ESSAYS ON BRAND TRUST

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ABSTRACT

Koushyar Rajavi: Essays on Brand Trust
(Under the direction of Tarun Kushwaha and Jan-Benedict Steenkamp)

Brand Trust is defined as the "willingness of the average consumer to rely on the ability of the brand to perform its stated function" (Chaudhuri and Holbrook 2001, p. 82). Trust plays a key role in brand success by lowering customers' purchase risk and easing their decision making. Despite the importance of brand trust, industry reports indicate alarming decline in consumer trust in brands across the world. For example, Young & Rubicam (2011) reported that the percentage of brands that customers trusted dropped from 49% in 2001 to 25% in 2010. In the meantime, despite growing managerial interest in brand trust, marketing literature lacks generalizable insights regarding antecedents and consequences of brand trust. Specifically, there is need for research to investigate the impact of marketing activities on brand trust, the implications and consequences of brand trust (and violation of brand trust), and the characteristics that explain the heterogeneity in relationships between brand trust and related concepts. I address these issues in three studies.

In the first study, I examine the relationship between five marketing mix instruments (advertising, new product introduction, distribution, price, price promotion) and brand trust. Using a unique dataset that combines consumer surveys and scanner panel data on 589 leading national brands in 46 CPG categories across 13 countries, I also examine category and country level characteristics that moderate the relationships between marketing mix activities and brand trust. In the second study of this dissertation, I examine the dynamics of the most important

consequence of brand trust – i.e., brand equity – and the impact of economic business cycles on brand equity. Moreover, I study category and brand level moderators that safeguard brand equity against macroeconomic fluctuations. In doing so, I use monthly data on 150 leading CPG brands in 36 categories across 17 years. In the final study, I investigate violation of brand trust. In doing so, I examine 143 product recalls in 12 European countries and focus on the impact of price promotions. Additionally, I study recall, category, and country level characteristics that explain the heterogeneity in post-recall performance and price promotion effectiveness.

To my wife, Mahnaz Parsanasab,
And my parents Mahboub Asri and Behzad Rajavi;
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CHAPTER 1: INTRODUCTION

In the Oxford dictionary, trust is defined as the "firm belief in the reliability, truth, or ability of someone or something", while Giffin (1967, p. 105) defined trust as the "reliance upon the characteristics of an object, or the occurrence of an event, or the behavior of a person in order to achieve a desired but uncertain objective in a risky situation". The essence of trust is the belief that another entity has the ability and the willingness to fulfill its promises.

Trust is crucial in our daily lives because it reduces uncertainty inherent in any economic or social transaction. It is difficult to open a newspaper or a magazine that does not talk about trust in one way or another. Indeed, there are few constructs that play a bigger role in international, national, economic, and social life than trust. Accordingly, trust has been studied across many fields including sociology (Lewis and Weigert 1985), psychology (Rotter 1967), economics (North 1990), political science (Newton 2001), and management (Rousseau et al. 1998). In marketing, while the role of trust has been extensively studied in B2B settings (e.g., Moorman, Deshpande, and Zaltman 1993; Morgan and Hunt 1994; Doney and Cannon 1997; Geyskens, Steenkamp, and Kumar 1998; Sirdeshmukh, Singh, and Sabol 2002), there has been little academic research investigating the role of trust in B2C contexts. Specifically, consumers' trust in brands has not been adequately addressed in the literature.

Philip Kotler defines brand as "a seller's promise to deliver a specific set of features, benefits and services consistent to the buyers" (Kotler 2002, p. 593). Hence, a brand is a pledge by the firm to deliver on its promises. Accordingly, the core idea behind branding is intertwined with the notion of trust. Today's marketplace has brought about huge complexities and uncertainties for consumers; a typical consumer is faced with lots of options and alternatives but limited time and budget. If consumers trust the brand to deliver on its promises, this eases their decision making, reduces their purchase risk, and reduces costs of information gathering and processing (Erdem, Swait, and Valenzuela 2006). Thus, brand trust – defined as the consumer's belief that the brand is willing and able to deliver on its promises (Chaudhuri and Holbrook 2001; Erdem and Swait 2004) – is key to brand success in the marketplace. Given the importance of brand trust, it is worrying that industry evidence indicates that trust in brands is slipping. For instance, according to Young & Rubicam, the proportion of brands that customers said they trusted dropped from 49% in 2001 to 25% in 2010 (Young & Rubicam 2011). Subsequently, consumer trust in brands has moved to the top of marketing managers' priority lists.

In my dissertation, I aim to contribute to marketing literature and practice by studying aspects of brand trust that have not been thoroughly investigated. More specifically, I address three facets of brand trust: (a) marketing mix activities as drivers of brand trust; (b) dynamics of brand equity as outcome of brand trust; and (c) product-harm crises as instances in which brand trust is violated. Additionally, I examine the role that brand, category, and country characteristics play in explaining the heterogeneity in strength of the observed relationships.

In the first essay, I study brand trust and the role of marketing mix activities as drivers of brand trust. Motivated by pioneering work in information economics on signaling value of brands, I examine the impact of advertising, new product introduction, distribution, price, and price promotion on brand trust. Furthermore, I explain why the impact of marketing mix instruments on brand trust depends on product category and national-cultural characteristics. I test my hypotheses using a unique dataset which contains primary (survey) data as well as secondary (household panel, country data) measures on brands in consumer packaged goods (CPG) categories. The dataset covers 13 countries, including the US, various European countries, as well as all the BRIC countries (Brazil, Russia, India, and China). I use hierarchical linear modeling for cross-classified data which controls for unobserved heterogeneity at country, category, brand, and respondent levels. I find that advertising, innovation, distribution, and price positively impact brand trust whereas price promotions damage brand trust. Furthermore, I find that the marketing mix instruments have stronger impact in categories with high brand relevance, countries high on secular-rational values, and countries high on survival values.

The main reason that brand managers care about brand trust is that it is an important antecedent of brand equity (Erdem and Swait 1998; Chaudhuri and Holbrook 2001). Some even argue that brand trust is the strongest determinant of brand equity (Ambler 1997). During the past few decades, the concept of brand equity has drawn considerable attention from both researchers and practitioners. Firms spend millions of dollars to build, track, and maintain brand equity because they believe they will benefit from such investments in product market outcomes as well as financial market outcomes (Erdem and Swait 1998; Keller 1998). However, it is not clear how brand equity evolves over time and what factors influence the evolution of brand equity. Specifically, the impact of business cycle changes on brand equity is unknown. This is an important research question because failure to understand and incorporate external factors that influence brand equity might lead to erroneous responses from brand managers; i.e., brand managers might wrongly associate increases or decreases in brand equity with their own actions. As such, in the second essay, I investigate the impact of business cycle fluctuations on the changes in brand equity over time and examine whether business cycle fluctuations have a differential impact on brand equity across different categories and brands. In doing so, I utilize monthly data on 150 leading CPG brands in 36 categories across 17 years. The results show that brand equity behaves cyclically; it increases (decreases) during economic upturns (downturns) and that such changes persist in the long run. Moreover, I find that business cycle fluctuations have a stronger impact on brand equity in low performance risk categories, for brands that are pricier, and brands that do not advertise a lot.

Although the importance of brand trust in building brand equity and thus contributing to brand's success is well-established, brand trust is often violated. The likes of Volkswagen, Wells Fargo, Uber, Facebook, and United Airlines are among a long list of firms which have recently violated their customers' trust in different ways. When trust is violated, managers are desperate to do something to mitigate the losses and regain customer trust. Marketing managers oftentimes turn to price promotions to reduce customer churn and regain customer trust. For example, after the Volkswagen emission scandal, the German auto manufacturer offered large discounts to avoid losing customers (Bloomberg 2015). However, it is not clear whether price promotions can be helpful in reducing the consequences of violation of customer trust and more importantly, under which conditions price promotions are more effective in helping the affected brands. In the third essay, I study product-harm crises as well-known instances in which brand trust is violated. This study is guided by two important questions: 1) Can price promotions help the recalled brands? 2) What explains the heterogeneity in post-recall brand performance and post-recall price promotion effectiveness? In doing so, I study country (i.e., uncertainty avoidance), category (i.e., product category risk), and recall (i.e., recall severity) characteristics that explain consumers' perceived risk associated with product recalls. I use large multi-country household-scanner panels to empirically examine impact of 143 packaged food recall instances in 12 European nations between 2010 and 2013. Findings suggest that in general the price promotion effectiveness increases after recall. However, post-recall price promotions are less effective when recall is associated with severe health concerns, or is in high risk product categories, or occurs in countries high on the uncertainty avoidance cultural value. The study findings help brand managers to more efficiently allocate their marketing budgets after a recall.

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CHAPTER 2: IN BRANDS WE TRUST? A GLOBAL STUDY INTO THE RELATIONSHIP BETWEEN MARKETING MIX ACTIVITIES AND BRAND TRUST IN CONSUMER PACKAGED GOODS INDUSTRY

Abstract

The essence of a brand is that it delivers on its promises. However, consumer trust in brands has declined around the world in recent decades. As a result, brand trust has become a major concern for managers. We study the relationship between marketing mix activities (i.e., advertising, new product introduction, distribution, price, and price promotion) and brand trust. We propose and show that the relationship between marketing mix and brand trust is moderated by cultural and category level factors. Using a unique data-set which consists of survey and scanner panel data in 46 CPG categories across 13 countries, we find that advertising, new product introduction, distribution, and price are positively associated with brand trust whereas price promotion and brand trust are negatively related. Furthermore, we find that marketing mix activities are more strongly related to brand trust in categories with high brand relevance, countries high on secular-rational values, and countries low on self-expression values. We also examine differences in the relationship between marketing mix activities and brand trust between developed and BRIC countries in an exploratory fashion. Limitations and implications for future research are discussed.

Keywords: Brand trust, Marketing mix, International marketing, Branding

Introduction

For most firms, brands are among their most valuable assets. According to brand consultancy Kantar Millward Brown, the value of the 100 most valuable global brands alone stood at $3.4 trillion in 2016 (Millward Brown 2016a). What makes brands so valuable? This can be understood by considering the definition of a brand: “a seller’s promise to deliver a specific set of features, benefits and services consistent to the buyers” (Kotler 2002, p. 593). Thus, a brand is a pledge by the firm to deliver on its promises. If consumers trust the brand to deliver on these promises, this eases their decision making, reduces costs of information gathering and processing information, reduces their purchase risk, and increases expected utility (Erdem, Swait, and Valenzuela 2006). Thus, trust is key to brand success in the marketplace. For example, Kantar Millward Brown found that B2B brands that rated high on brand trust grew 80% in brand value in the last decade while less trusted brands grew only 25%. As another example, industry analysts consider brand trust to be crucial for the success of the Internet of Things. Hence, it is not surprising that the word trust (trustworthy, trusted) occurred 64 times in Millward Brown’s (2016a) BrandZ global report.

Given the importance of brand trust, it is worrying that industry evidence indicates that trust in brands is slipping. According to Young & Rubicam, the proportion of brands that customers said they trusted dropped from 49% in 2001 to 25% in 2010, while in the same period, the correlation between brand trust and the brand’s future potential (defined as brand strength by Y&R) increased from 0.29 to 0.45 (Young & Rubicam 2011). The 2017 Edelman Trust Barometer found that in nearly half of the countries surveyed, the percentage of people that mistrust brands’ owners exceeds the percentage of people that trusts them (Edelman 2017). As a result, consumer trust in brands has moved to the top of management’s priority list. Indeed, in

2015 when the CEOs of leading consumer goods firms such as P&G, Nestlé, and PepsiCo gathered for the 59th Consumer Goods Forum's annual summit, 'Trust as a Foundation for Growth' was their main topic of discussion (Consumer Goods Forum 2015).

Academic research has recognized the importance of brand trust - defined as the consumer's belief that the brand is willing and able to deliver on its promises (Chaudhuri and Holbrook 2001; Erdem and Swait 2004). The focus of this stream of research has largely been on the consequences of brand trust, including expected utility (Erdem and Swait 1998), brand consideration and brand choice (Erdem and Swait 2004; Erdem, Swait, and Valenzuela 2006), brand loyalty (Chaudhuri and Holbrook 2001), and word of mouth (Becerra and Badrinarayanan 2013). We build upon and extend previous work in three meaningful ways. First, while there is considerable research evidence that consumer trust in one's brand is associated with favorable attitudinal and behavioral outcomes, there is little research on the relation between firm marketing mix activities and consumer trust in their brands. We conduct a comprehensive investigation into the relationship between five essential brand marketing mix activities that are under the control of the firm - advertising intensity, new product introduction intensity, price, price promotion, and distribution intensity - and brand trust. Our examination encompasses a large number of product categories. This allows for a rather comprehensive assessment of the relationship between marketing mix activities and brand trust.

Second, we examine the role of marketing mix activities on a global basis. Nowadays, with the increased globalization of marketing activities and the importance of brands in accomplishing firm strategies, there is a pressing need to test whether conclusions regarding marketing mix activities are globally generalizable (Steenkamp 2005; Erdem, Swait, and Valenzuela 2006). Indeed, there is evidence that brand trust is not exclusively a concern of US brands, or even

Western brands as it has been identified as a major factor in countries like China (Millward Brown 2017a), India (Millward Brown 2016b), and Latin America (Millward Brown 2017b).

Third, we examine boundary conditions to the findings within and across countries. More specifically, we investigate whether the relationship between marketing mix activities and brand trust systematically differs across product categories in function of the relevance that brands have in that category (Fischer, Völckner, and Sattler 2010) and across countries according to their national culture (Steenkamp and Geyskens 2014).

We put together a unique cross-sectional data set, which contains primary (survey) data as well as secondary (household panel, country) data from 15,073 respondents on 589 brands in 46 consumer packaged goods (CPG) categories. Our data set covers 13 countries, including the US, various European countries including France, Germany, and Great Britain, as well as the four BRIC countries (Brazil, Russia, India, and China). Several marketing mix instruments (new product introduction intensity, advertising intensity) are derived from the surveys, others (price, price promotion, distribution) are derived from household panels operated by Kantar Worldpanel, GfK, and IRI. We recognize that the cross-sectional nature of our empirical analysis, despite our best efforts to address biases and endogeneity concerns, has limitations. Therefore, we characterize our findings as descriptive. Our findings which are based on this broad database can direct future follow-up causal research using longitudinal and/or field experimental designs. We discuss this at the end of our paper.

Research Hypotheses

Previous Research

Trust has generally been defined as the "generalized expectancy held by an individual that the word of another ... can be relied on" (Rotter 1967, p. 651). Trust has been studied across many fields including psychology (Rotter 1967), sociology (Lewis and Weigert 1985), political science (Newton 2001), economics (Dasgupta 1988), and management (Rousseau et al. 1998). In marketing, the role of trust has been studied extensively in B2B settings (Ganesan 1994; Morgan and Hunt 1994; Doney and Cannon 1997; Geyskens, Steenkamp, and Kumar 1998). In comparison, there has been relatively little academic research examining the role of trust in B2C contexts in general, and in brand trust in particular. Grayson, Johnson, and Chen (2008) examined the role of customer trust in firms when the business environment is highly trusted by customers. Their research provides evidence on the importance of contextual (i.e., industry) and institutional (i.e., country) factors in shaping customers' trust.

Chaudhuri and Holbrook (2001) studied trust in brands, using cross-sectional survey data on 107 brands in 49 product categories. They found that highly trusted brands commanded higher attitudinal and purchase loyalty. They also examined the relation between utilitarian value (tangible product attributes) in the category versus hedonic value (nontangible, symbolic benefits) in the category and brand trust. They speculated that utilitarian value has a stronger relation with trust than hedonic value but found no support for this notion. This suggests that the promises encapsulated in the concept of brand trust may both refer to tangible outcomes (e.g., functional performance) as well as nontangible outcomes (e.g., mode of production or social welfare).

Erdem and colleagues (Erdem and Swait 1998, 2004; Erdem, Swait, and Valenzuela 2006) examined brand trust (also labeled brand credibility, defined as the ability and willingness of the brand to deliver what is promised; Erdem and Swait 1998, p. 137). Using an information economics perspective, they conceptualized brands as market signals. They developed and tested a cross-sectional structural equation (LISREL) model that related brand trust to brand advertising and consistency as antecedents and to brand purchase as consequence through the intervening constructs of perceived quality, information costs, and perceived risk. They found broad support for their model across two categories (juice and jeans) using a survey among undergraduate students. In another study conducted among students for six product categories, Erdem and Swait (2004) found that brand trust rather than brand expertise affects consumer choices and brand consideration. Erdem, Swait, and Valenzuela (2006) extended their earlier work by investigating the consequences of brand trust across countries for two product categories (juice, PCs) using surveys among students in seven countries around the world. They found strong support for the key role of brand trust in shaping consumer consideration and purchase of brands. Moreover, they documented the importance of culture in understanding how brand trust affects consumer choice. They reported that the positive effect of brand trust on choice is greater for consumers high on collectivism or uncertainty avoidance.

The previous discussion shows that managers' interest in brand trust is justified, it being associated with important market outcomes. However, our discussion also highlights that while the consequences of brand trust have received considerable research attention, there is a dearth of research on whether and how managers' marketing mix activities are related to brand trust. We build on previous research by adopting a signaling perspective to understand how marketing mix activities are associated with brand trust. Our study is unique in its coverage of the full marketing mix (advertising intensity, new product introduction intensity, distribution intensity, price, price promotion intensity); sample of brands (589); international scope (13 countries including the BRICs); investigation of the varying relationship between marketing mix activities and brand trust across categories is function of the relevance of brands in that category; investigation of the varying relationship between marketing mix activities and brand trust across countries is function of their national culture; and the use of over 15,000 real consumers. As a consequence, we can explore issues that previous research was not designed to address. For example, we can compare average trust in brands across countries. We will see that when it comes to trust in brands, the US is actually closer to China and India than to Germany or the UK. We provide insights into the effect of each marketing mix instrument is function of the brand's product category and the national-cultural context of its consumers. We will also compare and contrast the link between brand trust and marketing mix activities between the two important groups of countries in the world: developed countries versus emerging markets of BRICs nations. Overall, we investigate a set of issues that are important and not addressed by previous research.

Marketing Mix Instruments and Brand Trust

As discussed above, the essence of brand trust is that the brand delivers on its promises, time and time again. These promises can be of various nature such as physical attributes (e.g., organic ingredients, no artificial colors), functional benefits (taste of coffee, cleaning power of a detergent), and symbolic and self-expressive benefits (e.g., "smart shopper," brand corporate social responsibility). But what should hold a brand back from cheating the consumer by offering a high-priced product with the promise of superior quality while delivering inferior quality (e.g., selling products with regular (non-organic) ingredients, using cheaper coffee beans that taste less good, not being involved in CSR)? And how can the consumer trust the brand to deliver on these promises?

To find the answer, we turn to information economics (Klein and Leffler 1981; Shapiro 1983; Kihlstrom and Riordan 1984; Milgrom and Roberts 1986), which recognizes the imperfect and asymmetric information structure of the market and proposes that brands can use market signals to convey information to imperfectly informed consumers. In a seminal paper, Klein and

Leffler (1981) demonstrate theoretically that market prices above the competitive price and the presence of non-salvageable brand investments are means of enforcing brand promises. These authors assume that if a consumer receives a product of quality at least as high as implicitly contracted for, he or she will continue to purchase that brand. On the other hand, "if quality is less than contracted for, all consumers will cease to purchase from the particular sampled "cheating" firm" (Klein and Leffler 1981, p. 620). So, what is to persuade a "rational" firm from reneging on its promises? If they can charge a price premium so that the brand earns a continual stream of income whose discounted value exceeds the one-time profit increase obtained from cheating. They show analytically that in competitive markets, consumers can use price as market signal to infer whether the brand is likely to fulfill its promises, i.e., that the brand can be trusted.

