. By considering macroeconomic psychological factors such as future outlook negativity and uncertainty, the current research expands the role of the macro-environment and offers a psychological explanation as to why macroeconomic factors such as recession may influence the effects of ad spending. Finally, from a marketing practice perspective, this research suggests a need to consider readily available aggregate economic sentiment data in advertising budget allocation decisions. In today's fast-paced digital advertising environment, it presents firms with an opportunity to leverage macroeconomic sentiments to make more agile adjustments to their advertising spending for maximum effectiveness, especially for brands with low market shares.

CONCEPTUAL BACKGROUND

Mixed Effects of Advertising Spending on Sales

A rich body of research exists on the relationship between advertising spending and sales. The results of these studies have provided conflicting views on the effectiveness of advertising expenditure. One set of research finds significant positive effects of advertising spending on sales. It concludes that appropriate adjustment of advertising budget is essential to companies' profit maximization goal (Pagán et al., 2001), and that the positive outcome of advertising spending is manifested in both individuals' spending and aggregate sales (Newstead et al., 2009). For instance, investigating the U.S. automobile industry, Hu et al. (2014) found that intensifying advertising spending considerably increases brand sales.

Besides the direct positive impact of advertising spending on sales, some authors have also found that advertising spending can positively impact investors' response (Chan et al., 2001; Jedidi et al., 1999; Peterson and Jeong, 2010). For example, a study of 1000 top advertisers in a variety of industries shows that an unexpected increase in ad spending beyond the advertising response threshold causes a significant growth in sales and a corresponding increase in stock price and firm value (Kim and McAlister, 2011). The researchers attribute the findings to the significant carry-over effect of ad spending. Similarly, an investigation into major brands in the PC manufacturing and sporting goods industries revealed that an upsurge in advertising spending boosts sales and subsequently profit and firm value (Joshi and Hanssens, 2010). Wang et al. (2009) also reported sustainable and accumulative influence of advertising spending on firms' brand equity.

Since firms usually advertise in different media, research supporting a positive ad spending-sales relationship has also been conducted at different levels, including the impact of advertising in a single channel, the joint effect of advertising investment across all media, as well as possible cross-media and cross-channel interactions. An example of a within-channel effect study is Manchanda et al. (2006), which finds that more spending on banner advertising causes higher growth in online sales. Focusing on the joint effect of overall advertising spending instead, Sridhar et al. (2016) found that, although different channels of advertising can reduce each other's positive impact, the overall joint effect of advertising spending on sales is positive and significant. Finally, previous research shows that positive spillover across channels is possible. For example, increasing a brand's online advertising spending not only boosts the brand's online sales but also contributes to in-store purchases (Lewis and Reiley, 2014).

Although the literature in support of a positive ad spending-sales relationship seems vast, another set of studies offer evidence of a weak or rarely meaningful relationship. Some of these studies attribute the discrepancy in the results to method-based variations, suggesting previous research mainly relied on the correlation between advertising spending and sales rather than a causal relationship (Ashley et al., 1980; Darrat et al., 2016). When evaluating causality instead, employing procedures such as granger causality test, the variation in aggregate advertising spending no longer affects the level of consumption (Darrat et al., 2016). Another method-based variation is whether advertising expenditure is treated as a current expense or a long-term investment. Bloch (1974) claimed that treating advertising expenditure as a current expense is partly responsible for finding a significant relationship between ad spending and sales. Given the long-term effect of ad spending on sales, ad budget should be considered as an investment in the capital asset. Accordingly, treating advertising expenditure as an investment rather than current expenditure reduces the reported profit of firms.

In addition to method-based variation, different product categories have also shown different ad spending-sales relationships, with some product categories showing no or low impact of ad spending. For instance, Campbell Soup Company conducted 19 marketplace experiments on six Campbells' brands of inexpensive and frequently purchased products and reported no meaningful increase in sales from merely increasing advertising budget and repeating the same message more frequently (Eastlack and Rao, 1989). Similarly, investigating laundry detergent brands, which invest heavily in TV advertising, Tellis and Weiss (1995) showed an insignificant effect of TV advertisement on households' brand choices. For this product category, the effects of in-store display, in-store advertisements and price reductions are more pronounced than that of TV advertisements. As another example, several studies on the alcoholic beverages industry showed that increasing advertising spending has no effect on total demand for the product category (Duffy, 1987; Heimonen and Uusitalo, 2009).

Decay in Advertising Effects

Brands' sales performance is not only the result of current advertising spending but also the result of carryover effects from past advertising expenditures (Dekimpe and Hanssens, 1995; Graham Jr and Frankenberger, 2000; Leone, 1995; Ouyang et al., 2002; Zhou et al., 2003). Therefore, ad spending's long-term effect on sales, including its magnitude and its rate of decay over time, has also been subject to debate. Psychologically, the cumulative influence of an advertisement relates to consumers' memory of the ad. As time passes, consumers forget the advertisement, and the positive impact of the advertisement on demand will diminish (Leeflang and Reuijl, 1985). Depending on the industry, advertising type, study setting, and data time interval, the length of time that advertising spending effect has been reported to last varied widely, from one to 1,355 months (Clarke, 1976; Leone, 1995; Sethuraman et al., 2011). Based on these estimates, the time window for short-term advertising effect is typically considered to be three to fifteen months. Ninety percent of advertising's effect is expected to disappear after this period (Vakratsas and Ambler, 1999). Some estimates of the short-term effect window are even shorter (Heerde et al., 2013). For instance, using single-source data and tracking the same individuals' purchases, Newstead et al. (2009) showed that adverting has a half-life of only 3 to 4 weeks. As another example, Wood (2009) reported that ad exposure one day before shopping increases the choice share of the advertised brand by 75%. Yet, this share lift disappears merely one month after ad exposure. The faster decay rate reported in recent studies may have resulted from changes in the contemporary business environment characterized by more intense brand competition, ad clutter, and the advent of diverse advertising and communicating media. These environmental factors in turn could have decreased consumers' ability to memorize advertisements for a long time (Heerde et al., 2013).

Compared with the more concentrated short-term effect, existing research suggests a much weaker effect of advertising when looking over a longer time horizon. Along with the described changes in the contemporary business environment, other factors such as ad reach and competitors' marketing and advertising all contribute to the weak long-term advertising effect (Newstead et al., 2009). Together, the current consensus appears to be that advertising has an influence beyond its immediate impact, but the carryover period with a considerable effect is rather short (Kwoka Jr, 1993; Newstead et al., 2009; Ramos, 1988).

Micro-Level Moderators of the Advertising Spending-Sales Relationship

To understand why the relationship between advertising spending and sales can be so diverse, a stream of research has investigated variables that are likely to affect this relationship. Some of the moderators considered are micro-level factors that characterize the product or the firm. In a meta-analysis of 56 studies, Sethuraman et al. (2011) found that advertising elasticity depends on two factors: product life cycle stage and product type. In particular, the relationship between advertising spending and sales is stronger when products are in the early stages of their life cycle than in later phases. Moreover, advertising elasticities are higher for durable products than for non-durable products. Relatedly, product quality has been recognized to influence sales response to advertising spending (Landes and Rosenfield, 1994; Paton, 2002). Finally, research shows that firms' choice of advertising strategy may play an important role and that the impact of ad spending on sales depends on the advertisements' message content (MacInnis et al., 2002; Yiannaka et al., 2002). In support of this argument, Leach and Duncan Reekie (1996) demonstrated that quality instead of quantity of advertisements is more important in driving sales.

Macro-Level Moderators of Advertising Spending-Sales Relationship

Although insights derived from micro-level moderators discussed in the previous section are undoubtedly important, they do not capture the complete picture of how advertising spending may impact sales. At a more macro-level, companies are significantly affected by their environment (Miller, 1987; Miller and Friesen, 1983), and general market and economic conditions affect how well advertising works (Graham and Frankenberger, 2011; Heerde et al., 2013; Srinivasan et al., 2005). At the market level, research suggests that the effect of advertising spending on sales depends on the extent of rivalry in the target market, such that firms' ability to attract new consumers or increase current customers' purchases through advertising is higher in unsaturated markets (e.g., health foods) compared with saturated markets (e.g., soft drinks such as fruit juices). In the latter situation, intense competition leads to different brands' advertisements canceling out each other's effects (Elliott, 2001; Leeflang and Reuijl, 1985).

At the broader macroeconomic level, consumers have been shown to exhibit different levels of responsiveness to advertisements under different economic conditions (Lamey et al., 2012). For instance, consumers tend to ignore brands' image-based advertisements during economic hardship because of tightened households budgets (Heerde et al., 2013; Sethuraman et al., 2011). Yet, some believe that reducing advertising support in response to contractions in the business cycle is unnecessary and in some cases harmful (Heerde et al., 2013; Lamey et al., 2007; Steenkamp and Fang, 2011). For instance, Steenkamp and Fang (2011) provided evidence for stronger advertising effects on firm performance during economic contraction compared to economic expansion. Another set of studies showed that increasing advertising budget during and after a recession increases firm sales (Kamber, 2002; Srinivasan et al., 2011; Srinivasan et al., 2005; Tellis and Tellis, 2009). One explanation of these results is that decreased advertising spending by most brands during an economic downturn reduces advertising clutter and makes the environment less noisy; that in turn makes it easier for consumers to memorize specific brands' advertisements. From this perspective, an economic downturn can provide brands with an opportunity to invest in more impactful advertisements with longer carry-over effects.

Collectively, the reviewed literature suggests that the macro-environment significantly affects the advertising spending and sales relationship. However, existing studies in this area have focused on factual macroeconomic indicators such as recession and business cycles, which are not the only source for shaping individuals' impression of the economy and cannot fully explain day-to-day changes in consumers' macroeconomic sentiment. Previous research shows that how consumers feel about an economy is driven not only by economic facts but also by news and social media content (Blood and Phillips, 1995; Goidel and Langley, 1995; Hester and Gibson, 2003; Ju, 2008; Wu et al., 2002). For instance, a small change in news coverage about unemployment rate significantly affects household's economic perception (Garz, 2018). Understanding such more frequent changes in consumers' macroeconomic sentiment is important as it can drive aggregate consumption in society (Bryant and Macri, 2005; Carroll et al., 1994). Surprisingly little empirical research has evaluated the impact of this more psychological macroeconomic factor on the advertising spending-sales relationship. Addressing this gap, the current research investigates how future outlook negativity and uncertainty in macroeconomic sentiment play a role in the ad spending-sales relationship.

HYPOTHESIS DEVELOPMENT

Macro-Economic Sentiment

Consumers have extensive day-to-day personal experiences with the economy. Although many consumers may not be inherently interested in quantitative economic performance measures such as inflation and companies' performances, they become involved in these measures since the metrics affect their future financial well-being (Oswald, 1997; van Giesen and Pieters, 2019). Such economic information can alter daily life and consumption decisions. For example, during an economic depression with high unemployment rate, consumers may decide to tighten their budget and reduce discretionary expenses.

Beyond factual economic indicators such as GDP growth and unemployment rate, individuals' actions may also be affected by inferences about their future financial well-being from various other information sources (Van Raaij, 1989). One of the most important sources that inform people's expectations about their future financial situation is news and social media (Balahur and Steinberger, 2009). Individuals try to forecast economic changes through the tone and volume of economic reports and commentaries in news and social media channels (Doms and Morin, 2004). For instance, repeated speculations of a pending economic downturn in the news may encourage individuals to seek clarity about their job situation and consider making changes to their purchase behavior, even before quantitative economic indicators suggest an actual downturn.

Comparing the impact of real economic indicators and that from news coverage, existing evidence indicates that the impact of news coverage on future financial expectations may be stronger, and in some cases, may weaken the effect of reality (Goidel and Langley, 1995). This is exemplified by Hollanders and Vliegenthart (2011), who showed that exposure to bad news reduced consumer confidence above and beyond the extent justified by objective economic factors. These results imply that individuals' subjective perception of the economy may not always match objective economic conditions. Individuals can be wrong in making their inferences about the economy. However, if many consumers believe in the same inference, the belief can propagate and cause discrepancy between factual economic conditions and subjective perceptions, which subsequently influence aggregate follow-up behavior at the society level (Van Raaij, 1989).

The idea that subjective perceptions of the economy as derived from mass media may affect economic behavior began 70 years ago, when economists found fundamental economic rules to be insufficient in explaining the wild movements in stock market prices (Tetlock, 2007). In support of the idea, many investors have been found to adjust their investments based on news content, even though much of it is simply hype (Shiller, 2000). To define the economic sentiment reflected in mass media, finance scholars coined the term investor sentiment or market sentiment as propensity to speculate (Baker and Wurgler, 2006). Following this definition, market sentiment motivates relative demand for speculative investments. However, the effect of market sentiment is not only confined to investors' financial decisions. Because of the two-way feedback between the financial sector and the economy, a small sentiment shock in the financial market can cause macroeconomic fluctuations and have a large impact on the overall economy (Benhabib et al., 2016). That, in turn, may affect aggregate consumption at the society level (Bryant and Macri, 2005; Carroll et al., 1994; Van Raaij, 1989). Existing research has provided some evidence of this by showing households adjusting their consumption in reaction to news contents (Hollanders and Vliegenthart, 2011; Nguyen and Claus, 2013; Svensson et al., 2017).

Extending these previous studies, the current research proposes that macroeconomic sentiment can affect consumers' level of responsiveness to advertisements. Formally defined, macroeconomic sentiment refers to the prevalent mood in the market. The current research focuses on two central aspects of macroeconomic sentiment: future outlook negativity and uncertainty and explores their effects on the ad spending-sales relationship. It should be clear from the preceding discussion that although macroeconomic sentiment may be partly driven by objective economic facts, it exerts a separate influence on consumers and hence warrants its own examination.

Moderating Effect of Future Outlook Negativity

"Our present behavior can only be affected by the expected future – not the future as it will turn out but the future as it appears to us beforehand through the vail of the unknown" (Fisher, 1930). To understand the potential effects of future outlook negativity on consumers' responses to advertisements, it is necessary to consider its impact on three things: individuals' tendency to collect pre-purchase information, psychological tendency to switch between brands, and vulnerability to persuasion.

Pre-purchase Information Seeking. Prior to product acceptance, consumers must have the necessary information about a product (Settle, 1972). Individuals may seek more or less pre-purchase information partly depending on their perception about their future financial well-being (Lamey et al., 2012). In general, people tend to put little cognitive efforts in their mundane choices. Consequently, their purchase pattern tends to follow a habitual routine. However, a potential financial crisis or the threat of losing income can shake individuals out of their habitual behavior and force them to make more informed choices (Lamey et al., 2012). In line with this idea, Voinea and Filip (2011) demonstrate a disparity in consumer behavior between an economic slowdown (characterized by having a negative future outlook) and an economic expansion period (characterized by having a positive future outlook). Compared with an expansion period, individuals experiencing an economic slowdown seek more information about all alternatives in the market and strive for more reasons to justify their purchases. Similar changes in pre-purchase behavior can be observed following economic news and social media coverage, such that people adjust their purchase behavior more when perceiving anxiety, fear, and uncertainty from media coverage, compared to when news content conveys a sense of prosperity and tranquility (Garcia, 2013). Together, a negative future outlook in macroeconomic sentiment, regardless of its source, appears to make people more economical, price sensitive, and value aware, which in turn would encourage individuals to acquire more pre-purchase information.

In such an environment, companies need to provide more information to consumers to set themselves apart from similar products and to accelerate consumers' decision-making process. Advertising is one of the ways in which such information provision can occur (Kiel and Layton, 1981; Mizerski and Settle, 1979). Companies can advertise their products as providing superior value, or they can follow a price-based advertising strategy. Both can be effective when future outlook is negative. Increasing spending on value-based ads, which emphasize difficult-to-copy intangible benefits or stress acquisition value, can help justify higher prices and reduce consumers' price sensitivity (Comanor and Wilson, 1974). These ad campaigns can further decrease attrition among current customers (Xiong and Bharadwaj, 2013), as they reinforce the belief that the current choice is superior to other available options (Choi and Fishbach, 2011; Yoon and Kim, 2017). For price-based (e.g., price comparison or reference price) ads, increasing such ads may influence buyers who are looking for new lower-priced alternatives and increase a brand's ability to attract new customers (Grewal et al., 1998). This is supported by previous research showing that one of the ways to lure a loyal customer away from his/her favorite brand is to provide sufficient price difference (Agrawal, 1996). In summary, as consumers tend to engage in more pre-purchase information search when their feelings toward future outlook are negative, increasing advertising spending during such an environment is likely to be beneficial.

Psychological tendency to switch between brands: From a psychological standpoint, holding a negative sentiment toward the future increases one's urge to switch between brands. Yoon and Kim (2017) describe this phenomenon as variety seeking due to a lack of perceived economic mobility, which means one feels he/she is economically stuck and there is no chance to enhance the situation. Brand switching can be a mechanism for regaining some personal control in such a situation. Yang and Urminsky (2015) also suggest that optimism about the future enhances one's preference for self-continuity, whereas pessimism about the future leads to a preference for self-change. Therefore, when the environment signals a desirable future, individuals tend to keep their habitual routines and repeat their previous choices. In contrast, when circumstances signal a negative future outcome, people show more impulsive changes in their brand choices (Yang and Urminsky, 2015). In sum, a negative future outlook can make consumers psychologically ready to switch between brands. Under such situations, advertisements can act as an accelerator, since previous research shows that advertising has a large impact on switchers and works by attracting less loyal consumers to new brands (Deighton et al., 1994).

Vulnerability to Persuasion. As a negative future outlook increases financial distress and indirectly affects people's overall mood (Morselli, 2017), it may also increase individuals' vulnerability to persuasive efforts such as advertisements. Individuals have limited resources for self-control (Muraven and Baumeister, 2000; Muraven et al., 1998). Coping with a potentially unfavorable future requires a person to constantly monitor the environment to recognize threatening stimuli. Significant resources are therefore consumed to tackle the negative feelings, increasing the possibility of failure in self-control (Baumeister and Heatherton, 1996; Muraven et al., 1998). Individuals may also be motivated to engage in behaviors simply to alter the negative affective state (Leith and Baumeister, 1996; Muraven and Baumeister, 2000). Under such circumstances, consumers may fail to consider the implication of their activities and show higher receptivity to advice. This is especially likely if the incoming information promises a better feeling and precludes thoughts about long-term goals (Tice et al., 2001), even if the advice is misleading (Gino et al., 2012). For instance, a beer advertisement can act as an activating stimulus for a person experiencing a negative emotion and encourage one to respond impulsively to the advertisement (Baumeister and Heatherton, 1996). Overall, feeling negative about the future is likely to make individuals' vulnerable to persuasion through advertisements.

Taken together, the preceding discussions suggest that a negative future outlook puts individuals in a cognitive and affective state that makes them more susceptible to advertisements. This would suggest a higher effect of advertising spending on sales under such circumstances, as summarized in the hypothesis below:

H1*: Future outlook negativity in the macroeconomic sentiment moderates the effect of ad spending on sales, such that the effect is stronger when future outlook is negative than when it is positive.*

Moderating Effect of Macroeconomic Sentiment Uncertainty

Pavlou et al. (2007) define uncertainty as "the degree to which the future state of the environment cannot be accurately anticipated or predicted due to imperfect information" (P.107). The behavioral economics and psychology literature has considered uncertainty an emotional dimension that matters greatly to economic decision making (Garcia, 2013; Tiedens and Linton, 2001; Weary and Jacobson, 1997). Extending this body of work, I propose that a high level of uncertainty in the macroeconomic sentiment is likely to increase the overall impact of advertising spending. The proposition is built on individuals' information processing and decision patterns under high-uncertainty, high-risk situations.

Individuals are sensitive to risks (Pras and Summers, 1978). A high level of uncertainty has been shown to increase perceived risk in one's environment and cause a sense of unease (Loewenstein, 1994; Shani et al., 2008; Van Dijk and Zeelenberg, 2007; T. D. Wilson and Gilbert, 2003). Such a feeling motivates individuals to take actions to counter the risk and restore a sense of certainty. Some of these actions and tendencies can have a direct impact on individuals' attention to and receptivity to advertising messages. First, previous research shows that uncertainty can increase one's need for information and encourage information-seeking (Tiedens and Linton, 2001) to help make sense of one's situation. As discussed in the last section, more intensive information-seeking can increase individuals' attention to and leveraging of readily available information such as advertisements.

Second, under uncertain environment, individuals may cope with the challenges associated with decision-making through positive illusion and being unrealistically optimistic (Taylor and Brown, 1988). Put differently, people will be more likely to believe that the world is benevolent, that they deserve the best and nothing bad could happen to them. This tints individuals' information search and decision making with confirmation bias (Plous, 1993) and optimism bias (O'SULLIVAN, 2015), such as showing higher trust to marketing agents and believing that companies are helping them to make the best decision (A. E. Wilson and Darke, 2012). In other words, trust can act as a coping mechanism under high uncertainty to deal with the environment's complexity (Guseva and Rona-Tas, 2001). Individuals may be forced to rely on trust to make a decision, even when they believe opportunistic behavior is possible (Dunn and Schweitzer, 2005). To that end, a high level of uncertainty in macroeconomic sentiment may increase consumers' willingness to trust advertising messages and accept the conveyed information, which in turn would increase the effectiveness of advertisements.

Finally, uncertainty and risk tend to sensitize individuals to the possibility of missed opportunities and heighten the feeling of potential regret associated with missed opportunities (Bleichrodt et al., 2010). In general, people are sensitive to not only what they get but also to what they might have gotten if they decided differently. As every advertisement directly or indirectly presents the opportunity of possessing something "wonderful", the reluctance to forgo opportunities in a highly uncertain environment may prompt individuals to make purchases more readily. Taken together, the discussion above suggests that a high level of uncertainty in macroeconomic sentiment renders consumers more receptive to and trusting of information provided by advertisements. These factors ultimately increase the effectiveness of advertising spending, which leads to the next hypothesis:

H2*: Uncertainty in the macroeconomic sentiment moderates the effect of ad spending on sales such that the effect is stronger under a high level of uncertainty than under a low level of uncertainty.*

The Role of Market Share

The previous two sections argue that people's sensitivity to day-to-day fluctuations in macroeconomic sentiment may influence their responsiveness to advertising. In particular, a negative future outlook and a feeling of uncertainty in macroeconomic sentiment encourage people to seek more information about products and show higher vulnerability to and trust in advertisements. These processes in turn increase the sales impact of advertising spending. The question is whether the impact from macroeconomic sentiment is the same across brands. I argue that the moderating effects of macroeconomic sentiment on the ad spending-sales relationship will depend on a brand's market share.

Market share has significant implications for advertising expenditure and strategy. Established brands usually increase their sales by encouraging their current customers to repeat purchase and by providing values to reduce switching to other brands (Fader and Schmittlein, 1993). Manifested in advertising, brands with high market shares tend to use advertisements as a barrier mechanism against new and smaller brands to prevent these smaller brands' market share expansion (Karakaya and Stahl, 1989; Nagle, 1981). In contrast, small brands tend to use advertisements to increase brand awareness and exposure to product information in the hope of convincing consumers to try their products. Under "normal" circumstances with low threats from the environment, such as when macroeconomic sentiment future outlook is neutral or positive and has low uncertainty, people tend to put little cognitive efforts into their day-to-day purchases (Lamey et al., 2007). The minimal pre-purchase consideration drives the tendency to follow habitual purchase routines (Lamey et al., 2012) and repeat purchase the brands one already knows. Such situations are more favorable to brands with established market shares while decreasing the chance of low-share brands to introduce their products. As Agrawal (1996) noted, stronger brands find advertising less attractive since they face little threat from the weaker brands.

In contrast, a negative future outlook or an uncertain macroeconomic sentiment makes people more value oriented. As discussed previously, this value sensitivity encourages consumers to collect and process more information about a wider variety of products and to broaden their consideration set (Estelami et al., 2001; Lamey et al., 2007). Accordingly, the possibility of switching from one brand to another becomes higher. Previously unnoticed advertisements from small brands now have a higher chance of being seen, processed and trusted than in a normal situation, making the impact of advertising high. Although advertisements from larger brands may also be noticed more under a negative or uncertain situation, the high levels of familiarity and knowledge consumers already have with these major brands make the incremental impact from the brands' advertising less significant. Therefore, the impact of negative future outlook and uncertainty in macroeconomic sentiment on advertising effectiveness are likely to be more salient for brands with low market shares than brands with high market shares. This leads to the following hypotheses:

H3a: *The ad spending-sales relationship for low market share brands will be affected more by future outlook negativity in macroeconomic sentiment than for brands with high market shares.*

H3b: *The ad spending-sales relationship for low market share brands will be affected more by uncertainty in macroeconomic sentiment than for brands with high market shares.*

DATA AND VARIABLE OPERATIONALIZATIONS

I tested the hypotheses in the context of salty snack products. The data for my analysis came from a verity of sources. Sales data were obtained from Information Resources Incorporated (IRI), which captured retail sales of salty snacks from 2001 to 2012 in groceries and drugstores of 50 markets in the U.S (Bronnenberg et al., 2008). Advertising spending data came from Kantar Media and included weekly advertising spending for the various products within each brand across major online and offline advertising media. Macroeconomic sentiment measures were extracted from the Thomson Reuters Market-Psych Indices (TRMI). TRMI is created by mining the expressed emotions in millions of articles and posts from both traditional and online media channels on a daily basis (Sun et al., 2016). The two indices I used in this research were scores for overall negativity of future outlook and scores for uncertainty. To control for the effect of inflation, I also gathered the Consumer Price Index for Food and Beverage (CPIFABSL) from the U.S. Bureau of Labor Statistics. Table 1 summarizes the source and operationalization of each dependent, independents and control variables used in this study.