Klein and Leffler (1981) further show that market equilibrium requires the excess rental income from the price premium be dissipated. Brand-specific capital expenditures on advertising whose outcomes are observable to consumers are the only form of competition consistent with a zero-profit market equilibrium. These advertising expenditures become sunk cost that are lost if the brand cheats on its promises. Large advertising expenditures inform consumers of the magnitude of sunk capital costs and thereby supply information about the quasi-rent price premium being earned by the brand and hence the opportunity cost to the brand if it cheats.[1] In sum, advertising expenditure can be used by consumers as an indicator of likely (absence of) cheating. Shapiro (1983) and Kihlstrom and Riordan (1984) reach the same conclusion. Empirical research has confirmed that consumers do indeed regard heavy advertising as safeguard against cheating. Kirmani and Wright (1989) find support for the consumer attribution

[1] Brand-specific expenditures, like all sunk costs, are irrelevant in determining future firm behavior, including the decision to cheat or not. However, consumers know that such sunk costs can be profitable only if the future quasi rents (price premium on future sales) are large (Klein and Leffler 1981, p. 631).

that if a marketer spends heavily on advertising a new product, it is because the marketer believes strongly that it has high sales potential. This attribution is consistent with Klein and Leffler's predictions – after all, even the most naïve consumers will intuitively understand that the marketer can hardly be confident about the sales potential if their brand cheats. Erdem and Swait (1998) investigate the relationship between brand advertising and the credibility of juice and jeans brands using cross-sectional survey data. They find that advertising has a significant effect ($p < 0.10$) on credibility of juice brands but not on the credibility of jeans brands.

Klein and Leffler (1981) and Kihlstrom and Riordan (1984) focus on advertising as brand-specific investment, but while advertising has attracted most attention in the information economics literature, the analytical conclusions apply to any kind of observable brand-name expenditures (Milgrom and Roberts 1986, pp. 799-800), including new product introductions under a given brand name (Milgrom and Roberts 1986) and distribution (Rao and Mahi 2003). Frequent new product introductions help a brand differentiate itself with its competitors. The innovative brand relies on consumers' repeat purchases to recoup R&D, new packaging, and other innovation related costs. Thus, innovative brands signal to consumers that they are motivated to deliver on their promises; otherwise they would incur great losses (fixed cost of innovation) (Milgrom and Roberts 1986).

Similarly, a brand with an extensive distribution network is viewed as a strong and resourceful brand that has been able to attract interest from multiple retailers. Consumers interpret brand's ubiquitous presence as a sign of its consistent performance across different stores and markets. Extensive distribution costs, associated with high expenditures on slotting allowances, in-store promotion material, and other expensive retail investments would be lost if the brand does not consistently deliver on its promises (Rao and Mahi 2003).

Thus, the information economics literature suggests that consumers can – and do – use a brand's price, advertising activity, new product introduction activity, and distribution coverage as market signals to form perceptions of brand trust. But what is the role of price promotions? Price promotions are frequently used by marketing managers to increase short-term brand sales. From an economics of information perspective, price promotions may be regarded as a signal that undermines brand trust. First, they lower the price premium over costs – albeit temporarily – while a price premium is required to dissuade the brand from cheating. Second, price promotions work largely in the short run, while it is long-run revenues that motivate a firm from delivering on its promises (Klein and Leffler 1981). Thus, heavy price promotions may raise suspicions in the minds of consumers and undermine consumer attitude towards a brand (Blattberg and Neslin 1989; Yoo, Donthu, and Lee 2000). While consumers are prone to attribute heavy brand advertising to the marketer belief in the high sales potential of the brand (Kirmani and Wright 1989), heavy promotion sends exactly the opposite signal (Blattberg and Neslin 1989). Clearly, without discounting, the brand does not have adequate sales potential. Kantar Millward Brown's industry expert Nigel Hollis (2017) described consumer attributions to a heavily promoted brand as follows: "And consumers are not dumb – they are us after all – they interpret the scale and frequency of price reductions just like you do….What's wrong with it? Is there a better one out there? Maybe they introduced a new version? Look, it's on sale again! They must be in trouble."

Based on the above discussion, we hypothesize that:

H1: Brand-specific marketing mix activities are related to brand trust. More specifically, brand trust is positively related to (a) the brand's advertising intensity, (b) the brand's new product introduction intensity, (c), the brand's distribution intensity, and (d) the brand's price, while brand trust is negatively related to (e) the brand's price promotion intensity.

Variation in the Relationship between Marketing Mix Activities and Brand Trust across Categories

Hitherto, we have abstracted from considering that the signaling role of brand activities may differ across product categories. Implicit in the information economics perspective is that consumers can – and do – rely on brands in their decision making. Recent work by Fischer, Völckner, and Sattler (2010) has shown that product categories do systematically differ in the overall role of brands in consumer decision processes. For example, they found that on average brands play a more decisive role in the life of US consumers when it comes to cigarettes or beer than in paper tissues or headache tablets. Fischer and colleagues further showed that what they call "brand relevance in category" varies between consumers. While on average, brands may play a larger role in the beer category than in the paper facial tissue category, there may be some consumers for which the opposite is true.

Heterogeneity in the relationship between marketing mix activities and brand trust across different categories can be explained by accessibility-diagnosticity theory (Feldman and Lynch 1988). In a category where brands have high relevance for a particular consumer, brands are important to him or her. As a result, he or she is expected to more closely follow brands and their marketing activities in that category (Fischer, Völckner, and Sattler 2010). According to accessibility-diagnosticity theory, the likelihood that an input will be used for judgment is determined by accessibility of the input in memory (i.e., ease of retrieval), perceived diagnosticity of the input (i.e., attribute relevance), and availability of other inputs in memory. Factors that increase the accessibility of an input will increase the probability that the input will be used for judgment and decision making (Herr, Kardes, and Kim 1991).[2] Drawing on this

[2] Moreover, Menon and Raghubir posit that accessibility of an input can "be used as a reasonable proxy for the diagnosticity of the input" (Menon and Raghubir 2003, p. 231). Thus, factors that increase accessibility of an input also influence attitude by increasing diagnosticity value of that input.

theory, several studies have shown that when accessibility of brand-related information increases, the likelihood with which consumers use such information as an input for judgment and decision-making increases (e.g., Menon and Raghubir 2003; Li and He 2013). Similarly, we argue that when brands are important to consumers, brand-related information is more accessible to consumers and hence more likely to be used in their attitude formation. As a consequence, according to accessibility-diagnosticity theory, if brands are seen as highly relevant in a given category by a particular consumer, marketing mix activity by a brand in that category is likely to be relatively more strongly associated with that consumer's brand attitude. Conversely, in a category where brand relevance is low for that consumer, marketing mix activity will exhibit a relatively weaker association with his or her brand attitudes. Thus:

H2: The relevance of brands in a given category to a consumer moderates the (absolute) magnitude of relationships between marketing mix activities and brand trust. If a consumer attaches high (low) relevance to brands in a given category, brand marketing mix activities are strongly (weakly) related to brand trust.

<u>Variation in the Relationship between Marketing Mix Activities and Brand Trust across Countries</u>

Societal membership socializes people into a national culture with a specific set of values from early stages of life (Hofstede 2001). Becker (1996, p.12) argues that "individuals have less control over their culture than over other social capital…culture is largely 'given' to individuals throughout their lifetime." These cultural values influence the way society members find and process information and often persist by setting priorities for consumers throughout their lives (Steenkamp and de Jong 2010). According to Tse et al. (1988, p. 82), national culture influences consumers' "rules for selective attention, interpretation of environmental cues, and responses." Following accessibility-diagnosticity theory, this suggests that the accessibility of marketing signals varies predictably across countries depending on prevailing cultural values (Aaker 2000).

In countries where brands are important to consumers, marketing activities of brands are more accessible and hence are strongly linked to judgment formation.

The best-known national-cultural systems include the frameworks proposed by Hofstede, Inglehart, Schwartz, and Triandis (see Vinken, Soeters, and Ester 2004 for an overview and comparison). For our purposes, the Inglehart framework (Inglehart and Baker 2000; Inglehart and Welzel 2005) is especially useful because it is grounded in materialism and modernization theory (see Steenkamp and De Jong 2010 and Steenkamp and Geyksens 2014 for applications in marketing). Inglehart identifies four clusters of national-cultural values, which are organized in two bipolar dimensions: traditional versus secular-rational values and survival versus self-expression values. Countries that are low on the traditional/secular-rational dimension ("traditional" societies) emphasize the importance of deference to authority, along with absolute standards and traditional family values. These societies have high levels of national pride, and take protectionist and nationalist attitudes. Secular-rational societies' values have the opposite preferences on all of these topics. Important for our purposes is that secular-rational societies are characterized by materialistic ideologies (Inglehart and Welzel 2005, p. 26). Brands – as one of the most visible exponents of a materialistic world (McCracken 1986) – are expected to be of greater relevance in these societies (Rindfleisch, Burroughs, and Wong 2009). Applying the tenets of accessibility-diagnosticity theory in this context suggests that brand-related marketing mix activity is more accessible to consumers in these countries and hence more likely to be used in attitude formation. Thus, we expect that marketing mix activities are more strongly related to brand trust in secular-rational countries than in traditional countries.

H3: Traditional/secular-rational cultural values of the country in which consumers live moderate the (absolute) magnitude of relationships between marketing mix activities and brand trust. Brand marketing mix activities are strongly (weakly) related to brand trust in countries high (low) on secular-rational values.

Countries low on the survival/self-expression dimension ("survival" societies) emphasize economic and physical security. There are strong economic, cognitive, and social constraints on individual choice and autonomy. The opposite applies to countries high on self-expression ("self-expression" societies). In these societies, economic security is less of an issue, and individual autonomy is high. According to Inglehart, the contrast between materialist vs. post-materialist values is a key component of the survival/self-expression dimension (Inglehart and Welzel 2005). This pits values such as security, affluence, and economic well-being against values such as subjective well-being, quality of life, and protection of the environment. In self-expression societies, "the 'quality of experience' replaces the quantity of commodities as the prime criterion for making a good living" (Inglehart and Welzel 2005, p. 25). Maximizing well-being rather than maximizing material possessions becomes a guiding motivation to people and their interest in the marketplace for achieving life goals declines (Steenkamp and Maydeu-Olivares 2015). Postmaterialist priorities are associated with reduced importance of brands as well as strong consumer tendency to avoid marketing influences (Holt 2002). Anecdotally, this is supported by the success of Klein's (2000) No Logo and Boorman's (2007) Bonfire of Brands. Therefore, in countries high on self-expression values, marketing mix activities are expected to be weakly related to consumers' attitude and their trust in brands:

H4: Survival/self-expression cultural values of the country in which consumers live moderate the (absolute) magnitude of relationships between marketing mix activities and brand trust. Brand marketing mix activities are weakly (strongly) related to brand trust in countries high (low) on self-expression values.

Method

Data

We combine consumer survey data, scanner data, and country data to test our hypotheses. The individual level survey data was collected via the Internet by the global market research agencies GfK and Kantar Worldpanel in 2015 in 13 countries, including nine developed countries (Denmark, France, Germany, Great Britain, Italy, Netherlands, Spain, Sweden, and United States) and the four BRIC nations (Brazil, Russia, India, China). In each country, respondents – the person in the household that was responsible for grocery purchases – answered questions regarding a maximum of three CPG brands in a product category. The selected brands were the top three national brands in their category in 2013 (based on annual volume market share). The total number of different product categories included in the survey was 46. The specific categories included varied across countries to reflect usage patterns and needs of GfK and Kantar Worldpanel.

The questionnaire was developed in English and translated into local languages using the back-translation method. Respondents answered questions regarding marketing activities of a brand (i.e., advertising and innovation) and brand trust. Advertising and new product introduction intensity were operationalized with two items each, using items developed by Steenkamp and Geyskens (2014). Brand trust was operationalized using two items drawn from Chaudhuri and Holbrook (2001). About 50 respondents answered to questions about each brand. Respondents also answered questions regarding brand relevance in category with the four-item scale developed by Fischer, Völckner, and Sattler (2010). To account for differences across consumers, we include several demographic variables (i.e., age, gender, and education level of respondents).

We obtained household scanner data for all 13 countries from GfK, Kantar Worldpanel, and IRI. Specifically, we acquired average shelf price (price per volume for a brand), distribution intensity (percentage of retailers that sold a brand, weighted by retailers' annual market share), and price promotion intensity (brand's annual value sold on promotion divided by brand's total annual sales) during 2014. To render the measure for price comparable across categories, we compute z-scores for brand price based on price of the top 10 national brands in each category. To ensure temporal separation the scanner data are from 2014 so that they lag the brand trust measure collected in 2015.

We acquired country data on Inglehart's cultural values from World Values Survey (WVS). Figure 2.1 illustrates scores on the two Inglehart's dimensions across the 13 countries in our data (See Figure 2.1). We also obtained a measure of generalized societal trust from WVS to control for cross-country variations in people's disposition to trust. Variables and their operationalization are summarized in Table 2.1 (See Table 2.1).

We merged the scanner data with consumer survey data to construct our final data set. Our final sample consisted of 35,028 observations from 15,073 respondents and 589 brands across 46 distinct CPG categories in 13 countries (average of 26 CPG categories in each country). Table 2.2 presents category-country combinations in our dataset (as well as grouping them into low, medium, and high categories with respect to their brand relevance ratings; See Table 2.2). We provide examples of brands with low, medium, and high trust (compared to country mean) in Appendix 2.A (See Appendix 2.A).

Cross-National Measurement Validation

Before mean differences between countries can be examined and our hypotheses can be tested in cross-national research, we must establish that the measurement instruments are cross-nationally invariant (Steenkamp and Baumgartner 1998). We first test the configural and metric invariance of the brand relevance scale, using robust estimation. The fit of the one-factor configural invariance model is good: $\chi^2(26) = 95.8$ ($p < 0.01$), CFI = 0.997, RMSEA = 0.048. All factor loadings are large (typically exceeding 0.5) and significant. Next, we test metric invariance for brand relevance by setting the loadings to be equal across countries. Metric invariance is also supported: $\chi^2(62) = 225.3$ ($p < 0.01$), CFI = 0.993, RMSEA = 0.048. While the difference in chi-square is significant – which is not surprising given our sample size (over 15,000) – overall fit is good, RMSEA which contains a penalty against overfitting stays the same, and the decline in CFI is below 0.01. This supports metric invariance for the brand relevance scale (Cheung and Rensvold 2002).

Next, we test the invariance of all brand level measures simultaneously (i.e., brand trust, advertising intensity, and new product introduction intensity).[3] The configural invariance model yields a good fit: $\chi^2(84) = 932.4$ ($p < 0.01$), CFI = 0.992, RMSEA = 0.051. All factor loadings are large (typically exceeding 0.5) and significant. The full metric invariance model yields a good fit as well: $\chi^2(123) = 1{,}226.0$ ($p < 0.01$), CFI = 0.990, RMSEA = 0.048. Next, we estimate a model where we impose scalar invariance on brand trust.[4] Fit deteriorates slightly ($\chi^2(136) = 1{,}697.9$ ($p < 0.01$), CFI = 0.986, RMSEA = 0.054) but continues to be good and the decline in CFI is below 0.01 (Cheung and Rensvold 2002). These findings support scalar invariance for our dependent variable brand trust and metric invariance for brand relevance, brand trust, advertising intensity, and new product introduction intensity, as well as. Scale items were averaged for each scale to obtain composites.

Figure 2.2 shows country means for brand trust, with their 95% confidence intervals (See Figure 2.2). The three countries where brand trust is highest – Brazil, India, and China are all BRIC nations. Noteworthy is also that the US is significantly higher on brand trust than any other developed market. Brand trust is lowest in Denmark and Germany.

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[3] We use the entire universe of brands covered in the survey data provided by GfK and Kantar Worldpanel.

[4] Since we do within-country mean-centering for advertising and new product introduction intensity in our main analysis, scalar invariance is not required for advertising and new product introduction.

Model and Estimation

Our model consists of variables at three levels: brand, individual, and country. We develop the model step by step by presenting separate equations for each level, and then arriving to one final equation by substitution (Raudenbush and Bryk 2002).

Level 1: Within an individual – Across brands

(1) $BRTR_{ijk} = \alpha_{0jk} + \alpha_{1jk}ADV_{ijk} + \alpha_{2jk}NPI_{ijk} + \alpha_{3jk}DIST_{ik} + \alpha_{4jk}PRICE_{ik} + \alpha_{5jk}PROM_{ik}$
$+\varepsilon_{ijk} + v_{ik}^{brand}$

where *i* denotes the brands, *j* denotes the individuals, and *k* denotes the countries in our data. $BRTR_{ijk}$ denotes the trust that consumer *j* in country *k* has in brand *i*. ADV_{ijk}, NPI_{ijk}, $DIST_{ik}$, $PRICE_{ik}$, and $PROM_{ik}$ refer to advertising intensity, new product introduction intensity, distribution intensity, price, and promotion intensity.[5] Equation (1) models brand trust as a function of its marketing mix instruments, a random error term ε_{ijk}, which is normally distributed with zero mean and variance σ_1^2, and a cross-classified brand random effect v_{ik}^{brand}, which is normally distributed with zero mean and variance σ_2^2. v_{ik}^{brand} captures brand-specific unobserved heterogeneity that might impact trust scores.

Level 2: Across individuals – Within a country

(2) $\alpha_{0jk} = \beta_{00k} + \beta_{01k}BREL_{jk} + \sum_{p=2}^{p=9}\beta_{0pk}DEMOGRAPHICS_{pjk} + \sum_{q=10}^{q=13}\beta_{0qk}CATTYPE_{qjk} + u_{0jk}$

(3) $\alpha_{qjk} = \beta_{r0k} + \beta_{r1k}BREL_{jk}$, for r=1-5

Level 2 specifies all parameters from level 1 as dependent variables. Equation (2) shows that respondents' average trust in brands in a given category is a function of a country-specific intercept (β_{00k}), the relevance of brands in that category for that respondent ($BREL_{jk}$), and a random error term (u_{0jk}). We include several demographic related variables

[5] $DIST_{ik}$, $PRICE_{ik}$, and $PROM_{ik}$ do not vary across survey respondents (hence no *j* subscript).

($DEMOGRAPHICS_{pjk}$) to control for heterogeneity across consumers. We also include four category dummies ($CATTYPE_{qjk}$) to account for five different types of CPG categories (i.e., food, beverage, personal care, household care, and pet food). Equation (3) specifies the slopes of all marketing mixes in level 1 as a function of brand relevance in category.

Level 3: Across countries

(4) $\beta_{00k} = \delta_{000} + \delta_{001}SECRAT_k + \delta_{002}SELFEXPR_k + \delta_{003}STR_k + \delta_{004}EUR_k + u_{00k}$

(5) $\beta_{p0k} = \delta_{p00} + \delta_{p01}SECRAT_k + \delta_{p02}SELFEXPR_k + u_{p0k}$, p=1-5

(6) $\beta_{q1k} = \delta_{q10}$, q=0-5

(7) $\beta_{0rk} = \delta_{0r0}$, r=2-14

Level 3 incorporates predictors subscripted for the *k*-th country. Equation (4) specifies the average level of brand trust in a country (β_{00k}) as a function of an intercept (δ_{000}), four country-specific predictors, and an error term (u_{00k}). $SECRAT_k$ and $SELFEXPR_k$ refer to the secular-rational and self-expression dimensions, respectively. We include two country-level control variables in our model: STR_k and EUR_k. STR_k captures generalized trust in others in a country. It could be that trust scores are higher in societies that are generally more trusting. In our data, we have 9 European countries; therefore we include a dummy variable (i.e., EUR_k) to capture unobserved region-specific effects related to European countries. Equation (4) models cross-national variance in brand trust as a function of the cultural dimensions and an error term (u_{p0k}). Equation (5) models the moderating effect of national culture on the relation between marketing mix activity and brand trust. Finally, equations (6) and (7) specify demographics, category type, and interactions of brand relevance and marketing mix instruments as fixed effects. The error terms in equations (4) and (5) are assumed to be multivariate normally distributed over countries with an expected value of zero and variance-covariance matrix **T**.