INSERT TABLE 1 ABOUT HERE

Brand-Subcategory Sales. Many brands in the sample have sales in multiple sub-product categories (e.g., potato chips, pretzels, tortilla chips). As the same brand's advertising strategy and market position can be quite different across product categories, I opted to conduct my analysis at the brand-subcategory level. That is, I examined the relationship between a brand's advertising spending within each sub-category and the sales of that brand in each sub-category. These sub-categories are determined using the IRI's product category scheme. Following research practice, I selected the brands that totaled 99% of each sub-category and removed the really small brands at the tail end from each sub-category due to irregularity of data for those brands. The final sample accounted for more than 99% of the salty snacks market and contains 1,015 brand, sub-category combinations. The number of sub-categories within each brand ranged from 1 to 9. Figure 1 shows the number of brands in each product sub-category, and Figure 2 depicts distribution of sub-categories across brands. To derive the sub-category sales for each brand from the IRI data, total weekly sales volume (in pounds) of all sub-category UPCs for each brand across all stores is calculated. Weekly sub-category brand sales volume ranged from 0 to 824,419.3 pounds, with median weekly sales volume being 99 pounds, and mean being 3732 pounds. Due to skewness, log-transformed sub-category brand sales volume served as the dependent variable in the model. This is consistent with previous ad spending-sales effect studies (e.g., Du et al., 2015; Gijsenberg, 2017; Kopalle et al., 1999).

INSERT FIGURE 1 AND FIGURE 2 ABOUT HERE

Advertising Expenditure. Weekly sub-category advertising expenditures for each brand was calculated by summing expenditures across all media types during each week as reported by Kantar Media. To adjust for inflation, the weekly expenditures were further divided by the CPIFABSL. Weekly inflation-adjusted ad spending ranged from \$0 to \$5,434,920, with the median being \$0 and mean being \$2205. Similar to brand sales, ad spending was log-transformed due to its skewness (e.g., Danaher et al., 2008; Frison et al., 2014).

Macro-Economic Sentiment. The original macroeconomic sentiment data from TRMI was in a daily format. To aggregate the data to a weekly interval, I followed the practice recommended by TRMI (Reuters, 2013) and calculated the volume-weighted average of sentiments across the days of every week. For instance, for future outlook negativity, I first calculated the weighted negative future outlook for each day by multiplying the daily negative future outlook index by the total content volume (buzz) on that day. This daily weighted negative future outlook was summed across all days of each week and then divided by the total content volume of that week. The resulting future outlook negativity variable is defined between 0 and 1, with a higher number representing a more *negative* future outlook in each week's media contents. The same process was followed to create the weekly uncertainty measure, which is defined between 0 and 1 and depicts the extent of uncertainty and confusion expressed in each week's media content.

Market share. I calculated the market share of each brand in each sub-category at a yearly interval. A brand's market share in a sub-category equals the brand's annual sales in that category divided by total annual sales for all brands in the corresponding product category. A yearly interval was chosen to ensure that the market share information is relatively stable. I used the sub-category market share for each brand from the previous year as the market share moderator in the model.

Control variables. I controlled for brands' non-advertising marketing activities in the model. For marketing activities, I used a series of variables to indicate the extent to which various forms of in-store promotions were used by each brand sub-category. These control variables included in-store features (small ad, medium ad, large ad, and in-store coupon/rebate), displays (minor display and major display), and price reduction. For in-store features and displays, I calculated the pervasiveness of each promotional format as the percentage of stores offering the promotion weighted by store sales. That is, the intensity of each promotional format is the percentage of the brand's weekly sales in that sub-category that occurred in the stores offering that promotional format. These promotional variables ranged from 0 to 1, with 0 meaning the brand did not use the corresponding promotional format for the sub-category in a given week and 1 meaning the brand used the corresponding promotional format for the sub-category in all stores that week. Besides promotions, I also controlled for product price by calculating a weighted unit price for each brand in each sub-category. This is done by first deriving the per pound price for each UPC each week. The weighted average of prices for all UPCs a brand sells in a sub-category is then calculated, with the weight being the relative share of each UPC in the brand sub-category's overall sales (see Table 1 for the exact formula). This weighting ensures that the more dominant products offered by a brand have a larger influence on the brand's average price in the sub-category each week. These weekly prices were divided by the CPIFABSL to create the final inflation-adjusted prices. Table 2 reports the descriptive statistics and correlations among all the variables.

INSERT TABLE 2 ABOUT HERE

THE MODEL

A Koyck mixed-effect model (equation 1) was employed to model the dynamic relationship between advertising spending and sales:

$$\mathbf{Sales}_{bct} = \beta_0 + \beta_1\, Sales_{bc(t-1)} + \beta_2\, AdSpending_{bct} + \beta_3\, Future\ Outlook\ Negativity_t + \beta_4 Uncertainty_t + \beta_5\, MarketShare_{bc(prior\text{-}year)} + \beta_6\, AdSpending_{bct} * Future\ Outlook\ Negativity_t + \beta_7\, AdSpending_{bct} * Uncertainty_t + \beta_8\, MarketShare_{bc(prior\text{-}year)} * Future\ Outlook\ Negativity_t + \beta_9\, MarketShare_{bc(prior\text{-}year)} * Uncertainty_t + \beta_{10}\, MarketShare_{bc(prior\text{-}year)} * AdSpending_{bct} + \beta_{11}\, AdSpending_{bct} * Future\ Outlook\ Negativity_t * MarketShare_{bc(prior\text{-}year)} + \beta_{12}\, AdSpending_{bct} * Uncertainty_t * MarketShare_{bc(prior\text{-}year)} + \beta_{13}\, InflationAdjusted\_Price_{bct} + \beta_{14}\, SmallFeatureAd_{bct} + \beta_{15}\, MediumFeatureAd_{bct} + \beta_{16}\, LargeFeatureAd_{bct} + \beta_{17}\, Coupon_{bct} + \beta_{18}\, MinorDisplay_{bct} + \beta_{19}\, MajorDisplay_{bct} + \beta_{20}\, Price\ Reduction_{bct} + \eta_c + \eta_Y + \tau_{bc} + \varepsilon_{bct} \quad (1)$$

where

$Sales_{bct}$ and $Sales_{bc(t-1)}$ = log-transformed sales volume for brand *b* in sub-category *c* during week *t* and *t*-1 respectively;

$AdSpending_{bct}$ = log-transformed and inflation adjusted advertising spending for brand *b* in sub-category *c* in week *t*;

$Future\ Outlook\ Negativity_t$ and $Uncertainty_t$ = future outlook negativity and uncertainty in week *t*;

$MarketShare_{bc(prior\text{-}year)}$ = market share for brand *b* in sub-category *c* from the previous calendar year;

$InflationAdjusted\_Price_{bct}$ = inflation-adjusted weighted unit price for brand *b* in sub-category *c* in week *t*;

$SmallFeatureAd_{bct}$, $MediumFeatureAd_{bct}$, $LargeFeatureAd_{bct}$, $Coupon_{bct}$, $MinorDisplay_{bct}$, $MajorDisplay_{bct}$ and $PriceReduction_{bct}$ = the intensity of these in-store promotional tools for brand b in sub-category *c* in week *t*, as described previously.

η_c = fixed effect for a sub-category *c*;

η_Y = fixed effect for each calendar year;

τ_{bc} = random idiosyncratic effect associated with each brand sub-category *bc*; and

ε_{bct} = random error that is not captured by the model.

With the log-transformation for both sales volume and ad spending, the effect of ad spending in the model represents the advertising elasticity of sales volume.

RESULTS

Main Model Results

The final data used for estimating the model consisted of an unbalanced panel of 1015 unique brand sub-category combinations, with the number of weekly time intervals available per brand-subcategory ranging from 56 to 574. All key variables (ad spending, future outlook negativity, uncertainty, and market share) were mean centered before entering into the model. The R^2 of the model equaled 0.92, indicating a good model fit. Table 3 reports the full model estimation results (overall markets column).

INSERT TABLE 3 ABOUT HERE

As expected, ad spending had a significant positive effect on sales (β_2 = .0032, t= 2.26, $p < 0.05$). I will focus my discussion first on the moderating effects of macroeconomic sentiment at the mean level of market share ($M_{marketshare}$ = 0.012). For future outlook negativity, the results showed a significant positive two-way interaction between ad spending and future outlook negativity (β_6= 0.442, t= 2.26, $p < 0.05$). To better interpret the interaction, I conducted a spotlight analysis at the lowest (*Min* = 0.025) and highest levels (*Max* = 0.050) of future outlook negativity, as suggested by Spiller et al. (2013). A more pronounced effect of ad spending on sales was observed at the high end of negative future outlook ($\beta_{2(\text{High negative future outlook})}$= 0.012 , t= 3.05, $p < 0.05$) than at the low end of negative future outlook ($\beta_{2(\text{Low negative future outlook})}$= 0.001 , t= 0.45, $p > 0.05$), lending support to H1. That is, a high level of negativity in future outlook increases sales responsiveness to advertising spending.

The interaction between ad spending and uncertainty was also significant and positive (β_7= 0.942, t= 2.99, $p < 0.05$). I conducted a similar spotlight analysis as earlier at the lowest (*Min* = 0.016) and highest (*Max* = 0.025) levels of uncertainty, given the mean market share. Results showed a positive and more pronounced impact of ad spending on sales at the high end of uncertainty ($\beta_{2(\text{High uncertainty})}$ = 0.01 , t= 4.58, $p < 0.05$) than at the low end of uncertainty ($\beta_{2(\text{Low uncertainty})}$= - 0.001 , t= -0.38, $p > 0.05$). Supporting H2, as uncertainty in macroeconomic sentiment increases, advertising spending exerts a stronger effect on sales.

The above results were based on a mean level of market share (i.e., mean-centered *MarketShare* = 0). H3a and H3b predicted that the moderating effect of macroeconomic sentiment should be stronger for smaller brands than larger brands. Consistent with H3a, there was a significant negative three-way interaction among ad spending, future outlook negativity and market share (β_{11}= - 2.305, t= -2.74, $p < 0.05$). To identify the regions where negative future outlook significantly moderates the ad spending-sales relationship, I conducted a floodlight analysis ((Johnson and Neyman, 1936)). Figure 3 plots the results. As shown in the figure, future outlook negativity strengthened the ad spending-sales relationship for brands with a market share lower than 5% but weakened the ad spending-sales relationship for brands with a market share higher than 49%. For brands with a market share between 5% and 49%, negative future outlook did not moderate the ad spending-sales relationship.

To dig deeper into the three-way interaction, I re-examined the simple effect of ad spending on sales at the lowest and highest levels of negative future outlook for both high-share and low-share brands. For brands with a market share lower than 5%, the results show a more positive ad-sales elasticity under high negativity in future outlook ($\beta_{2\ (\text{High NFO- Low MS})}$ = 0.009, t= 2.75, $p < 0.05$) than under low negativity in future outlook ($\beta_{2\ (\text{Low NFO- Low MS})}$ = 0.001, t= 0.59, $p > 0.05$). In other words, consumers show higher responsiveness to advertising efforts by low market share brands when prevalent future outlook is more negative. In contrast, for brands with a market share higher than 49%, I found that advertising spending did not have a significant effect on sales when macro-level negative sentiment toward future outlook was low ($\beta_{2\ (\text{Low FON- High MS})}$ = 0.002, t= 0.85, $p > 0.05$). Surprisingly, the effect of ad spending on sales became significant negative at the high end of future outlook negativity ($\beta_{2\ (\text{High FON- High MS})}$ = -0.014, t= - 2.20, $p < 0.05$).

In summary, the above results suggest that a negative macro-level future outlook favors low market share brands and increases consumers' responsiveness to their advertising efforts. In contrast, a negative future outlook makes the impact of adverting on sales weaker for high market share brands. Overall H3a was partially supported. Instead of future outlook negativity having a weaker effect on bigger brands, it appears that its effect on the ad-sales relationship may be entirely different for brands that hold close to or more than half of the market share. I explore this further in the "Additional Analysis" section.

Turning to uncertainty, the model results showed a significant negative three-way interaction among ad spending, uncertainty and market share (β_{12}= - 3.658, t= - 2.58, $p < 0.05$), in line with the prediction in H3b. Further floodlight analysis suggests that the moderating effect of uncertainty on the advertising spending-sales relationship was significant for brands with a market share lower than 13% and for brands with a market share higher than 78%. Between those two market share levels, uncertainty in the macroeconomic sentiment had no influence on the ad spending-sales relationship. Figure 4 plots the results from the floodlight analysis.

To test H3b, I again examined the simple effect of ad spending on sales at the lowest and highest levels of uncertainty for both high-share and low-share brands. For brands with a low market share (lower than 13%), the effect of advertising on sales ($\beta_{2\text{(High uncertainty-Low MS)}}$= 0.005, t= 3.10, $p < 0.05$) was stronger when macro-level uncertainty was high than when it was low ($\beta_{2\text{(Low uncertainty- Low MS)}}$ = -0.0001, t = -0.061, $p > 0.05$). That is, consumers showed higher responsiveness to advertisements from brands with a low market share when exposed to higher uncertainty in the macroeconomic sentiment. However, the opposite was true for brands with a very high market share (higher than 78%). The effect of advertising on sales ($\beta_{2\text{ (High uncertainty- High MS)}}$ = -0.014, t= -2.66, $p < 0.05$) became negative when macroeconomic uncertainty was at the highest level in comparison to a non-significant ad-sales relationship when macroeconomic uncertainty was at the lowest level ($\beta_{2\text{(Low uncertainty- High MS)}}$= 0.002 , t= 0.57, $p > 0.05$). Overall, the results on macro-level uncertainty reveal that consumers show higher responsiveness to advertising under high uncertainty but only for low market share brands. Therefore, H3b is partially supported. Similar to the future outlook negativity results, the negative and significant effect of advertising spending on sales for high market share brands will be investigated further in the next section.

INSERT FIGURE 1 AND FIGURE 2 ABOUT HERE

For the control variables, the effects of all in-store promotion variables were positive and significant, consistent with previous research (Tellis and Weiss, 1995). Lagged sales volume also had a significant positive effect on current period sales (β_1=0.9, t=1896.16, $p < 0.05$). However, contrary to expectation, the effect of weighted unit price on sales was positive and significant (β_{13}=0.114, t=81.82, $p < 0.05$).

Exploring Market Concentration

Thus far, I have demonstrated significant moderating effects of future outlook negativity and uncertainty on the ad spending-sales relationship, in support of my theoretical arguments. I have also shown that this effect is in favor of low-market-share brands. In the meantime, ad spending of high market share brands has a surprisingly negative effect on sales when future outlook negativity and uncertainty is high. This finding may be due to the fact that advertising for dominant brands does not work in the same way as does advertising for less dominant brands (Kent and Allen, 1994; Machleit et al., 1993). In general, advertisements are beneficial up to a certain level, and continued repetition may evoke negative feelings toward a brand (Laroche et al., 2003). While in competitive markets a greater number of exposures would be required to reach the wear-out point, in concentrated markets where a specific brand name is associated with the product class, a lower level of exposure would be needed to surpass the effectiveness threshold (Laroche et al., 2006). Moreover, as I have argued previously, when prevalent future outlook is negative and uncertainty in macroeconomic sentiment is high, consumers tend to switch from dominant brands to less-known brands, which may in turn reduce their responsiveness to advertising efforts of high market share brands. Together, the preceding arguments suggest that the negative ad spending-sales relationship at the high end of future outlook negativity and uncertainty should be more likely to happen in concentrated markets and for brands with dominant control over the market. To test this possible explanation empirically, I conducted a few additional analyses.

First, to identify dominant brands in each product sub-category, I examined simple effects of advertising at all possible market share values in the sample (from less than 1% to 84%), holding negative future outlook negativity and uncertainty at the mean level. The results indicated that, for brands with a market share higher than 65%, advertising spending had a negative effect on sales. In other words, under normal circumstances, some larger brands may be allocating too much money to advertising, surpassing the effectiveness threshold. This finding is consistent with Aaker and Carman (1982), who found that most of the well-established and frequently purchased consumer brands are overspending on advertising. Looking over the current data, there were three brands with market shares higher than 65% in three product categories: Fritos in the corn snacks product category with an 84% market share, Cheetos in the cheese snacks product category with 73% market share, and Chex Mix in the snack mix product category with 66% market share. Therefore, corn snacks, cheese snacks and snack mix markets seemed to be highly concentrated markets, and dominant brands in each of these markets seemed to have spent too much on their advertisements.

To investigate the market concentration level in all product categories, I calculated the yearly Herfindahl-Hirschman Index (HHI) for each market. HHI is a commonly used measure to determine market competitiveness. It is calculated by squaring 100*market share of each brand in a market and then summing across all brands. HHI ranges from close to zero to 10,000. A market with an HHI less than 1500 is considered to be a competitive market, an HHI of 1,500 to 2,500 suggests a moderately concentrated market, and an HHI higher than 2,500 indicates a highly concentrated market. Table 4 shows the concentration level for each market on a yearly basis. Consistent with the brand analysis earlier, results indicated that the corn snack, cheese snack, and snack mix markets were all highly concentrated across all years in the observation window. In contrast, potato chips, pork rind and popcorn were considered competitive markets across all years. Markets for the rest of product categories were moderately concentrated, with different concentration levels in different years.

To test if market concentration levels may have affected the findings in the main model, I re-estimated the model using two restricted samples. In one, I took a time-centric approach and excluded the years related to a product sub-category if the market was concentrated. In the second analysis, I only excluded four dominant brands in four concentrated markets as identified earlier from the analysis.

INSERT TABLE 4 ABOUT HERE

Results Excluding Concentrated Markets

In order to re-estimate the model for competitive and moderately concentrated markets, I excluded markets with HHIs indicating a highly concentration. This more restricted sample consisted of an unbalanced panel of 802 brand sub-category combinations, with 322,554 weekly observations. The market share ranged from 0% to 47%, with the mean value being 1%. Re-estimating the model using this restricted sample yielded an R^2 of 0.91, indicating a good model fit. The results showed significant positive two-way interactions between ad spending and future outlook negativity (β_6= 0.602, t= 2.40, $p < 0.05$) and between ad spending and uncertainty (β_7= 1.524, t= 3.66, $p < 0.05$). That is, in competitive and moderately concentrated markets, similar to the overall market, a highly negative future outlook and high uncertainty in macroeconomic sentiment increase advertising spending effect on sales. In addition, as predicted, both the three-way interaction among ad spending, future outlook negativity, and market share (β_{11}= - 3.347, t= -2.47, $p < 0.05$), and the three-way interaction among ad spending, uncertainty, and market share (β_{12}= - 7.952, t= - 3.57, $p < 0.05$) were significant. The "Excluding Concentrated Markets" column in Table 3 reports the model estimates.

Similar to the main model, I conducted two floodlight analyses to further examine the significant three-way interactions (see Figures 5 and 6). The results suggest that the moderating effect of negative future outlook on ad spending-sales relationship was only significant for brands with market shares lower than 7%, and that negative future outlook had no significant impact on the ad spending-sales relationship for brands with market shares above 7%. Similarly, the moderating effect of uncertainty on the ad spending-sales relationship was significant for brands with market shares lower than 9% but not for brands with market shares higher than 9%. Overall, these results show that in competitive and moderately concentrated markets, a high level of future outlook negativity and uncertainty is more in favor of brands with low market shares, while it does affect the sales response to advertising for high market share brands, consistent with H3a and H3b.

After excluding concentrated markets, the negative relationship between advertising spending and sales no longer applies.

INSERT FIGURES 5 AND 6 ABOUT HERE

Results Excluding Dominant Brands

In the second auxiliary analysis, I excluded four dominant brand-subcategories from the sample (Fritos from corn cnack category with an 84% market share, Cheetos from cheese cnack category with a 73% market share, Chex Mix from mix snack category with a 66% market share, and sun chips in other snack category with a 46% market share). The first three brands dominated the corresponding categories across all 11 years, while the last brand dominated the other snacks market in some years. This restricted sample consisted of an unbalanced panel of 1010 brand sub-category combinations, with 422,172 weekly observations. The market share ranged from 0% to 42%, with a mean of 1%. Estimating the model using this restricted sample yielded an R^2 value of 0.92, indicating a good model fit. Similar to the previous analyses, results showed significant positive two-way interactions between ad spending and future outlook negativity (β_6= 0.492, t= 2.42, $p < 0.05$) and between ad spending and uncertainty (β_7= 1.156, t= 3.54, $p < 0.05$). In addition, both the three-way interaction among ad spending, future outlook negativity, and market share (β_{11}= - 3.053, t= -2.38, $p < 0.05$), and the three-way interaction among ad spending, uncertainty, and market share (β_{12}= - 6.512, t= -3.12, $p < 0.05$) were significantly negative. The “Excluding Dominant Brands” column in Table 3 reports the coefficient estimates from this analysis.

Floodlight analyses show that the moderating effect of negative future outlook on the ad spending-sales relationship was significant for brands with market shares lower than 6% and not significant for brands with market shares higher than 6% (see Figure 7). Similarly, the moderating effect of uncertainty on the ad spending-sales relationship was significant and positive only when market share was lower than 10%, and it had the opposite effect when market shares exceeded 40% (see Figure 8). Looking over the market share of brands, the only remaining brand-subcategory with a market share higher than 40% was Frito-lay in the other snacks category, with an average market share of 42% and nearly dominated the market in years 2010, 2011 and 2012. In fact, the HHI values for the other snacks market in these three years were above 2200, indicating a moderately concentrated market. Therefore, when the level of future outlook negativity and uncertainty in macroeconomic sentiment was high, a dominant brand in moderately concentrated markets could also pass the advertising effectiveness threshold (e.g., spending too much).

INSERT FIGURES 7 AND 8 ABOUT HERE

GENERAL DISCUSSION

Conclusions and Implications

The impact of advertising on sales has attracted a lot of attention from marketing researchers. This study adds novel insights to this body of research by demonstrating that two macroeconomic sentiments, future outlook negativity and uncertainty, can play a moderating role in the ad spending-sales relationship. Specifically, utilizing sales and advertising data for salty snacks along with macroeconomic sentiment measures, this study finds that a prevailing negative future outlook and a high level of uncertainty in macro-level sentiment amplifies sales responsiveness to ad spending. These findings are consistent with the reasoning that both a negative future outlook and a high level of uncertainty put individuals in a cognitive and affective state that makes them more receptive to brands' advertisements.

Furthermore, I find the moderating effect of future outlook negativity and uncertainty on ad spending-sales relationship is contingent upon brands' market share. In particular, a prevailing negative future outlook and a high level of uncertainty in macroeconomic sentiment are more in favor of brands with low market shares by increasing the sales responsiveness to these brands' ad spending. In contrast, such macroeconomic sentiments largely do not change the effectiveness of advertising for higher market share brands. These findings are in congruent with the arguments that holding a negative future outlook and a high level of uncertainty make consumers ready to switch from high market share brands to low market share ones.

The current study also supports the general proposition in the literature that advertising works differently for brands with a dominating control over their markets. Specifically, for limited cases in our sample, where a brand has dominating control over a specific market or if the market is highly concentrated, these macroeconomic sentiment factors can have the opposite effect by turning the ad spending-sales relationship negative for such dominating brands. I attribute this to a lower turning point in the advertising effectiveness curve for dominating brands in highly concentrated markets, where more ad exposures can evoke negative feelings (Laroche et al., 2006). When a negative future outlook and high uncertainty in macroeconomic sentiment drive consumers to switch from established brands to less-known ones, it is easy for bigger brands to over-invest in advertising to the detriment of their sales.

Managerial Implication

Advertising spending is a great concern for managers since inefficient spending contributes to sales loss and lower profit (Luo and Donthu, 2005). A longitudinal analysis of advertising efficacy among top 100 U.S. companies by Cheong et al. (2014) suggests that companies not only were inefficient in their ad spending, but the inefficiency has also increased overtime. The current paper addresses the above issue by suggesting macroeconomic sentiments as a novel proxy for deciding optimal advertising spending across time. The overall conclusion is that brands with low market shares should increase their ad spending when there is a general society-level sentiment with a negative future outlook and high uncertainty. In the meantime, higher market share brands in a competitive to moderately competitive market are best served maintaining their advertising spending under such situations. Finally, for dominant brands in concentrated markets, they should be very careful not to overspend on advertising during such times since it can negatively affect their sales. Contrary to previous methods for optimal ad budget allocation that is often based on annual data (Aravindakshan et al., 2012), the macroeconomic sentiments discussed in this research fluctuate more frequently and are often available in near real-time. They can allow more agility in companies advertising budgeting decisions.

Limitation and Future Research

This paper has a few limitations that should be addressed in future research. First, my data consisted of only salty snacks which is a non-durable product category. Future studies should generalize the current findings to other non-durable and durable product contexts. It would be interesting to compare the moderating role of macroeconomic sentiment on the ad spending-sales relationship between durable versus non-durable product categories.

Second, this study focused on the effect of advertising spending (in dollars) on sales, without considering advertising content (e.g., message type or information content). It would be valuable for future research to examine whether macroeconomic sentiments should also lead to adjustments in ad creatives in order to maximize effectiveness.

Finally, the current paper considered only two macroeconomic sentiments. There are other types of macroeconomic sentiments that can have an impact on consumers' response to advertisements. Furthermore, prevailing sentiments in a society may also be driven by non-economic reasons such as catastrophic or uplifting events. Future research should extend the current study to examine a wider range of society-level sentiments on the ad-sales relationship.

REFRENCES

Aaker, D. A., & Carman, J. M. (1982). Are you over-advertizing. *Journal of Advertising Research, 22*(4), 57-70.

Agrawal, D. (1996). Effect of brand loyalty on advertising and trade promotions: A game theoretic analysis with empirical evidence. *Marketing Science, 15*(1), 86-108.

Aravindakshan, A., Peters, K., & Naik, P. A. (2012). Spatiotemporal allocation of advertising budgets. *Journal of Marketing Research, 49*(1), 1-14.

Ashley, R., Granger, C. W., & Schmalensee, R. (1980). Advertising and aggregate consumption: An analysis of causality. *Econometrica: Journal of the Econometric Society*, 1149-1167.

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The Journal of Finance, 61*(4), 1645-1680.

Balahur, A., & Steinberger, R. (2009). Rethinking Sentiment Analysis in the News: from Theory to Practice and back. *Proceeding of WOMSA, 9*.

Baumeister, R. F., & Heatherton, T. F. (1996). Self-regulation failure: An overview. *Psychological inquiry, 7*(1), 1-15.

Benhabib, J., Liu, X., & Wang, P. (2016). Sentiments, financial markets, and macroeconomic fluctuations. *Journal of Financial Economics, 120*(2), 420-443.

Bleichrodt, H., Cillo, A., & Diecidue, E. (2010). A quantitative measurement of regret theory. *Management Science, 56*(1), 161-175.

Bloch, H. (1974). Advertising and profitability: a reappraisal. *Journal of political Economy, 82*(2, Part 1), 267-286.

Blood, D. J., & Phillips, P. C. (1995). Recession headline news, consumer sentiment, the state of the economy and presidential popularity: A time series analysis 1989–1993. *International Journal of Public Opinion Research, 7*(1), 2-22.

Bronnenberg, B. J., Kruger, M. W., & Mela, C. F. (2008). Database paper—The IRI marketing data set. *Marketing Science, 27*(4), 745-748.

Bryant, W. A., & Macri, J. (2005). Does sentiment explain consumption? *Journal of economics and finance, 29*(1), 97-110.

Carroll, C. D., Fuhrer, J. C., & Wilcox, D. W. (1994). Does consumer sentiment forecast household spending? If so, why? *The American Economic Review, 84*(5), 1397-1408.

Chan, L. K., Lakonishok, J., & Sougiannis, T. (2001). The stock market valuation of research and development expenditures. *The Journal of Finance, 56*(6), 2431-2456.

Cheong, Y., De Gregorio, F., & Kim, K. (2014). Advertising spending efficiency among top US advertisers from 1985 to 2012: Overspending or smart managing? *Journal of Advertising, 43*(4), 344-358.

Choi, J., & Fishbach, A. (2011). Choice as an end versus a means. *Journal of Marketing Research, 48*(3), 544-554.

Clarke, D. G. (1976). Econometric measurement of the duration of advertising effect on sales. *Journal of Marketing Research*, 345-357.

Comanor, W. S., & Wilson, T. A. (1974). *Advertising and market power*: Harvard University Press.

Danaher, P. J., Bonfrer, A., & Dhar, S. (2008). The effect of competitive advertising interference on sales for packaged goods. *Journal of Marketing Research, 45*(2), 211-225.

Darrat, M. A., Wilcox, G. B., Funches, V., & Darrat, M. A. (2016). Toward an Understanding of Causality Between Advertising and Sales: New Evidence from a Multivariate Cointegrated System. *Journal of Advertising, 45*(1), 62-71.

Deighton, J., Henderson, C. M., & Neslin, S. A. (1994). The effects of advertising on brand switching and repeat purchasing. *Journal of Marketing Research, 31*(1), 28-43.

Dekimpe, M. G., & Hanssens, D. M. (1995). The persistence of marketing effects on sales. *Marketing Science, 14*(1), 1-21.

Doms, M. E., & Morin, N. J. (2004). Consumer sentiment, the economy, and the news media.

Du, R. Y., Hu, Y., & Damangir, S. (2015). Leveraging trends in online searches for product features in market response modeling. *Journal of Marketing, 79*(1), 29-43.

Duffy, M. H. (1987). Advertising and the inter-product distribution of demand: a Rotterdam model approach. *European Economic Review, 31*(5), 1051-1070.

Dunn, J. R., & Schweitzer, M. E. (2005). Feeling and believing: the influence of emotion on trust. *Journal of personality and social psychology, 88*(5), 736.

Eastlack, J. O., & Rao, A. G. (1989). Advertising experiments at the campbell soup company. *Marketing Science, 8*(1), 57-71.

Elliott, C. (2001). A cointegration analysis of advertising and sales data. *Review of Industrial Organization, 18*(4), 417-426.

Estelami, H., Lehmann, D. R., & Holden, A. C. (2001). Macro-economic determinants of consumer price knowledge: A meta-analysis of four decades of research. *International Journal of Research in Marketing, 18*(4), 341-355.

Fader, P. S., & Schmittlein, D. C. (1993). Excess behavioral loyalty for high-share brands: Deviations from the Dirichlet model for repeat purchasing. *Journal of Marketing Research*, 478-493.

Fisher, I. (1930). *Theory of interest: as determined by impatience to spend income and opportunity to invest it*: Augustusm Kelly Publishers, Clifton.

Frison, S., Dekimpe, M. G., Croux, C., & De Maeyer, P. (2014). Billboard and cinema advertising: Missed opportunity or spoiled arms? *International Journal of Research in Marketing, 31*(4), 425-433.

Garcia, D. (2013). Sentiment during recessions. *The Journal of Finance, 68*(3), 1267-1300.

Garz, M. (2018). Effects of unemployment news on economic perceptions–Evidence from German Federal States. *Regional Science and Urban Economics, 68*, 172-190.

Gijsenberg, M. J. (2017). Riding the Waves: Revealing the Impact of Intrayear Category Demand Cycles on Advertising and Pricing Effectiveness. *Journal of Marketing Research, 54*(2), 171-186.

Gino, F., Brooks, A. W., & Schweitzer, M. E. (2012). Anxiety, advice, and the ability to discern: Feeling anxious motivates individuals to seek and use advice. *Journal of personality and social psychology, 102*(3), 497.

Goidel, R. K., & Langley, R. E. (1995). Media coverage of the economy and aggregate economic evaluations: Uncovering evidence of indirect media effects. *Political Research Quarterly, 48*(2), 313-328.

Graham Jr, R. C., & Frankenberger, K. D. (2000). The contribution of changes in advertising expenditures to earnings and market values. *Journal of Business Research, 50*(2), 149-155.

Graham, R. C., & Frankenberger, K. D. (2011). The earnings effects of marketing communication expenditures during recessions. *Journal of Advertising, 40*(2), 5-24.

Grewal, D., Monroe, K. B., & Krishnan, R. (1998). The effects of price-comparison advertising on buyers' perceptions of acquisition value, transaction value, and behavioral intentions. *The Journal of Marketing*, 46-59.

Guseva, A., & Rona-Tas, A. (2001). Uncertainty, risk, and trust: Russian and American credit card markets compared. *American sociological review*, 623-646.

Heerde, H. J. V., Gijsenberg, M. J., Dekimpe, M. G., & Steenkamp, J.-B. E. (2013). Price and advertising effectiveness over the business cycle. *Journal of Marketing Research, 50*(2), 177-193.

Heimonen, K., & Uusitalo, O. (2009). The beer market and advertising expenditure. *Marketing Intelligence & Planning, 27*(7), 945-975.

Hester, J. B., & Gibson, R. (2003). The economy and second-level agenda setting: A time-series analysis of economic news and public opinion about the economy. *Journalism & Mass Communication Quarterly, 80*(1), 73-90.

Hollanders, D., & Vliegenthart, R. (2011). The influence of negative newspaper coverage on consumer confidence: The Dutch case. *Journal of economic psychology, 32*(3), 367-373.

Hu, Y., Du, R. Y., & Damangir, S. (2014). Decomposing the impact of advertising: Augmenting sales with online search data. *Journal of Marketing Research, 51*(3), 300-319.

Jedidi, K., Mela, C. F., & Gupta, S. (1999). Managing advertising and promotion for long-run profitability. *Marketing Science, 18*(1), 1-22.

Johnson, P. O., & Neyman, J. (1936). Tests of certain linear hypotheses and their application to some educational problems. *Statistical research memoirs*.

Joshi, A., & Hanssens, D. M. (2010). The direct and indirect effects of advertising spending on firm value. *Journal of Marketing, 74*(1), 20-33.

Ju, Y. (2008). The asymmetry in economic news coverage and its impact on public perception in South Korea. *International Journal of Public Opinion Research, 20*(2), 237-249.

Kamber, T. (2002). The brand manager's dilemma: Understanding how advertising expenditures affect sales growth during a recession. *Journal of Brand Management, 10*(2), 106-120.

Karakaya, F., & Stahl, M. J. (1989). Barriers to entry and market entry decisions in consumer and industrial goods markets. *Journal of Marketing*, 80-91.

Kent, R. J., & Allen, C. T. (1994). Competitive interference effects in consumer memory for advertising: the role of brand familiarity. *Journal of Marketing, 58*(3), 97-105.

Kiel, G. C., & Layton, R. A. (1981). Dimensions of consumer information seeking behavior. *Journal of Marketing Research*, 233-239.

Kim, & McAlister, L. M. (2011). Stock market reaction to unexpected growth in marketing expenditure: negative for sales force, contingent on spending level for advertising. *Journal of Marketing, 75*(4), 68-85.

Kopalle, P. K., Mela, C. F., & Marsh, L. (1999). The dynamic effect of discounting on sales: Empirical analysis and normative pricing implications. *Marketing Science, 18*(3), 317-332.

Kwoka Jr, J. E. (1993). The sales and competitive effects of styling and advertising practices in the US auto industry. *The Review of Economics and Statistics*, 649-656.

Lamey, L., Deleersnyder, B., Dekimpe, M. G., & Steenkamp, J.-B. E. (2007). How business cycles contribute to private-label success: Evidence from the United States and Europe. *Journal of Marketing, 71*(1), 1-15.

Lamey, L., Deleersnyder, B., Steenkamp, J.-B. E., & Dekimpe, M. G. (2012). The effect of business-cycle fluctuations on private-label share: what has marketing conduct got to do with it? *Journal of Marketing, 76*(1), 1-19.

Landes, E. M., & Rosenfield, A. M. (1994). The durability of advertising revisited. *The Journal of Industrial Economics*, 263-276.

Laroche, M., Cleveland, M., & Maravelakis, I. (2006). Competitive advertising and ad repetition effects: comparing high-share and low-share brands. *International journal of advertising, 25*(3), 271-307.

Laroche, M., Pons, F., Zgolli, N., Cervellon, M.-C., & Kim, C. (2003). A model of consumer response to two retail sales promotion techniques. *Journal of Business Research, 56*(7), 513. doi:10.1016/S0148-2963(01)00249-1

Leach, D. F., & Duncan Reekie, W. (1996). A natural experiment of the effect of advertising on sales: the SASOL case. *Applied Economics, 28*(9), 1081-1091.

Leeflang, P. S., & Reuijl, J. C. (1985). Advertising and industry sales: An empirical study of the West German cigarette market. *Journal of Marketing*, 92-98.

Leith, K. P., & Baumeister, R. F. (1996). Why do bad moods increase self-defeating behavior? Emotion, risk tasking, and self-regulation. *Journal of personality and social psychology, 71*(6), 1250.

Leone, R. P. (1995). Generalizing what is known about temporal aggregation and advertising carryover. *Marketing Science, 14*(3_supplement), G141-G150.

Lewis, R. A., & Reiley, D. H. (2014). Online ads and offline sales: measuring the effect of retail advertising via a controlled experiment on Yahoo! *Quantitative Marketing and Economics, 12*(3), 235-266. doi:10.1007/s11129-014-9146-6

Loewenstein, G. (1994). The psychology of curiosity: A review and reinterpretation. *Psychological bulletin, 116*(1), 75.

Luo, X., & Donthu, N. (2005). Assessing advertising media spending inefficiencies in generating sales. *Journal of Business Research, 58*(1), 28-36.

Machleit, K. A., Allen, C. T., & Madden, T. J. (1993). The mature brand and brand interest: An alternative consequence of ad-evoked affect. *Journal of Marketing, 57*(4), 72-82.

MacInnis, D. J., Rao, A. G., & Weiss, A. M. (2002). Assessing when increased media weight of real-world advertisements helps sales. *Journal of Marketing Research, 39*(4), 391-407.

Manchanda, P., Dubé, J.-P., Goh, K. Y., & Chintagunta, P. K. (2006). The effect of banner advertising on internet purchasing. *Journal of Marketing Research, 43*(1), 98-108.

Miller, D. (1987). The structural and environmental correlates of business strategy. *Strategic management journal, 8*(1), 55-76.

Miller, D., & Friesen, P. H. (1983). Strategy-making and environment: the third link. *Strategic management journal, 4*(3), 221-235.

Mizerski, R. W., & Settle, R. B. (1979). The influence of social character on preference for social versus objective information in advertising. *Journal of Marketing Research*, 552-558.

Morselli, D. (2017). Contextual determinants of hopelessness: Investigating socioeconomic factors and emotional climates. *Social indicators research, 133*(1), 373-393.

Muraven, M., & Baumeister, R. F. (2000). Self-regulation and depletion of limited resources: Does self-control resemble a muscle? *Psychological bulletin, 126*(2), 247.

Muraven, M., Tice, D. M., & Baumeister, R. F. (1998). Self-control as a limited resource: Regulatory depletion patterns. *Journal of personality and social psychology, 74*(3), 774.

Nagle, T. T. (1981). Do advertising-profitability studies really show that advertising creates a barrier to entry? *The Journal of Law and Economics, 24*(2), 333-349.

Newstead, K., Taylor, J., Kennedy, R., & Sharp, B. (2009). The total long-term sales effects of advertising: Lessons from single source. *Journal of Advertising Research, 49*(2), 207-210.

Nguyen, V. H., & Claus, E. (2013). Good news, bad news, consumer sentiment and consumption behavior. *Journal of economic psychology, 39*, 426-438.

O'SULLIVAN, O. P. (2015). The Neural Basis of Always Looking on the Bright Side. *Dialogues in Philosophy, Mental & Neuro Sciences, 8*(1).

Oswald, A. J. (1997). Happiness and economic performance. *The Economic Journal, 107*(445), 1815-1831.

Ouyang, M., Zhou, D., & Zhou, N. (2002). Estimating marketing persistence on sales of consumer durables in China. *Journal of Business Research, 55*(4), 337-342.

Pagán, J., Sethi, S., & Soydemir, G. A. (2001). The impact of promotion/advertising expenditures on citrus sales. *Applied Economics Letters, 8*(10), 659-663.

Paton, D. (2002). Advertising, quality and sales. *Applied Economics, 34*(4), 431-438. doi:10.1080/00036840110046025

Pavlou, P. A., Liang, H., & Xue, Y. (2007). Understanding and mitigating uncertainty in online exchange relationships: A principal-agent perspective. *MIS quarterly*, 105-136.

Peterson, R. A., & Jeong, J. (2010). Exploring the impact of advertising and R&D expenditures on corporate brand value and firm-level financial performance. *Journal of the Academy of Marketing Science, 38*(6), 677-690.

Plous, S. (1993). *The psychology of judgment and decision making*: Mcgraw-Hill Book Company.

Pras, B., & Summers, J. O. (1978). Perceived risk and composition models for multiattribute decisions. *Journal of Marketing Research, 15*(3), 429-437.

Ramos, F. F. (1988). Causality among sales, advertising and prices: new evidence from a multivariate cointegrated system. *Journal of Econometrics*.

Reuters, T. (2013). Thomson Reuters MarketPsych Indices. In.

Sethuraman, R., Tellis, G. J., & Briesch, R. A. (2011). How well does advertising work? Generalizations from meta-analysis of brand advertising elasticities. *Journal of Marketing Research, 48*(3), 457-471.

Settle, R. B. (1972). Attribution theory and acceptance of information. *Journal of Marketing Research, 9*(1), 85-88.

Shani, Y., Tykocinski, O. E., & Zeelenberg, M. (2008). When ignorance is not bliss: How feelings of discomfort promote the search for negative information. *Journal of economic psychology, 29*(5), 643-653.

Shiller, R. (2000). Irrational Exuberance, Princeton Univ. In: Press.

Spiller, S. A., Fitzsimons, G. J., Lynch Jr, J. G., & McClelland, G. H. (2013). Spotlights, floodlights, and the magic number zero: Simple effects tests in moderated regression. *Journal of Marketing Research, 50*(2), 277-288.

Sridhar, S., Germann, F., Kang, C., & Grewal, R. (2016). Relating online, regional, and national advertising to firm value. *Journal of Marketing, 80*(4), 39-55.

Srinivasan, R., Lilien, G. L., & Sridhar, S. (2011). Should firms spend more on research and development and advertising during recessions? *Journal of Marketing, 75*(3), 49-65.

Srinivasan, R., Rangaswamy, A., & Lilien, G. L. (2005). Turning adversity into advantage: Does proactive marketing during a recession pay off? *International Journal of Research in Marketing, 22*(2), 109-125. doi:10.1016/j.ijresmar.2004.05.002

Steenkamp, J.-B. E., & Fang, E. (2011). The impact of economic contractions on the effectiveness of R&D and advertising: evidence from US companies spanning three decades. *Marketing Science, 30*(4), 628-645.

Sun, L., Najand, M., & Shen, J. (2016). Stock return predictability and investor sentiment: A high-frequency perspective. *Journal of Banking & Finance, 73*, 147-164.

Svensson, H. M., Albæk, E., van Dalen, A., & de Vreese, C. H. (2017). The impact of ambiguous economic news on uncertainty and consumer confidence. *European Journal of Communication, 32*(2), 85-99.

Taylor, S. E., & Brown, J. D. (1988). Illusion and well-being: a social psychological perspective on mental health. *Psychological bulletin, 103*(2), 193.

Tellis, G. J., & Tellis, K. (2009). Research on advertising in a recession: a critical review and synthesis. *Journal of Advertising Research, 49*(3), 304-327.

Tellis, G. J., & Weiss, D. L. (1995). Does TV advertising really affect sales? The role of measures, models, and data aggregation. *Journal of Advertising, 24*(3), 1-12.

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *The Journal of Finance, 62*(3), 1139-1168.

Tice, D. M., Bratslavsky, E., & Baumeister, R. F. (2001). Emotional distress regulation takes precedence over impulse control: If you feel bad, do it! *Journal of personality and social psychology, 80*(1), 53.

Tiedens, L. Z., & Linton, S. (2001). Judgment under emotional certainty and uncertainty: the effects of specific emotions on information processing. *Journal of personality and social psychology, 81*(6), 973.

Vakratsas, D., & Ambler, T. (1999). How advertising works: what do we really know? *Journal of Marketing*, 26-43.

Van Dijk, E., & Zeelenberg, M. (2007). When curiosity killed regret: Avoiding or seeking the unknown in decision-making under uncertainty. *Journal of Experimental Social Psychology, 43*(4), 656-662.

van Giesen, R. I., & Pieters, R. (2019). Climbing out of an economic crisis: A cycle of consumer sentiment and personal stress. *Journal of economic psychology, 70*, 109-124.

Van Raaij, W. F. (1989). Economic news, expectations and macro-economic behaviour. *Journal of economic psychology, 10*(4), 473-493.

Voinea, L., & Filip, A. (2011). Analyzing the main changes in new consumer buying behavior during economic crisis. *International Journal of Economic Practices and Theories, 1*(1), 14-19.

Wang, F., Zhang, X.-P. S., & Ouyang, M. (2009). Does advertising create sustained firm value? The capitalization of brand intangible. *Journal of the Academy of Marketing Science, 37*(2), 130-143.

Weary, G., & Jacobson, J. A. (1997). Causal uncertainty beliefs and diagnostic information seeking. *Journal of personality and social psychology, 73*(4), 839.

Wilson, A. E., & Darke, P. R. (2012). The optimistic trust effect: Use of belief in a just world to cope with decision-generated threat. *Journal of Consumer Research, 39*(3), 615-628.

Wilson, T. D., & Gilbert, D. T. (2003). Affective forecasting. *Advances in experimental social psychology, 35*(35), 345-411.

Wood, L. (2009). Short-term effects of advertising: Some well-established empirical law-like patterns. *Journal of Advertising Research, 49*(2), 186-192.

Wu, H. D., Stevenson, R. L., Chen, H. C., & Güner, Z. N. (2002). The conditioned impact of recession news: A time-series analysis of economic communication in the United States, 1987–1996. *International Journal of Public Opinion Research, 14*(1), 19-36.

Xiong, G., & Bharadwaj, S. (2013). Asymmetric roles of advertising and marketing capability in financial returns to news: Turning bad into good and good into great. *Journal of Marketing Research, 50*(6), 706-724.

Yang, A. X., & Urminsky, O. (2015). The foresight effect: Local optimism motivates consistency and local pessimism motivates variety. *Journal of Consumer Research, 42*(3), 361-377.

Yiannaka, A., Giannakas, K., & Tran, K. C. (2002). Medium, message and advertising effectiveness in the Greek processed meats industry. *Applied Economics, 34*(14), 1757-1763.

Yoon, S., & Kim, H. C. (2017). Feeling economically stuck: The effect of perceived economic mobility and socioeconomic status on variety seeking. *Journal of Consumer Research, 44*(5), 1141-1156.

Zhou, N., Zhou, D., & Ouyang, M. (2003). Long-term effects of television advertising on sales of consumer durables and nondurables--The case of China. *Journal of Advertising, 32*(2), 45-54.

TABLES AND FIGURES

TABLE 1: VARIABLE OPERATIONALIZATION AND DATA SOURCES

Variable	Description	Source
Brand Sub-Category Sales	Log-transformed weekly brand sub-category sales in volume across all stores.	IRI
Advertising Spending	Log-transformed and inflation adjusted weekly advertising expenditures for each brand sub-category across all media types.	Kantar Media
Future Outlook negativity in Macro-Economic Sentiment	Weekly future outlook negativity measure is created by first calculating the daily weighted future outlook negativity (multiplying the daily negative future outlook index by the total content volume (buzz) in that day). Then, weekly future outlook negativity was calculated by first aggregating the weighted negative future outlook across all days of the week, and finally dividing it by total content volume (buzz) of that week). The formula is as follows: $(\text{Buzz}_1 \times \text{Sentiment } 1 + \text{Buzz } 2 \times \text{Sentiment } 2 + \ldots + \text{Buzz } 7 \times \text{Sentiment}_7) / (\text{Buzz } 1 + \text{Buzz } 2 + \ldots + \text{Buzz}_7)$	TRMI
Uncertainty in Macro-Economic Sentiment	Weekly uncertainty measure is created by first calculating the daily weighted uncertainty (multiplying the uncertainty index by the total content volume (buzz) in that day). Then, weekly uncertainty is created by aggregating the weighted uncertainty across all days of the week, and finally dividing it by total content volume (buzz) of that week). The formula is as follows:	TRMI

Variable	Description	Source
	(Buzz $_1$× Uncertainty 1 + Buzz 2 × Uncertainty 2 + … + Buzz 7 × Uncertainty $_7$) / (Buzz 1 + Buzz 2 + … + Buzz $_7$)	
Market Share	Market share for each brand sub-category is calculated as the brands' annual sales in that product category divided by the total annual sales of all brands in corresponding category in previous year.	IRI
In-Store Feature – Small Ad	The percentage of the brand's weekly sales in each product category that occurred in the stores using small in-store advertising.	IRI
In-Store feature – Medium Ad	The percentage of the brand's weekly sales in each product category that occurred in the stores using medium in-store advertising.	IRI
In-Store Feature – Large Ad	The percentage of the brand's weekly sales in each product category that occurred in the stores using large in-store advertising.	IRI
In-Store Feature – Coupon	The percentage of the brand's weekly sales in each product category that occurred in the stores offering coupons.	IRI
In-Store Feature - Minor Display	The percentage of the brand's weekly sales in each product category that occurred in the stores using minor display.	IRI

Variable	Description	Source
In-Store Feature – Major Display	The percentage of the brand's weekly sales in each product category that occurred in the stores using major display.	IRI
In-Store Feature – Price Reduction	The percentage of the brand's weekly sales in each product category that occurred in the stores offering discounts.	IRI
Inflation-Adjusted Weighted Unit Price	Inflation-adjusted weighted unit price for each brand in each sub-category, calculated as: $\sum_{i=1}^{n}$ $UPC_i\_Price_t \times UPC_i\_TotalSales_t$ / (Brand-subCategory_Total $Sales_t$)) × 100 / CPIFABSL where *t* denotes the week and *i* denotes the corresponding UPC	IRI
CPIFABSL	Weekly consumer price index for food and beverage	U.S. Bureau of Labor Statistics

TABLE 2: DESCRIPTIVE STATISTICS AND CORROLATIONS

Descriptive Statistics

Variables	Mean	Median	S.D.	Min	Max
Sales Volume	4.609	4.605	2.650	0	13.622
Ad Spending	0.170	0	1.280	0	15.508
Market Share	0.012	0.001	0.056	0	0.841
Uncertainty	0.012	0.020	0.002	0.016	0.025
Negative Future Outlook	0.031	0.031	0.003	0.025	0.049
Weighted Unit Price	2.311	1.953	0.002	0.045	59.950
In-Store Feature – Small Ad	0.002	0	0.021	0	1
In-Store Feature – Medium Ad	0.018	0	0.077	0	1
In-Store Feature – Large Ad	0.009	0	0.053	0	1
In-Store Feature – Coupon	0.001	0	0.053	0	1
In-Store Feature – Minor Display	0.185	0.093	0.240	0	1
In-Store Feature – Major Display	0.062	0	0.125	0	1
In-Store Feature – Price Reduction	0.180	0.040	0.251	0	1

Variable Correlations

Variables	1	2	3	4	5	6	7	8	9	10	11	12
1: Sales Volume												
2: Ad Spending	0.20											
3: Market Share	0.42	0.33										
4: Uncertainty	0.02	0	0									
5: Negative Future Outlook	0	-0.01	0	-0.30								
6: Weighted Unit Price	-0.09	0.03	-0.03	0.02	0							
7: InSF- Small Ad	0.08	0.02	0.03	0	0.01	-0.02						
8: InSF – Medium Ad	0.31	0.12	0.20	0	-0.01	-0.07	0.05					
9: InSF – Large Ad	0.27	0.16	0.27	0	0.01	-0.05	0.02	0.14				
10: InSF – Coupon	0.09	0.06	0.08	0.01	0.01	-0.02	0.01	0.04	0.05			
11: InSF – Minor Display	0.05	-0.01	-0.01	0.02	-0.03	0.09	0	0	0.01	0.01		
12: InSF – Major Display	0.27	0.08	0.13	0	0	-0.06	0.04	0.21	0.19	0.07	-0.01	
13: InSF – Price Reduction	0.43	0.1	0.16	0.02	-0.02	-0.09	0.09	0.33	0.25	0.08	0.04	0.35

Notes: Sales volume values are reported after log transformation. Ad spending values are reported after inflation adjustment and log-transformation. Weighted unit price values are reported after inflation adjustment.