By successive substitution we arrive at the final model:

$$(8)\ BRTR_{ijk} = \delta_{000} + \delta_{100}ADV_{ijk} + \delta_{200}NPI_{ijk} + \delta_{300}DIST_{ik} + \delta_{400}PRICE_{ik} + \delta_{500}PROM_{ik} + \delta_{010}BREL_{jk}$$
$$+\delta_{110}BREL_{jk} * ADV_{ijk} + \delta_{210}BREL_{jk} * NPI_{ijk} + \delta_{310}BREL_{jk} * DIST_{ik} + \delta_{410}BREL_{jk} * PRICE_{ik}$$
$$+\delta_{510}BREL_{jk} * PROM_{ik} + \delta_{001}SECRAT_{k} + \delta_{101}SECRAT_{k} * ADV_{ijk} + \delta_{201}SECRAT_{k} * NPI_{ijk}$$
$$+\delta_{301}SECRAT_{k} * DIST_{ik} + \delta_{401}SECRAT_{k} * PRICE_{ik} + \delta_{501}SECRAT_{k} * PROM_{ik}$$
$$+\delta_{002}SELFEXPR_{k} + \delta_{102}SELFEXPR_{k} * ADV_{ijk} + \delta_{202}SELFEXPR_{k} * NPI_{ijk}$$
$$+\delta_{302}SELFEXPR_{k} * DIST_{ik} + \delta_{402}SELFEXPR_{k} * PRICE_{ik} + \delta_{502}SELFEXPR_{k} * PROM_{ik}$$
$$+ \sum_{p=2}^{p=9} \delta_{0p0}DEMOGRAPHICS_{pjk} + \sum_{q=10}^{q=13} \delta_{0q0}CATTYPE_{qjk} + \delta_{003}STR_{k} + \delta_{004}EUR_{k} + \Psi_{ijk}$$

δ_{100}, δ_{200}, δ_{300}, δ_{400}, and δ_{500} represent the main effect relations of marketing mix instruments with brand trust, thereby testing H1. δ_{110}, δ_{210}, δ_{310}, δ_{410}, and δ_{510} represent the moderating effect of brand relevance on the relation between marketing mix instruments and brand trust (H2). δ_{101}, δ_{201}, δ_{301}, δ_{401}, and δ_{501} represent the moderating role of secular-rational values (H3) and δ_{102}, δ_{202}, δ_{302}, δ_{402}, and δ_{502} test the moderating role of self-expression values (H4).

We use within-group centering at levels 1 and 2 and grand-mean centering at level 3. We estimate the model with iterative maximum likelihood, which permits a simultaneous estimation of relationships at multiple levels.

Endogeneity and Common Method Variance

While we are interested in examining the relationship between marketing mix instruments and brand trust, one could argue that the observed relationships between the marketing mix instruments and brand trust could be because the level of brand trust influences managerial strategy in setting level of marketing activities. This possibility creates challenges for our inferences. For example, if price promotions are used frequently by a brand in a particular country, is it because the brand has problems in that country (e.g., low brand trust), or did the price promotions reduce brand trust? The same concern is also valid for the relationship between brand relevance in a category and brand trust; one could argue that when consumers trust brands in a particular category, brands become more relevant in their decision making in that category. Moreover, there could be unobserved variables that influence both marketing activities and brand trust. For example, unobserved brand-country effects like access to capital, managerial talent, suppliers, and social media capabilities can affect both trust and marketing investment. Hence, the association between marketing mix instruments and brand trust can be overstated if, for example, managerial talent drives both. Additionally, the same individuals who rate brand trust also rate advertising intensity, new product introduction intensities, and brand relevance in category. This could lead to common method bias. In order to fully address the common method bias issue and partially account for endogeneity concerns, we generate instrumental variables.[6]

We exploit the multimarket nature of our dataset to construct valid instruments (Hausman 1996; Nevo 2001). We obtain meaningful instrumentation for marketing mix instruments by using a brand's average marketing mix values in the same category across other countries in which the brand operates. To ensure that the IVs are correlated with the endogenous variables, we divide countries into three groups based on GDP per capita.[7] If a brand exists in the same category in similar countries (i.e., same GDP per capita group), we use the average value of its marketing mix instruments in such countries; if not, we use average values of its marketing mix across all other countries. If the focal brand does not appear in any other country (in the same product category), we expand the procedure to other brands of the same manufacturer as well as

[6] In the limitation section, we will discuss certain types of endogeneity concerns that our approach does not address. As such, even with instruments, our findings should still be interpreted as correlational rather than causal.

[7] First group consists of countries with GDPPC below 20,000$ (i.e., India, Russia, China, and Brazil). Second group has countries with GDPPC above 20,000$ but below 50,000$ (i.e., Spain, Italy, France, the UK, and Germany). Finally, the last group consists of countries with GDPPC above 50,000$ (i.e., the US, Netherlands, Denmark, and Sweden).

similar product categories (first in the same country group, next across all countries).[8] For the remaining brands in the data for which we do not find matches in other countries and categories, we use the average value of marketing mix instruments of all brands in the same product category across other countries. Our instruments are valid because 1) marketing mix instruments of a brand should be correlated across different markets (Che, Sudhir, and Seetharaman 2007) and 2) since market-specific valuations are independent across markets (Ghose, Ipeirotis, and Li 2012), marketing activities of a brand in country X does not directly affect customers' level of trust in the focal brand in country Y (i.e., they only indirectly influence customers' level of trust in the focal brand through their effect on marketing mix instruments of the focal brand). Similarly, for brand relevance in category, we use average *BREL* values in other countries (first we use countries in the same GDP group, if there are no matches, we use all other countries). An important advantage of our approach is that it also addresses the common method bias problem. The instruments that we use for advertising intensity, new product introduction intensity, and brand relevance in category are obtained from responses by *other respondents* across different countries. According to Podsakoff et al. (2003), having different respondents score criterion versus predictor variables is the best method to address common method bias.

To assess instrument strength, we regress each endogenous variable first against the exogenous variables in the brand trust model and then add the instruments to conduct an incremental F-test. The instruments are sufficiently strong, as evidenced by the first-stage R-squared and F-statistics. Across the six scenarios, we obtain an average R-squared of 30%, and all incremental F-values exceed the common threshold of ten (on average, the incremental F-values are 3,021). We estimate six predicted residuals from the first-stage regressions and then

[8] Similar product categories are defined as categories within a particular *CATTYPE*.

add the estimated residuals as control functions to the main model specification (Petrin and Train 2010). Given that the instruments are valid and not weak, we use the Hausman-Wu test to formally probe for endogeneity of marketing mix instruments and brand relevance. The results confirm existence of endogeneity for advertising intensity, price promotion intensity, and brand relevance in category ($p < 0.10$).

Results

Model-Free Evidence

In Appendix 2.B we present model-free evidence regarding the relationship between marketing mix instruments and brand trust as well as the heterogeneity in the relationship between marketing mix and brand trust across different categories and countries (See Appendix 2.B). Groups with high (low) values of a particular variable (e.g., *ADV*, *BREL*, etc.) represent observations that are at least one standard deviation above (below) mean of that variable. The evidence indicates that brands with high advertising intensity, new product introduction intensity, distribution intensity, and price are more trusted than other brands. However, brands that promote intensively are trusted less than those with low promotional intensity. Moreover, the positive (negative) relationship between marketing mix and brand trust appears to be stronger in categories high on brand relevance, countries high on secular-rational values, and countries high on survival values.

Model Fit

Following previous research (Palmatier, Gopalakrishna, and Houston 2006; Steenkamp and Geyskens 2014), we build our model by successively adding blocks of predictors. Table 2.3 provides the results of our incremental model building approach (See Table 2.3). Because the models are nested, we can assess whether model fit improves significantly by comparing the deviance statistic (-2 log likelihood) between models. We start by a simple model without any covariates and with only a constant and a random term (M1). Adding the random intercept at the individual level (M2) yields a significant improvement in model fit (Δdev(1) = 4,729.4 , $p <$ 0.01). Next, we allow for mean differences in trust between countries (See Figure 2.2) by adding a random intercept at the country level (M3). Fit improves significantly (Δdev(1) = 1,338.2, $p <$ 0.01). These results highlight that there exists significant variation in brand trust within and across countries, which reinforces the need to explore the effects of brand, category, and country level variables on brand trust. Model 4 adds the control variables, the main effects of brand relevance and national culture, and the brand random effect and model fit improves significantly (Δdev(7) = 3,840.8, $p < 0.01$). Model 5 adds the main effects of the marketing mix instruments. The improvement in model fit (Δdev(5) = 3,610.4, $p < 0.01$) shows that marketing mix activities explain the variation in brand trust. In model 6 we add country level random slopes for marketing mix instruments and the six control functions (Δdev(11) = 558.4, $p < 0.01$). Next, we add the five interactions between BREL and marketing mix instruments (M7). Model fit improves significantly (Δdev(5) = 149.8, $p < 0.01$), which indicates that the effect of the marketing mix instruments varies across categories in function of the relevance of brands in that category. Finally, we add the interactions involving the two national-culture variables to build the full model shown in equation (8). The improvement in model fit (Δdev(10) = 53.6, $p < 0.01$) provides initial support for the moderating role of national culture. Analysis of AIC and BIC confirms that all blocs of our model contribute to its explanatory power.

Hypothesis Testing

Parameter estimates for model M8 are reported in Table 2.4 (See Table 2.4). Note that we report unstandardized coefficients. In multilevel modeling, standardized coefficients are problematic because variance is partitioned across different levels. Advertising intensity (γ_{100} = 0.063; $p < 0.05$), new product introduction intensity (γ_{200} = 0.422; $p < 0.01$), distribution intensity (γ_{300} = 0.151; $p < 0.10$), and price (γ_{400} = 0.026; $p < 0.05$) are positively related to brand trust, while price promotion intensity is negatively related to brand trust (γ_{500} = -0.240; $p < 0.10$). These results support H1 implying that more advertising, new product introduction, distribution, and higher prices are associated with higher brand trust, whereas heavy price promotions are negatively related to brand trust.

The Moderating Role of Brand Relevance. The coefficient for the main effect of brand relevance is positive and significant (γ_{010} = 0.203; $p < 0.01$) suggesting that in categories in which brands are important for consumers, brand trust is higher. Turning to the individual interaction effects, we find that advertising intensity (γ_{110} = 0.020; $p < 0.01$), new product introduction intensity (γ_{210} = 0.020; $p < 0.01$), distribution intensity (γ_{310} = 0.069; $p < 0.01$), and price (γ_{410} = 0.014; $p < 0.01$) are more strongly associated with brand trust in categories with high brand relevance vis-à-vis categories with low brand relevance. However, brand relevance in category does not moderate the negative relationship between price promotion intensity and brand trust (γ_{510} = 0.017; $p > 0.10$). In sum, these results support our hypothesis that the degree to which brands are relevant to a consumer systematically affects the impact of marketing mix activities on brand trust. We find further evidence for the moderating role of *BREL* for four out of five individual marketing instruments as specified in H2.

In order to enhance the interpretability of results, we plot interaction effects in Figure 2.3

(See Figure 2.3). We use one standard deviation above and below country level mean of our focal variables as high and low values to evaluate their moderating impact (See Table 2.2 for classification of categories).[9] We also report simple slopes and their statistical significance in Figure 2.3. We find that in low *BREL* categories, distribution and price are not significantly related to brand trust, the relationship between advertising and brand trust is weak but significant, and the relationship between new product introductions and brand trust remains strong and significant. Conversely, in high *BREL* categories the relationships between brand trust and marketing activities are all significant.

The Moderating Role of Secular-Rational National Culture Dimension. H3 posits that a country's score on the secular-rational dimension moderates the strength of the relation between brand marketing mix activities and brand trust, and more specifically that the relation is stronger in countries that are high on this dimension. We find significant interactions in the direction specified in H3, albeit not for all instruments. Consistent with H3, we find that new product introduction intensity ($\gamma_{201} = 0.071$; $p < 0.01$), price ($\gamma_{401} = 0.056$; $p < 0.01$), and price promotion intensity ($\gamma_{501} = -0.728$; $p < 0.01$) are more strongly associated with brand trust in countries high on secular-rational values vis-à-vis countries low on secular-rational values. However, the interactions for advertising and distribution intensity are not significant. Figure 2.4 depicts the significant interactions graphically (See Figure 2.4). The most prominent associations are found for price and price promotion. In low *SECRAT* countries, price and price promotion are not significantly related to brand trust while their relationships with brand trust are significant in high *SECRAT* countries.

[9] For simplicity, we only consider the effects that are significant at 0.10 level.

The Moderating Role of Self-Expression National Culture Dimension. We find that brands are less trusted in countries high on self-expression values (γ_{002} = -0.121; p < 0.05). This finding is consistent with previous research, which argued that brands are expected to do worse in post-materialistic countries (Holt 2002; Steenkamp and Geyskens 2014). We find significant interactions in the direction specified in H4, albeit not for all marketing mix instruments. Consistent with H3, we find that advertising intensity (γ_{102} = -0.064; p < 0.01), new product introduction intensity (γ_{202} = -0.053; p < 0.01), and price (γ_{402} = -0.025; p < 0.05) are more strongly related to brand trust in countries low on self-expression values vis-à-vis countries high on self-expression values. However, the interactions for price and price promotion intensity are not significant. Figure 2.5 depicts the significant interactions graphically (See Figure 2.5). The most prominent relations are found for advertising intensity and price. In high *SELFEXPR* countries, change in advertising intensity and price are not significantly related to the level of brand trust. However, in low *SELFEXPR* countries, increase in price and advertising intensity is associated with higher brand trust.

Control Variables. Generalized societal trust (STR) is not significantly related to brand trust (γ_{003} = -0.001; p > 0.10), but we find that brands are less trusted in European countries (γ_{004} = -0.440; p < 0.01). This finding is in line with the fact that private labels have become increasingly popular in European countries to the point that in 2014, private label market share exceeded 30% in 15 countries, including Spain (51%) and Switzerland (53%).[10] With regards to sociodemographics, we find that while age is not significantly related to brand trust (γ_{020} = -

[10] http://www.cpgmatters.com/International100114.html

0.001; $p > 0.10$),[11] women have lower trust in brands than men ($\gamma_{030} = -0.057$; $p < 0.01$). We also find that brands in personal care ($\gamma_{0120} = -0.114$; $p < 0.01$) and animal food ($\gamma_{0130} = -0.281$; $p < 0.01$) product categories are less trusted compared to brands in other categories.

Developed Countries vs. BRIC Countries

Finally, we examine differences in the relationships between marketing mix activities and brand trust between developed and BRIC countries in an exploratory fashion. We do not have a priori expectations about differences in effects, but given the rapidly growing importance of emerging markets in general and the BRIC nations in particular and the relative dearth of substantive findings in these markets (Burgess and Steenkamp 2006; Narasimhan, Srinivasan, and Sudhir 2015), this seems a worthwhile endeavor. We run separate analyses on the BRIC countries and on the developed countries with only the marketing mix instruments as regressors. Table 2.5 provides the results (See Table 2.5).

We find that advertising and price are more strongly related to brand trust in BRIC countries than in developed markets. Because brands have been around less long in emerging markets, knowledge about products and brands is generally less deep than in developed markets (Dawar and Chattopadhyay 2002). In these contexts, advertising fulfills a more important role in creating brand awareness and communicating the brand message (Pauwels, Erguncu, and Yildirim 2013). Furthermore, since advertising pressure is generally less in emerging markets, heavy advertising for a brand stands out more, i.e., there is less clutter, which should positively affect its effect (Danaher, Bonfrer, and Dhar 2008). The larger role of price in emerging markets is consistent with recent research that showed that while consumers in emerging markets are more price

[11] Additional analysis showed that a quadratic term for age is significantly related to brand trust. The relationship follows an inverse-U shape, showing that people around 40 years old have higher trust in brands compared to those above 50 or below 30.

conscious, they also rely more on price as indicator to infer product performance (Zielke and Komor 2015). Distribution has a strong relationship with brand trust in developed markets but not in BRIC countries. This may be due to the fact that in emerging markets, informal distribution and small and relatively unsophisticated mom-and-pop shops play a large role while in developed markets, brands are almost exclusively offered in large, sophisticated, and expensive looking supermarkets (Child, Kilroy, and Naylor 2015). Such outlets have more characteristics of expensive brand-specific capital expenditures that signal sunk costs.

<u>Robustness Checks</u>

We use a median-split analysis to assess the robustness of our findings. Based on the median value of *BREL*, we divide observations into two groups (high *BREL* and low *BREL*). Furthermore, we conduct a median split of the countries based on their secular-rational score and a median split of the countries based on their self-expression score. We estimate the relationship between marketing mix and brand trust for each group separately. Dichotomizing continuous variables reduces the statistical power for detecting effects (Irwin and McClelland 2001) and as such the median-split analysis is a conservative test of hypotheses. We replicate the direction of the effects, and 9 out of 10 significant interactions in these analyses. More specifically, we find that advertising, new product introduction, price, and distribution are more strongly related to brand trust in the high *BREL* group vis-à-vis the low *BREL* group (See Table 2.6). Price and price promotion are more strongly related to brand trust in countries high on the secular-rational dimension vis-à-vis countries that score low on this dimension. Finally, advertising, new product introduction, and price have stronger relationship with brand trust in countries low on self-expression vis-à-vis countries high on this dimension.

To ensure that our findings are not driven by observations in a specific country we ran 13 separate analyses, excluding each country once. In Appendix 2.C, we report the number of times each hypothesis was supported at 0.05 and 0.10 levels across the 13 analyses (See Appendix 2.C). We find that our findings are highly robust.

Our focal analysis accounts for the fact that different brands might have different levels of trust by including a cross-classified brand random effect (v_{0jk}^{brand}). However, given that individuals are not fully nested within brands (i.e., one individual rates several brands) and brands are not fully nested within countries (i.e., one brand might exist in several countries), estimating random slopes for marketing mix at the brand level (which is cross-classified) is not computationally feasible in an HLM setting. This means that our focal analysis does not allow for the possibility that marketing mix instruments of different brands might have heterogeneous impact on brand trust. We address this concern using two different procedures.

In the first approach, we randomly keep one observation for each individual. Now that each respondent has only one response in the data, we do not need to model level 1 (within an individual). The new model would have brands and countries as cross-classified levels, with random slopes for marketing mix instruments at the brand level. The results which are similar to our focal analysis are reported in Table 2.7 (See Table 2.7).

In the second approach, we use MCMC simulations in MLWin to estimate a cross-classified hierarchical model. Similar to our focal analysis, we model individuals as nested within countries and brands as a cross-classified level. We allow marketing mix instruments to have random slopes at both country and brand levels. After an initial run, we find that the variance in the random slopes for price and distribution at the brand level, and for price promotion at the country level were insignificant, so we respecified them as fixed effects (Raudenbush and Bryk 2002).

We ran MCMC simulations (6,000 draws, with the first 1,000 draws serving as burn-ins). Mean posterior estimates are reported in Table 2.7. Again, the results are similar to our focal analysis.

Discussion

Consumer skepticism regarding brands is growing across the world. Whereas in 1997 US consumers trusted more than half of the brands, in 2008 Americans only trusted 22% of the brands in the marketplace (Rozdeba 2016). A similar trend has been observed in other countries (Edelman 2017). As a result, brand trust has become a major concern for managers. Managers are well aware that advertising, new product introduction activity, and distribution coverage have a positive effect on brand sales. In this paper, we show that these marketing activities are also positively related to brand trust. Our framework focuses on brand-specific marketing mix activities, and how their influence vary predictably across product categories and countries. Drawing on information economics (Klein and Leffler 1981; Milgrom and Roberts 1986), accessibility-diagnosticity theory (Feldman and Lynch 1988; Herr, Kardes, and Kim 1991), and Inglehart's (Inglehart and Baker 2000; Ingelhart and Welzel 2005) cultural theory of (post)materialism, specific hypotheses were developed. The hypotheses were tested using a dedicated data set that combined consumer surveys, household scanner data, and country data across 589 brands in 46 CPG categories, across 13 countries, including major developed countries like the US, the UK, Germany, and France, as well as the BRICs. In general, support was found for our hypotheses. Brand trust was positively associated with brand-specific new product introduction activity, advertising pressure, price, and distribution coverage, and negatively related to price promotion. We further find support for the hypotheses that marketing mix activities have an overall stronger relationship with brand trust in categories in which brand relevance is high, in countries that are high on secular-rational values, and in countries that are low on self-expression values.