TABLE 3: MODEL ESTIMATION RESULTS

Coefficients:	Overall Markets		All markets excluding concentrated ones		All markets excluding dominant brands	
$Sales_{t-1}$	0.9310 ***	(1931.39)	0.9294***	(1658.44)	0.9306***	(1916.44)
Ad Spending	0.0032***	(4.88)	0.0034***	(3.97)	0.0035***	(5.15)
Future Outlook Negativity	-0.5930*	(-2.37)	-0.8853**	(-3.068)	-0.5970*	(-2.36)
Uncertainty	0.0216	(0.045)	-0.2095	(-0.38)	0.0390	(0.080)
Market Share	0.9259***	(17.02)	1.1436***	(16.12)	1.1826***	(18.71)
Ad Spending * Future Outlook Negativity	**0.4415***	**(2.26)**	**0.6020***	**(2.40)**	**0.4921***	**(2.42)**
Ad Spending * Uncertainty	**0.9416****	**(2.99)**	**1.5240*****	**(3.66)**	**1.1557*****	**(3.54)**
Ad Spending * Market Share	-0.0108***	(-3.33)	-0.01989***	(-3.59)	-0.0191***	(-3.64)
Future Outlook Negativity * Market Share	6.1237	(1.53)	4.3135	(0.60)	5.3789	(0.73)
Uncertainty * Market Share	8.2933	(1.26)	8.5773	(0.72)	4.3663	(0.36)
Ad Spending * Future Outlook Negativity * Market Share	**-2.3053****	**(-2.74)**	**-3.3474***	**(-2.47)**	**-3.0528***	**(-2.38)**
Ad Spending * Uncertainty* Market Share	**-3.6575****	**(-2.58)**	**-7.9523*****	**(-3.57)**	**-6.5123****	**(-3.12)**
Weighted Unit Price	0.0244***	(29.73)	0.0226***	(25.22)	0.0243***	(29.60)
In-Store Ad.(Small)	0.5943***	(22.29)	0.6251***	(21.38)	0.5957***	(22.03)
In-Store Ad.(Medium)	0.6652***	(83.27)	0.6645***	(73.23)	0.6653***	(82.83)
In-Store Ad.(Large)	0.7562***	(64.71)	0.7679***	(56.96)	0.7542***	(63.93)
In-Store Coupon.	0.7906***	(21.16)	0.8273***	(19.73)	0.7937***	(21.01)
In-Store Display (minor)	0.1501***	(49.53)	0.1507***	(43.71)	0.1501***	(49.43)
In-Store Display (major)	0.2178***	(39.97)	0.2322***	(36.08)	0.2183***	(39.96)
Price Reduction	0.1975***	(69.70)	0.1944***	(59.70)	0.1977***	(69.59)
Number of Obs	424620		322554		422172	
R-Squared	0.92		0.91		0.92	
Brand Sub-Category Fix Effect	YES		YES		YES	
Year Fixed Effect	YES		YES		YES	

'***' $p < 0.001$, '**' $p < 0.01$, '*' $p < 0.05$,'$\cdot$' $p < 0.1$

Notes: Dependent variable is sales in volume. Sales in volume and the first lag of sales in volume are log-transformed. All the variables in dollars including ad-spending and weighted unit price are adjusted for inflation rate. Ad spending is also log-transformed. The focal variables of interest and their statistically significant coefficient estimates are highlighted. The value in the parentheses show t-value. Variables in interactions are mean-centered.

TABLE 4: MARKET CONCENTRATION OF PRODUCT CATEGORIES THROUGH YEARS

Product Category	**HHI 2002**	**HHI 2003**	**HHI 2004**	**HHI 2005**	**HHI 2006**	**HHI 2007**	**HHI 2008**	**HHI 2009**	**HHI 2010**	**HHI 2011**	**HHI 2012**
Cheese Snack	3292.96	3706.93	3859.78	4213.35	4427	4376.55	4463.49	5161.60	5437.44	5478.35	5008.44
Corn Snack	5647.26	5679.38	5684.89	6079.25	6613.23	6735.67	6835.50	7127.11	6704.43	6319.10	6275.81
Snack Mix	3339.57	3491.63	3691.52	3621.75	3791.56	3989.43	4254.87	4639.83	4595.70	4045.36	3699.13
Popcorn	658.75	673.37	744.44	723.62	756.21	811.32	792.30	729.93	715.50	687.31	756.64
Pork Rind	1161.78	1028.26	1194.68	1134.49	1075.51	1025.10	1001.66	847.72	915.10	947.33	985.84
Pretzel	1628.36	1657.13	1621.35	1637.53	1788.65	1898.40	1903.70	2031.74	2216.27	2216.29	2212.05
Potato Chips	1395.84	1369.67	1385.22	1483.84	1485.90	1448.92	1384	1506.68	1591.74	1672.32	1591.38
Tortilla Chips	2343.56	2266.22	2247.37	2248.97	2240.39	2239.14	2229.80	2280.75	2183.42	1927.85	1949.60
Other Snacks	3082.99	2606.37	2308.40	2195.63	2415.23	2490.31	2494.98	2293.98	2224.32	2233.31	2292.52

Notes: A market with HHI lower than 1500 is considered to be a competitive market. A HHI between 1500 to 2500 indicates a moderately concentrated market, and an HHI of 2500 or higher shows a highly concentrated market. Highly Concentrated markets are highlighted with red color.

FIGURE 1: NUMBER OF BRANDS IN EACH SUB-CATEGORY

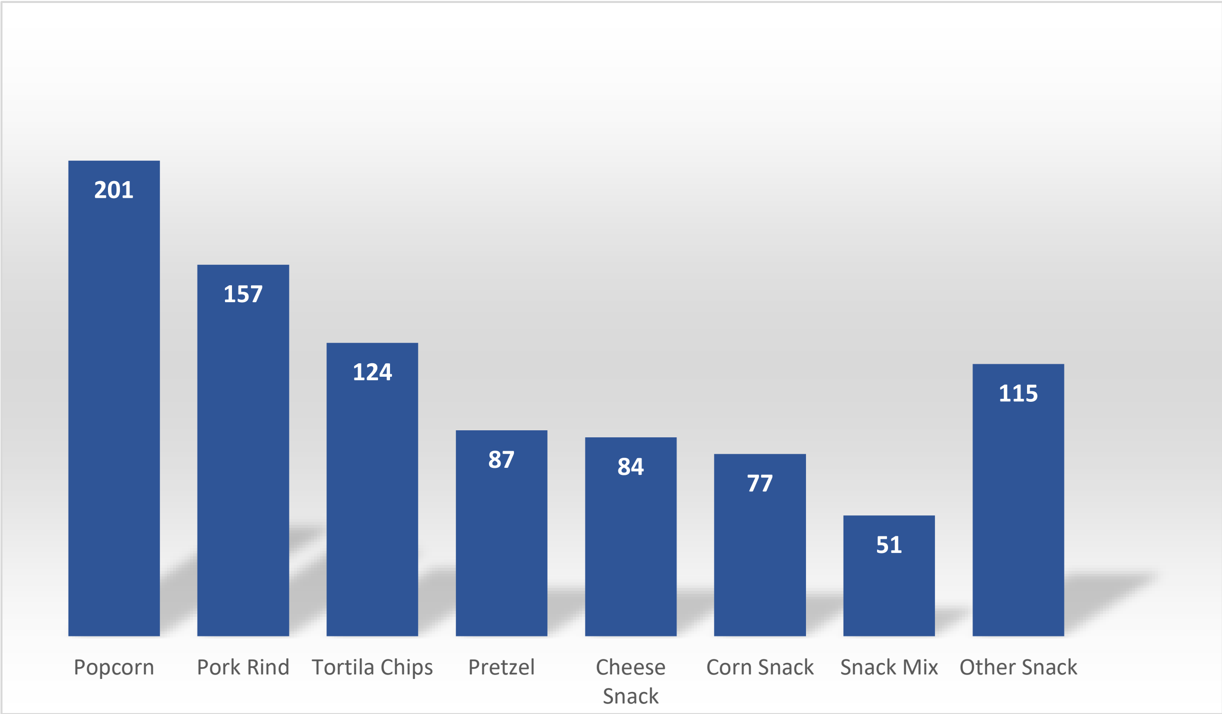


FIGURE 2: DISTRIBUTION OF THE NUMBER OF SUB-CATEGORIES IN EACH BRAND

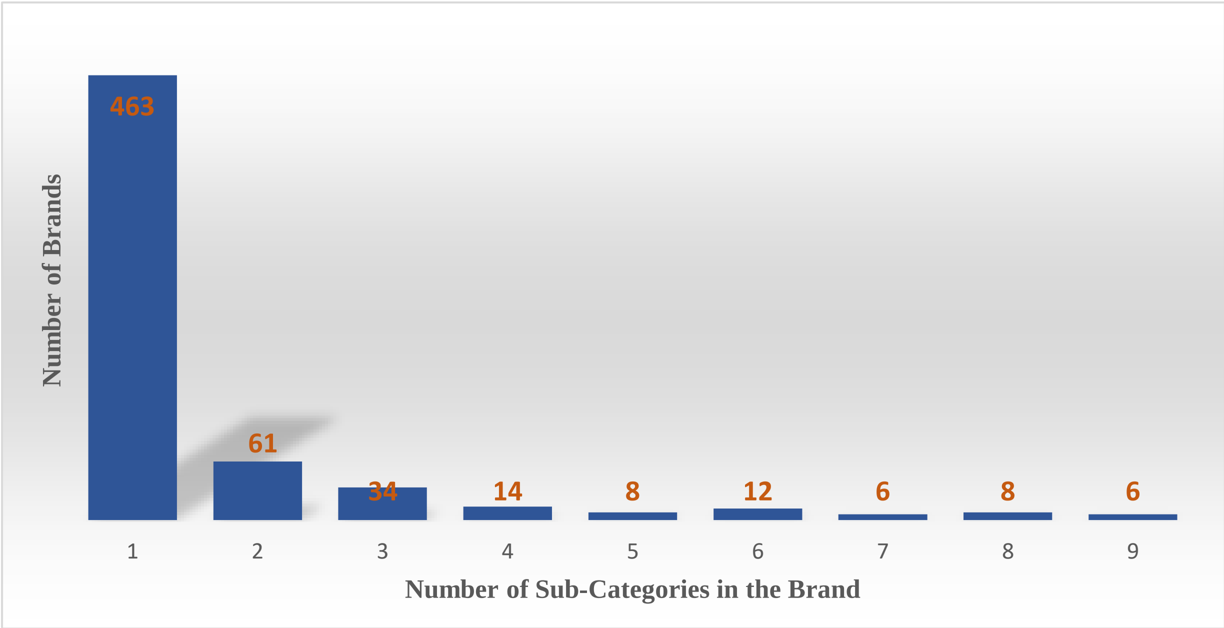
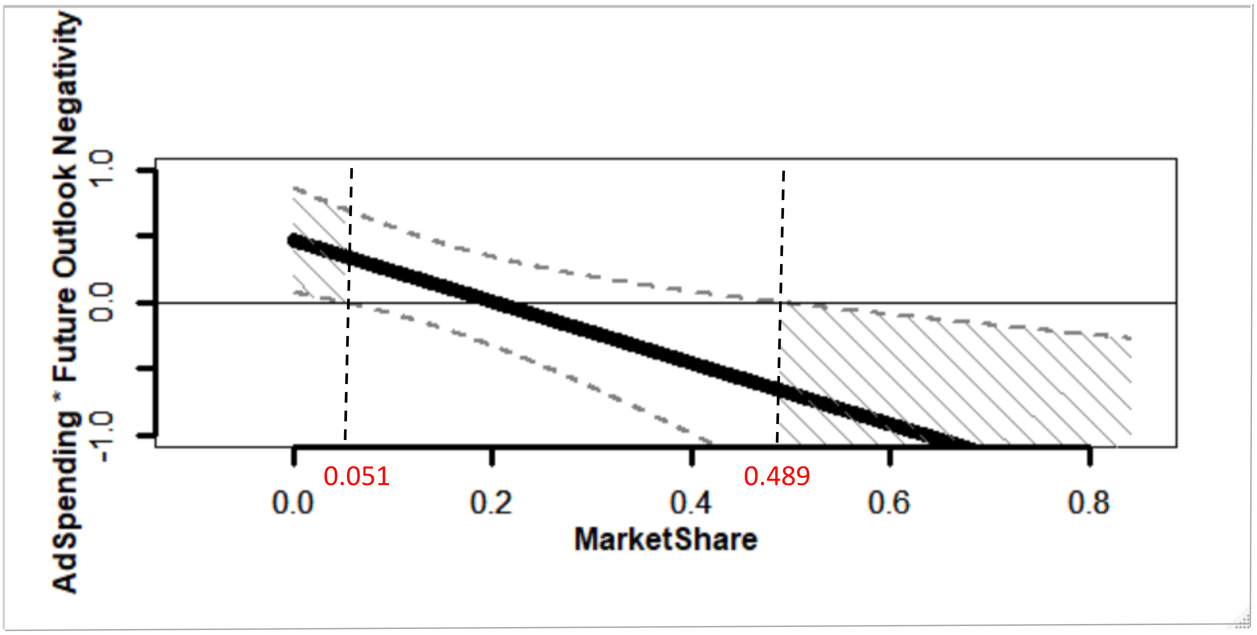
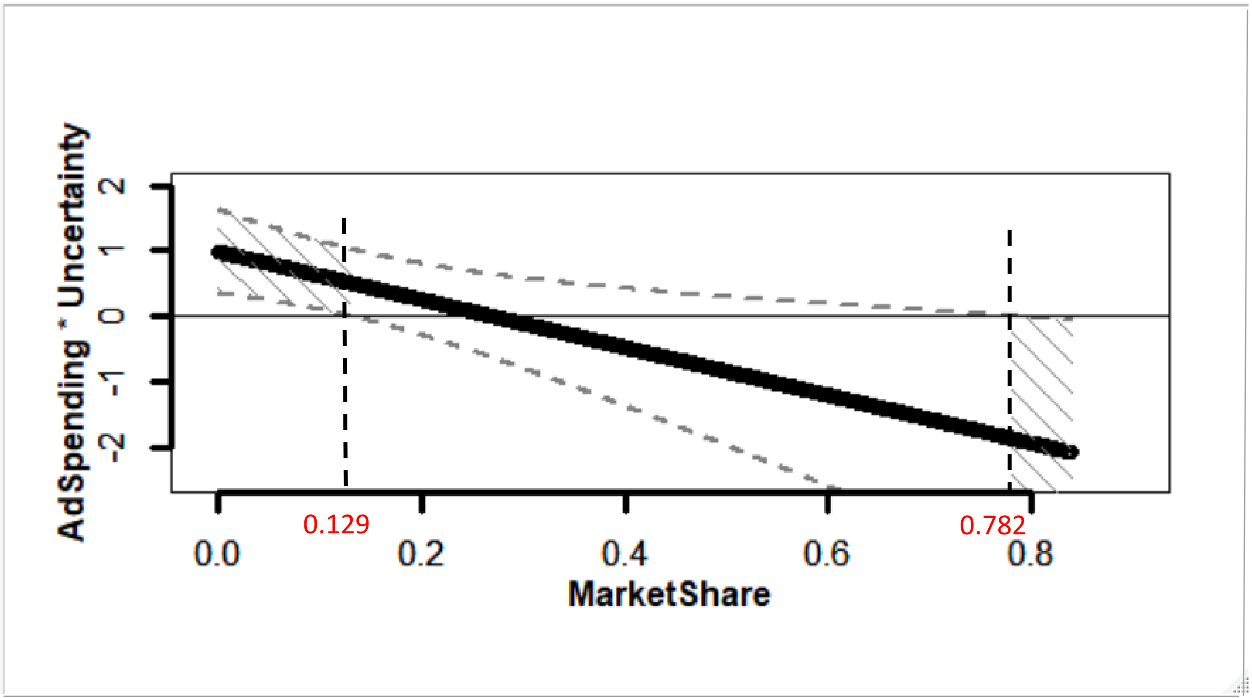


FIGURE 3: FLOODLIGHT ANALYSIS ON MODERATING EFFECT OF NEGATIVE FUTURE OUTLOOK ON AD SPENDING-SALES RELATIONSHIP BASED ON MARKET SHARE (OVERALL MARKET)



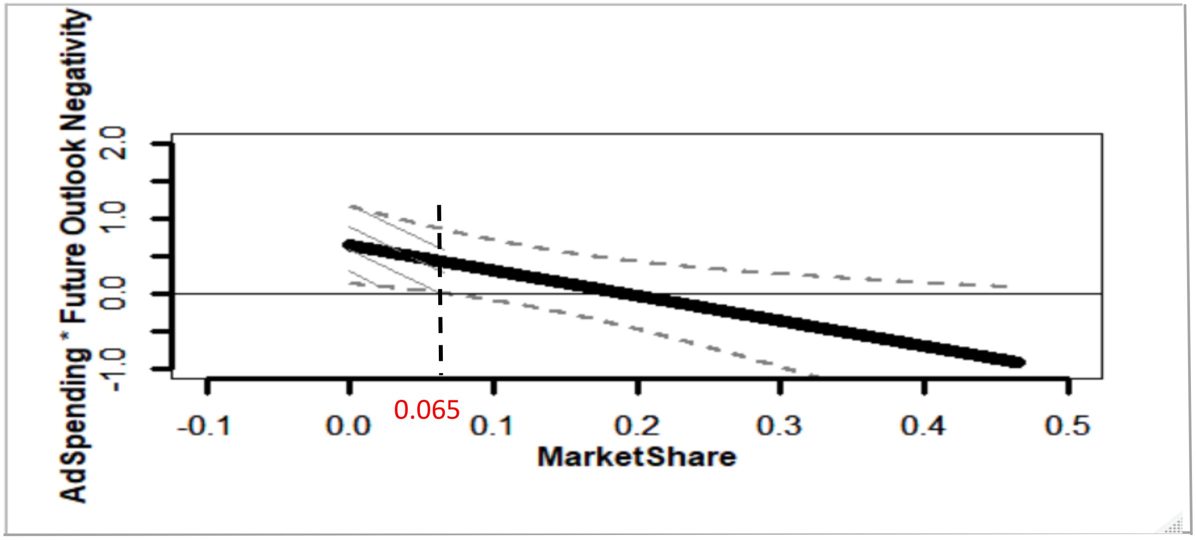
Notes: This graph identifies regions in the range of market share in which the moderating effect of future outlook negativity on ad spending- sales relationship is significant. The shading area shows significant region that is starting from 0 to 5% and from 49% to 84%. Not shaded area in the middle shows non-significant region.

FIGURE 4: FLOODLIGHT ANALYSIS ON MODERATING EFFECT OF UNCERTAINTY ON AD SPENDING-SALES RELATIONSHIP BASED ON MARKET SHARE (OVERALL MARKET)



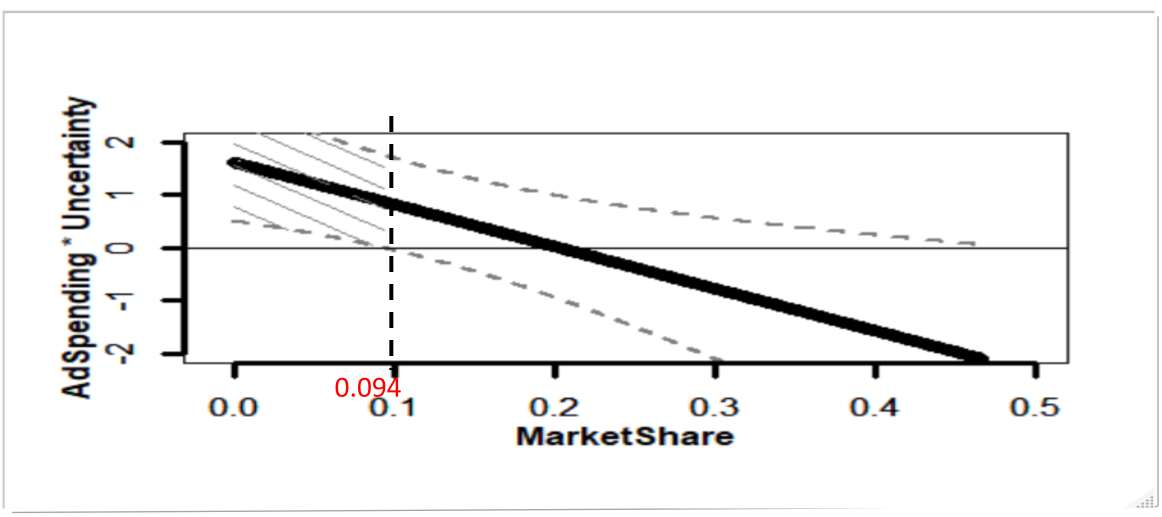
Notes: This graph identifies regions in the range of market share in which the moderating effect of uncertainty on ad spending- sales relationship is significant. The shading area shows significant region that is ranging from 0 to 13% and 78% to 84%. Not shaded area in the middle shows non-significant region.

FIGURE 5: FLOODLIGHT ANALYSIS ON MODERATING EFFECT OF NEGATIVE FUTURE OUTLOOK ON AD SPENDING-SALES RELATIONSHIP BASED ON MARKET SHARE (All MARKETS EXCLUDING CONCENTRATED ONES)



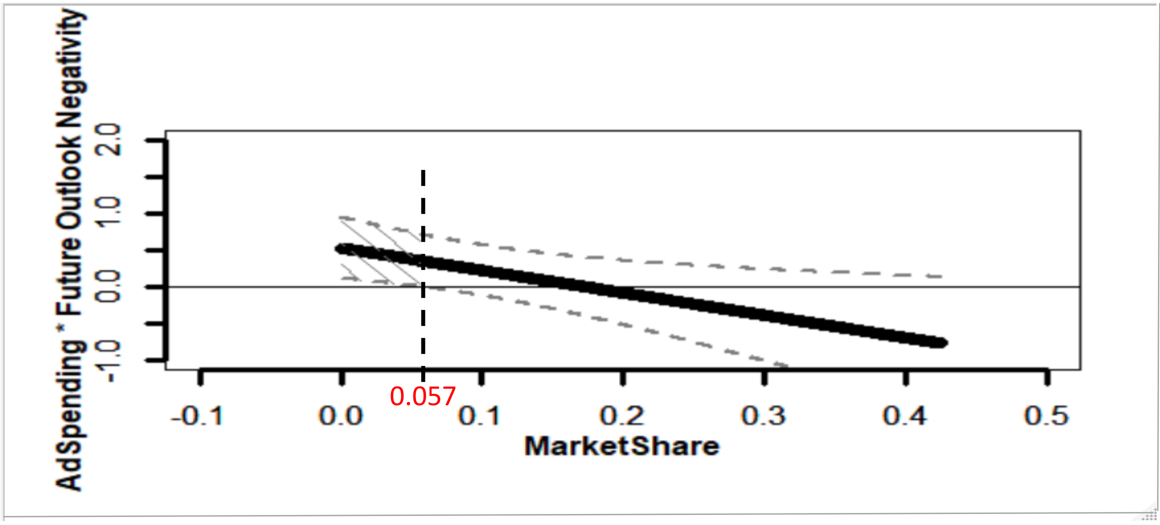
Notes: This graph identifies regions in the range of market share in which the moderating effect of future outlook negativity on ad spending- sales relationship is significant. The shading area shows significant region that is ranging from 0 to 7%. Not shaded area in the middle shows non-significant region.

FIGURE 6: FLOODLIGHT ANALYSIS ON MODERATING EFFECT OF UNCERTAINTY ON AD SPENDING-SALES RELATIONSHIP BASED ON MARKET SHARE (All MARKETS EXCLUDING CONCENTRATED ONES)



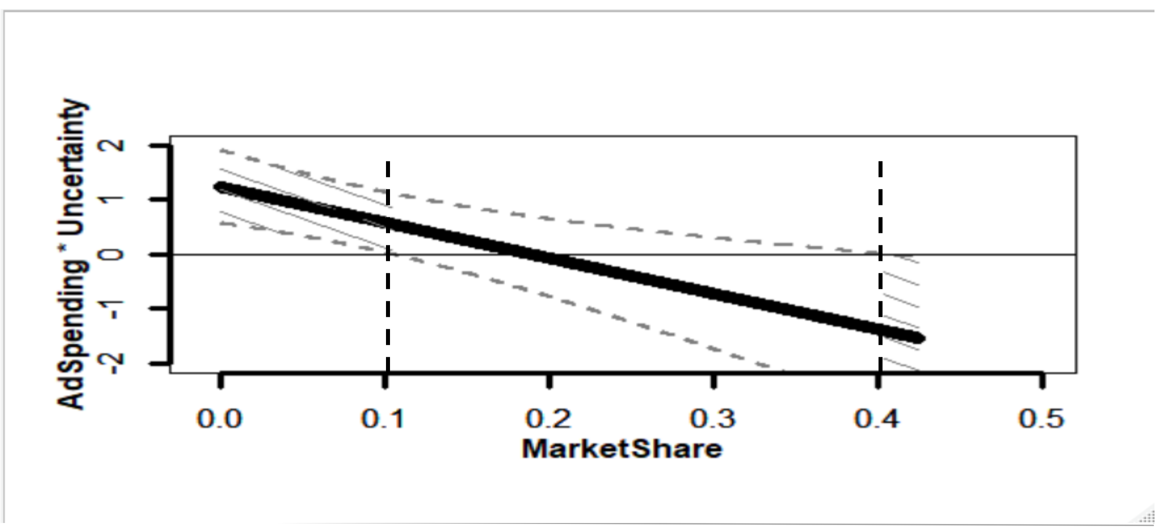
Notes: This graph identifies regions in the range of market share in which the moderating effect of uncertainty on ad spending- sales relationship is significant. The shading area shows significant region that is ranging from 0 to 9%. Not shaded area in the middle shows non-significant region.

FIGURE 7: FLOODLIGHT ANALYSIS ON MODERATING EFFECT OF NEGATIVE FUTURE OUTLOOK ON AD SPENDING-SALES RELATIONSHIP BASED ON MARKET SHARE (All MARKETS EXCLUDING DOMINANT BRANDS)



Notes: This graph identifies regions in the range of market share in which the moderating effect of future outlook negativity on ad spending- sales relationship is significant. The shading area that shows significant region is ranging from 0 to 6%. Not shaded area in the middle shows non-significant region.

FIGURE 8: FLOODLIGHT ANALYSIS ON MODERATING EFFECT OF UNCERTAINTY ON AD SPENDING-SALES RELATIONSHIP BASED ON MARKET SHARE (All MARKETS EXCLUDING DOMINANT BRANDS)



Notes: This graph identifies regions in the range of market share in which the moderating effect of uncertainty on ad spending- sales relationship is significant. The shading area that shows significant region is ranging from 0 to 10% and from 40% to 42%. Not shaded area in the middle shows non-significant region.

ESSAY 2

IT WAS THE BEST OF TIMES; IT WAS THE WORST OF TIMES: THE EFFECT OF EMOTIONAL UNCERTAINTY AND AROUSAL ON HEALTHY FOOD CHOICES

ABSTRACT

Although notable literature exists on individuals' mood valence and food consumption choices, the findings are somewhat mixed showing the possibility of unhealthy food choices in both highly positive and highly negative affective states. Furthermore, the effect of affective dimensions other than valence has been explored much less, and limited research in this stream has focused exclusively on positive emotions. Addressing these gaps, the current research investigates the effect of emotional arousal and uncertainty on individuals' food consumption choice in the negative emotional domain. Analyzing the sales data of 1,128 salty snack products over five years (2008-2012) from Information Resource Incorporated (IRI) and consumer well-being data from the weekly Gallup U.S. poll, along with two lab experiments, I find that, not all negative emotions have an equal impact on food choices. Among negative emotions, high-arousal, and uncertain emotions are more likely to lead to unhealthy food consumption choices than low-arousal and certain emotions. However, the process underlying the influence of arousal and uncertainty are different, which necessitate different interventions to counter their effects.

INTRODUCTION

Obesity is an increasingly serious issue in the United States. As many as 40% of US adults were estimated to be obese in 2015 and 2016, an increase from 33.7% in 2007 and 2008 (Richtel and Jacobs, 2018). Among the multitude of reasons behind the problem, poor food consumption choice is often cited as a driving factor (Raghunathan, Naylor, and Hoyer 2006; Sinha 2016). Examples of poor food consumption choices include food intake above and beyond one's daily calorie needs and favoring unhealthy food alternatives (e.g., cake) over healthy ones (e.g., fruit). Given the U.S. epidemic obesity, an increasing amount of research has been devoted to understanding why individuals make unhealthy food choices. A key finding from this research stream is that one's affective state (i.e., how one is feeling mood- or emotion-wise) can influence the amount and content of one's food intake at a given moment. Earlier research in this area has mostly focused on the effect of valence (good or bad mood) on food intake. The findings are somewhat mixed, suggesting possible proclivity toward unhealthy food intake when individuals are at two ends of the valence continuum. That is, highly negative (Cleobury and Tapper, 2014; Oliver et al., 2000; Renner et al., 2012; Verplanken et al., 2005) and highly positive moods (Evers et al., 2013; Verhoeven et al., 2015) may both trigger unhealthy eating.

More recently, researchers have started to go beyond valence to study how other aspects of one's emotional state can affect food consumption choices. This stems from the recognition that distinct emotions lead to different appraisal and choices, even if they are of the same valence (Lerner and Keltner, 2000). For example, Fedorikhin and Patrick (2010) found that feeling calmly positive helps individuals resist unhealthy foods, but a positive affective state with an elevated level of arousal does not help. As another example, Winterich and Haws (2011) classified positive emotions by their temporal focus into future-focused emotions such as hopefulness and past- or present-focused emotions such as happiness and pride. They found that future-focused positive emotions increase self-control and lead to a lower preference for unhealthy snacks than past- or present-focused affective states.

Although these previous studies provide convincing evidence that individuals' feelings do indeed affect their choice for or against unhealthy food, much remains to be understood about the complex roles different emotions play in this process. At least three gaps in the literature can be identified. First, as mentioned earlier, the role of emotional valence on food intake has yielded mixed results. This suggests contingent factors that may have been neglected in the earlier research. Second, limited recent research on the other dimensions of emotion such as arousal has focused exclusively on positive emotions. However, negative emotions vary widely as well, and their differing effects on individual self-regulation in the food domain are not well understood. Finally, decades of psychology research on human emotions suggest many subtleties of emotions beyond valence and arousal variations. For example, Smith and Ellsworth (1985) propose a six-dimensional structure of emotions, while Fontaine et al. (2007) discover a four-dimensional structure encompassing pleasantness, arousal, control, and unpredictability. Different combinations of these emotional characteristics may create subtly different emotions that can translate into not-so-subtle differences in food consumption choices.

The current paper investigates how emotional arousal and uncertainty embedded in negative affective states influence individuals' food consumption choices. It proposes that not all negative emotions are similar. Among negative emotions, high-arousal and uncertain emotions lead to more unhealthy food choices than low-arousal and certain emotions. While both emotional dimensions result in the same outcome, my findings suggest that the processes underlying the influence of arousal and uncertainty are different. That in turn necessitates different interventions to counter the influence of perceived arousal and uncertainty on unhealthy food consumption. Specifically, I find both passive and active emotion regulation strategies are effective in attenuating the impact of elevated arousal on individuals' tendency to choose unhealthy food, whereas active self-regulation strategies are more effective in countering the influence of uncertainty on unhealthy food choices than passive emotion regulation strategies.

The current research provides several contributions to marketing theory and practice. First, previous valence-based research has yielded controversial findings regarding the effect of individuals' experienced affective state on unhealthy food choices. By considering other dimensions of emotional state, this research can create a deeper understanding of the effects of emotions on healthy/unhealthy food choices. That, in turn, can inform effective regulation strategies for countering the lure of unhealthy food alternatives in a particular situation. Second, the current research contributes to the literature on cognitive appraisal of emotions. It provides insight into the different processes by which cognitive appraisals of arousal and uncertainty operate. From a practical perspective, this research points to effective communication and consumer education strategies that can foster healthier food choices by leveraging health-facilitative emotions and countering the effects of health-inhibitive emotions.

CONCEPTUAL BACKGROUND

Reasons Behind Poor Food Consumption Choices

The rising obesity problem is a big concern for consumers, firms and policymakers in the United States. Many reasons have been cited for the obesity epidemic, including genetic proposition (E. S. Moore et al., 2016), long hours watching TV (Tucker and Bagwell, 1991), and smoking (Musaiger et al., 2003). Among the multitude of reasons behind the problem, poor food consumption choice has been considered as a driving factor (Jain and Li, 2018; Raghunathan et al., 2006; Sinha, 2016). Unhealthy food consumption choices refer to food intake above one's daily calorie needs or adoption of an unhealthy diet that often does not contain adequate nutrients.

One stream of research has investigated external causes of unhealthy food consumption. For instance, some blame policymakers for their failure in allocating adequate resources to provide healthy food at reasonable prices (Charlebois et al., 2007; Drewnowski and Darmon, 2005; Drewnowski and Specter, 2004). In fact, in the U.S. a meal containing healthy nutrients costs more than calorically dense foods that also taste good. That in turn encourages people to choose unhealthy alternatives over healthy ones. As another external factor, some researchers blame firms for their advertisements that justify and encourage unhealthy food consumption (Halford et al., 2004; Henderson and Kelly, 2005). Even though supporters of this idea have not found a causal relationship between food advertisements and obesity, they believe exposing people to food advertisements influence their choices. Children and adolescents are found to be the most vulnerable groups. This is attributed to children's inability to evaluate possible risks of unhealthy foods along with firms' attempt to distract children's attention from such risks (Effertz et al., 2014; Halford et al., 2004). Furthermore, adolescents show a high level of vulnerability to food advertisements since their quality of information processing is poor and they are attracted to products that provide immediate gratification (Pechmann et al., 2005). Together, food advertisements may negatively influence individuals' food intake.

Another external cue in guiding healthy vs. unhealthy food choices is social pressure or social norm. In a tempting situation with a high level of conflict between short-term and long-term goals, people are likely to adopt the behavior of other people around them as the correct choice (Wooten and Reed, 1998). Lowe and Haws (2014) called this mechanism parallel self-control. From this perspective, individuals' perception about the self-control power of other people around them can influence their own self-regulation efforts. When faced with unhealthy foods, consumers may use this rationalization because such foods are desirable but hard to justify. In fact, seeing someone indulging in unhealthy food can serve as social evidence of the appropriateness of poor food choices (Poor et al., 2013). Herman et al. (2003) and McFerran et al. (2010) made a similar argument and found that the presence of a confederate helps people to establish a norm of eating and adjust their behavior accordingly. That is, people adjust their food portion based on the other's choices, or they get easily persuaded to choose an unhealthy snack if a confederate recommends it to them. The association between watching TV and unhealthy eating among adults is also likely the result of social norm justification of unhealthy food consumption by actors. Specifically, seeing a picture or video of someone indulging in unhealthy food serves as a proof of the acceptability of this behavior and justifies unhealthy food consumption choice (Pearson et al., 2014; Poor et al., 2013).

Although the literature clearly supports external influences on individuals' poor food consumption choices, another body of research has shown that food consumption choices are primarily driven by internal cues. When choosing what food to consume, people tend to follow two goals: healthiness and enjoyment. In most cases, eating unhealthy food evokes a sense of conflict between these two goals. Recent studies have demonstrated that even exposure to the picture of unhealthy food could evoke both senses of willingness to indulgence and self-regulation (Fletcher et al., 2007; Killgore et al., 2003). This conflict between immediate gratification with unhealthy but tasty choices and a long-term goal of being healthy is a common dilemma.

Consumers usually rely on several internal cues including licensing behavior and their experienced emotional state to resolve this conflict and make their final decision on food alternatives.

Licensing behavior applies to situations when individuals make a series of decisions in sequence. These choices are not single shots or isolated from each other; rather they are a chain of systematically related choices. The preference among alternatives is licensed by prior decisions and by the extent to which one's previous actions have fulfilled his goals (Khan and Dhar, 2006). When food alternatives prime a tempting feeling, people tend to focus on their long-term goal of being healthy. However, individuals may license themselves to indulge with enticing options if they believe their previous actions were enough to attain their long-term goals (Fishbach and Dhar, 2005). Chandon and Wansink (2007) made a similar argument and showed that restaurants' claims to offer healthy foods lead consumers to order more unhealthy options. People consider ordering a healthy main dish as attaining their long-term goal of being healthy, and they take this as a license to indulge in unhealthy side dishes, drinks, and desserts. Other studies similarly suggest that individuals who intend to work out in the near future are more likely to eat an unhealthy meal (Fishbach and Dhar, 2005). Licensing effect in the food domain may also manifest itself as indulging in unhealthy food as a reward (Verhoeven et al., 2015). For example, perceiving progress in dieting may justify individuals' unhealthy food choices (e.g., a chocolate bar) over a healthy option (e.g., an apple) (Fishbach and Dhar, 2005).

The Valence of Affective State and Food Consumption Choice

Research on the influence of internal cues on individuals' food consumption choices shows that food choice is nontrivially influenced by individuals' experienced emotional state (Fedorikhin and Patrick, 2010; Garg et al., 2007; Macht et al., 2002). In everyday life, people are constantly exposed to affect triggering stimuli. Individuals try not to show an impulsive response to the source of their emotions; instead, they try to exert some control over their feelings and engage in various forms of affect regulation strategies (Davidson, 1998), including choosing what and how much to eat.

Research on the relationship between affective state and food consumption has mostly utilized a valence-based approach, contrasting positive and negative emotional states with each other or with a neutral emotional state. Even though insights derived from these studies are comprehensive and useful, their results are somewhat mixed. One stream of research supports a direct relationship between negative affective state and increased tendency toward unhealthy food choices. This set of arguments has been built on individuals' power of self-control, which is one of the most essential and distinctive characteristics of human beings (Muraven and Baumeister, 2000; Muraven et al., 1998). When a person is exhausted from many simultaneous demands, or when the situation is upsetting, regulatory resources will be utilized to tackle the negative feeling, and the possibility of failure in self-control is higher (Baumeister and Heatherton, 1996; Muraven et al., 1998). In a situation with a high motivational conflict between long-term and short-term goals, negative emotions encourage people to prefer options with immediate benefits and delayed-costs (Fedorikhin and Patrick, 2010), such as unhealthy eating. Supporting this idea, Verplanken et al. (2005) found that unhealthy diet in the form of frequent snacking of high calorie, fatty or sweet foods between meals can be fueled by negative moods and the hope to feel better. Similarly, obese people tend to increase their frequency of eating when experiencing negative mood states like boredom or depression (Cleobury and Tapper, 2014; Ouwens et al., 2009). Slochower and Kaplan (1980) made a similar argument about the effect of anxiety on overall eating in obese people. Finally, more evidence of unhealthy food consumption choices triggered by a negative affective state is offered by Kemp and Kopp (2011). They found that sad or anxious people tend to consume foods with a hedonic nature such as cheesecake to regulate their negative emotions.

While unhealthy food consumption can function as a coping strategy for negative emotional state (Cleobury and Tapper, 2014; Oliver et al., 2000; Renner et al., 2012; Verplanken et al., 2005), the opposite perspective has been adopted by a second stream of research providing evidence of a positive relationship between positive affective state and unhealthy food intake. This relationship may result from individuals' desire to maintain or intensify their positive emotions. In line with this idea, Verhoeven et al. (2015) showed that one of the common excuses that individuals use to justify their overconsumption and unhealthy snacking is enjoyment of a special occasion. In many cultures celebration of happy occasions has been closely associated with food consumption. There are often diverse pleasant occasions in which people indulge themselves with food (Patel and Schlundt, 2001; Rozin, 1999). Another explanation for unhealthy food consumption choices induced by a positive affective state may be derived from individuals' emotion-oriented behavior. Positive affective state signals a safe environment that biases one's focus toward short-term goals of enjoying the moment and away from long-term goals of being healthy or slim (Evers et al., 2013). Consistent with this view, previous research shows that people with positive emotions show higher tendency toward risky behaviors such as drug intake or alcohol consumption (Tamir and Robinson, 2007).

Taken together, the research reviewed above suggests that individuals' feelings play a major role in their food intake choices. However, findings on exactly what type of emotional state can lead to unhealthy food choices are mixed. Individuals appear to be inclined toward unhealthy food intake at both ends of the valence continuum. This discrepancy may result from a valence-based approach of these studies that mainly contrasted positive and negative affective states with each other or with a neutral emotional state. To that end, much remains to be understood about the complex roles other emotional dimensions may play in this process.

Non-Valence Dimensions of Affective State and Food Consumption Choices

Previous research on emotions suggests that distinct emotions of the same valence can result in different appraisal and decisions (Lerner and Keltner, 2000). Researchers have started to go beyond valence to study how other aspects of one's emotional state can affect food consumption choices. For instance, Labroo and Mukhopadhyay (2009) found that the effect of emotional valence on individuals' choice is contingent upon the effect of emotion transience. That is, when experiencing an emotion, people are likely to appraise the extent to which their current feeling will persist. If they believe the perceived affective state to be short-term, they may not engage in immediate self-regulation behavior. However, if they convince themselves that their negative affective state will last or their positive feeling will pass very soon unless they take action, they will indulge themselves in different activities such as unhealthy snacking as an attempt to regulate their feelings. The level of arousal in individuals' emotional state is another dimension that may influence one's food choice between healthy vs. unhealthy alternatives. Fedorikhin and Patrick (2010) found that, compared with a neutral emotional state, a low-arousal positive affective state can facilitate resistance to unhealthy food consumption both in terms of choosing what to consume and how much to consume. However, this is not the case if people experience a positive emotion with a high arousal level.

In another study on different dimensions of emotional state beyond valence, Winterich and Haws (2011) introduced the temporal focus of an emotion as an influential factor in consumers' snack choices. The results show that future-focused positive affective states (such as hopefulness) enhance individuals' self-control power in comparison with past- or present-focused affective states (such as happiness and pride). Therefore, consumers who experience hopefulness have a lower preference for unhealthy snacks and consume less unhealthy food than those in present- or past-focused positive emotional states. Fishbach and Labroo (2007) proposed that the effect of incidental affective state on healthy behavior depends on individuals' accessible goal at that moment. A positive affective state improves healthy behavior and self-control when choosing between healthy vs. unhealthy food alternatives if a self-improvement goal is available. However, when a mood-management goal is accessible, a positive affective state does not encourage people to focus on their long-term goal of being healthy.

Although the studies reviewed above demonstrate the value of looking beyond valence to other dimensions of emotions, these studies have focused mainly on positive emotions. Negative emotions can vary widely as well, and not all negative emotions may lead to the same degree of unhealthy food choices. These varying effects of different negative emotions on individual self-regulation in the food domain are not well understood. Furthermore, although existing research has started to examine aspects of emotions beyond valence, the dimensions explored so far have been limited. There are other nuances in emotions that still need to be examined. For example, building on cognitive appraisal theory, Smith and Ellsworth (1985) identified six cognitive dimensions which define different feelings: pleasantness, certainty, control, attention, anticipated efforts, and responsibility. Fontaine et al. (2007) further proposed a four-dimensional framework of affect encompassing pleasantness, arousal, control, and unpredictability. Building on these existing frameworks, the current research investigates how the arousal and uncertainty dimensions of negative emotions can affect individuals' unhealthy food consumption choices.

HYPOTHESES DEVELOPMENT

A Two-Stage Process of Emotional Appraisal and Response

To understand how arousal and uncertainty may affect individuals' food consumption, we draw upon a two-stage process that a person experiences when making a choice under a particular mood (Berkowitz, 2014, p. 12). The first stage is called lower-order affective reaction. It is affective in nature and happens automatically and quickly before engaging in any form of appraisal. Individuals in this stage conduct a rapid assessment of the choice options and their influence on the experienced emotional state. That in turn shapes the action tendency toward the alternatives. In the second higher-order cognitive reaction stage, choice is subject to more cognitive and deliberate processing. The outcome from this stage may strengthen or weaken the action tendency resulting from lower-order affective reactions (Shiv and Fedorikhin, 1999). For instance, when a person visits a coffee shop while feeling angry about his morning car accident, the lower-order affective reaction may prompt a rude behavioral tendency toward the coffee shop employees. However, the higher-order cognitive process is likely to remind the individual of social norms and magnify the inappropriateness of that behavior. This thought process is likely to suppress the action tendency that arose from the lower-order affective reaction. As another example, consider a customer who is unhappy with the received service. Affective appraisal of the situation may urge him to file a complaint. However, in the cognitive evaluation of alternative actions, the person may decide not to complain after considering all the efforts required to do so.

Since the higher-order processing in the second stage is deliberate and controlled in nature, individuals need to allocate processing resources to succeed in this stage (Shiv and Fedorikhin, 1999). In a situation where available resources are limited, individuals' ability to engage in higher-order processing will be limited, and the choice outcome is likely to be based on lower-order affective processing. In contrast, in a situation with enough available resources for controlled processing, the final action tendency would result from a combination of affective and cognitive appraisal of the alternatives. This mechanism is similar to the automatic versus controlled human information processing offered by Schneider and Shiffrin (1977). They state that automatic processing will always activate without individuals' attention or control. However, controlled processing needs active attention and thus is significantly limited by processing capability. Therefore, the essential element that determines the final choice between alternatives is often the extent of individuals' cognitive capabilities.

The Role of Emotional Arousal

Individuals' cognitive appraisal ability is influenced by the level of arousal in their experienced mood state. Arousal refers to a feeling of activation ranging from a mild to an elevated state (Mehrabian and Russell, 1974; Russell, 1980). An elevated level of arousal can interfere with individuals' cognitive capacity (Fedorikhin and Patrick, 2010; Mano, 1992) and decrease their focus on cues that need cognitive appraisal (Sanbonmatsu and Kardes, 1988). According to the hot and cold model of decision making, hot decision making involving superficial processing and emotional responses tend to result from experiencing a high-arousal emotional state, whereas cold decision making associated with rational and cognitive evaluation of alternatives is more likely under a low-arousal emotional state (Magar et al., 2008). These tendencies suggest a more prominent role of cognitive appraisal and self-control under low arousal than under high arousal (Ayduk et al., 2002).

Applying this process to a food consumption context, consider a typical situation in which a person decides what to eat for lunch among multiple healthy and unhealthy alternatives. If the individual is in a negative mood, he or she will have a higher tendency to indulge in unhealthy food or over-consume to regulate the feelings (Andrade, 2005). That is, this individual's action tendency resulting from lower-order affective reaction would be more in favor of unhealthy alternatives in comparison with someone in a neutral emotional state. Emotional arousal plays a role in the final choice by determining the likelihood that a further higher-order second stage will take place. If the second stage takes place, it can draw individuals' attention to the harmful consequences of unhealthy food consumption and override the action tendency from affective processing. The individual's decision may switch from an unhealthy option to a healthy one. If, however, the individual's cognitive appraisal capacity is impaired by high arousal, the individual will be less likely to engage in the thoughtful process and alter his or her instinctive decision.

In summary, experiencing a negative emotional state may increase the chance of following lower-order action tendencies toward unhealthy food choices. If the negative emotional state has a low level of arousal such as in the case of sadness or guilt, the person still has the power to cognitively process the choices and to prevent poor food consumption choices. In contrast, if the negative emotional state is high arousal in nature such as in the case of anger or worry, the capacity for altering the decision through cognitive processing would be impaired. As a result, the unhealthy consequences from negative emotions may be especially strong when arousal is high. This leads to the first hypothesis:

H1: Individuals are more likely to make unhealthy food choices when experiencing high-arousal negative emotions than when experiencing low-arousal negative emotions.

The Role of Uncertainty

Emotional uncertainty refers to feelings resulting from a lack of information about an event (Bar-Anan et al., 2009). The experienced uncertainty may consist of both an informational component (lack of information) and a subjective component (a feeling of not knowing) (J. D. Smith and Washburn, 2005). The extent of perceived uncertainty in one's feelings comes from two distinct appraisals: how much the current situation is violating one's past expectations and to what extent the person is unsure about what is going to happen in the future (Smith and Ellsworth, 1985). Unlike the arousal dimension that decreases individuals' likelihood of engaging in higher-order processing, emotional uncertainty affects choice by altering the substance of the higher-order assessment.

When assessing the proper actions to take in the presence of a negative emotion, an individual can choose to tackle the root problem that causes the negative emotion (i.e., problem-based coping) or deal directly with the emotion itself in the form of emotion-based coping (Baker and Berenbaum, 2007; Carver et al., 1989). For example, a person worried about losing her job may choose to update her resume and look for new job opportunities, or she may decide to enjoy some ice cream and watch her favorite TV show to put the worry out of her mind. Uncertainty can affect which of these two approaches the individual is more likely to take. When uncertainty level is high, it is difficult to clearly define the exact problem to be solved. As a result, the right way to solve the problem is often ambiguous. Individuals in such situations tend to engage in some form of mood management to distract themselves from the situation that can still end up being good or bad (Houston and Holmes, 1974).

Applied to the food domain, an individual experiencing a highly uncertain negative emotion may assess the situation as being too ambiguous for meaningful problem-based coping. As an alternative, she can decide to indulge in unhealthy food to manage her unpleasant mood, as consumption of such food has been shown to improve one's mood state and bring about pleasure (Christensen, 1993; Patel and Schlundt, 2001). Therefore, despite having pursued higher-order processing to assess the situation, the outcome from that assessment reinforces the action tendency toward unhealthy food options instead of tempering it. This results in a stronger tendency to consume unhealthy food when one experiences a highly uncertain negative emotion than when the negative emotion is more certain, as hypothesized below:

H2: Uncertain negative emotions will increase individuals' unhealthy food choices more than certain negative emotions.

Interventions to Counter the Effects of Arousal and Uncertainty

Given the exaggerated impact of negative emotion on unhealthy food consumption under high arousal and high uncertainty, it would be helpful to identify effective interventions that can alleviate the impact of these emotional dimensions. As arousal and uncertainty exert influence on peoples' choice through different mechanisms, the interventions to counter their effects need to differ.

The literature on emotion regulation mechanisms divide coping strategies into two categories: Active or effortful coping strategies and passive or effortless emotional regulation strategies. Active emotion regulations include mechanisms such as (1) *cognitive reappraisal*, which changes the way one thinks about a situation and relabels events as helpful rather than harmful (Gross, 2001); (2) *effortful distraction*, which increases the load on one's working memory through a distracting task in order to leave less room for feeling the negative emotion (Van Dillen and Koole, 2007); and (3) *suppression of emotional response*, which works by avoiding emotion-expressive behavior to keep one's cool (Richards and Gross, 2000). A commonality across all these active methods is their reliance on conscious and deliberate reappraising of the situation, which requires additional cognitive efforts and is resource demanding.