In summary, our findings provide broad support for the relevance of the different types of variables included for understanding the degree of trust consumers around the world have in brands. The findings of the present study also underline the important role of the recently proposed construct of brand relevance in category and of national-cultural variables in understanding brand trust. Our results show that the relationships between marketing mix activities and brand trust are affected by category and national-cultural environment. Thus, combining category-level and national culture-level variables in an integrated approach enhanced our understanding of brand trust. These findings are important as it may help to understand why certain marketing mix instruments are less strongly related to brand trust in certain categories: their context may not be conducive to such relations. Drawing on accessibility-diagnosticity theory, we argued that when brands are important to consumers, marketing mix instruments of brands would be more accessible to them and hence more likely to be used in their attitude formation. As a result, marketing mix instruments will be more strongly related to brand trust in categories and countries where brands are important for consumers. As such, our study offers a generalizable framework to explain why marketing mix instruments are more strongly associated with brand trust in certain categories and countries. Our findings also help to understand why the relationships between marketing mix instruments and brand trust vary in function of the national-cultural context. Drawing on Inglehart’s work, we show that in secular-rational countries, consumers are more oriented towards brands and their marketing mix instruments. Moreover, postmaterialistic values associated with self-expression culture helps us understand why in these societies, brands and their marketing mix are in acute danger of losing importance.

Limitations and Further Research

Our research is not without limitations, which provide opportunities for future research. As we mentioned earlier, the cross-sectional nature of our empirical setting does not allow us to address all possible endogeneity concerns. We used instruments to address concerns regarding common method bias, reverse causality, and brand-country specific omitted variables. However, there might still be concerns regarding omitted brand-specific attributes (that are common across markets) which influence brand marketing mix activities and brand trust. For example, a certain brand-specific attribute (e.g., Coca-Cola's taste) could impact both brand trust and strategic decisions regarding the level of brand marketing mix activities. If this attribute is common across different countries, then our instrument will be correlated with this omitted variable because managers in different countries will consider the same missing attribute when setting their marketing activities. We include brand random effects in our model to capture such unobserved brand-specific heterogeneity. However, the ideal solution to this problem would be to include brand fixed effects. Since some of the brands in our data only appear in one country, including brand fixed effects is not a possibility in our research.

Future research can adopt different approaches to address these potential endogeneity concerns. As we see it, this study is an element in a virtuous cycle of scientific development, first described by Bass (1995). We document associations between marketing mix activity and brand trust, and how this varies across categories according to their brand relevance and across countries according to the Inglehart dimensions of national culture. Our empirical setting casts a wide net, leading to empirical generalizations. These findings in turn call for a more detailed causal explanation of the observed regularities (Bass 1995). One way to do so is to collect consumer surveys and scanner panel data over multiple data points. Such a longitudinal setting would enable researchers to include brand fixed effects to partial out the variation in brand trust due to brand-specific time-invariant characteristics. However, considerable costs of conducting multiple waves of international surveys would be a challenge to marketing research agencies and academic scholars. Alternatively, researchers could use field experiments or lab experiments across multiple categories and countries to assess the causal impact of marketing mix activities on brand trust.

These causal methods allow one to pinpoint the causal sequence – or perhaps the reciprocity in relations – between marketing activity and brand trust. But the nature and complexity of causal designs (time, resources) make it challenging to test causal effects across many categories and/or countries. Our moderating variables can help directing the selection of study contexts (a category that is low versus high in brand relevance, or possibly two countries that are high versus low on a cultural dimension). Undoubtedly, this causal modeling effort will generate new insights that may next be tested in a larger, probably cross-sectional setting to examine generalizability, and so on.

In information economics theory, it is crucial that consumers observe brand-specific investments as counterweight against cheating. The brands in our study were the largest brands in their category. It is likely that their marketing mix activity is more easily observable than those of minor brands. Future research could extend our work by examining brand trust and the role of marketing mix activities therein for lesser-known brands. Furthermore, product innovation and advertising were measured using survey data, as we were unable to acquire this information for all countries and categories. Although these measures were validated in previous research (Steenkamp, Van Heerde, and Geyskens 2010; Steenkamp and Geyskens 2014) future research should replicate and refine our findings using objective measures.

Our unique dataset allowed us to study brand trust across 13 countries from different continents. While collecting surveys across different countries might be costly and infeasible for researchers, future research can use social networks (e.g., Twitter) and data mining techniques to measure brand trust. The time-varying nature of such measure could be helpful in studying new topics. For example, researchers can look at the impact of brand trust in mitigating product-harm crisis consequences. Finally, future research could extend empirical testing to consumer durables. In these product categories repeat purchases are so far in the future that the 'correction' mechanism against cheating underlying information economics models like Klein and Leffler (1981) and Milgrom and Roberts (1986) may not be effective. Do marketing mix activities still play the same trust-building role in these categories? We speculate that this will indeed be the case since the emergence of e-WOM means that any attempt by the durable brand to renege on its promises will quickly be known to multitudes of consumers who just entered the market. We believe this topic requires further investigation.

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TABLE 2.1: Variables and descriptions

Variable	Operationalization	Reference	Source
Brand Trust ($\bar{\alpha}$ = 0.79) [*BRTR*]	1) Brand 'm' is a brand I trust. 2) Brand 'm' delivers what it promises.	Chaudhuri and Holbrook (2001)	Consumer surveys
Advertising Intensity ($\bar{\alpha}$ = 0.87) [*ADV*]	1) Brand 'm' is heavily advertised in newspapers, magazines, TV, or internet. 2) Brand m advertises a lot.	Steenkamp et al. (2010)	Consumer surveys
New Product Introduction Intensity ($\bar{\alpha}$ = 0.84) [*NPI*]	1) Brand 'm' frequently introduces new products. 2) Brand 'm' has many new product introductions.	Steenkamp et al. (2010)	Consumer surveys
Distribution Intensity [*DIST*]	Percentage of retailers that sold brand 'm' during a year, weighted by retailers' market shares in the previous year	Sotgiu and Gielens (2015)	Scanner data
Price [*PRICE*]	Value sales of brand 'm' divided by its volume sales, averaged over all purchase occasions, per year (in the previous year). For comparability across categories and countries, based on price of the top 10 national brands in category 'n', we computed z-scores for brand prices.	Sotgiu and Gielens (2015)	Scanner data
Price Promotion Intensity [*PROM*]	Total absolute value sales sold on promotion by brand 'm', divided by total absolute value sold by brand 'm', per year (in the previous year).	Sotgiu and Gielens (2015)	Scanner data
Brand Relevance in Category ($\bar{\alpha}$ = 0.89) [*BREL*]	1) In category 'n' the brand plays - compared to other things - an important role. 2) In category 'n' I focus mainly on the brand. 3) In category 'n' it is important to purchase a brand name product. 4) In category 'n' the brand plays a significant role as to how satisfied I am with the product.	Fischer et al. (2010)	Consumer surveys
Traditional vs. Secular-Rational Values [*SECRAT*]	Country scores derived from responses to multiple items in large representative surveys. Scores range from -2.0 to 2.0. Higher scores indicate a stronger secular-rational culture.	Inglehart and Welzel (2005)	WVS – Wave 5
Survival vs. Self-Expression Values [*SELFEXPR*]	Country scores derived from responses to multiple items in large representative surveys. Scores range from -2.5 to 2.5. Higher scores indicate a stronger self-expression culture.	Inglehart and Welzel (2005)	WVS – Wave 5
Societal trust [*STR*]	Self-reported trust in others, constructed as the percentage of respondents answering yes to the question "generally speaking, would you say that most people can be trusted?"		WVS – Wave 5
Demographic Variables [*DEMOGRAPHICS*]	Consumer's age; consumer's gender (0=male; 1=female); consumer's education level (0= no formal education; 1= up to age 12; 2= up to age 14; 3= up to age 16; 4= up to age 18; 5= higher education; 6= university)		Consumer surveys
Product Category Type [*CATTYPE*]	General product category specification (0= food; 1= beverage; 2= household care; 3= personal care; 4= animal food)		Consumer surveys

BRTR, *ADV*, *NPI*, and *BREL* were scored on a seven-point scale where 1="very strongly disagree," 2="disagree," 3="somewhat disagree," 4="neither agree nor disagree," 5="somewhat agree," 6="agree," and 7="very strongly agree."

TABLE 2.2: Categories and countries in our dataset

	BRA	CHN	DNK	FRA	DEU	IND	ITA	NLD	RUS	ESP	SWE	GBR	USA
Cutoff; Low-Medium	4.25	5.33	2.96	3.85	3.30	5.17	4.20	2.79	4.16	4.06	3.25	3.45	3.98
Cutoff; Medium-High	4.50	5.46	3.25	4.25	3.65	5.34	4.33	3.13	4.41	4.27	3.57	3.75	4.17
Bathroom Tissue	L												
Beer	L	M	M	H	H		H	H	M	H	M	H	H
Body Cream & Skin Care	M	H	H		M		M	H	L		H		H
Breakfast Cereal	M	H	L	L	M		L	M	M	L	H	L	L
Candy Bar		L											
Cat Food (Wet)		L	M	M	L			L	L	H		H	
Chocolate Spread			H	H	H		H	M		L			H
Chocolate Tablet	M	H	M	L	H		L	M	M	L	M		
Coffee	M		H	M	L		H	H	H	M	H	M	L
Cola		M	H	H	H		H	M	H	H	M	H	H
Concentrated Fruit Squash		H											
Cooking Oil	M	L	L	L	L		H	L	L	H	M	L	L
Cooking Sauce		M	H	H	H	H	L	M		H	M		L
Deodorants	M		H		M		M	M	H		M	L	
Diapers		H											
Dish Soap		H	L	H	L		L	L	M	M	H	L	M
Dog Food (Dry)	H	M		H	H		M	M	H	M			
Fabric Conditioner	L	L	L	L	L		L	L	L	L	H	H	M
Flavored Carbonates		H											
Frozen Pizza			H	L	H		M	L	H	M	M	H	L
Hair Conditioner		L											
Hairspray		H											
Household Cleaner	H		M	L	L	M	M	M	L	M	H	L	L
Ice Cream	H	L									L		
Instant Coffee	H	H											
Jam						H							

Table 2.2 (Continued): Categories and countries in our dataset

	BRA	CHN	DNK	FRA	DEU	IND	ITA	NLD	RUS	ESP	SWE	GBR	USA
Cutoff; Low-Medium	4.25	5.33	2.96	3.85	3.30	5.17	4.20	2.79	4.16	4.06	3.25	3.45	3.98
Cutoff; Medium-High	4.50	5.46	3.25	4.25	3.65	5.34	4.33	3.13	4.41	4.27	3.57	3.75	4.17
Ketchup	H		H	M	L		H	M	M		H		M
Kitchen Towels		L	L	M	L		H	L	H	L		M	
Laundry Detergent	L	H	H	M	M	L	L	H	M	L	M		M
Lavatory Cleaner	L	M	M	H	L	L		L	L	L	H		M
Lemonade		M											
Margarine and Spreads	L		M	M	M		M	L	M	H	M	L	L
Milk		M				M							
Mineral Water (Still)	M	L	L	L	M		M	L	M	M	L		H
Pasta	H									M	L	L	
Potato Crisps		H	M	L	H		H	H	H	L	H		H
Razor Blades	M	L	H	H	H		M	H	H	H		H	H
Sanitary Pad	L	H	L	H	H		L	H	L		L		M
Shampoo	M	M	M	M	L	L	L	H	M		M	M	L
Shaving Foams and Soaps					M	M	H	H	L			M	M
Shower & Bath Additives		M	M	H							L	M	H
Tea		M	L	L		H	M	M	H		M		M
Toilet Soap	H	L									L		
Toothbrush	H	M											
Toothpaste	L	L	H	M	M	L	H	H	H		M	H	H
Yoghurt		M	L	M	M		L	L	L	M	L	M	M

L= bottom third *BREL* categories, M= middle third *BREL* categories, H= top third *BREL* categories (specifications based on *BREL* values in each country)

TABLE 2.3: Model fit

	Model 1 (M1) *Intercept-only model without random effects*	**Model 2 (M2)** *M1+ random intercept at individual level*	**Model 3 (M3)** *M2+ random intercept at country level*	**Model 4 (M4)** *M3 + control variables and brand random effect*	**Model 5 (M5)** *M4 + main effect of marketing mix*	**Model 6 (M6)** *M5 + control functions and random slopes for marketing mix*	**Model 7 (M7)** *M6 + BREL interactions*	**Model 8 (M8)** *M7 + country level interactions*
Log-Likelihood	-53,112.6	-50,747.9	-50,078.8	-48,158.4	-46,353.2	-46,074.0	-45,999.1	-45,972.3
ΔDoF	-	1	1	7	5	11	5	10
P-value	-	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
AIC	106,229.2	101,501.8	100,165.6	96,360.8	92,760.5	92,224.0	92,084.3	92,040.6
BIC	106,229.2	101,501.8	100,165.6	96,547.0	92,989.0	92,545.6	92,448.2	92,446.9

TABLE 2.4: Results

Covariate	Parameter	Expected Sign	Estimate	Standard Error
Intercept	γ_{000}		5.308***	0.141
Main Effects of Marketing Mix				
Advertising Intensity (*ADV*)	γ_{100}	H1a: (+)	0.063**	0.037
New Product Introduction Intensity (*NPI*)	γ_{200}	H1b: (+)	0.422***	0.051
Distribution Intensity (*DIST*)	γ_{300}	H1c: (+)	0.151*	0.099
Price (*PRICE*)	γ_{400}	H1d: (+)	0.026**	0.012
Price Promotion Intensity (*PROM*)	γ_{500}	H1e: (-)	-0.240*	0.156
Brand Relevance in Category				
BREL	γ_{010}		0.203***	0.047
*BREL * ADV*	γ_{110}	H2: (+)	0.020***	0.003
*BREL * NPI*	γ_{210}	H2: (+)	0.020***	0.004
*BREL * DIST*	γ_{310}	H2: (+)	0.069***	0.026
*BREL * PRICE*	γ_{410}	H2: (+)	0.014***	0.003
*BREL * PROM*	γ_{510}	H2: (-)	0.017	0.039
National Culture: Secular-Rational				
SECRAT	γ_{001}		-0.125	0.126
*SECRAT * ADV*	γ_{101}	H3: (+)	-0.004	0.025
*SECRAT * NPI*	γ_{201}	H3: (+)	0.071***	0.035
*SECRAT * DIST*	γ_{301}	H3: (+)	0.066	0.178
*SECRAT * PRICE*	γ_{401}	H3: (+)	0.056***	0.018
*SECRAT * PROM*	γ_{501}	H3: (-)	-0.728***	0.269
National Culture: Self-Expression				
SELFEXPR	γ_{002}		-0.121**	0.056
*SELFEXPR * ADV*	γ_{102}	H4: (-)	-0.064***	0.018
*SELFEXPR * NPI*	γ_{202}	H4: (-)	-0.053***	0.027
*SELFEXPR * DIST*	γ_{302}	H4: (-)	0.119	0.120
*SELFEXPR * PRICE*	γ_{402}	H4: (-)	-0.025**	0.015
*SELFEXPR * PROM*	γ_{502}	H4: (+)	0.137	0.217
Controls				
Socio-demographics (*DEMOGRAPHICS*)	γ_{020}-γ_{090}		Included	
Category Type (*CATTYPE*)	γ_{0100}-γ_{0130}		Included	
Generalized Societal Trust (*STR*)	γ_{003}		-0.001	0.002
European Countries dummy (*EUR*)	γ_{004}		-0.440***	0.097
Six Control Functions			Included	
Brand Random Effect	ν_{ik}		0.253***	0.009

N= 35,028

*$p < 0.10$; ** $p < 0.05$; *** $p < 0.01$ (p-values are one-sided for directional hypotheses and two-sided for others)

TABLE 2.5: The relationships between marketing mix activities and brand trust in BRIC countries and developed countries

	BRIC Countries	Developed	*p-value*
Advertising	0.130 (0.034)	0.052 (0.014)	0.00
New Products	0.409 (0.039)	0.377 (0.028)	0.17
Distribution	0.018 (0.125)	0.418 (0.056)	0.00
Price	0.054 (0.029)	0.010 (0.012)	0.02
Promotion	-0.272 (0.147)	-0.289 (0.089)	0.44

Numbers in parentheses are standard errors of coefficient estimates.

TABLE 2.6: The relationships between marketing mix activities and brand trust in median split analysis

	High Brand Relevance Categories	Low Brand Relevance Categories	*p-value*	Low Secular-Rational Countries	High Secular-Rational Countries	*p-value*	Low Self-Expression Countries	High Self-Expression Countries	*p-value*
Advertising	0.082 (0.016)	0.030 (0.018)	0.00	0.063 (0.023)	0.061 (0.029)	0.95	0.106 (0.020)	0.005 (0.017)	0.00
New Products	0.427 (0.019)	0.358 (0.026)	0.00	0.408 (0.042)	0.435 (0.025)	0.42	0.462 (0.026)	0.387 (0.028)	0.01
Distribution	0.276 (0.064)	0.154 (0.077)	0.04	0.131 (0.090)	0.148 (0.092)	0.86	0.103 (0.069)	0.185 (0.137)	0.42
Price	0.064 (0.016)	0.002 (0.018)	0.00	-0.004 (0.008)	0.056 (0.017)	0.00	0.055 (0.014)	0.012 (0.013)	0.00
Promotion	-0.351 (0.127)	-0.360 (0.128)	0.45	0.024 (0.141)	-0.478 (0.146)	0.00	-0.265 (0.132)	-0.161 (0.170)	0.49

Numbers in parentheses are standard errors of coefficient estimates.

TABLE 2.7: Random slopes for marketing mix at the brand level

Covariate	Expected Sign	Focal Analysis	Random Slopes for MM	MCMC – Cross Classification
Intercept		5.308***	5.412***	5.260***
Main Effects of Marketing Mix				
Advertising Intensity (*ADV*)	H1a: (+)	0.063**	0.051*	0.062***
New Product Introduction Intensity (*NPI*)	H1b: (+)	0.422***	0.374***	0.387***
Distribution Intensity (*DIST*)	H1c: (+)	0.151*	0.157***	0.151**
Price (*PRICE*)	H1d: (+)	0.026**	0.034***	0.025***
Price Promotion Intensity (*PROM*)	H1e: (-)	-0.240*	-0.437***	-0.291***
Brand Relevance in Category (BREL)				
BREL		0.203***	0.199***	0.213***
*BREL * ADV*	H2: (+)	0.020***	0.011***	0.016***
*BREL * NPI*	H2: (+)	0.020***	0.017***	0.025***
*BREL * DIST*	H2: (+)	0.069***	0.069**	0.057**
*BREL * PRICE*	H2: (+)	0.014***	0.012***	0.020***
*BREL * PROM*	H2: (-)	0.017	-0.043	0.003
National Culture: Secular-Rational (SECRAT)				
SECRAT		-0.125	-0.094	-0.142
*SECRAT * ADV*	H3: (+)	-0.004	0.035**	-0.006
*SECRAT * NPI*	H3: (+)	0.071***	0.087***	0.079***
*SECRAT * DIST*	H3: (+)	0.066	0.137	0.106
*SECRAT * PRICE*	H3: (+)	0.056***	0.036**	0.048***
*SECRAT * PROM*	H3: (-)	-0.728***	-0.737***	-0.788***
National Culture: Self-Expression (SELFEXPR)				
SELFEXPR		-0.121**	-0.118**	-0.101**
*SELFEXPR * ADV*	H4: (-)	-0.064***	-0.088***	-0.064***
*SELFEXPR * NPI*	H4: (-)	-0.053***	-0.040***	-0.060***
*SELFEXPR * DIST*	H4: (-)	0.119	0.085	0.136
*SELFEXPR * PRICE*	H4: (-)	-0.025**	-0.040***	-0.031***
*SELFEXPR * PROM*	H4: (+)	0.137	-0.281	0.036
Number of Observations		35,028	15,073	35,028

*$p < 0.10$; ** $p < 0.05$; *** $p < 0.01$ (*p*-values are one-sided for directional hypothesis and two-sided for others). Parameter estimates for the control variables and control functions are not reported.