In contrast, passive or effortless emotion regulation involves modifying the quality, intensity, or duration of the experienced emotion without any conscious effort (Koole and Rothermund, 2011). This strategy is especially helpful in situations where active emotion regulation is impossible due to the lack of cognitive resources (Schwager and Rothermund, 2014). One example of a passive coping strategy is to unobtrusively prime angry individuals with emotional control words (e.g., calm, relax). Previous research shows that using such control words can successfully decrease individuals' anger level in comparison with when angry individuals are primed with emotion descriptive words (e.g., violate, boiled) (Mauss et al., 2007).

As indicated previously, experiencing a negative affective state with a high level of arousal impairs individuals' ability to engage in cognitive processing and makes it more difficult to counter the action tendency toward unhealthy food choice. Based on this rationale, active emotion regulation strategies are less likely to bring about favorable changes in individuals' choices due to the effortful and resource-demanding nature of these strategies. Instead, passive emotion regulation strategies are more likely to reduce the experienced arousal and free cognitive resources for individuals to better evaluate the alternatives and make healthier choices.**H3a:** A passive emotion regulation strategy is more effective than an active emotion regulation strategy to counter the effect of high-arousal negative emotions on unhealthy food choices.

In comparison, when experiencing negative emotions with a high level of uncertainty, the main concerns are related to being in a situation opposite to one's expectations, not understanding what is happening in that situation, and not knowing what is going to happen next or exactly when it is going to happen. While engaging in unhealthy eating in the described situation is a possible self-regulatory strategy to alleviate the effect of uncertainty, there are numerous other strategies which individuals can use to reduce the need to resort to unhealthy eating. For instance, Monat et al. (1972) argued that when there is no way to be prepared for an uncertain situation, distracting individuals with other tasks can be helpful. As an alternative, cognitive reappraisal of a situation is shown to be beneficial in altering the trajectory of one's emotions (Haga et al., 2009). Therefore, when experiencing a highly uncertain negative emotion, engaging in active emotion regulation strategies such as effortful distraction or cognitive reappraisal is likely to be helpful in alleviating the effect of uncertainty.

H3b: An active emotion regulation strategy is more effective than a passive emotion regulation strategy to counter the effect of high-uncertainty negative emotions.

OVERVIEW OF THE STUDIES

Four studies were conducted to investigate the influence of negative affective state on food consumption choices at different levels of arousal and uncertainty. A multi-method approach incorporating both primary and secondary data was adopted. Study 1 combined sales data of 1128 salty snack products from IRI and sentiment data from Gallup between 2008 and 2012 to verify if the proposed emotional effects hold at the macro-level. Following the secondary data analysis, three lab experiments were conducted to confirm the results in a more controlled setting. The first lab experiment (Study 2) utilized an autographic recall task to elicit different negative emotions and aimed to replicate the results from Study 1 at the individual level. I performed Study 3A and 3B with two goals. First, in these studies negative emotional states with different level of arousal and uncertainty were elicited ,through video clips, to make sure the observed effects in study 2 were caused by the level of arousal and uncertainty and not by the effect of specific negative emotions. Second, these studies tested the effectiveness of different intervention strategies in countering the effect of arousal and uncertainty as hypothesized in H3.

STUDY 1: MACRO-LEVEL ANALYSIS

The Data

The first study verified if the suggested emotion effects hold at a macro-level. The data for this study came from four sources. The first dataset comprised sales data for salty snacks from IRI. The data were collected from retail scanners at grocery stores and drugstores across 50 markets in U.S. regions. It captured weekly retail sales of salty snack products for a period of five years (2008-2012). Second, consumer well-being data from the same matching period were obtained from the Gallup U.S. Poll, which involved telephone surveys of approximately 1,000 US adults each day (between 2008-2012). The survey consisted of a large number of measures related to individual well-being and health, including emotional measures. The responses across participants were aggregated after correcting for unusual selection probabilities and non-response and with sample weighting to match the U.S. population based on gender, age, race, Hispanic ethnicity, education, region and population density. This study utilized four measures of negative emotions from the survey to represent low and high levels of arousal and uncertainty: guilt (low arousal, certain), sadness (low arousal, uncertain), anger (high arousal, certain), and worry (high arousal, uncertain) (see Fontaine et al. (2007); Smith and Ellsworth (1985); Tiedens and Linton (2001) for the classification of these emotions).

The third dataset comprised advertising spending data for salty snacks from Kantar Media. The data included weekly advertising spending for various products within each brand across major online and offline advertising media. Finally, the USDA Branded Food Product Database (BFPD) was used to classify each salty snack into healthy and unhealthy categories. The BFPD is a national food composition database with nutrition information of all branded food products sold in the U.S.

Variable Operationalization

Food Type: To determine the healthfulness of each product, I extracted the nutritional information for each product from the BFPD dataset by matching the Universal Product Code (UPC) of products in the IRI and BFPD datasets. Each nutrient value was calculated as the amount of the nutrient per 100g of each product. Then I followed the approach suggested by Lobstein and Davies (2009), which calculated a nutritional score for each food item based on key nutritional dimensions. The process involved assigning “bad” points based on the food’s energy, saturated fat, sugar, and sodium levels and “good” points based on three healthy ingredients: fruit, vegetables and nuts percentage, fiber, and protein. The final nutritional score for each product was calculated as a transformed difference between the “bad” points and the “good” points, with the exact formula used depending on the ranges of these points. A product with a final score of 4 or higher was classified as “less healthy” (Food Type = 0), and one with a score of 3 or lower was classified as healthy (Food Type = 1). The detailed calculation process is presented in Table 1.

INSERT TABLE 1 ABOUT HERE

Salty Snack Product Sales: The IRI data contained weekly sales of each salty snack product identified by its UPC in grocery stores and drugstores. I summed the dollar sales for each UPC across the two channels. UPCs with sales less than 52 weeks out of the 5 years were excluded due to irregularity of data for those products. Weekly dollar sales per UPC ranged from $0 to $515,789.5, with median weekly sales being $430.4. To adjust for inflation, the weekly dollar sales were divided by the Consumer Price Index for Food and Beverage (CPIFABSL) from the U.S. Bureau of Labor Statistics. Moreover, due to skewness, log-transformed sales served as the dependent variable in the model. This is consistent with previous studies (e.g., Du et al., 2015; Gijsenberg, 2017; Kopalle et al., 1999).

Negative Emotions: As mentioned earlier, this study utilized four negative emotions (guilt, sadness, anger, and worry) from the Gallup U.S. Poll. Each emotion was rated as the percentage of the sample that experienced the feeling “during a lot of the day” on the day before the survey. The original data collected by Gallup U.S. Poll was in a daily format. However, Gallup offers aggregated responses in a weekly interval, which was used in the current study.

Control Variables: I used a series of variables to control for each product’s marketing activities, including in-store promotions, product price, and advertising spending. In-store promotions included in-store features (small ad, medium ad, large ad, and coupon), in-store displays (minor display and major display), and price reduction. For each of these promotional tools, I derived the percentage of each product's sales that occurred under each format as an indicator of the pervasiveness of that promotional activity. Therefore, each of these variables ranged from 0 to 1, with 0 meaning the product did not use the corresponding promotional tool in that week, and 1 meaning the product used the corresponding promotional format everywhere that week. Each product's price was calculated by dividing the total dollars sales by the total sales volume for that product in each week. Unit price was adjusted for inflation similar to sales. Finally, advertising spending for each product was extracted from the weekly amount spent on advertising across all media types by the associated brand for all of the brand's products in the sub-category. This was divided by the number of UPCs a brand has in that sub-category to arrive at the per product ad spending. Similar to sales and price, advertising spending was adjusted for inflation. Weekly ad spending ranged from \$0 to \$24,612.32 per product, with median weekly spending being \$0. In the model, I log-transformed the ad spending due to its skewness (e.g., Danaher et al., 2008; Frison et al., 2014). Table 2 presents descriptive statistics of the variables.

INSERT TABLE 2 ABOUT HERE

Model Overview

The Koyck fixed-effect model (equation 1) was employed to model macro-level unhealthy food consumption as a function of experiencing negative emotions.

$$\boldsymbol{Sales_{it}} = \beta_0 + \beta_1\, Sales_{it-1} + \beta_2\, Food\ Type + \beta_3\, Guilt_t + \beta_4\, Sadness_t + \beta_5\, Anger_t + \beta_6\, Worry_t + \beta_7\, Food\ Type * Guilt_t + \beta_8\, Food\ Type * Sadness_t + \beta_9\, Food\ Type * Anger_t + \beta_{10}\, Food\ Type * Worry_t + \beta_{11}\, SmallFeatureAd_{it} + \beta_{12}\, MediumFeatureAd_{it} + \beta_{13}\, LargeFeatureAd_{it} + \beta_{14}\, Coupon_{it} + \beta_{15}\, MinorDisplay_{it}$$

$+ \beta_{16}\, MajorDisplay_{it} + \beta_{17}\, PriceReduction_{it} + \beta_{18}\, Unit\_Price_{it} + \beta_{19}\, Ad\_Spending_{it} + \eta_{UPC} + \varepsilon_{it}$

(1)

where $Sales_{it}$ and $Sales_{it-1}$ represent the inflation adjusted and log-tranformoed sales of product *i* in week *t and t-1 respectively*; *Food Type* is a dummy variable which determines the food healthiness. It is set to 0 when food is unhealthy and is set to 1 when it is healthy; $Guilt_t$, $Sadness_t$, $Anger_t$, and $Worry_t$, represent the degree to which each of these emotions was experienced at the macro-level in week t; $SmallFeatureAd_{it}$, $MediumFeatureAd_{it}$, $LargeFeatureAd_{it}$, $Coupon_{it}$, $MinorDisplay_{it}$, $MajorDisplay_{it}$, and $\mathrm{PriceReduction}_{it}$ represent the pervasiveness of these in-store promotional tools used by product i in week t, as described previously. $Unit\_Price_{it}$ represents the price of product i in week t. $Ad\_Spending_{it}$ shows the inflation adjusted and log-transformed of advertising spending for product i in week t, by its corresponding brand. η_{UPC} shows the product fixed effect, and finally ε_{it} is the model error term.

The Results

The final data used for estimating the model consisted of an unbalanced panel of 1128 unique products, with the number of observed weekly time intervals per product ranging from 47 to 255. The R^2 of the model was 79%, indicating a good model fit. Table 3 reports the model estimation results. The analysis revealed significant positive effects of guilt ($\beta_2 = 0.220$, $t = 2.96$, $p < 0.05$), anger ($\beta_4 = 0.611$, $t = 4.95$, $p < 0.05$), and worry ($\beta_5 = 0.815$, $t = 13.48$, $p < 0.05$), and a significant negative effect of sadness ($\beta_3 = -0.5091$, $t = -5.30$, $p < 0.05$). Since unhealthy products functioned as the baseline in the model, these coefficients suggest that guilt, anger and worry increased the sales of unhealthy foods, whereas sadness surprisingly decreased unhealthy food product sales.

INSERT TABLE 3 ABOUT HERE

To formally test H1 and H2, I compared pairs of emotion coefficients to see if they were significantly different from each other. For arousal, I compared the coefficients of the two certain emotions (anger vs. guilt) and then the coefficients of the two uncertain emotions (worry vs. sadness). For the two low-uncertainty emotions, the positive effect of the high-arousal emotion (anger) was significantly higher than that of the low-arousal emotion (guilt; t = 502.76, p < 001), consistent with expectations. For the two high-uncertainty emotions, worry (high-arousal) and sadness (low-arousal) had opposite effects on unhealthy food choice, with worry having a positive effect and sadness having a negative impact. Although the sign of the sadness effect was unexpected, the high-arousal emotion indeed had a strong impact on unhealthy food consumption. Even ignoring the signs of the coefficients, the absolute magnitude of the worry effect was significantly stronger than the absolute magnitude of the sadness effect (t = 60.98, p < 0.001). Taken together, these results suggest that high-arousal negative emotions were more strongly associated with unhealthy salty snack sales than low-arousal negative emotions, supporting H1.

Turning to the effect of uncertainty, I compared the coefficients of the two low-arousal emotions (sadness vs. guilt) and then the coefficients of the two high-arousal emotions (worry vs. anger). For the low-arousal emotions pair, the two emotions had opposite effects on unhealthy food consumption, due to the surprisingly negative effect of sadness on unhealthy food sales. Comparing the absolute magnitude of the two coefficients showed a significantly stronger effect of the high-uncertainty emotion (sadness) than that of the low-uncertainty emotion (t = 477.27, p < 0.001). For the two high-arousal emotions, the high-uncertainty emotion in the pair (worry) showed a directionally large impact than the low-uncertainty emotion anger, this difference was also statistically significant (t = 26.66, $p < 0.001$). Taken together, H2 is partially supported. Although the absolute magnitude of the high-uncertainty sadness effect was significantly larger than that of the low-uncertainty guilt effect, sadness reduced unhealthy food consumption instead of increasing it.

For the control variables, the effects of all in-store promotion variables were positive and significant, consistent with previous research (Tellis and Weiss, 1995). Lagged sales in dollar also had a significant positive effect on current period sales (β_1=0.8386, t=826, $p < 0.05$). The effect of weighted unit price on sales was negative and significant (β_{18}= - 0.0753, t = - 9.3, $p < 0.05$). Finally, advertising spending did not have significant effect on sales.

Discussion

Through secondary data analysis, I found negative emotions with high level of arousal increase tendency to unhealthy consumption choices, regardless of their level of uncertainty. However, the effect of negative emotions with high level of uncertainty surprisingly was in the opposite direction. Why did sadness reduce instead of increasing unhealthy food sales? I suspect it has to do with the core defining theme of sadness as an emotion. In sadness, the main construct is a sense of loss or helplessness (Garg and Lerner, 2013). The helplessness component of sadness is closely related to the sense of lack of control often associated with uncertainty. As explained earlier, I expected the level of perceived uncertainty embedded in sadness increases the overall tendency to unhealthy consumption. However, the degree to which individuals perceived helplessness and lack of control in their sadness depends on who they blame for their experiencing negative emotion. Specifically, the level of helplessness would be higher when they blame others for their loss and sadness, in comparison to when they hold themselves responsible for their feeling. Munichor and Friedlander (2019) argue whether people attributes the cause of their sadness to others or themselves will influence their tendency to engage in unhealthy food consumption. In effect, self-licensing to indulge with unhealthy food only happens when people blame others or external sources for their sadness. In contrast, if people attribute the failure to themselves, the likelihood in engaging in any sort of mood management activities will decrease (Mick and Faure, 1998; Munichor and Friedlander, 2019). Therefore, the mediation role of responsibility attribution can be a possible explanation for the opposite effect that I found for sadness – unhealthy consumption relationship.

LAB EXPRIMENTS

Study 1 provided some preliminary support for the idea that non-valence based dimensions of negative emotions can affect unhealthy food consumption. However, the aggregate nature of the secondary data reflects macro-level relationships that may not manifest themselves at the individual level. It also does not allow the test of intervention strategies that could alleviate the impact of arousal and uncertainty on unhealthy food consumption as hypothesized in H3a and H3b. To address these issues, three lab experiments were conducted. Study 2 manipulated the same four negative emotions in a more controlled setting to replicate Study 1 results. Studies 3A and 3B were designed with two goals. First, in these studies the negative emotional states with different level of arousal and uncertainty were elicited, through video clips, to make sure the observed effects in study 2 were caused by the level of arousal and uncertainty and not by the effect of specific emotions. Second, these studies tested the effectiveness of different intervention strategies in countering the effect of arousal and uncertainty as hypothesized in H3.

PRETEST

Snack Choice Pretest

The goal of the pretest was to identify pairs of snacks to be used as stimuli in the main studies that are significantly different from each other on healthiness but equivalent on other possible confounding factors. In this test, 102 undergraduate students from a public university in the United States participated for course credit. Participants assessed the perceived healthiness and taste preference of an array of snacks (see **TABLE 4** for the measurement items) on 7-point scales anchored at "Strongly Disagree" and "Strongly Agree". The list of healthy options included *Greek yogurt*, *baby carrots*, *fruit salad*, *grapes*, *granola bar*, *salted almonds*, *salted peanuts*, and *mixed nuts*. The list of unhealthy options included *ice cream*, *chocolate bar*, *chocolate candy*, *potato chips*, *popcorn*, *coated peanuts*, *cheese crackers*, and *cheesecake*. The order in which the items were presented to the participants were randomized. Based on participants' answers, I chose granola bar as the healthy snack option and popcorn as the unhealthy snack option to use in the main studies. A t-test showed a significantly higher mean score of healthiness for granola bar than for popcorn (M = 5.223 vs. 2.752, t = 11.753, $p < 0.05$). In the meantime, the mean taste preferences for the two options were on par with each other (M = 4.888 vs. 4.763, t = 0.418, $p > 0.05$).

STUDY 2

Participants and Procedures

Study 2 was designed to examine the influence of negative affective state on consumers' food choice at different levels of arousal and uncertainty. This study used a 2 (Arousal: *Negative-*

low arousal vs. *Negative-high arousal*) * 2 (Uncertainty: *low* vs. *high*) between-subjects design. To completely replicate Study 1, the same set of emotions were used. These emotions were manipulated through a writing task to represent the high and low levels of arousal and uncertainty. Writing task are frequently used to induce emotions (Labroo and Mukhopadhyay, 2009). Participants were asked to write about three experiences that made them feel the allocated emotion (guilt, sadness, anger and worry) and then to describe in detail the experience which induced the highest level of that particular emotion. Participants were eighty-eight undergraduate students from a public university in the United States who received course credit for their participation (mean age = 28, 57% female). They were randomly assigned to one of the four experimental conditions. The study started with the autobiographic recall task. Immediately after the task, the levels of experienced arousal and uncertainty were measured. Then participants were asked to indicate which snack in the pair of healthy and unhealthy snacks identified from the pretest they would choose if they were to have a snack at that moment. After the snack choice, participants reported the perceived healthiness and taste preference for each of the snacks using the same set of questions as the pretest (see TABLE 4 for the items). Finally, to control for potential confounds, participants reported how hungry they were at the time, if they were on a specific diet, and if they wanted to lose weight.

Manipulation Check

Immediately after the recall task, I asked participants to report the level of arousal they were feeling at that moment using the self-assessment manikin developed by Morris (1995). The level of perceived uncertainty was also measured by a three-item scale adapted from Faraji-Rad and Pham (2017), on 7-point scales anchored at “Strongly Disagree” (1) and “Strongly Agree” (7).

To evaluate the success of arousal manipulation, I conducted a two-way ANOVA with arousal rating as the dependent variable, arousal condition, uncertainty condition and their interaction as independent variables. Result showed only a significant main effect of arousal condition ($F(1, 84) = 8.288$, $p < 0.05$). A follow-up pairwise comparison indicated a higher level of perceived arousal in the high arousal conditions than in the low arousal conditions ($M = 5.875$ vs. 4.650, $t = 2.63$, $p < 0.05$). I repeated the two-way ANOVA with uncertainty rating as the dependent variable and the same set of independent variables to examine the success of the uncertainty manipulation. The result showed only a significant main effect of uncertainty condition ($F(1, 84) = 8.080$, $p < 0.05$). A follow-up pairwise comparison indicated a higher level of experienced uncertainty in the high-uncertainty conditions than in the low-certainty conditions ($M = 3.203$ vs. 2.220, $t = 2.73$, $p < 0.05$).

I also checked the participants' ratings of the snack options. As expected, the granola bar was rated as significantly healthier than the popcorn ($M = 5.504$ vs. 2.701, $t = 19.06$, $p < 0.05$). In the meantime, the taste preference rating for the granola bar did not significantly differ from that for the popcorn ($M = 5.683$ vs. 5.724, $t = 0.23$, $p > 0.05$).

The Results

To model the effects of arousal and uncertainty on snack choice, I ran a logistic regression with snack choice as the dependent variable (1= unhealthy choice, 0 = healthy choice), and arousal (1= *high arousal conditions*, 0= *low arousal conditions*), uncertainty (1= *high uncertainty conditions*, 0= *low uncertainty conditions*), and their two-way interaction as the independent variables. I also controlled for the effects of hunger, special diet status, active weight loss status, taste preference for the snack options, and gender, as shown in equation (2) below.

$$\textbf{\textit{Choice}} = \beta_0 + \beta_1\, Arousal + \beta_2\, Uncertainty + \beta_3\, Arousal * Uncertainty + \beta_4\, Hunger + \beta_5\, Diet + \beta_6\, Gender + \beta_7\, Weight\ Loss + \beta_8\, Liking_{popcorn} + \beta_9\, Liking_{granola} + \varepsilon \qquad (2)$$

McFadden's pseudo–R^2 was 0.6 for the model, showing a good fit. As expected in H1, arousal significantly increased the likelihood of choosing the unhealthy snack option ($\beta_1 = 2.954$, $p < 0.05$). The effect of uncertainty on unhealthy snack choice was also positive and significant ($\beta_2 = 1.905$, $p < 0.05$), suggesting that a high level of uncertainty led to a higher tendency to select the unhealthy snack (popcorns). Therefore, H2 was also supported.

A significant and negative two-way interaction between arousal and uncertainty ($\beta_3 = -3.690$, $p < 0.05$) also emerged from the model, suggesting that arousal and uncertainty tempered each other's effect on snack choice. To look closer at the interaction, I derived the simple slope of uncertainty on unhealthy choice under high and low arousal conditions. Results showed that uncertainty increased the possibility of unhealthy choices when the level of arousal was low ($\beta_2 = 1.905$, $p < 0.05$), but the effect disappeared when the level of arousal was high ($\beta_2 = -1.784$, $p > 0.05$). These results are expected. As explained earlier, a high level of arousal affects individuals' choices in the lower order affective processing of options, while a high level of uncertainty affects choices in the higher order cognitive processing stage. Therefore, the arousal process tends to take precedence over the uncertainty process. A high level of arousal makes it less likely for individuals to engage in the higher order cognitive processing needed for uncertainty to exert an effect.

I also compared the proportions of participants in each condition choosing the unhealthy snack option. unhealthy choices in emotions, using chi-square comparisons. Figure 1 depicts the results. Corroborating the earlier analysis, the percentages of participants choosing the unhealthy snack were similar between high and low uncertainty under high arousal conditions (70% vs. 68%,

$\chi^2(1) = 0.0249$, $p > 0.05$). However, when arousal was low, the difference in the proportion of participants choosing the unhealthy option between high and low uncertainty became more pronounced; that is, the effect of uncertainty was stronger under low arousal. However, despite a large percentage of difference, the chi-squared test was not significant, most likely due to the small sample size (62% vs. 47%, $\chi^2(1) = 0.852$, $p > 0.05$).

INSERT FIGURE 1 ABOUT HERE

Among the control variables, self-reported weight loss significantly decreased the possibility of choosing the unhealthy option (β_7= -1.161, $p < 0.05$). Liking popcorns had a significant positive impact on unhealthy choice (β_8 = 1.05, $p < 0.05$), while liking granola bars decreased the chance of the choosing unhealthy option (β_9 = - 1.429, $p < 0.05$). The other control variables did not significantly influence the possibility of choosing the unhealthy option.

STUDY 3: INTERVENTION STRATEGIES

Study 3A and Study 3B aimed to achieve two goals. First, to make sure that the observed effects of arousal and uncertainty so far were not limited to the specific emotions that were used in study 1 and study 2, I used video clips in Studies 3A and 3B to elicit different levels of arousal and uncertainty. Video clips are often used to manipulate emotional states that vary in arousal, uncertainty, and valence (Leith and Baumeister, 1996). Second, these two studies tested the effectiveness of passive versus active intervention strategies as hypothesized in H3A and H3B.

Study 3A focused on the intervention strategies for arousal, while Study 3B focused on countering the uncertainty effect.

STUDY 3A: INTERVENTION STRATEGIES FOR AROUSAL

Participants and Procedures

Study 3A featured a 2 (Arousal: *Negative-low arousal* vs. *Negative-high arousal*) * 3 (Coping Strategy: *Passive vs. Active vs. No coping*) between-subjects design. Three hundred and seventy-seven participants were recruited from Amazon Mechanical Turk (mean age = 36, 54% female). At the beginning of the study, participants were assigned at random to view one of the two video clips that were designed to manipulate arousal. Those in the low arousal condition watched a video about plastic pollutions in the ocean, while participants in the high arousal condition watched a video clip about credit cards frauds. After watching the video, participants reported their experienced arousal and uncertainty using the same scales as in study 2. The valence of participants' feelings were also measured using the self-assessment manikins developed by Morris (1995). Then participants were randomly assigned into one of the three coping strategy groups. Participants in the passive coping group were asked to relax and watch another video while the next part of the survey were being prepared. The video clip contained a beautiful scene along with calming music. Some calming words also appeared in the video, including: *Relax, All is well*, *Breathe freely, Good things are coming*, and *Be calm and peaceful*. Participants in the active coping condition were given the following instruction to engage in cognitive reappraisal: "*Please take a moment and manage your mood until you can adopt a more neutral attitude. Research studies have found that trying to distance oneself from the source of negative emotions can help.*

We'd like you to close your eyes for a minute and imagine yourself mentally walk away from the negative source into a more neutral territory". After the one-minute activity, participants were asked to write what they did to calm themselves down from the negative emotions they may have experienced earlier. In addition, participants in the active coping condition were asked to rate the extent to which they reappraised their emotion on a 7-point scale anchored at "Not at all" (1) and "Extremely" (7). These passive and active coping strategies were taken from previous research (Fitzpatrick et al., 2019; K. S. Moore, 2013). Following the coping tasks, participants in the active and passive coping conditions both proceeded to the second part of the study. Those in the no coping condition did not engage in any coping tasks and proceeded to the second part directly after the initial video clip and emotion rating questions. In the second part of the study, participants were asked to choose whether they would prefer a granola bar (healthy option) or popcorns (unhealthy option) if they were to have a snack at that moment. After the snack choice, participants completed the same snack healthiness and taste preference questions as in Study 2, and their emotional state was measured again. Finally, to control for potential confounds, participants reported how hungry they were at the time, if they were on a specific diet, if they wanted to lose weight and if they are health conscious.

Manipulation Check

I first checked the arousal manipulation. I performed a one-way ANOVA with the pre-coping arousal rating as the dependent variable and arousal condition the independent variable. The results showed a significant main effect of arousal condition (F (1, 375) = 4.96, $p < 0.05$). A follow-up pairwise comparison indicated a higher level of arousal elicited by watching the high-arousal video clip than by watching the low-arousal video clip (M = 5.856 vs. 5.371, t = 2.254, *p*

<0.05). To make sure the other dimensions of emotions were not affected by the arousal manipulation, I performed two t-tests. First, I compared the levels of experienced uncertainty (pre-coping) between the high and low arousal conditions. The results indicated that the levels of uncertainty elicited by both video clips were low and were insignificantly different from each other (M = 3.707 vs. 3.224, t = 4.99, $p > 0.05$). Then I compared the valence of the elicited feelings across conditions. Both video clips evoked a similar level of negativity in feelings (M = 3.122 vs. 3.188, t = - 0.486, $p > 0.05$).

To verify if the passive and active coping strategies worked as intended, I conducted a repeated-measures ANOVA with arousal ratings as dependent variable and coping condition, measurement sequence and their interactions as independent variables. Results revealed a significant main effect of measurement sequence (F (1, 374) = 6.965, $p < 0.05$) and a significant interaction between coping condition and measurement sequence (F (2, 374) = 5.243, $p < 0.05$). Further pairwise comparisons showed that participants in the passive coping condition experienced a significant decrease in arousal from their first (pre-coping) arousal measure to the second (post-coping) arousal measure (M = 5.700 vs. 4.927, t = 3.481, $p < 0.05$). Engaging in active coping also significantly reduced the experienced level of arousal, although the magnitude of the decrease was smaller (M = 6.013 vs. 5.520, t = 2.217, $p < 0.05$). Finally, as expected, the levels of experienced arousal for participants in the no coping condition were similar between the two measurements (M = 5.310 vs. 5.428, t = - 0.649, $p > 0.05$).

Snack manipulation check also approved a significantly higher mean score of healthiness for granola bar in comparison with popcorn (M = 5.389 vs. 2.876, t = 30.891, $p < 0.05$). In contrast, the rating of liking granola bar did not significantly differ from liking the popcorn (M = 5.671 vs. 5.432, t = 2.47, $p > 0.05$).

The Results

To model the effectiveness of different coping strategies in countering the impact of high-arousal negative emotions on food consumption choice, I conducted a logistic regression with the unhealthy food choice as dependent variable (1= unhealthy, 0 = healthy). Arousal (High vs Low), coping strategy (Active vs. Passive vs. No coping), and their respective two-way interactions served as the independent variables. I also controlled for the effects of hunger, being on diet, being health conscious, losing weight status, and gender of participants in the model (3).

$$\textbf{\textit{Choice}} = \beta_0 + \beta_1\, Arousal + \beta_2\, Coping\ Strategy + \beta_3\, Arousal * Coping\ Strategy + \beta_4\, Hunger + \beta_5\, Diet + \beta 6\ Health\_Conscious + \beta_7\, Weight\ Loss + \beta_8\, Gender + \varepsilon \qquad (3)$$

The McFadden's pseudo R^2 for the model was 0.069. As expected, the direct effect of arousal on the likelihood of choosing the unhealthy option was positive and significant ($\beta_1 = 0.950$, $p < 0.05$). Furthermore, the interaction between arousal and passive coping was negative and significant ($\beta_3 = -0.969$, $p < 0.1$), suggesting that passive coping decreased the impact of arousal on unhealthy snack choice. To better interpret the interaction effect, I derived the simple slope of arousal on unhealthy choice under passive coping vs. no-coping conditions. Results indicated that the pronounced impact of arousal on unhealthy choice in the no-coping condition ($\beta_1 = 0.950$, $p < 0.05$) became insignificant in the passive coping condition ($\beta_1 = -0.019$, $p > 0.05$). Therefore, passive coping strategies were helpful in countering the impact of high-arousal negative emotions on unhealthy food consumption. I also found a significant negative interaction between active coping and arousal ($\beta_3 = -0.877$, $p < 0.1$), which suggests that engaging in active coping was also helpful in alleviating the effect of high arousal on unhealthy choice. To better interpret the moderating effect, I compared the simple effect of arousal on unhealthy choice under no-coping vs. active coping conditions. Results showed that the positive impact of arousal on unhealthy choice in the no-coping condition ($\beta_1 = 0.950$, $p < 0.05$) became insignificant in the active coping condition ($\beta_1 = 0.073$, $p > 0.05$). Thus, active coping strategies were also helpful in countering the effect of high arousal on unhealthy choices.

I further compared the proportion of unhealthy choices between the high and low arousal conditions, under each coping strategy. Figure 2 depicts the results. With no coping, a significantly higher proportion of participants chose the unhealthy snack when the level of arousal was high compared to when the level of arousal was low (M = 0.556 vs. 0.391, $\chi^2(1) = 4.218$, $p < 0.05$). In the passive coping condition, the difference between the unhealthy choice proportions in high vs. low arousal conditions was not significant ($\chi^2(1) = 0.029$, M = 0.536 vs. 0.519, $p > 0.05$). That is, passive coping was effective in alleviating the tendency to choose unhealthy option when experiencing a high-arousal negative emotion. Similarly, the proportion comparison in the active coping conditions suggested an insignificant difference between high and low arousal in terms of unhealthy consumption ($\chi^2(1) = 0$, M= 0.49 vs. 0.492, $p > 0.05$). As the passive coping strategy and the active coping strategy appeared equally capable of countering the effect of arousal, H3A was rejected.

INSERT FIGURE 2 ABOUT HERE

Among the control variables, self-reported hunger significantly decreased the possibility of choosing the unhealthy option (β_4= -0.142, $p < 0.05$). Similarly, being health-conscious had a significant negative impact on unhealthy choice (β_6= -0.280, $p < 0.05$). The other control variables did not significantly influence the possibility of unhealthy choice.

STUDY 3B: INTERVENTION STRATEGIES FOR UNCERTAINTY

Participants and Procedures

Study 3B featured a 2 (Uncertainty: *Negative-Certain* vs. *Negative-Uncertain*) * 3 (Coping Strategy: *Passive vs. Active vs. No coping*) between subject design. Two hundred and thirty-seven participants were recruited from Amazon Mechanical Turk (mean age = 39, 52% female). The study procedure was the same as Study 3A, except for the videos used. The same video on plastic pollutions in oceans served as the low-uncertainty video, and a clip from the "Bridge to Terabithia" movie served as the high-uncertainty video.

Manipulation Check

To test the success of the uncertainty manipulation, I performed a two-way ANOVA with uncertainty ratings as dependent variable and uncertainty condition, coping condition and their interaction as independent variables. The results showed a significant main effect of uncertainty condition ($F(1,231) = 8.203$, $p < 0.05$). A follow-up pairwise comparison indicated a higher level of uncertainty elicited by watching the uncertain video clip than by watching the certain clip ($M = 4.872$ vs. 4.501, $t = 2.85$, $p < 0.05$). To make sure the other dimensions of emotions were equivalent between the two uncertainty conditions, I compared the experienced emotional valence and arousal between the two conditions. The results indicated that the level of arousal elicited by both video clips were low and insignificantly different from each other ($M = 5.836$ vs. 5.234, $t = 1.736$, $p < 0.05$). Both video clips also evoked a similar level of negativity in feelings ($M = 3.394$ vs. 3.083, $t = 1.11$, $p > 0.05$).

To verify if the passive and active coping strategies worked as intended, I conducted a repeated-measures ANOVA with the uncertainty rating as the dependent variable and coping condition, measurement sequence and their interaction as the independent variables. Results revealed a significant main effect of measurement sequence ($F (1, 234) = 116.18$, $p < 0.05$) and a marginally significant interaction between coping condition and measurement sequence ($F (2, 234) = 4.66$, $p < 0.1$). Further pairwise comparisons showed that participants in the active coping condition reported a significantly higher level of uncertainty before the coping than they did after the coping ($M = 4.758$ vs. 3.75, $t = 8.407$, $p <0.05$). Similarly, engaging in passive coping significantly reduced the experienced uncertainty ($M = 4.532$ vs. 3.863, $t = 5.605$, $p < 0.05$). Finally, as expected, the uncertainty ratings for participants in the no-coping condition was similar between the pre-coping measure and the post-coping measure ($M = 4.749$ vs. 4.379, $t = 4.637$, $p > 0.05$).

Snack manipulation check also approved a significantly higher mean score of healthiness for granola bar in comparison with popcorn ($M= 5.330$ vs. 2.940, $t= 23.09$, $p < 0.05$). In contrast, the rating of liking granola bar did not significantly differ from liking the popcorn ($M= 5.746$ vs. 5.511, $t = 2.05$, $p > 0.05$).

The Results

To model the effectiveness of the different coping strategies in countering the influence of uncertainty on food consumption choice, I conducted a logistic regression with the unhealthy food choice as the dependent variable (1= unhealthy, 0 = healthy). Uncertainty (High vs Low), coping strategy (Active vs. Passive vs. No coping), and their respective two-way interactions served as the independent variables. I also controlled for the effects of hunger, special diet status, active weight loss status, health-consciousness, and gender, as shown in equation (3).

$$\textbf{\textit{Choice}} = \beta_0 + \beta_1\ \textit{Uncertainty} + \beta_2\ \textit{Coping Strategy} + \beta_3\ \textit{Uncertainty} * \textit{Coping Strategy} + \beta_4\ \textit{Hunger} + \beta_5\ \textit{Diet} + \beta 6\ \textit{Health\_Conscious} + \beta_7\ \textit{Weight Loss} + \beta_8\ \textit{Gender} + \varepsilon \qquad (3)$$

The McFadden's pseudo-R^2 for the model was 0.088. As expected, the direct effect of uncertainty on the likelihood of choosing the unhealthy option was positive and significant (β_1 = 1.092, $p < 0.05$). The interaction between uncertainty and active coping was negative and marginally significant (β_3 = - 1.330, $p < 0.1$), suggesting that engaging in active coping marginally decreased the impact of uncertainty on the likelihood of unhealthy choices. To better interpret the interaction, I compared the simple slopes of uncertainty on unhealthy choice between active coping and no coping conditions. Results indicated that the pronounced impact of uncertainty on unhealthy choice in the no coping condition (β_1 = 1.092, $p < 0.05$) became negative and insignificant under the active coping condition (β_1 = -0.238, $p > 0.05$). Therefore, the active coping strategy was helpful in countering the impact of high uncertainty on individuals' tendency to engage in unhealthy consumption. The interaction between passive coping and uncertainty was not significant (β_1 = -131, $p > 0.05$), which suggests that passive coping was not helpful in alleviating the effect of high uncertainty on unhealthy choices.

I further compared the proportions of unhealthy choices between the high and low uncertainty conditions within each coping strategy. Figure 3 depicts the results. When no coping was provided, there was a more pronounced tendency to choose the unhealthy option when the negative emotion had high uncertainty compared to when the negative emotion had low uncertainty (60% vs. 37%, $\chi^2(1) = 4.818$, $p < 0.05$). In the active coping condition, the proportions of unhealthy choices between the high vs. low uncertainty conditions were not significantly different from each other (57% vs. 53%, $\chi^2(1) = 0.088$, $p > 0.05$). That is, active coping was effective in alleviating the tendency to choose the unhealthy option when experiencing a high-uncertainty negative emotion. In contrast, even after passive coping, the proportion of unhealthy choices was still significantly higher under high uncertainty than under low uncertainty (41% vs. 63%, $\chi^2(1) = 3.519$, $p > 0.05$). Overall, active coping was more effective in countering the effect of uncertainty than passive coping, supporting H3b.

INSERT FIGURE 3 ABOUT HERE

Among the control variables, being health-conscious significantly decreased the possibility of choosing the unhealthy option (β_6= -0.123, $p < 0.05$). The other control variables did not significantly influence the likelihood of choosing the unhealthy snack.

GENERAL DISCUSSION

Conclusions and Implications

The impact of individuals' emotions on food consumption has attracted a lot of attention from both marketing and health researchers. Through a secondary data analysis and three experiments, the current paper contributes to this body of research by investigating the impact of arousal and uncertainty embedded in negative emotions on consumers' tendency to engage in unhealthy food consumption. Specifically, the first study utilized sales and advertising data for salty snacks along with consumers well-being data. It found that not all negative emotions are equal. Among the four tested negative emotions, the effects of anger (high arousal) and worry (high uncertainty) on unhealthy consumption were the most pronounced. This finding is consistent with the reasoning that high-arousal negative emotions lead to more unhealthy food consumption choices than low-arousal negative emotions. Guilt also increased unhealthy consumption but at a smaller magnitude. Sadness, a low arousal uncertain negative emotion, had an unexpected negative effect on unhealthy food consumption, suggesting sadness actually decreased the tendency to choose unhealthy food rather than increasing it.

Study 2 was designed to replicate the first study. This study successfully proved that high arousal and uncertain negative emotions increase individuals' tendency to engage in unhealthy food consumption more than negative emotions with low levels of arousal or uncertainty. Furthermore, I found the effect of uncertainty on unhealthy choice to be contingent on the arousal level. This finding is consistent with the argument that a high level of arousal affects individuals' lower order affective processing of the choice options. Consequently, high arousal reduces individuals' likelihood of engaging in the higher order cognitive process through which uncertainty affects choices.

As the arousal and uncertainty dimensions of negative emotions affect food choice through different mechanisms, different intervention strategies are needed to counter their effects. Two more lab experiments were conducted to explore the effectiveness of passive versus active coping strategies in alleviating the effects of arousal and uncertainty. Study 3A suggests that both active and passive coping strategies are helpful in countering the effect of arousal on unhealthy consumption. Study 3B suggests that only an active coping strategy can alleviate the effect of uncertainty on unhealthy consumption.

This research is highly relevant to practice considering the societal and health issues arising from unhealthy food consumption. Our results suggest that consumers should consider not only the valence of their emotions but also the level of experienced arousal and uncertainty to prevent unhealthy emotional eating. Moreover, both consumers and health professionals know it is challenging simply not eating unhealthy food when experiencing a negative emotion. The current research suggests that educating consumers about effective coping strategies may be the best approach to alleviating the negative effect of their emotions. Overall, an important implication of the current findings is that different negative emotions affect individuals' food consumption in different ways and therefore different coping strategies should be utilized to better control their effects.

Limitations and Future Research

This paper has a few limitations that should be addressed in future research. First, my secondary data consisted of only salty snacks. Future studies should generalize the current findings to other unhealthy food options. It would be interesting to compare the effects of arousal and uncertainty between salty and sweet product categories.

Second, this research focused on only two dimensions of negative emotions as level of arousal and uncertainty. It would be valuable for future research to examine the other dimensions embedded in emotions. Especially, the sense of controllability in emotions which is closely related to uncertainty.

Finally, although the two lab experiments in this paper helped explore strategies for countering the effects of high arousal and uncertainty, I only examined the effectiveness of one passive strategy and one active strategy. Future research should examine a wider range of coping strategies for countering the effects of high arousal and uncertainty.

REFRENCES

Andrade, E. B. (2005). Behavioral consequences of affect: Combining evaluative and regulatory mechanisms. *Journal of Consumer Research, 32*(3), 355-362.

Ayduk, O., Mischel, W., & Downey, G. (2002). Attentional mechanisms linking rejection to hostile reactivity: The role of "hot" versus "cool" focus. *Psychological science, 13*(5), 443-448.

Baker, J. P., & Berenbaum, H. (2007). Emotional approach and problem-focused coping: A comparison of potentially adaptive strategies. *Cognition and Emotion, 21*(1), 95-118.

Bar-Anan, Y., Wilson, T. D., & Gilbert, D. T. (2009). The feeling of uncertainty intensifies affective reactions. *Emotion, 9*(1), 123.

Baumeister, R. F., & Heatherton, T. F. (1996). Self-regulation failure: An overview. *Psychological inquiry, 7*(1), 1-15.

Berkowitz, L. (2014). Towards a general theory of anger and emotional aggression: Implications. *Perspectives on anger and emotion: Advances in social cognition, 6*, 1-46.

Carver, C. S., Scheier, M. F., & Weintraub, J. K. (1989). Assessing coping strategies: a theoretically based approach. *Journal of personality and social psychology, 56*(2), 267.

Chandon, P., & Wansink, B. (2007). The biasing health halos of fast-food restaurant health claims: lower calorie estimates and higher side-dish consumption intentions. *Journal of Consumer Research, 34*(3), 301-314.

Charlebois, S., Tamilia, R. D., & Labrecque, J. (2007). Food marketing and obesity: a public policy and channels perspective. *Innovative Marketing, 3*(1), 83-100.

Christensen, L. (1993). Effects of eating behavior on mood: a review of the literature. *International Journal of Eating Disorders, 14*(2), 171-183.

Cleobury, L., & Tapper, K. (2014). Reasons for eating 'unhealthy'snacks in overweight and obese males and females. *Journal of Human Nutrition and Dietetics, 27*(4), 333-341.

Danaher, P. J., Bonfrer, A., & Dhar, S. (2008). The effect of competitive advertising interference on sales for packaged goods. *Journal of Marketing Research, 45*(2), 211-225.

Davidson, R. J. (1998). Affective style and affective disorders: Perspectives from affective neuroscience. *Cognition & Emotion, 12*(3), 307-330.

Drewnowski, A., & Darmon, N. (2005). Food choices and diet costs: an economic analysis. *The Journal of nutrition, 135*(4), 900-904.

Drewnowski, A., & Specter, S. E. (2004). Poverty and obesity: the role of energy density and energy costs. *The American journal of clinical nutrition, 79*(1), 6-16.

Du, R. Y., Hu, Y., & Damangir, S. (2015). Leveraging trends in online searches for product features in market response modeling. *Journal of Marketing, 79*(1), 29-43.

Effertz, T., Franke, M.-K., & Teichert, T. (2014). Adolescents' assessments of advertisements for unhealthy food: An example of warning labels for soft drinks. *Journal of Consumer Policy, 37*(2), 279-299.

Evers, C., Adriaanse, M., de Ridder, D. T., & de Witt Huberts, J. C. (2013). Good mood food. Positive emotion as a neglected trigger for food intake. *Appetite, 68*, 1-7.

Faraji-Rad, A., & Pham, M. T. (2017). Uncertainty increases the reliance on affect in decisions. *Journal of Consumer Research, 44*(1), 1-21.

Fedorikhin, A., & Patrick, V. M. (2010). Positive mood and resistance to temptation: The interfering influence of elevated arousal. *Journal of Consumer Research, 37*(4), 698-711.

Fishbach, A., & Dhar, R. (2005). Goals as excuses or guides: The liberating effect of perceived goal progress on choice. *Journal of Consumer Research, 32*(3), 370-377.

Fishbach, A., & Labroo, A. A. (2007). Be better or be merry: How mood affects self-control. *Journal of personality and social psychology, 93*(2), 158.

Fitzpatrick, S., MacDonald, D. E., McFarlane, T., & Trottier, K. (2019). An experimental comparison of emotion regulation strategies for reducing acute distress in individuals with eating disorders. *Canadian Journal of Behavioural Science/Revue canadienne des sciences du comportement*.

Fletcher, B. C., Pine, K. J., Woodbridge, Z., & Nash, A. (2007). How visual images of chocolate affect the craving and guilt of female dieters. *Appetite, 48*(2), 211-217.

Fontaine, J. R., Scherer, K. R., Roesch, E. B., & Ellsworth, P. C. (2007). The world of emotions is not two-dimensional. *Psychological science, 18*(12), 1050-1057.

Frison, S., Dekimpe, M. G., Croux, C., & De Maeyer, P. (2014). Billboard and cinema advertising: Missed opportunity or spoiled arms? *International Journal of Research in Marketing, 31*(4), 425-433.

Garg, N., & Lerner, J. S. (2013). Sadness and consumption. *Journal of consumer psychology, 23*(1), 106-113.

Garg, N., Wansink, B., & Inman, J. J. (2007). The influence of incidental affect on consumers' food intake. *Journal of Marketing, 71*(1), 194-206.

Gijsenberg, M. J. (2017). Riding the Waves: Revealing the Impact of Intrayear Category Demand Cycles on Advertising and Pricing Effectiveness. *Journal of Marketing Research, 54*(2), 171-186.

Gross, J. J. (2001). Emotion regulation in adulthood: Timing is everything. *Current directions in psychological science, 10*(6), 214-219.

Haga, S. M., Kraft, P., & Corby, E.-K. (2009). Emotion regulation: Antecedents and well-being outcomes of cognitive reappraisal and expressive suppression in cross-cultural samples. *Journal of Happiness Studies, 10*(3), 271-291.

Halford, J. C., Gillespie, J., Brown, V., Pontin, E. E., & Dovey, T. M. (2004). Effect of television advertisements for foods on food consumption in children. *Appetite, 42*(2), 221-225.

Henderson, V. R., & Kelly, B. (2005). Food advertising in the age of obesity: content analysis of food advertising on general market and African American television. *Journal of nutrition education and behavior, 37*(4), 191-196.

Herman, C. P., Roth, D. A., & Polivy, J. (2003). Effects of the presence of others on food intake: A normative interpretation. *Psychological bulletin, 129*(6), 873.

Houston, B. K., & Holmes, D. S. (1974). Effect of avoidant thinking and reappraisal for coping with threat involving temporal uncertainty. *Journal of personality and social psychology, 30*(3), 382.

Jain, S., & Li, K. J. (2018). Pricing and Product Design for Vice Goods: A Strategic Analysis. *Marketing Science, 37*(4), 592-610.

Kemp, E., & Kopp, S. W. (2011). Emotion regulation consumption: When feeling better is the aim. *Journal of Consumer Behaviour, 10*(1), 1-7.

Khan, U., & Dhar, R. (2006). Licensing effect in consumer choice. *Journal of Marketing Research, 43*(2), 259-266.

Killgore, W. D., Young, A. D., Femia, L. A., Bogorodzki, P., Rogowska, J., & Yurgelun-Todd, D. A. (2003). Cortical and limbic activation during viewing of high-versus low-calorie foods. *Neuroimage, 19*(4), 1381-1394.

Koole, S. L., & Rothermund, K. (2011). “I feel better but I don't know why”: The psychology of implicit emotion regulation. *Cognition and Emotion, 25*(3), 389-399.

Kopalle, P. K., Mela, C. F., & Marsh, L. (1999). The dynamic effect of discounting on sales: Empirical analysis and normative pricing implications. *Marketing Science, 18*(3), 317-332.

Labroo, A. A., & Mukhopadhyay, A. (2009). Lay theories of emotion transience and the search for happiness: A fresh perspective on affect regulation. *Journal of Consumer Research, 36*(2), 242-254.

Leith, K. P., & Baumeister, R. F. (1996). Why do bad moods increase self-defeating behavior? Emotion, risk tasking, and self-regulation. *Journal of personality and social psychology, 71*(6), 1250.

Lerner, J. S., & Keltner, D. (2000). Beyond valence: Toward a model of emotion-specific influences on judgement and choice. *Cognition & Emotion, 14*(4), 473-493.

Lobstein, T., & Davies, S. (2009). Defining and labelling 'healthy'and 'unhealthy'food. *Public health nutrition, 12*(3), 331-340.

Lowe, M. L., & Haws, K. L. (2014). (Im) moral support: the social outcomes of parallel self-control decisions. *Journal of Consumer Research, 41*(2), 489-505.

Macht, M., Roth, S., & Ellgring, H. (2002). Chocolate eating in healthy men during experimentally induced sadness and joy. *Appetite, 39*(2), 147-158.

Magar, E. C., Phillips, L. H., & Hosie, J. A. (2008). Self-regulation and risk-taking. *Personality and Individual Differences, 45*(2), 153-159.

Mano, H. (1992). Judgments under distress: Assessing the role of unpleasantness and arousal in judgment formation. *Organizational Behavior and Human Decision Processes, 52*(2), 216-245.

Mauss, I. B., Cook, C. L., & Gross, J. J. (2007). Automatic emotion regulation during anger provocation. *Journal of Experimental Social Psychology, 43*(5), 698-711.

McFerran, B., Dahl, D. W., Fitzsimons, G. J., & Morales, A. C. (2010). Might an overweight waitress make you eat more? How the body type of others is sufficient to alter our food consumption. *Journal of consumer psychology, 20*(2), 146-151.

Mehrabian, A., & Russell, J. A. (1974). *An approach to environmental psychology*: the MIT Press.

Mick, D. G., & Faure, C. (1998). Consumer self-gifts in achievement contexts: The role of outcomes, attributions, emotions, and deservingness. *International Journal of Research in Marketing, 15*(4), 293-307.

Monat, A., Averill, J. R., & Lazarus, R. S. (1972). Anticipatory stress and coping reactions under various conditions of uncertainty. *Journal of personality and social psychology, 24*(2), 237.

Moore, E. S., Wilkie, W. L., & Desrochers, D. M. (2016). All in the Family? Parental roles in the epidemic of childhood obesity. *Journal of Consumer Research, 43*(5), 824-859.

Moore, K. S. (2013). A systematic review on the neural effects of music on emotion regulation: implications for music therapy practice. *Journal of music therapy, 50*(3), 198-242.