FIGURE 2.1: Country scores on the two Inglehart dimensions

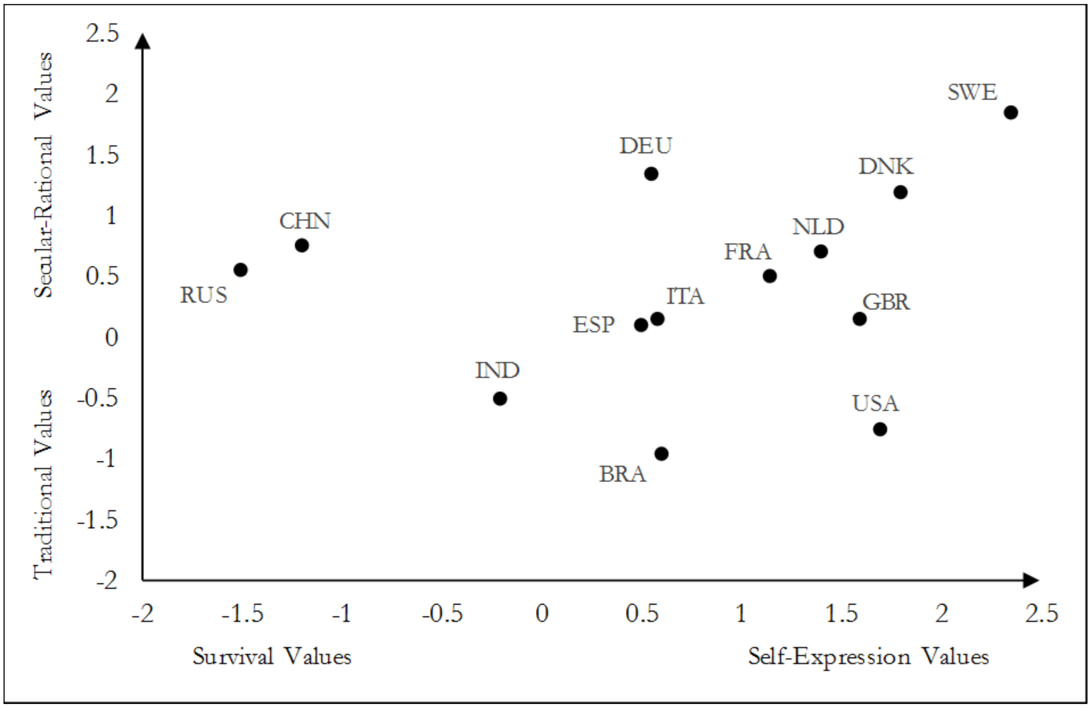


FIGURE 2.2: Mean brand trust across the countries in our study

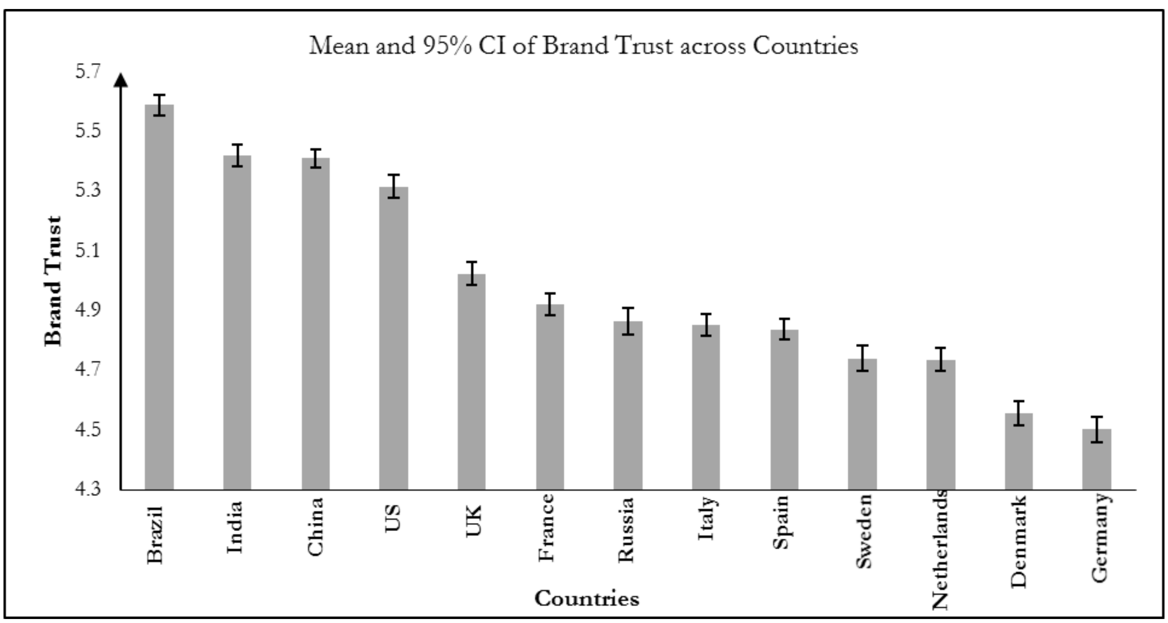


FIGURE 2.3: Moderating role of BREL on the relationship between marketing mix and brand trust

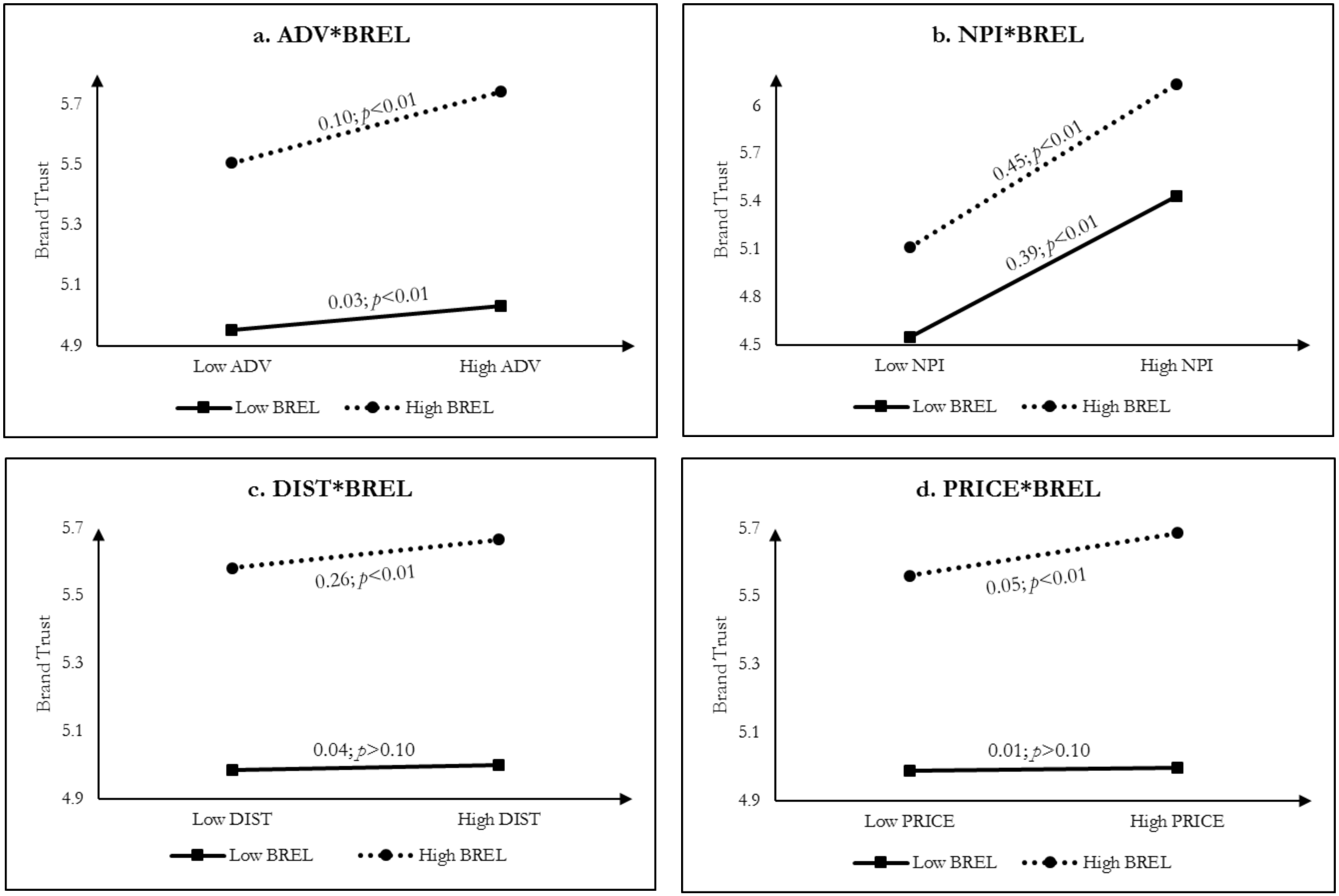


FIGURE 2.4: Moderating role of secular-rational cultural values on the relationship between marketing mix and brand trust

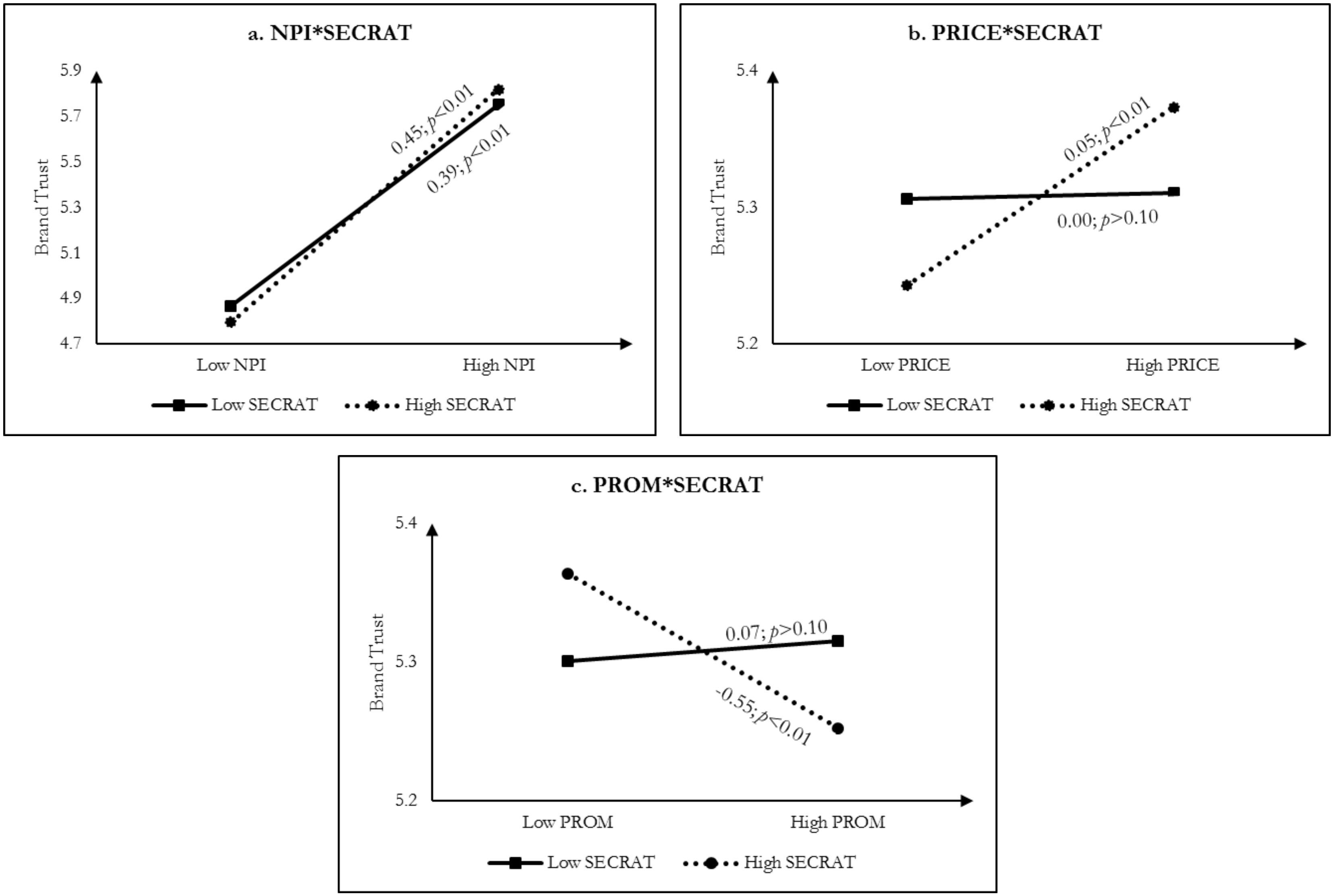
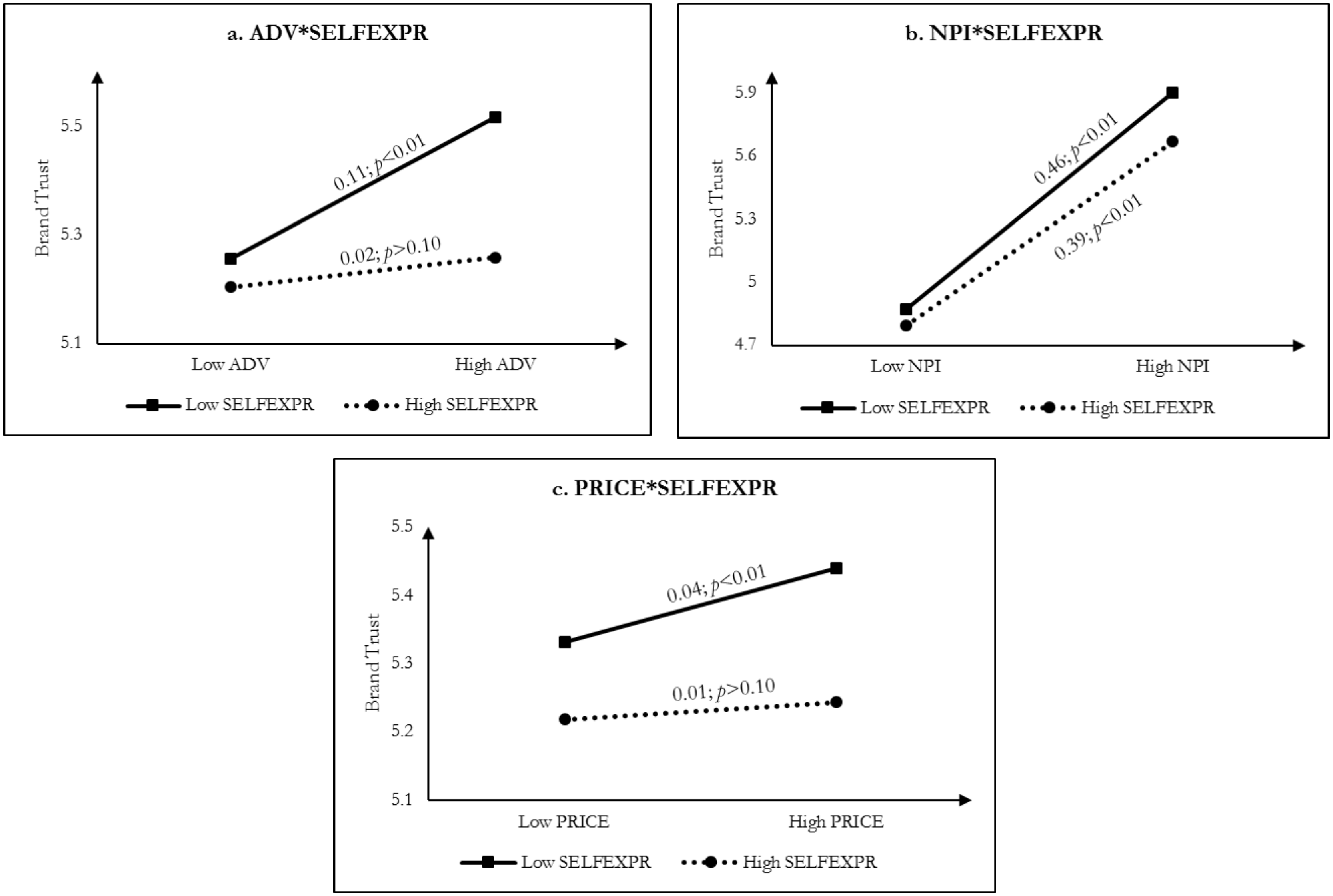


FIGURE 2.5: Moderating role of self-expression cultural values on the relationship between marketing mix and brand trust



CHAPTER 3: IMPACT OF ECONOMIC BUSINESS CYCLES ON EVOLUTION OF BRAND EQUITY: ROLE OF BRAND AND PRODUCT CHARACTERISTICS

Abstract

Firms spend millions of dollars to build and maintain brand equity because they believe they will benefit from such investments in product market outcomes. However, it is not clear how brand equity evolves over time and what factors influence the evolution of brand equity. Specifically, the impact of business cycle changes on brand equity is unknown. In this research, we investigate the role of business cycle fluctuations on the changes in brand equity over time and examine whether business cycle fluctuations have a differential impact on brand equity across different categories and brands. In doing so, we utilize monthly data on 150 leading CPG brands in 36 categories across 17 years in the United Kingdom. The results show that brand equity behaves cyclically; it increases (decreases) during economic upturns (downturns). We also find that business cycle fluctuations have permanent impact on brand equity. Moreover, business cycle fluctuations have stronger impact on brand equity in low performance risk categories, for brands that are pricier, and brands that do not advertise a lot. Managerial implications of the findings are discussed.

Keywords: Brand Equity, Business Cycle, Performance Risk, Price Tier, Advertising Tier, Time Series, Hodrick-Prescott Filtering

Introduction

The concept of brand equity has drawn considerable attention from marketing researchers and practitioners. For most firms, brand equity is an invaluable asset. Firms spend millions of dollars to build and maintain brand equity because they believe they will benefit from such investments in product market outcomes as well as financial market outcomes (Erdem and Swait 1998; Keller 1998). Companies often create the position of brand equity manager to focus on building brand equity and consulting firms like Interbrand, Millward Brown, and Young & Rubicam evaluate and track brand equity, and offer guidance to firms on how to improve brand equity. In an era of ever greater accountability, brand managers are more interested in tracking the equity of their brands (Sriram, Balachander, and Kalwani 2007; Datta, Ailawadi, and Van Heerde 2017). A decline in brand equity may call for remedial action while an increase in brand equity may be regarded as a signal that the current strategy is effective. However, we submit that brand equity may be systematically affected by factors that are out of managers' control. Failure to understand and incorporate such factors may lead to erroneous responses (e.g., panic when brand equity goes down or complacency when it increases). Hence, implementing a successful branding strategy calls for full understanding and awareness regarding factors that are out of managers' control yet influence brand equity.

Macroeconomic conditions surrounding the marketplace are inevitable factors that are shown to impact marketing-related phenomena (Estelami, Lehmann, and Holden 2001; Deleersnyder et al. 2004; Lamey et al. 2007; Deleersnyder et al. 2009; Kamakura and Du 2011; Ma et al. 2011; Lamey et al. 2012; Gordon, Goldfarb, and Li 2013; Van Heerde et al. 2013). Although managers cannot influence macroeconomic conditions, it is critical for marketers to understand how consumers react to business cycle fluctuations. Knowing about reliance of consumers on brand names in their purchase decisions is important for brand managers who are responsible for setting marketing mix of their brands and for retail managers who care about choosing the right mixture of products in order to maximize store revenues. Regarding importance of brands at different macroeconomic conditions, previous research imply that at times of economic difficulty, consumers become more price sensitive (Estelami, Lehmann, and Holden 2001), and as a result of the increased weight of price in consumer decision making, it is highly likely that brands become less important to consumers (Quelch and Jocz 2009; Lamey et al. 2012). On the other hand, in economic upturns, less budgetary restrictions for consumers is expected to translate to higher brand equity. Industry reports have also found that during economic downturns consumers become less loyal towards branded products suggesting a reduction in their equity (Pointer Media Network 2009; Bowmer 2011). Despite theoretical arguments and anecdotal evidence, marketing literature lacks empirical evidence on this important matter.