Morris, J. D. (1995). Observations: SAM: the Self-Assessment Manikin; an efficient cross-cultural measurement of emotional response. *Journal of Advertising Research, 35*(6), 63-68.

Munichor, N., & Friedlander, N. (2019). Sadly, you made me earn it: The effect of responsibility attributions for sadness on food indulgence. *Journal of Consumer Behaviour, 18*(5), 415-428.

Muraven, M., & Baumeister, R. F. (2000). Self-regulation and depletion of limited resources: Does self-control resemble a muscle? *Psychological bulletin, 126*(2), 247.

Muraven, M., Tice, D. M., & Baumeister, R. F. (1998). Self-control as a limited resource: Regulatory depletion patterns. *Journal of personality and social psychology, 74*(3), 774.

Musaiger, A., Lloyd, O., Al-Neyadi, S., & Bener, A. (2003). Lifestyle factors associated with obesity among male university students in the United Arab Emirates. *Nutrition & Food Science, 33*(4), 145-147.

Oliver, G., Wardle, J., & Gibson, E. L. (2000). Stress and food choice: a laboratory study. *Psychosomatic medicine, 62*(6), 853-865.

Ouwens, M. A., van Strien, T., & van Leeuwe, J. F. (2009). Possible pathways between depression, emotional and external eating. A structural equation model. *Appetite, 53*(2), 245-248.

Patel, K. A., & Schlundt, D. G. (2001). Impact of moods and social context on eating behavior. *Appetite, 36*(2), 111-118.

Pearson, N., Biddle, S. J., Williams, L., Worsley, A., Crawford, D., & Ball, K. (2014). Adolescent television viewing and unhealthy snack food consumption: the mediating role of home availability of unhealthy snack foods. *Public health nutrition, 17*(2), 317-323.

Pechmann, C., Levine, L., Loughlin, S., & Leslie, F. (2005). Impulsive and self-conscious: Adolescents' vulnerability to advertising and promotion. *Journal of Public Policy & Marketing, 24*(2), 202-221.

Poor, M., Duhachek, A., & Krishnan, H. S. (2013). How images of other consumers influence subsequent taste perceptions. *Journal of Marketing, 77*(6), 124-139.

Raghunathan, R., Naylor, R. W., & Hoyer, W. D. (2006). The unhealthy= tasty intuition and its effects on taste inferences, enjoyment, and choice of food products. *Journal of Marketing, 70*(4), 170-184.

Renner, B., Sproesser, G., Strohbach, S., & Schupp, H. T. (2012). Why we eat what we eat. The Eating Motivation Survey (TEMS). *Appetite, 59*(1), 117-128.

Richards, J. M., & Gross, J. J. (2000). Emotion regulation and memory: the cognitive costs of keeping one's cool. *Journal of personality and social psychology, 79*(3), 410.

Richtel, M., & Jacobs, A. (2018). Americans Still Packing on the Pounds. *The New York Times, A13*.

Rozin, P. (1999). Food is fundamental, fun, frightening, and far-reaching. *Social Research*, 9-30.

Russell, J. A. (1980). A circumplex model of affect. *Journal of personality and social psychology, 39*(6), 1161.

Sanbonmatsu, D. M., & Kardes, F. R. (1988). The effects of physiological arousal on information processing and persuasion. *Journal of Consumer Research, 15*(3), 379-385.

Schneider, W., & Shiffrin, R. M. (1977). Controlled and automatic human information processing: I. Detection, search, and attention. *Psychological review, 84*(1), 1.

Schwager, S., & Rothermund, K. (2014). On the dynamics of implicit emotion regulation: Counter-regulation after remembering events of high but not of low emotional intensity. *Cognition and Emotion, 28*(6), 971-992.

Shiv, B., & Fedorikhin, A. (1999). Heart and mind in conflict: The interplay of affect and cognition in consumer decision making. *Journal of Consumer Research, 26*(3), 278-292.

Sinha, J. (2016). We are where we eat: How consumption contexts induce (un) healthful eating for stigmatized overweight consumers. *Journal of consumer psychology, 26*(2), 289-297.

Slochower, J., & Kaplan, S. P. (1980). Anxiety, perceived control, and eating in obese and normal weight persons. *Appetite, 1*(1), 75-83.

Smith, & Ellsworth, P. (1985). Patterns of cognitive appraisal in emotion. *Journal of personality and social psychology, 48*(4), 813.

Smith, J. D., & Washburn, D. A. (2005). Uncertainty monitoring and metacognition by animals. *Current directions in psychological science, 14*(1), 19-24.

Steptoe, A., Pollard, T. M., & Wardle, J. (1995). Development of a measure of the motives underlying the selection of food: the food choice questionnaire. *Appetite, 25*(3), 267-284.

Tamir, M., & Robinson, M. D. (2007). The happy spotlight: Positive mood and selective attention to rewarding information. *Personality and Social Psychology Bulletin, 33*(8), 1124-1136.

Tellis, G. J., & Weiss, D. L. (1995). Does TV advertising really affect sales? The role of measures, models, and data aggregation. *Journal of Advertising, 24*(3), 1-12.

Tiedens, L. Z., & Linton, S. (2001). Judgment under emotional certainty and uncertainty: the effects of specific emotions on information processing. *Journal of personality and social psychology, 81*(6), 973.

Tucker, L. A., & Bagwell, M. (1991). Television viewing and obesity in adult females. *American Journal of Public Health, 81*(7), 908-911.

Van Dillen, L. F., & Koole, S. L. (2007). Clearing the mind: a working memory model of distraction from negative mood. *Emotion, 7*(4), 715.

Verhoeven, A. A., Adriaanse, M. A., de Vet, E., Fennis, B. M., & de Ridder, D. T. (2015). It's my party and I eat if I want to. Reasons for unhealthy snacking. *Appetite, 84*, 20-27.

Verplanken, B., Herabadi, A. G., Perry, J. A., & Silvera, D. H. (2005). Consumer style and health: The role of impulsive buying in unhealthy eating. *Psychology & Health, 20*(4), 429-441.

Winterich, K. P., & Haws, K. L. (2011). Helpful hopefulness: The effect of future positive emotions on consumption. *Journal of Consumer Research, 38*(3), 505-524.

Wooten, D. B., & Reed, A. (1998). Informational influence and the ambiguity of product experience: Order effects on the weighting of evidence. *Journal of consumer psychology, 7*(1), 79-99.

TABLES AND FIGURES

TABLE 1: NUTRITIOUS PROFILING

1. Calculate the total 'A' points

A maximum of 10 points can be awarded for each ingredient (energy, saturated fat, sugar and sodium). The total 'A' points are the sum of the points scored for each ingredient.

Total 'A' points = [points for energy] + [points for saturated fat] + [points for sugars] + [points for sodium].

Points	Energy (KJ)	Sat. fat (g)	Total sugar (g)	Sodium (mg)
0	<=335	<=1	<=4.5	<=90
1	>335	>1	>4.5	>90
2	>670	>2	>9	>180
3	>1005	>3	>13.5	>270
4	>1340	>4	>18	>360
5	>1675	>5	>22.5	>450
6	>2010	>6	>27	>540
7	>2345	>7	>31	>630
8	>2680	>8	>36	>720
9	>3015	>9	>40	>810
10	>3350	>10	>45	>900

If a food or drink scores 11 or more 'A' points, then it cannot score points for protein unless it also scores 5 points for fruit, vegetables and nuts.

2. Calculate the total 'C' points

A maximum of 5 points can be awarded for each ingredient. The total 'C' points are the sum of the points for each ingredient (note that you should choose one or other of the dietary fibre columns according to how the fibre content of the food or beverage was calculated).
Total 'C' points5[points for fruit, vegetables and nut content]1[points for fibre (either NSP or AOAC)]1[points for protein].
(NB: Guidance on scoring fruit, vegetables and nuts is available from the Food Standards Agency.)

Points	Fruit, vegetables and nuts (%)	NSP fibre (g)	Or AOAC fibre (g)	Protein (g)
0	<=40	<=0.7	<=0.9	<=1.6
1	>40	>0.7	>0.9	>1.6
2	>60	>1.4	>1.9	>3.2
3	-	>2.1	>2.8	>4.8
4	-	>2.8	>3.7	>6.4
5	>80	>3.5	>4.7	>8.0

3. Calculate the overall score

If a food scores less than 11 'A' points then the overall score is calculated as follows:
Overall score 5 [total 'A' points] 2 [total 'C' points].
If a food scores 11 or more 'A' points but scores 5 points for fruit, vegetables and nuts then the overall score is calculated as follows:
Overall score = [total 'A' points] - [total 'C' points].
If a food scores 11 or more 'A' points but also scores less than 5 points for fruit, vegetables and nuts then the overall score is calculated without reference to the protein value, as follows:
Overall score = [total 'A' points] - [fibre points + fruit, vegetables and nuts points only].
The model can be adjusted to take account of changes in public health nutritional policy. Within the model, any threshold can be defined according to the judgement of the policy makers and their scientific advisers. For the purposes of the advertising controls being introduced in the UK in 2007:
a food is classified as 'less healthy' where it scores 4 points or more, and
a drink is classified as 'less healthy' where it scores 1 point or more.

Note: Source: (Lobstein and Davies, 2009)

TABLE 2: DESCRIPTIVE STATISTICS AND CORROLATIONS

Descriptive Statistics

Variables	Mean	Median	S.D.	Min	Max
Sales in dollar	5.031	5.265	2.419	0	12.373
Guilt	0.337	0.340	0.012	0.300	0.370
Sadness	0.179	0.180	0.010	0.160	0.22
Anger	0.139	0.140	0.009	0.100	0.160
Worry	0.321	0.320	0.019	0.250	0.370
Ad Spending	0.428	0	1.437	0	10.111
Weighted Unit Price	1.007	0.985	0.594	0.055	8.129
In-Store Feature – Small Ad	0.002	0	0.023	0	1
In-Store Feature – Medium Ad	0.037	0	0.108	0	1
In-Store Feature – Large Ad	0.109	0	0.053	0	1
In-Store Feature – Coupon	0.002	0	0.031	0	1
In-Store Feature – Minor Display	0.163	0.087	0.207	0	1
In-Store Feature – Major Display	0.083	0.023	0.136	0	1
In-Store Feature – Price Reduction	0.220	0.097	0.267	0	1

Variables Correlations

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13
1: Sales in dollar													
2: Guilt	-0.01												
3: Sadness	0	0											
4: Anger	0	-0.08	0.30										
5: Worry	0.01	-0.07	0.51	0.563									
6: Ad Spending	0.14	-0.04	-0.02	0	0.01								
7: Weighted Unit Price	0.37	0	0.01	0	0	-0.03							
8: INF- Small Ad	0.09	-0.01	0.01	0.01	0.01	0	0.02						
9: INF – Medium Ad	0.31	-0.02	-0.01	-0.01	-0.01	0.06	0.06	0.06					
10: INF – Large Ad	0.22	-0.01	-0.01	0.01	-0.01	0.125	0.03	0.02	0.14				
11: INF – Coupon	0.06	0	0	0.01	0.01	0.03	0.02	0	0.02	0.04			
12: INF – Minor Display	-0.01	0.02	-0.01	0	0	0.02	-0.26	0	-0.02	0	0.04		
13: INF – Major Display	0.26	0.02	-0.01	0.01	0	0	0.05	0.05	0.23	0.15	0.08	0.01	
14: INF – Price Reduction	0.39	-0.02	-0.01	0	-0.01	0.04	0.14	0.10	0.41	0.25	0.12	-0.04	0.4

Notes: Sales in dollar and ad spending values are reported after inflation adjustment and log-transformation. Weighted unit price values are reported after inflation adjustment.

TABLE 3: MODEL ESTIMATION RESULTS – STUDY 1

Coefficients:	Overall Model	
$Sales_{t-1}$	0.8386 ***	(826.01)
Guilt	**0.2202 ****	**(2.96)**
Sadness	**-0.5091 *****	**(-5.30)**
Anger	**0.6114 *****	**(4.95)**
Worry	**0.8146 *****	**(25.70)**
Ad Spending	0.002	(0.22)
Weighted Unit Price	-0.0753 ***	(-9.30)
In-Store Ad.(Small)	0.2809 ***	(4.95)
In-Store Ad.(Medium)	0.3816 ***	(46.01)
In-Store Ad.(Large)	0.5116 ***	(34.25)
In-Store Coupon.	0.4716 ***	(19.46)
In-Store Display (minor)	0.2653 ***	(52.72)
In-Store Display (major)	0.3045 ***	(39.73)
Price Reduction	0.1429 ***	(32.67)
Food Type * Guilt	0.2779 *	(2.13)
Food Type * Sadness	57.42 ***	(3.41)
Food Type * Anger	-02567	(-1.19)
Food Type * Worry	-0.3452 **	(-3.28)
Number of Obs.	208,482	
Adj. R-Squared	0.79	
UPC Fix Effect	YES	

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, "." $p < 0.1$

Notes: Dependent variable is sales in dollar. Food Type is set on 0 for unhealthy products. Therefore, the direct effect of emotions manifests the magnitude of their influence on unhealthy consumption. The focal variables of interest and their statistically significant coefficient estimates are highlighted. The values in the parentheses show t-value. Ad spending and sales in dollar are log-transformed and adjusted for inflation rate. Weighted unit price is adjusted for inflation.

TABLE 4: SNACK CHOICE QUESTIONAIRE

Healthiness
1. This snack keeps me healthy.
2. This snack contains a lot of vitamins and minerals.
3. This snack is nutritious.
4. This snack is high in protein.
5. This snack is good for my skin/teeth/hair etc.
6. This snack is high in fiber and roughage.
Liking the taste
I like the taste of this snack.

Note: Source: (Steptoe et al., 1995)

FIGURE 1: PROPORTION OF UNHEALTY CHOICE – STUDY 2

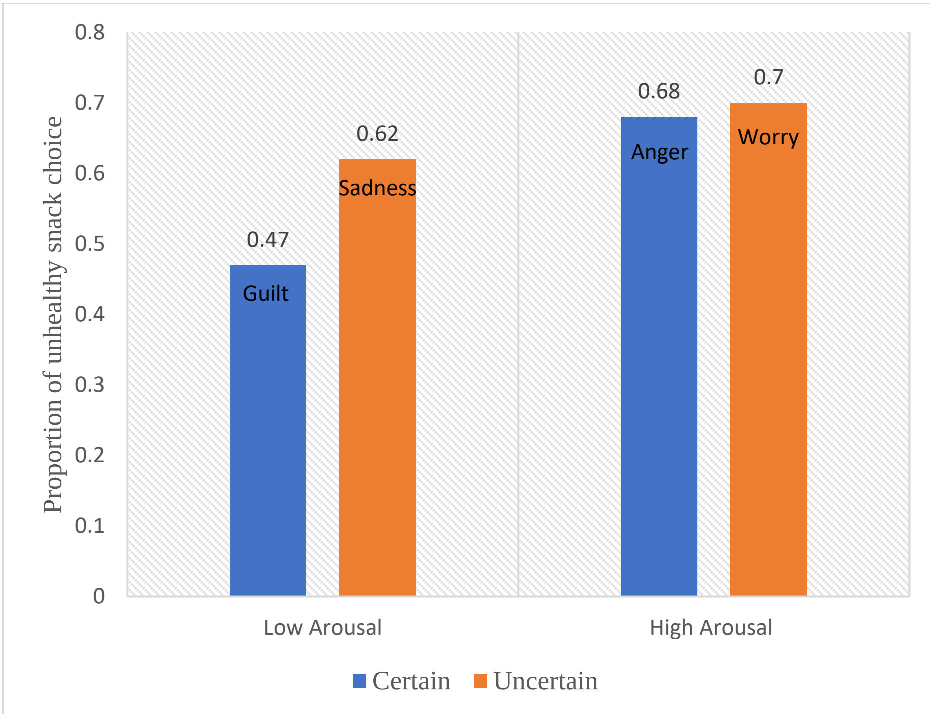


FIGURE 2: PROPORTION OF UNHEALTY CHOICE – STUDY 3A

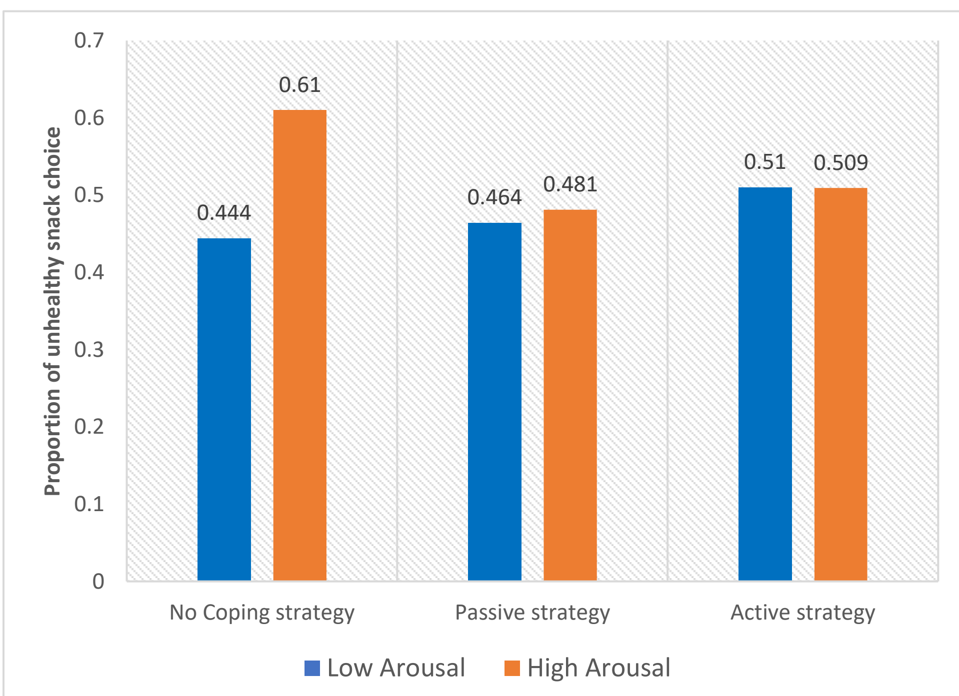
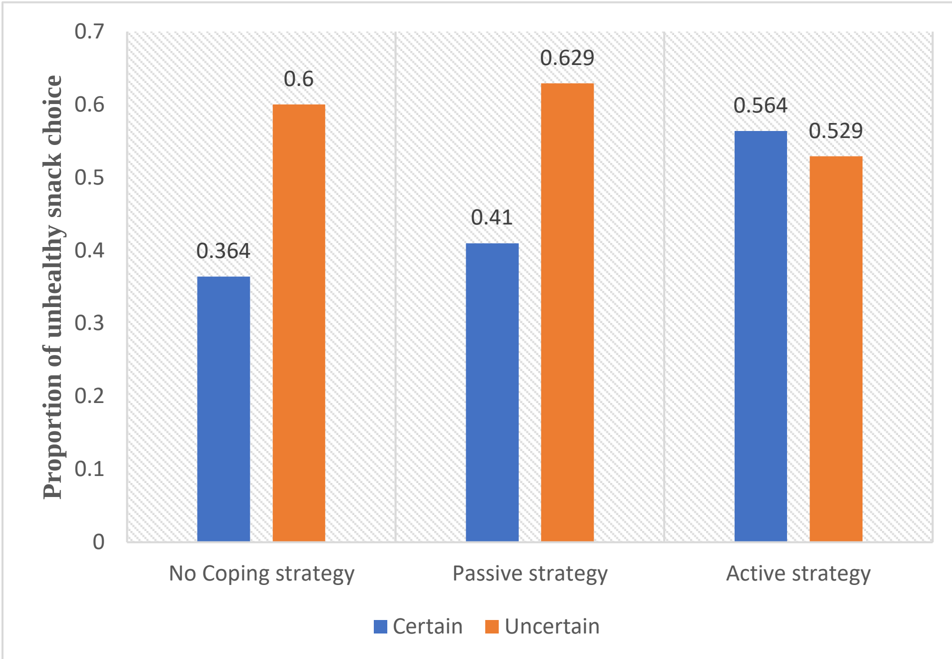


FIGURE 3: PROPORTION OF UNHEALTY CHOICE – STUDY 3B



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EDUCATION

Ph.D. in Business Administration – Marketing (Major)- International Business (Minor), May *2020*

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MBA - Marketing, May 2014

Mazandaran University of Science and Technology, Iran

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RESEARCH INTERESTS

Online and Offline Interactive Marketing in two streams:

- Online and Offline Promotion (The Role of sentiments in Effective Promotion)
- Salesforce Engagement with Consumers (Salesforce interaction with consumers in Offline and Online Setting)

TEACHING INTERESTS

Social Media Marketing, Advertising Strategy (Integrated Marketing Communication), Web Analytics, Principles of Marketing

COMPUTER SKILLS

Proficient in statistical analysis software (R, C++, SQL Server, SPSS, AMOS, Excel)

Databases: Thomson Reuters, Kantar Media, Gallup Analytics, Information Resources Incorporated (IRI), WRDS

PUBLICATIONS

- **Leila Khoshghadam**, Elika Kordrostami, & Yuping Liu-Thompkins**.** (2019) Experiencing Nostalgia through the Lens of Life Satisfaction. *European Journal of Marketing,* 53(3), 524-544

- Aaron D. Arndt**, Leila Khoshghadam**, Kenneth Evans. (2019) Who Do I Look At? Mutual Gaze in Triadic Sales Encounters. *Journal of Business Research*

- Aaron Arndt, Kiran Karande, Kristina Harrison, & **Leila Khoshghadam.** Goal-Relevant versus Incidental Similarity when Choosing between Multiple Service Providers. *Journal of Business Research*

WORKS IN PROGRESS

- Hamed Yousefi & **Leila Khoshghadam,** It's Cheaper if They Know You: The Effect of Advertising Expenses on Cost of Capital, Data Analysis in Progress. Target Journal: *Journal of Business Research*

- **Leila Khoshghadam**, Finding the Right Appeal for Prestige Seekers: The Effect of Advertising Message Framing on Symbolic Consumption. Data collection in progress. Target Journal: *Journal of Advertising*

CONFERENCE PROCEEDINGS

- **Leila Khoshghadam** & Yuping Liu-Thompkins (Forthcoming). How We Feel: The Role of Macro-economic Sentiment in Advertising Spending- Sales Relationship. *American Marketing Association's Conference*, Chicago,IL

- **Leila Khoshghadam** & Elika Kordrostami (2018). Advertising for Symbolic Consumption: Exploring the Moderating Effects of Conspicuous Consumption and Materialism. *American Marketing Association's Conference*, Boston, MA

- Aaron Arndt & **Leila Khoshghadam** (2018). Who Do I Look at? Mutual Gaze in Triadic Sales Encounters. *American Marketing Association's Conference*, Boston, MA.

- Aaron Arndt, Kiran Karande, Kristina Harrison, & **Leila Khoshghadam** (2018). Goal-Relevant versus Incidental Similarity when Choosing between Multiple Service Providers. *American Marketing Association's Conference*, Boston, MA.

- **Leila Khoshghadam** & Elika Kordrostami (2018). The Power of Music in Advertisement: Exploring the Moderating Role of Personality on The Effectiveness of Music-Evoked Nostalgia. *American Academy of Advertising's conference.* New York, NY

- **Leila Khoshghadam** & Kiyan Norozi (2018). Advertising for Symbolic Consumption: Exploring the Moderating Effects of Social Inequality in Generating Purchase Intention. *American Marketing Association's conference (Winter),* New Orleans, LA

- **Leila Khoshghadam** & Chuanyi Tang (2017). The Relationship between Advertising Appeals and the Effectiveness of the International Luxury Services Advertising: Exploring the Moderating Effects of Cultural Differences. *American Marketing Association's conference (Winter),* Orlando, FL

- **Leila Khoshghadam** & Hamed Yousefi (2016). Opportunities of Foreignness for MNEs Investing in a Developing Country; Marketing and Financial Approach. *Academy of International Business's conference,* Philadelphia. PA

- Junzhou Zhang, Kristina Stuhler, & **Leila Khoshghadam** (2016), A General Conceptual Model of Product Harm Crisis. *Society for Marketing Advances' conference,* Atlanta, GA

TEACHING EXPERIENCE

Social Media Marketing

- Fall 2018, Evaluation: 4.1 / 5

Principles of Marketing

- Spring 2019, Evaluation: 4.6/5
- Fall 2018, Evaluation: 4.4/5
- Spring 2018, Evaluation: 4.4/5
- Spring 2017, Evaluation: 4.1/5

Introduction to Business

- Summer 2018, Evaluation: 4.5/5

Advertising Strategy (Integrated Marketing Communication)

- Summer 2019, (ongoing)

Web Analytics (as Teaching Assistant) **–** Fall 2018, 2019

AWARDS AND HONORS

- ODU Summer Research Fellowship Program Award (As Co-PI) (2019)
- AMS- Doctoral Consortium, University of British Columbia (2019)
- Preparing Future Faculty Certificate (PFF) – Old Dominion University (2019)
- Graduate Student Research Travel Award - Old Dominion University (2016-2017)
- Student with the Best Academic Performance – Azad University, Iran (2004)

SERVICE

- President – ODU Business Administration Doctoral Student Association (BADSA) (2017-2018)
- Ad-hoc Reviewer - AMA Summer and winter Educators' Conference (2016, 2017, 2018)
- Ad-hoc Reviewer – AMA Marketing and Public Policy winter Conference (2018)
- Representative of Strome College of Business in Graduate Teaching Assistantship Institute (GTAI) – Old Dominion University (2016)
- Representative of Strome College of Business in New Graduate Student Orientation (2015)
- Mentor in the Office of Intercultural Relations (OIR) (2016)

OTHER WORK EXPERIENCES

- Market Research Expert, Product Development and Export Department, Avrand Company, Iran (2008-2015)