Moreover, there is indication that different brands across different categories get heterogeneously affected by business cycles (i.e., recurring fluctuations in overall economic activity that occur around its long-term growth trend). Past research argues that at times of economic difficulty, some brands can leverage their risk reduction roles, especially in categories where brands are important for consumers (Fischer, Völckner, and Sattler 2010). Consistent with this viewpoint, in a 2010 Interbrand study on consumer spending during the financial crisis it was reported that “consumers have been reluctant to decrease spending on certain categories that are considered either life-essentials or related to health. […] There are some categories, however, where consumers are willing to switch to private label and store brand products in an effort to save.” (Lowham and MacLennan 2010, p. 3). Moreover, the Interbrand study reported that consumers remained loyal towards certain brands (e.g., Coca-Cola, Pampers) even during the global financial crisis. What makes certain product categories and brands more resilient to business cycle fluctuations? In order to answer this important question, we investigate brand level and category level factors that explain the heterogeneity in the relationship between business cycles and brand equity.

Previous research has shown that business cycles can have long lasting effects on consumer behavior and their product preferences (Deleersnyder et al. 2009; Lamey et al. 2012; Van Heerde et al. 2013). As such, another question that warrants attention is whether the effect of business cycle on brand equity persists in the long run or it only affects the brand temporarily. We therefore study both temporary and permanent effects of the business cycles on changes in brand equity. Overall, we aim to address the following key research questions:

- *Do the business cycle fluctuations contribute to temporary changes in brand equity?*
- *Do the business cycle fluctuations have permanent impact on brand equity?*
- *Which brand and product category characteristics explain heterogeneous effect of business cycle fluctuations on brand equity?*

We investigate our research questions in the context of leading national brands in the CPG industry in the United Kingdom (UK). In doing so, we utilize monthly data on 150 CPG brands in 36 categories across 17 years. We use well-established econometric techniques to measure time-varying brand equity estimates and business cycle fluctuations. We find that brand equity is temporarily and permanently impacted by business cycles and that it behaves cyclically; brand equity increases in economic upturns and decreases during economic downturns. We also find that brand equity of brands that advertise more, are lower priced, and brands in high performance risk product categories are more resilient to business cycle fluctuations.

Our findings help brand managers gain insights regarding potential changes in their brand's equity due to the business cycle changes, heterogeneity in brands' susceptibility to business cycle variations across different categories, and marketing mix instruments that could make brands more resilient to macroeconomic changes. Thus, our findings would help brand managers be more strategic regarding their marketing mix instruments across different macroeconomic conditions. The findings would also be important to retail managers. By knowing about dynamics of brand equity over time and across different product categories, retail managers will be able to understand in which categories brands might hurt during economic slowdowns and therefore choose the appropriate product assortment in order to maximize store revenues.

Conceptual Background

Brand Equity Definition and Measurement

During the past few decades, the concept of Brand equity has generated a lot of interest among marketing scholars. Brand equity has been defined as "outcomes that accrue to a product with its brand name compared with those that would accrue if the same product did not have the brand name" (Ailawadi, Lehmann, and Neslin 2003, p. 1). Higher levels of brand equity is associated with higher brand loyalty, premium pricing, lower price sensitivity, higher brand revenues, and higher advertising effectiveness (Keller 1998). The vast benefits associated with higher brand equity imply that it is essential for marketers to measure and monitor the level of brand equity (Sriram, Balachander, and Kalwani 2007).

There has generally been three different approaches to measuring brand equity: based on customer mindset, based on financial market outcomes, and based on product market outcomes (Keller and Lehmann 2003). Customer mind-set metrics capture customers' awareness, attachments, attitudes, and loyalty towards brands. There are instances in academic research (e.g., Rego, Billet, and Morgan 2009; Srinivasan, Vanhuele, and Pauwels 2010; Stahl et al. 2012) and industry reports (e.g., Millward Brown's Brand Z, Young & Rubicam's BAV) which have adopted customer mindset based brand equity measures. The second approach, i.e. measuring brand equity based on financial market outcomes, captures current and future potential value of a brand by quantifying its value as a financial asset. The financial market approach has been used in marketing literature (Simon and Sullivan 1993), albeit not as frequently as the other two. In the third approach, brand equity is measured as the benefits that brands accrue in the marketplace. Here, the rationale is that brand equity should be reflected in brand sales. The main approach in estimating *sales-based* brand equity is the intercept method. According to this approach which has been frequently adopted in the marketing literature, after accounting for marketing mix instruments of the brand, whatever is left in the brand intercept should reflect the effect of brand name on sales (Kamakura and Russell 1993; Sriram, Balachander, and Kalwani 2007; Sriram and Kalwani 2007; Goldfarb, Lu, and Moorthy 2009; Datta, Ailawadi, and Van Heerde 2017). This approach, in contrast with consumer mindset metrics, relies on consumers' actual preferences in the marketplace rather than their measurement error prone stated "relative brand preferences" (Park and Srinivasan 1994, p. 286; Sriram, Balachander, and Kalwani 2007).

Although sales-based brand equity is related to measures of brand performance (e.g., sales, market share, revenue), it is conceptually different. Measures of brand performance like sales or market share capture the combination of brand strength as well as its marketing activities. As such, high sales figures could wrongly be associated with strength of a brand whereas they are merely due to deep price promotions that the brand offers. However, sales-based brand equity captures how much a brand and particularly its name add to brand performance in the marketplace after accounting for marketing mix instruments of the brand; that is, it captures the importance of a particular brand name in consumer purchases.

Consistent with past research, we use national data for a large number of product categories throughout a long period to estimate brand equity using the intercept method. The model, which we describe in detail subsequently, accounts for marketing mix activities of the brands, heterogeneity in effectiveness of marketing mix instruments across brands, and seasonal and category level differences in sales.

Business Cycle and Its Relationship with Brand Equity

There is a rich and growing literature in marketing that investigates the effects of macroeconomic changes and business cycle fluctuations on marketing-related phenomena. Past research shows that business cycle and macroeconomic factors influence customers' price sensitivity and brands' price elasticity (Estelami, Lehmann, and Holden 2001; Gordon, Goldfarb, and Li 2013; Van Heerde et al. 2013), sales of durable goods (Allenby, Jen, and Leone 1996; Deleersnyder et al. 2004), consumers' relative preferences towards different categories (Kamakura and Du 2011), consumers' shopping frequency and purchase volume (Fornell, Rust, and Dekimpe 2010; Ma et al. 2011), advertising effectiveness (Deleersnyder et al. 2009; Van Heerde et al. 2013), private label share (Lamey et al. 2007), marketing conduct over the business cycle (Lamey et al. 2012), allocation of consumption budget (Du and Kamakura 2008), inventory investment (Kesavan and Kushwaha 2014), and response strategy of retailers (Kesavan, Kushwaha, and Gaur 2016). Previous research shows that during economic downturns consumers become more price sensitive (Estelami, Lehmann, and Holden 2001; Van Heerde et al. 2013). Past research shows that private label shares react counter-cyclically; suggesting that consumers switch more frequently to less expensive product offerings in economic downturns (Lamey et al. 2007; Lamey et al. 2012). While some studies imply that overall category level performance declines for brands (Lamey et al. 2007; Lamey et al. 2012), the aggregate category level nature of these studies does not allow authors to evaluate a brand's performance with respect to its own marketing mix instruments (See Table 3.1 for a review of related research on the impact of business cycles). The brand level nature of the dependent variable we use permits us to provide brand-level insights (e.g., do business cycle fluctuations have heterogeneous impact on brand equity of different types of brands?).

Economic upturns indicate that the businesses in a country are experiencing growth and that individuals in the country are more likely to have higher disposable incomes and thus fewer budgetary restrictions (Van Heerde et al. 2013). In economic downturns however, consumers have lower disposable incomes. As such, economic downturns are likely to result in more budgetary restrictions for consumers. The resulting restrictions in consumers' purchasing power and the additional limitations on their budgets are expected to make them more price sensitive (Estelami, Lehmann, and Holden 2001) and therefore the importance of brand names in their decision making process is likely to decline. As a result, in order to reduce their expenditures, customers might switch to less desirable, lower priced product offerings (Quelch and Jocz 2009). Hence, we expect to find a positive association (cyclical relationship) between business cycle changes and brand equity.

Permanent Effect of Business Cycle on Brand Equity

Habitual purchases – i.e., tendency to repeat past purchases – constitute a great portion of consumer purchases across "a wide range of products and services including potato chips, bread, tissue, laundry detergent, ketchup, jeans, and restaurants" (Ji and Wood 2007, p. 261). In good economic times, consumers do not put a lot of cognitive effort into their purchase decision making. Most of the time, consumers continue with their prior purchasing habits. In difficult economic times however, consumers experience stricter budgetary restrictions and are motivated to spend less whenever it is possible. As such, they might switch to less expensive offerings in the market. After switching to such lower priced offerings, consumers might habitually continue to purchase these products even after the economy starts doing well. Moreover, after trying the less expensive products during difficult economic times, consumers might realize that their (negative) prior beliefs regarding quality of such products were exaggerated and not accurate (Lichtenstein and Burton 1989). Therefore, they might update their beliefs regarding quality of such products. Their improved preferences for less expensive products as well as their habitual tendencies imply that consumers are likely to stick with them even after economy starts doing well. In other words, business cycle fluctuations are likely to permanently influence brand equity.

<u>The Relationships between Business Cycle Fluctuations and Brand Equity across Different Brand Segments</u>

Industry reports and previous research in marketing suggest that macroeconomic conditions have dissimilar impact on different brands (Lowham and MacLennan 2010; Van Heerde et al. 2013). Understanding brand level factors that alleviate or strengthen the effect of macroeconomic fluctuations on brand equity would be critical to brand managers who set up marketing strategy for their brands. To provide insights into the differences between brands with respect to their susceptibility to business cycle changes, we look at different brand segments depending on their marketing mix activities. Two of the marketing mix instruments are especially critical in affecting consumers' purchase decisions during economic slowdowns. First, since consumers become more price sensitive in bad economic conditions, higher priced brands are expected to be more susceptible to business cycle changes. Second, brands need to differentiate themselves and convey to consumers that they are different than other products in the marketplace. In other words, "In a recession, it becomes even more critical for companies to aggressively and tirelessly create a compelling case for their brand. The brand must be perceived as truly special, clearly differentiated, and have attributes that are unique enough to create a strong and lasting value proposition for its customers. Otherwise, consumers will just choose to not buy it." (Lowham and MacLennan 2010, p. 5). Advertising is the primary tool that brand managers can use to differentiate their products. Hence, brands that advertise more are expected to be more robust to macroeconomic changes.

<u>The Relationships between Business Cycle Fluctuations and Brand Equity across Different Product Categories</u>

It is well established in the marketing literature that the importance of brands for consumers and their reliance on brand names varies across different product categories. Fischer, Völckner, and Sattler (2010) argue that the heterogeneity in importance of brands for consumers across different product categories can be explained by the risk reduction roles that brands play for consumers. They categorize the risk reduction roles that brands play alongside two functions: functional risk reduction and social demonstration functions of brands. Their study shows that in categories where brands play a stronger role in reducing consumers' perceived functional risks or cultivating consumers' self-concept, brands are more relevant to consumers and brands names play a more pronounced role in consumers' buying decisions. Moreover, they show that in categories where brands are more important in reducing consumers' perceived functional and social risks, consumers are less price sensitive and more loyal to their preferred brands. It can be argued that during economic slowdowns, in categories where brands play strong functional and social risk reduction roles, customers are less likely to stop purchasing their favorite national brands as doing so is associated with high perceived functional and social losses. For example, during economic downturns, consumers are likely to stick to their preferred baby food brand as they might associate purchasing lower quality products in this category with severe consequences. On the other hand, consumers might be more willing to change their shopping behavior in a category like mineral water in which making the wrong purchase is not associated with great losses. In other words, consumers' preferences towards brands are expected to be more robust to business cycle fluctuations in product categories where brands play more pronounced functional and social risk reduction roles.

Data

We empirically investigate our research questions in the context of consumer packaged goods (CPG) categories. Our choice of CPG industry was guided by the importance of brand equity in this sector as well as availability of sales data over a large period of time. We acquired household scanner panel data from Kantar Worldpanel for 36 CPG categories in the United Kingdom. The data covers monthly brand-level data throughout a 17 year period from January-1994 to November-2010 (203 months) and has information on monthly volume sales, price per volume, distribution intensity, and product line length for up to five leading national brands in each CPG category (See Table 3.2). We use (log-transformed) monthly brand volume sales as the measure for brand performance. We complement our data by acquiring information on monthly advertising expenditures for brands in our sample from Nielsen Media (United Kingdom). In some categories (e.g., frozen fish, artificial sweeteners), there were fewer than five brands that were present throughout the whole period. As a result, our sample consists of 150 brands (instead of 180 brands). We obtained annual data on inflation-adjusted gross domestic product per capita (*GDPPC*) from the World Bank as our measure for business cycle fluctuations. Finally, for category level performance risk and social risk, we use category level survey measures collected by TNS and GfK.

Model and Estimation

Consistent with previous research (e.g., Datta, Ailawadi, and Van Heerde 2017), we estimate yearly brand intercepts in a model with marketing activities of the focal brands (i.e., advertising, paid price, distribution, and product line length) as predictors and brand volume sales used as the dependent variable (Step 1). We then use the yearly brand intercept estimates as our measure of brand equity. Next, we extract the cyclical and trend components of the brand equity estimates from the first stage as well as the cyclical component of the business cycle (Step 2). Then we use cyclical component of the business cycle to explain the variation in cyclical (trend) components of the brand equity estimates to assess temporary (permanent) changes in brand equity (Step 3). Finally, we explain the heterogeneity in the relationship between business cycle and brand equity using category and brand level factors (Step 4). In Figure 3.1, we summarize empirical strategy (See Figure 3.1).

Step 1: Estimating Brand Equity

We model brand performance as a function of its marekting activities using following log-log specification:

(1) $$ln(SALES_{ijyt}) = \delta_{ijy} + \sum_{m=1}^{m=4} \delta_{mij}\, ln(MARKETING_{mijyt}) + \sum_{n=1}^{n=35} \theta_n CATEGORY_{mj} + \sum_{o=1}^{o=3} \vartheta_{oij} QUARTER_{oyt} + \sum_{p=1}^{p=4} \mu_p COPULA_{pijyt} + e_{ijyt}$$

where $MARKETING_{mijyt}$, represents the level of m^{th} marketing activity undertaken by brand *i* in category *j* at month *t* of year *y*. Consistent with previous research (Sriram, Balachander, and Kalwani 2007; Datta, Ailawadi, Van Heerde 2017), we use the following marketing activities:

$ADSTOCK_{ijyt}$: Smoothed advertising spending (i.e., advertising stock) of brand *i* in category *j* at month *t* of year *y* where: $ADSTOCK_{ijyt} = \alpha\, ADSTOCK_{ijy,t-1} + (1- \alpha)ADVERTISING_{ijyt}$. In the *ADSTOCK* formula, advertising represents monthly advertising expenditure by brand *i* in category *j* in month *t* of year *y*. α is chosen by grid search on the interval of [0, 0.9] in increments of 0.10 (Datta, Ailawadi, and Van Heerde 2017). Advertising expenditure is adjusted by yearly consumer price index in the UK.

$PRICE_{ijyt}$: Paid price per volume for brand *i* in category *j* at month *t* of year *y*; this measure captures both list price and promotional discount offered by the brand and is adjusted by yearly consumer price index in the UK.

$ASSORTMENT_{ijyt}$: Product line length; that is, number of stock keeping units offered by brand *i* in category *j* at month *t* of year *y*.

$DISTRIBUTION_{ijyt}$: Percentage of UK retailers that sold brand *i*'s SKUs during month *m* of year *y*, weighted by retailer's volume market share in category *j*.

In equation 1, *i* represents brands, *j* represents categories, *y* represents years, and *t* represents months. $SALES_{ijyt}$ represents volume sales of brand *i* in category *j* at month *t* of year *y*. $CATEGORY_{mj}$ includes 35 category dummies. By including category fixed effects we ensure that we control for differences in product volume scales and volume sales across categories and that such differences are not reflected in the annual brand intercepts. $QUARTER_{oyt}$ includes three quarter dummies that account for seasonality. To reduce sensitivity of the estimates to outliers we take natural log of the dependent variable and independent variables. The log-transformation also allows us to interpret the effect of marketing mix instruments as elasticities. e_{ijyt} is random error term which is clustered at the brand level to account for possible heteroskedasticity and autoregression in residuals.[12]

Marketing activities of brands are potentially endogenous. Managers strategically set advertising, price, and other marketing activities of their brands. First, we include quarter fixed effects to capture seasonal demand shocks that might influence managers' decision making. Next, we allow all four marketing mix instruments as well as quarter fixed effected to have random slopes at the brand level. Finally, we control for other potential unobserved

[12] We also considered including marketing mix instruments of competitor brands in Equation (1) but since the resulting equity estimates were highly correlated with brand equity estimates from our main model (correlation > 0.90), to be consistent with prior research, we proceed without including competitors' marketing mix instruments.

heterogeneity that could lead to endogeneity of marketing activities using Gaussian copulas. The copula method does not require instrumental variables and directly models the joint distribution of the endogenous marketing activities and the error term (Park and Gupta 2012). Gaussian copulas are especially useful when finding valid instruments is a challenge. An important identification requirement for this approach is that endogenous regressors are not normally distributed. Shapiro-Wilk test strongly rejects normality of all marketing variables for more than 95% of brands at $p < 0.10$ level. Hence, we implement and include copula terms for each of the four marketing activities to account for possible endogeneity.

From the above equation, we derive yearly brand equity estimates ($\widehat{\delta_{\iota J y}}$). We will further extract the cyclical and trend components of the brand equity estimates and use the cyclical/trend components as dependent variables in models with cyclical component of the business cycle as predictors.

<u>Step 2: Extracting Cyclical and Trend Components in Each of the Time-Series</u>

In this stage, we use the well-known Hodrick and Prescott (1997) filter (hereinafter, HP filter) to extract the cyclical and trend components of the brand equity estimates as well as the cyclical component in the business cycle. The HP filter breaks down a series into (1) a gradually evolving trend component and (2) cyclical fluctuations around the trend component (Lamey et al. 2007). For the brand equity estimates:

(2) $\widehat{\delta^{c}_{\iota J,y}} = \widehat{\delta_{\iota J,y}} - \widehat{\delta^{trend}_{\iota J,y}}$

where $\widehat{\delta^{c}_{\iota y}}$ is the cyclical component of the log-transformed brand equity estimates which captures temporary changes in brand equity (y – i.e., year – is the only time indicator in this stage). $\widehat{\delta^{trend}_{\iota J y}}$ is the trend component of the log-transformed brand equity that captures permanent changes in brand equity estimates after controlling for cyclical fluctuations. The trend component is extracted by minimizing the following formula:

(3) $\sum_{y=1}^{y=Y}\left(\widehat{\delta_{\iota J,y}}-\widehat{\delta_{\iota J,y}^{trend}}\right)^2+\lambda\sum_{y=2}^{y=Y-1}\left[\left(\widehat{\delta_{\iota J,y+1}^{trend}}-\widehat{\delta_{\iota J,y}^{trend}}\right)-\left(\widehat{\delta_{\iota J,y}}-\widehat{\delta_{\iota J,y-1}^{trend}}\right)\right]^2$

In the above equation, λ is the smoothing parameter. For larger values of λ, the trend component of the time series becomes smoother (Hodrick and Prescott 1997). Following standard procedure for annual data, we set $\lambda = 10$ (Baxter and King 1999; Deleersnyder et al. 2009; Lamey et al. 2012).[13]

Past research has used GDP (or GDP per capita) changes as the proxy for business cycle fluctuations (e.g., Deleersnyder et al. 2009; Lamey et al. 2012; Van Heerde et al. 2013; Kesavan and Kushwaha 2014). Gross Domestic Product Per Capita (GDPPC) represents the total value of goods and services produced in a country during a particular time period (quarter or year) divided by its population. GDPPC is frequently used as an indicator of economic well-being and standard of living in a country. We obtained annual data on real gross domestic product per capita (*GDPPC*) from the World Bank. We inflate the series using consumer price index and anchor it to November 2010. Similarly, for log-transformed *GDPPC*, we extract its cyclical component:

(4) $GDPPC_y^c = GDPPC_y - GDPPC_y^{trend}$

Accordingly, $GDPPC_y^c$ is the cyclical component of the log-transformed real gross domestic product per capita. Based on values of $GDPPC_y^c$, five business cycles happened during the time period between 1994 and 2010 (which is consistent with Figure 2 in Van Heerde et al. (2013)).

[13] We also used other values for λ such as 6.25 which has sometimes been used in economics literature (Ravn and Uhlig 2002). Using other values for λ did not change our substantive findings and produced very similar results.

Step 3a: Assessing Temporary Impact of Business Cycle Fluctuations on Brand Equity

In order to assess the impact of business cycle fluctuations on temporary changes in brand equity, we regress the cyclical component of the brand equity estimates ($\widehat{\delta^{c}_{ij,y}}$) for each brand-category combination on the cyclical component of *GDPPC*:

(5) $\widehat{\delta^{c}_{ij,y}} = \alpha_{ij0} + \alpha_{ij1} GDPPC^{c}_{y} + \varepsilon_{ijy}$

Since both variables in equation 5 were log-transformed before filtering, α_{ij1} can be interpreted as elasticity (Stock and Watson 1999); that is, it captures percentage deviation in the cyclical component of brand equity due to one percentage change in the cyclical component of gross domestic product per capita. A positive α_{ij1} suggests pro-cyclical change in brand equity (i.e., increase in brand equity during economic upturns and decrease in brand equity in economic downturns) whereas a negative α_{ij1} suggests counter-cyclical change in brand equity (i.e., increase in brand equity during economic downturns and decrease in brand equity in economic upturns).

It has been shown that adopting HP filters on macroeconomic variables induces serial correlation (Deleersnyder et al. 2009; Lamey et al. 2012). Using the Durbin-Watson test, we checked for presence of first order serial correlation in each of the series. For 139 brands, presence of first order serial correlation could not be rejected at the critical value for Durbin-Watson test.[14] For these 139 series we adopted Newey-West estimator with appropriate number of lags specified in the autocorrelation structure.

The dependent variable in this model is an estimated variable (with varying degrees of accuracy across yearly brand equity estimates). We therefore use weighted least squares

[14] The critical value for Durbin-Watson test statistic with 17 observations and two covariates (including intercept term) is 1.1329 at 0.05 level.

approach; that is, both dependent and independent variables in this stage are weighted by the inverse of the standard error of the dependent variable (Nijs et al. 2001; Gielens 2012).

<u>Step 3b: Assessing Permanent Impact of Business Cycle Fluctuations on Brand Equity</u>

The trend component of brand equity captures permanent changes in brand equity. Before specifying the model, we tested the log-transformed trend components of brand equity for stationarity. We applied Levin, Lin, and Chu's (2002) test, allowing for different parameters (fixed-effects, time trend, lag-lengths, and autoregressive parameters) but the null hypothesis of presence of unit root could not be rejected at 0.10 level. As such, we regress the first-differenced trend component of the brand equity ($\Delta\widehat{\delta_{ij,y}^{trend}} = \widehat{\delta_{ij,y}^{trend}} - \widehat{\delta_{ij,y-1}^{trend}}$) on the first-differenced cyclical component of *GDPPC* ($\Delta GDPPC_y^c = GDPPC_y^c - GDPPC_{y-1}^c$):

(6) $\Delta\widehat{\delta_{ij,y}^{trend}} = \beta_{ij0} + \beta_{ij1}\Delta GDPPC_y^c + \varepsilon_{ijy}$

Similar to the model for assessing temporary impact of business cycle fluctuations on brand equity, the dependent variable in equation 6 is an estimated variable, therefore we use weighted least squares approach. The intercept (β_{ij0}) is a drift parameter that accounts for unobserved heterogeneity and (β_{ij1}) captures permanent impact of business cycle fluctuations on brand equity. In the above equation, since first-differencing can be ignored when interpreting the coefficient estimates (Ho-Dac, Carson, and Moore 2013), β_{ij1} can still be interpreted as elasticity. A positive value for β_{ij1} suggests that increase in cyclical component of *GDPPC* is associated with permanent positive change in brand equity.[15]

[15] Since we are using identical regressors in equations 5 and 6, OLS regression will produce identical results to seemingly unrelated regressions – SUR (Greene 2008, p. 257) and therefore we proceed with OLS regression.

Step 4: Assessing Heterogeneity in Temporary and Permanent Impacts of Business Cycle Fluctuations on Brand Equity across Different Product Categories

Finally, we investigate whether temporary (α_{ij1}) and permanent (β_{ij1}) impacts of business cycle changes on brand equity varies across product categories – in function of the perceived functional and social risk reduction roles that brands play in a product category – and across different price and advertising brand segments. Accordingly, we run the following regressions:

(7) $\widehat{\alpha_{ij1}} = \gamma_0 + \gamma_1 PERFRISK_j + \gamma_2 SOCRISK_j + \gamma_3 ADVSEG_{ij} + \gamma_4 PRICESEG_{ij} + u_{ij}$

(8) $\widehat{\beta_{ij1}} = \delta_0 + \delta_1 PERFRISK_j + \delta_2 SOCRISK_j + \delta_3 ADVSEG_{ij} + \delta_4 PRICESEG_{ij} + v_{ij}$

In the above regressions $PERFRISK_j$ and $SOCRISK_j$ are dummy variables indicating whether the product category to which brand *i* belongs is a high performance risk (=1) or high social risk (=1) product category or not (=0), respectively. Details regarding survey items used for these variables can be found in Appendix 3.A (See Appendix 3.A). In line with Van Heerde et al. (2013), based on median category level values of advertising and price, we group brands into different segments. $ADVSEG_{ij}$ specifies whether brand *i* belongs to the high advertising brand segment (=1) in category *j* or not (i.e., whether brand *i*'s advertising expenditures exceeds median advertising expenditures in its product category *j* or not). Similarly, $PRICESEG_{ij}$ captures whether brand *i* belongs to the high price brand segment (=1) in category *j* or not (=0). The parameters γ_1-γ_4 (δ_1- δ_4) capture the heterogeneity in temporary (permanent) impacts of business cycle changes on brand equity across different product categories and brand segments. Since the dependent variables in equations 7 and 8 are both estimated variables, we use weighted least squares approach with the inverse of standard errors of (α_{ij1}) and (β_{ij1}) as weights. Moreover, since observations belonging to a particular product category are correlated with each other, linear regression is likely to result in small standard errors (and wrong inferences). Hence, we estimate robust standard errors clustered at the product category level.[16]

Results

Brand Equity Estimation (Step 1)

We begin by discussing the results from the brand equity estimation analysis (Step 1). Elasticities for the four marketing mix instruments are reported in Table 3.3 (See Table 3.3). As expected, advertising stock, distribution intensity, and product line length are positively associated with volume sales whereas paid price is negatively related with volume sales. Price and advertising elasticities are consistent with findings of prior meta-analytic research (Tellis 1988; Bijmolt, Van Heerde, and Pieters 2005; Sethuraman, Tellis, and Briesch 2011). Our estimates for elasticities of distribution intensity and product line length are comparable with previous research in marketing (e.g., Sriram, Balachander, and Kalwani 2007; Datta, Ailawadi, and Van Heerde 2017). Hence, the eslaticities have face validity. Category and quarter fixed effects are all significant at 0.10 level. The Guassian copula correction terms are all statistically significant at 0.10 level highlighting the importance of addressing endogeneity.

We next illustrate (log-transformed) yearly brand equity estimates across four product categories: Instant Coffee, Razor Blades, Soft Drinks, and Breakfast Cereals. As it can be seen in Figure 3.2, Nescafé, Gillette, Coca-Cola, Pepsi, and Kellogg's which are regarded as popular and respected brands are estimated to have higher brand equity in comparison to their competitors (See Figure 3.2). Similarly, the likes of Mellow Birds, Red Mountain, Tango, Personna, and Jordans which are lesser known brands are estimated to have the lowest brand equity in their

[16] We dichotomized variables to ease the interpretation of coefficient estimates. Using continuous measures in equations 7-8 will not change our substantive findings (See Appendix 3.B).

categories. Figure 3.2 shows that while in some categories brand equity estimates have changed considerably over years (e.g., Razor Blades, Soft Drinks), in other categories brand equity has remained relatively constant (e.g., Instant Coffee). Moreover, while some brands (e.g., Schweppes, Quaker Oats) have experienced considerable brand equity growth over years, other brands have only faced small changes (e.g., Weetabix, Nescafé) or even declines in their brand equity (e.g., Mellow Birds). Overall, while Figure 3.2 provides face validity for our brand equity estimates, it shows considerable heterogeneity in the evolution of brand equity across different product categories and brands which we will subsequently investigate.[17]

Temporary Impact of Business Cycle Fluctuations on Brand Equity (Step 3a)

We next apply HP filters on *GDPPC* and each of the 150 brand equity series. From the filtering procedure, we obtain cyclical component of business cycle ($GDPPC_y^c$), cyclical components of brand equity estimates ($\widehat{\delta_{ijy}^{c}}$), and trend components of brand equity estimates ($\widehat{\delta_{ijy}^{trend}}$). To assess temporary changes of business cycle fluctuations on brand equity, we run 150 regressions that are presented by equation 5 (Step 3a). The findings are presented in Table 3.4 and show that majority of brands (137 brands) show pro-cyclical behaviors; that is, their equity temporarily increases in economic upturns and decreases in economic downturns (See Table 3.4). However, we find that 13 brands show counter-cyclical behaviors; their equity increases during economic downturns and decreases during economic upturns. Brand-specific estimates for α_{ij1} are reported in Appendix 3.C (See Appendix 3.C). To get a better idea about

[17] We also analyzed the trends in the brand equity estimates by regressing them on the time indicator (i.e., year). The analysis showed that 125 brands have a positive trend in their equity. For the remaining 25 brands in our sample we found a negative trend. The weighted mean trend in brand equity estimates is 0.056 (meta-analytic $p < 0.01$). Accordingly, in step 3b, we first-difference the trend components of brand equity estimates to remove existing time trends in the series.

average temporary effect of business cycle changes on brand equity, we compute weighted mean of all 150 effect sizes (i.e., $\bar{\alpha}_{ij1}$).[18] The weighted mean for the temporary impact of business cycles on brand equity across all 150 brands is 0.8349 (Meta-Analytic Z = 12.3554, Meta-Analytic $p < 0.001$). The weighted mean suggests that each time economic activity increases 1% above (falls 1% below) its predicted long-term trend, brand equity increases 0.8349% higher (lower) than its expected long-term value. We present category-specific meta-analytic results in Appendix 3.D (See Appendix 3.D).

Permanent Impact of Business Cycle Fluctuations on Brand Equity (Step 3b)

To assess permanent changes of business cycle fluctuations on brand equity, we run 150 regressions that are presented by equation 6 (Step 3b). We report meta-analytic findings in Table 3.4. The findings suggest that 96% of brands (145 brands) behave pro-cyclically; i.e., their equity permanently increases in economic upturns and decreases in economic downturns. Brand-specific estimates for β_{ij1} are reported in Appendix 3.E (See Appendix 3.E). The weighted mean of permanent changes in brand equity due to cyclical changes in business cycles (i.e., $\bar{\beta}_{ij1}$) across all 150 brands is 0.2747 (Meta-Analytic Z = 8.9048, Meta-Analytic $p < 0.001$). The weighted elasticity of 0.2747 suggests that each time economic activity increases (decreases) 1%, brand equity increases (decreases) 0.2747%. Unlike temporary changes in brand equity, this change is not reversed in the following time periods. The mean effect for the permanent changes in brand equity (0.2747) is considerably smaller than the mean effect for the temporary changes in brand equity (0.8349). We report category-specific meta-analytic findings in Appendix 3.F (See Appendix 3.F).

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[18] $\bar{\alpha}_{ij1} = \sum_{ij=1}^{150} w_{ij}\alpha_{ij1} \,/\, \sum_{ij=1}^{150} w_{ij}$. The weight 'w_{ij}' is the inverse of the estimate's (α_{ij1}) standard error.

Heterogeneity in Temporary and Permanent Impacts of Business Cycle Fluctuations on Brand Equity across Different Product Categories (Step 4)

We next discuss whether temporary and permanent changes in brand equity due to business cycle fluctuations vary across product categories (i.e., in function of performance risk and social category risk) and brand segments (based on their level of advertising and price). The findings from equations 7-8 are presented in Table 3.5 (See Table 3.5). We find that while brand equity is more robust to business cycle fluctuations in high performance risk categories vis-à-vis low performance risk categories ($\gamma_1 = -0.2968$, $p < 0.10$), there is no significant difference in the impact of business cycle changes on temporary variations in brand equity across low and high social risk categories ($\gamma_2 = 0.0472$, $p > 0.10$). This suggests that compared to low performance risk categories (e.g., mineral water, artificial sweeteners, tinned fruit), in high performance risk categories (e.g., frozen fish, razor blades, instant coffee) consumers are more loyal towards their favorite brands and macroeconomic conditions do not sharply affect their purchasing habits. We report category level values for performance risk and social risk in Appendix 3.G (See Appendix 3.G). Additionally, we find that brands that advertise more (relative to their category competitors) are less susceptible to macroeconomic fluctuations ($\gamma_3 = -0.2814$, $p < 0.05$). This is consistent with the idea that advertising helps brands differentiate themselves and convey their unique value to customers. Moreover, we find that compared to low priced brands, high priced brands are more vulnerable to business cycle changes ($\gamma_4 = 0.2494$, $p < 0.05$). This outcome indicates that consumers become more (less) price sensitive during economic downturns (upturns) and that the higher priced brands are more affected by consumers' price sensitivity. Overall, we find that business cycle fluctuations temporarily impact brand equity more strongly in categories with low performance risk and brands with lower advertising expenditures and higher prices.

The analysis on permanent changes in brand equity due to business cycle fluctuations yields similar findings. Permanent impact of business cycle changes on brand equity is less pronounced in high performance risk categories (δ_1 = -0.2558, $p < 0.01$) and for high advertising brands (δ_3 = -0.1076, $p < 0.01$). Unlike the previous analysis on temporary changes, we do not find significant difference in the permanent impact of business cycles on brand equity across low and high priced brands (δ_4 = 0.0202, $p > 0.10$). This suggests that although high priced brands temporarily lose brand equity in economic downturns, the change in brand equity is not long-lasting. We also do not find significant difference in the impact of business cycles on brand equity across low and high social risk categories (δ_2 = 0.0606, $p > 0.10$). Overall, our findings highlight the prominent role of advertising in mitigating the effects of macroeconomic fluctuations on brand equity.

Additional Analysis

Our findings showed that the temporary impact of business cycle fluctuations on brand equity is more pronounced for high priced brands. This suggests that in economic downturns, due to increased consumer price sensitivity, higher priced brands are more likely to lose brand equity, at least temporarily. It would be instructive and managerially relevant to examine whether such effect exists across all product categories or not. Prior research in marketing suggests that price can also signal product quality to consumers (McConnell 1968; Rao and Monroe 1989). However, consumers' reliance on price as an indicator of product quality is not universal (Zeithaml 1988) and varies greatly across product categories (Gardner 1971; Lichtenstein and Burton 1989). In some product categories, consumers rely heavily on price as an indicator of quality whereas in other product categories such relationship is weak or non-existent. In product categories with high price-(perceived) quality relationship, consumers associate higher priced brands with better product quality and therefore might be less willing to switch to less expensive products during economic slowdowns. However, in categories with low price-quality relationship, since consumers do not strongly associate higher price with better product quality, they are more likely to switch to less expensive products during economic slowdowns. We therefore use a category level measure for price-quality relationship to investigate whether the impact of business cycles on brand equity across different price segments is dissimilar in different product categories. Since we only found temporary differences across price segments, here we only focus on temporary changes in brand equity estimates.

In Figure 3.3, we compare temporary changes in brand equity due to business cycle fluctuations across low and high priced brands and low and high price-quality product categories (See Figure 3.3). For this median-split analysis, we computed four different weighted means for α_{ij1}s across brands in each of the four groups. We find that while there is no significant difference (with respect to the impact of business cycles on brand equity) among low and high priced brands in categories with high price-quality relationship ($p > 0.10$), in categories low on price-quality relationship, high priced brands are significantly more sensitive to business cycle fluctuations vis-à-vis low priced brands ($p < 0.01$). As a result, we can conclude that the role of price in enhancing the temporary impact of business cycle changes on brand equity is only relevant in categories with low price-quality relationship. It seems that in categories high on price-quality relationship, during economic downturns, the quality signaling role that higher priced brands play cancels out consumers' increased price sensitivity towards these products, whereas in categories low on price-quality relationship, since higher price is not associated with better quality and consumers do not associate higher price with better product quality, their increased price sensitivity dominates and thus they are more likely to switch to less expensive products.

Discussion

During the past few decades, brand equity has been one of the most important topics among marketing scholars and practitioners. Marketers have been keen to understand the factors that make brands more or less valuable to customers. It is believed that managers can influence the equity of their brands by devising proper long term strategy and adopting appropriate marketing mix instruments (Lemon, Rust, and Zeithaml 2004; Keller and Lehmann 2006). However, our understanding regarding brand equity changes over time and the influence of macroeconomic factors on brand equity is limited. Macroeconomic changes and business cycle fluctuations and their impact on consumer behavior and attitude have recently generated great interest among marketing scholars. Past research showed that macroeconomic conditions influence consumers' sensitivity to brand price and advertising, shopping frequency, purchase volume, and consumption of private label offerings (Estelami, Lehmann, and Holden 2001; Ma et al. 2011; Lamey et al. 2012; Gordon, Goldfarb, and Li 2013; Van Heerde et al. 2013). Despite the evidence in past research on the link between macroeconomic conditions and various facets of consumer behavior, no study has looked at the relationship between business cycle changes and the importance of brands and customers' reliance on brand names (i.e., brand equity) in their purchase decision making process. Using unique monthly data on 150 leading CPG brands in 36 categories across 17 years, we studied temporary and permanent impacts of business cycle fluctuations on brand equity. Our empirical analysis suggested that cyclical business cycle changes have temporary and permanent impacts on brand equity. We showed that for majority of brands, brand equity shows cyclical behavior; that is, brand equity increases in economic upturns and decreases in economic downturns. Our meta-analytic analysis suggested that these results are statistically significant.

However, the degree to which brand equity is temporarily/permanently affected by business cycle variations is not homogenous across different product categories and different brands. We showed that in categories with low performance risk, brands are more strongly influenced by business cycle changes than in categories with high performance risk. Customer's reliance on brand name products to reduce their perceived risk in high performance risk categories makes brand equity less vulnerable to macroeconomic shifts. We also showed that brands that advertise more are more resistant to temporary and permanent impacts of business cycle fluctuations. Additionally, whereas higher priced brands temporarily lose brand equity, such decline in brand equity does not persist in the long run. Finally, we showed that the heterogeneity in the temporary impact of business cycles on brand equity across low and high priced brands is only meaningful in categories with low price-quality relationship.

Our study contributes to two streams of research. A large body of research in marketing has focused on the drivers of brand equity. Past research shows that different factors such as marketing mix instruments (Yoo, Donthu, and Lee 2000), consumer attitudes (Whan Park et al. 2010), corporate social responsibility (Torres et al. 2012), order of entry (Simon and Sullivan 1993), and intergenerational influences (Moore, Wilkie, and Lutz 2002) affect brand equity. Past research primarily focuses on factors that can be influenced by marketing managers and places less emphasis on external factors that could influence brand equity. Our study complements the literature on drivers of brand equity by studying important external factors – i.e., business cycle fluctuations – and their impact on brand equity.

Our study also contributes to the growing body of research on the impact of macroeconomic factors and business cycle fluctuations on marketing and business related phenomena. Past research has established that business cycles influence sales of durable goods (Deleersnyder et al.

2004), consumers' shopping frequency (Ma et al. 2011), advertising effectiveness (Van Heerde et al. 2013), marketing conduct over the business cycle (Lamey et al. 2012), private label share (Lamey et al. 2007), and inventory investment (Kesavan and Kushwaha 2014). Our study complements this body of research by investigating the impact of business cycles on brand equity. Comparing temporary impact of business cycles on brand equity with findings from past research is noteworthy. Whereas we find the weighted average cyclical elasticity of brand equity to be 0.8349, past research reports greater (in magnitude) average elasticities for advertising (1.39; Deleersnyder et al. 2009) and private label share (2.26; Lamey et al. 2012). This comparison suggests that although brand equity is influenced by business cycle fluctuations, it is more robust to business cycles in comparison to advertising expenditures and private label shares.

Managerial Implications

Our findings have significant implications for brand managers. Knowing how much brand names matter in consumer decision making is helpful in setting marketing mix instruments of the brands, namely their prices. Hence, brand managers can charge additional price premium in economic upturns and be confident that the higher brand equity in such economic conditions protects their brands. Moreover, since we found that brand equity is not strongly affected by business cycles in high performance risk categories, brand managers can still rely on their brand's equity (without making changes to their brand's marketing mix) in such categories even in economic slowdowns. Our findings also suggested that the impact of business cycle changes on brand equity varies significantly across low and high advertising brands; we found that brand equity of the brands that advertise less is more sensitive to business cycle changes. Hence, as opposed to cutting back on marketing support which is the action that managers usually undertake in economic contractions (Lamey et al. 2007), brand managers should increase their advertising expenditures to temporarily and permanently defend their brands against external macroeconomic factors.

Similarly, we found that brand equity of higher priced brands is more susceptible to business cycle fluctuations, although such difference between low and high priced brands does not persist in the long run. Moreover, as seen in Figure 3.3, the heterogeneity in sensitivity to business cycle changes across low and high priced brands is primarily relevant in categories low on price-quality relationship. One remedy is to lower brand's regular price in categories low on price-quality relationship when economy is not doing well. However, many brand managers might be reluctant to do so as lowering brand's price reduce profit margin and the brand might be perceived as a lower quality brand (Marn, Roegner, and Zawada 2003). An alternative solution might be to increase the frequency/depth of price promotions that brand offers during difficult economic times (albeit not excessively, after all frequent price promotions do not convey a positive image either). This strategy could be especially helpful in categories low on price-quality relationship (managers can refer to Appendix 3.G for information about level of price-quality relationship across different categories). Another strategy could be to offer product variants that convey lower price. For example, during the Argentinian economic crisis of 2002, Unilever's Skip laundry brand introduced smaller packages (i.e., lower price per unit) and large economy sizes that offered people lower price per volume (Hollis 2008). The different product sizes offered price sensitive customers multiple ways to bring down their shopping expenses.

Our findings also offer several managerial implications for retail managers who can modify their strategy during different macroeconomic conditions in order to maximize category and store revenues. For example, in economic downturns, instead of focusing on more expensive national brands, they could be more receptive to lower priced national brands which show more resistance towards business cycle changes. This finding could also be helpful in adjusting brand marketing mix instruments, specifically in the CPG industry. For instance, when it comes to promotional activities, retail managers can allow higher retail price-through rates for more expensive national brands. On the other hand, for lower priced national brands – which might be tempted to offer excessive price promotions in difficult economic times – retail managers can decide to set lower retail price-through rates. By doing so, they can maintain brand revenues and possibly increase their profits. Additionally, they can leverage their private label offerings. For example, their new product introduction and packaging could strategically target higher priced brands. Offering premium store brands that copycat the expensive national brands in the category but are priced lower than them could be one way to increase store profit margin as well as forcing brand manufacturers to lower their prices.

Limitations and Directions for Future Research

Our study has several limitations which future research can address. The set of brands that we studied are leading brands that have been around for a relatively long time. It is not clear whether business cycle fluctuations have similar impact on lesser known national brands. On the one hand, such brands do generally spend less on advertising and as such their unique value is likely to be not properly communicated to consumers. On the other hand, these brands are generally less expensive compared to leading national brands and therefore less likely to be affected by increased consumer price sensitivity during difficult economic times. Therefore, our findings might not be generalizable to lesser known brands. Future research should study the impact of business cycle fluctuations on brand equity of lesser known brands.

Our study only focused on consumer packaged goods categories. Although the CPG industry constitute an integral part of any economy, they are very different than other industries (e.g., high tech, financial sector, automobile industry, etc.). Whereas it is easier for consumers to limit their spending on certain durable products (e.g., TV, automobile), in CPG categories, it is more challenging for consumers to limit their purchases during economic slowdowns as these categories are generally considered as essentials (Deleersnyder et al. 2004). Therefore, brands across other industries might be more susceptible to business cycle fluctuations. Moreover, in comparison to other industries (e.g., automobile industry), CPG categories are relatively low in terms of social risk. Relatedly, the measure that we used for social risk had considerably lower variation compared to performance risk. This could explain why our analysis showed no significant difference between low and high social risk categories with respect to the impact of business cycle changes on brand equity. Future research can look into other product categories and industries to uncover additional patterns regarding how brand equity is affected by business cycle fluctuations.

Our research only focused on brand equity in one country; i.e., the UK. Past research shows that importance of brands, brand loyalty, and customers' price sensitivity vary across different countries and cultures (Dawar and Parker 1994; Erdem, Swait, and Valenzuela 2006). Future research should study dynamics of brand equity across different cultures and examine national cultural values (e.g., individualism vs. collectivism) that can moderate the impact of business cycle changes on brand equity. Another area for future research is to investigate different types of customers and their preferences for branded goods in different economic times. Future research can look at the role of personality traits, consumer values, and their attitude towards marketing activities as moderators of the impact of business cycle fluctuations on brand equity.

Previous research by Datta, Ailawadi, and Van Heerde (2017) estimated time-varying brand equity by including both marketing mix instruments and brand-specific *time-invariant* product attributes as predictors. Our model does not account for product attributes but because of the nature of our research questions and the methodology that we adopted, our findings are robust to inclusion/exclusion of time-invariant product attributes. This is because the cyclical component of brand equity which we used for assessing temporary changes in brand equity due to business cycle changes (equation 5) relies solely on temporal changes in brand equity and is not sensitive to the time-invariant portion of brand equity. In other words, including time-invariant product attributes (e.g., size, flavor, and calorie) in the first step will not change the cyclical component of brand equity estimates. Omission of such variables do impact trend component of brand equity estimates. However, due to the presence of unit root in the trend component of brand equity, we first-differenced the trend components (equation 6). The first-differencing makes our inferences robust to omission of time-invariant product attributes. Nonetheless, future research should consider including *time-varying* product attributes to obtain more accurate brand equity estimates. Additionally, previous research shows that the impact of business cycle fluctuations on marketing-related phenomena is different in economic upturns and economic downturns (Lamey et al. 2007). For simplicity, we only calculated one parameter that restricted the impact of economic upturns and economic downturns to be equal. Future research can specify separate parameters for economic expansions and contractions to examine whether the size of these effects vary considerably or not.

Although the intercept method has been frequently used in the past research, it does not paint the whole picture about a brand's equity. Drawing on conceptualization of brand equity as differential customer preference for marketing activities of brands (Keller 1998), to gain a thorough understanding about the impact of business cycle on brand equity, investigating the impact of business cycle fluctuations on changes in a brand's marketing mix effectiveness is warranted. Similar to research by Van Heerde et al. (2013) which looked at the impact of macroeconomic conditions on the effectiveness of brands' price and advertising over time, future research can estimate yearly brand-specific coefficients for advertising, price, distribution, and product line length of the brands and investigate the interplay between changes in marketing mix effectiveness and changes in the intercept term.

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TABLE 3.1: Related research on the impact of business cycles on marketing-related phenomena

Paper	Subject of Interest	Measure of Business Cycles	Moderating Effects	Level of Analysis	Key Findings
Deleersnyder et al. 2004	Sales of Durables	GNP	Product Type, Product Life Cycle, etc.	Industry	Durables are very sensitive to business-cycle fluctuations. Nature of the durable and the stage in a product's life cycle moderate the extent of sensitivity in durable sales patterns.
Lamey et al. 2007	Share of Private Labels	GDP Per Capita	-	Product Category	Private label share behaves cyclically and business cycles have temporary and permanent impacts on private label share.
Deleersnyder et al. 2009	Advertising Spending	GDP	National Culture	Advertising Media	Advertising is sensitive to business-cycles. Advertising behaves less cyclically in countries high in long-term orientation and power distance and low in uncertainty avoidance.
Kamakura and Du 2011	Customer Preferences for Categories	GDP	Type of Goods and Services	Household	For any given consumption budget, expenditure shares for positional goods/services will decrease during a recession, while shares for non-positional goods/services will increase.
Lamey et al. 2012	Share of Private Labels	GDP	National Brands' Marketing	Product Category	Private-label share behaves counter-cyclically. Brands' pro-cyclical behavior regarding new product introductions, advertising, and promotions is associated with more pronounced cyclical changes in PL share.
Gordon, Goldfarb, and Li 2013	Price Elasticity	GDP	Category's Price Sensitivity	Household	Price sensitivity is counter-cyclical and rises when the economy weakens. The relationship between price sensitivity and business cycles correlates strongly with the average level of price sensitivity in a category.
Van Heerde et al. 2013	Advertising and Price Elasticity	GDP	Brand Segments, Product Type	Brand	Long-term price sensitivity decreases during expansions, whereas long-term advertising elasticities increase. These patterns vary across different product categories and brands.
This Study	Brand Equity	GDP Per Capita	Price/Adv. Segments, Product Functional/ Social Risks	Brand	Brand equity behaves cyclically; it increases (decreases) during economic upturns (downturns) and that such changes persist in the long run. Business cycle fluctuations have stronger impact on brand equity in low performance risk categories, for brands that are pricier, and brands that do not advertise a lot.

TABLE 3.2: Focal variables in this study

Variable	Operationalization	Source
Volume Sales (*SALES*)	Total monthly brand volume sales	Kantar Worldpanel
Advertising Stock (*ADSTOCK*)	Smoothed monthly advertising spending: $ADSTOCK_{ijyt}=\alpha\ ADSTOCK_{ijy,t-1}+(1-\alpha)ADV_{ijyt}$	Nielsen Media
Price (*PRICE*)	Weighted average of monthly paid price per volume of brand's SKUs (weighted by SKU monthly volume sales)	Kantar Worldpanel
Product Line Length (*ASSORTMENT*)	Number of distinct SKUs the brand sold during the month	Kantar Worldpanel
Distribution Intensity (*DISTRIBUTION*)	Percentage of retailers that a brand sold during each month (weighted by retailers' volume market share in that product category)	Kantar Worldpanel
Annual Brand Equity ($\widehat{\delta_{ijy}}$)	Portion of yearly brand volume sales that is not explained by its marketing activities and marketing activities of its competitors	Kantar Worldpanel
Brand Equity - Cyclical ($\widehat{\delta_{ijy}^{c}}$)	Cyclical component of annual brand equity estimates that captures temporary variations in brand equity estimates (extracted using Hodrick-Prescott Filter)	Kantar Worldpanel
Brand Equity – Trend ($\widehat{\delta_{ijy}^{trend}}$)	Trend component of annual brand equity estimates that captures permanent trend in brand equity estimates after controlling for temporary fluctuations (extracted using Hodrick-Prescott Filter)	Kantar Worldpanel
Gross Domestic Product Per Capita (*GDPPC*)	Sum of the gross values added of all UK resident and institutional units engaged in production divided by UK's population	World Bank
GDPPC - Cyclical ($GDPPC_{y}^{c}$)	Short term fluctuations in gross domestic product per capita in the UK (extracted from Hodrick-Prescott Filter)	World Bank
Performance Risk (*PERFRISK*) [$\overline{\alpha}$ = 0.79]	Seriousness of consequences of making the wrong purchase in a product category if the purchased product does not deliver its functional objectives, measured by 3 items (1= high performance risk; 0= low performance risk)	TNS and GFK
Social Risk (*SOCRISK*) [$\overline{\alpha}$ = 0.92]	Seriousness of consequences of making the wrong purchase in a product category if the purchased product does not deliver its social/psychological objectives, measured by 3 items (1=high social risk; 0= low social risk)	TNS and GFK
Advertising Segment (*ADVSEG*)	Dummy variable indicating whether a brand's advertising expenditures exceeds median category level advertising expenditures (=1) or not (=0)	Nielsen Media
Price Segment (*PRICESEG*)	Dummy variable indicating whether a brand's price exceeds median category price (=1) or not (=0)	Kantar Worldpanel
Price-Quality Relationship (*PRICEQUAL*) [$\overline{\alpha}$ = 0.79]	The degree by which consumers associate higher price with better product quality in a category, measured by 2 items (1= high price-quality inference; 0= low price-quality inference)	TNS and GFK

TABLE 3.3: Summary of elasticities in the first stage model

Covariates	Estimate	Standard Error	95% Interval of Elasticities
Marketing Elasticities For			
Advertising Stock	0.0516^{***}	0.0026	[0.0465, 0.0566]
Paid Price	-0.6669^{***}	0.0337	[-0.7329, -0.6008]
Distribution Intensity	0.4721^{***}	0.0516	[0.3709, 0.5732]
Product Line Length	0.1623^{***}	0.0225	[0.1182, 0.2064]
Quarter Indicators	Included		
Category Indicators	Included		
Copula	Included		
Number of Observations	30,450		
Number of Brands	150		
Number of Categories	36		

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$

TABLE 3.4: Impact of business cycle fluctuations on brand equity

	Pro-Cyclical (>0)	**Counter-Cyclical (<0)**	**Weighted Mean**	**Meta-Analytic Z**	**Meta-Analytic *p***
Temporary Impact of Business Cycle Fluctuations on Brand Equity (α_{ij1})	137	13	0.8349	12.3554	<0.001
Permanent Impact of Business Cycle Fluctuations on Brand Equity (β_{ij1})	145	5	0.2747	8.9048	<0.001

Weighted means of α_{ij1} and β_{ij1} are weighted by the inverse of their corresponding standard errors. The Meta-Analytic Z-values and one-sided *p*-values are obtained by the method of adding weighted Zs (Rosenthal 1991).

TABLE 3.5: Heterogeneity in temporary and permanent impacts of business cycle fluctuations on brand equity across product categories and brand segments

Covariates	***DV= Temporary Effect of Business Cycle on Brand Equity (α_{ij1})*** Estimate	Standard Error	*p*-value	***DV= Permanent Effect of Business Cycle on Brand Equity (β_{ij1})*** Estimate	Standard Error	*p*-value
Performance Risk [1= High Risk; 0= Low Risk]	-0.2968	0.1779	<0.10	-0.2558	0.0853	<0.01
Social Risk [1= High Risk; 0= Low Risk]	0.0472	0.1861	>0.10	0.0606	0.0788	>0.10
Advertising Segment [1= Heavy Advertisers; 0= Others]	-0.2814	0.1522	<0.05	-0.1076	0.0356	<0.01
Price Segment [1= High Priced Brands; 0= Others]	0.2494	0.1205	<0.05	0.0202	0.0384	>0.10
Intercept	0.9793	0.1762	<0.01	0.3922	0.0748	<0.01
Number of Brands		150			150	
Number of Categories		36			36	

N=150 across both regressions. Since the dependent variables are estimated variables (α_{ij1} and β_{ij1}), we adopt WLS and use inverse of standard errors of (α_{ij1} and β_{ij1}) as weights. One-sided *p*-values are reported. Robust cluster-adjusted standard errors (at the category level) are reported.

FIGURE 3.1: Empirical framework

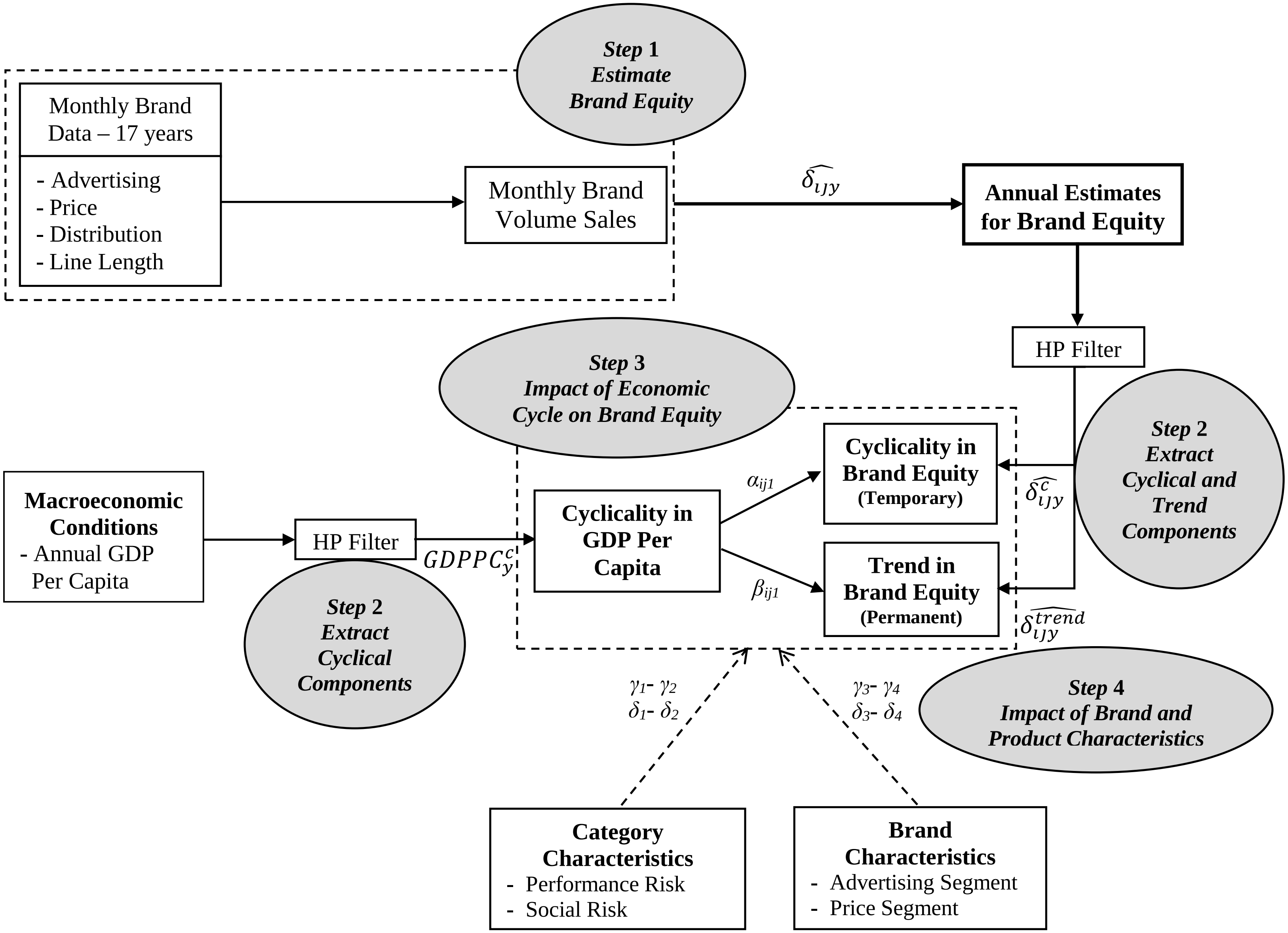


FIGURE 3.2: Brand equity estimates in four product categories

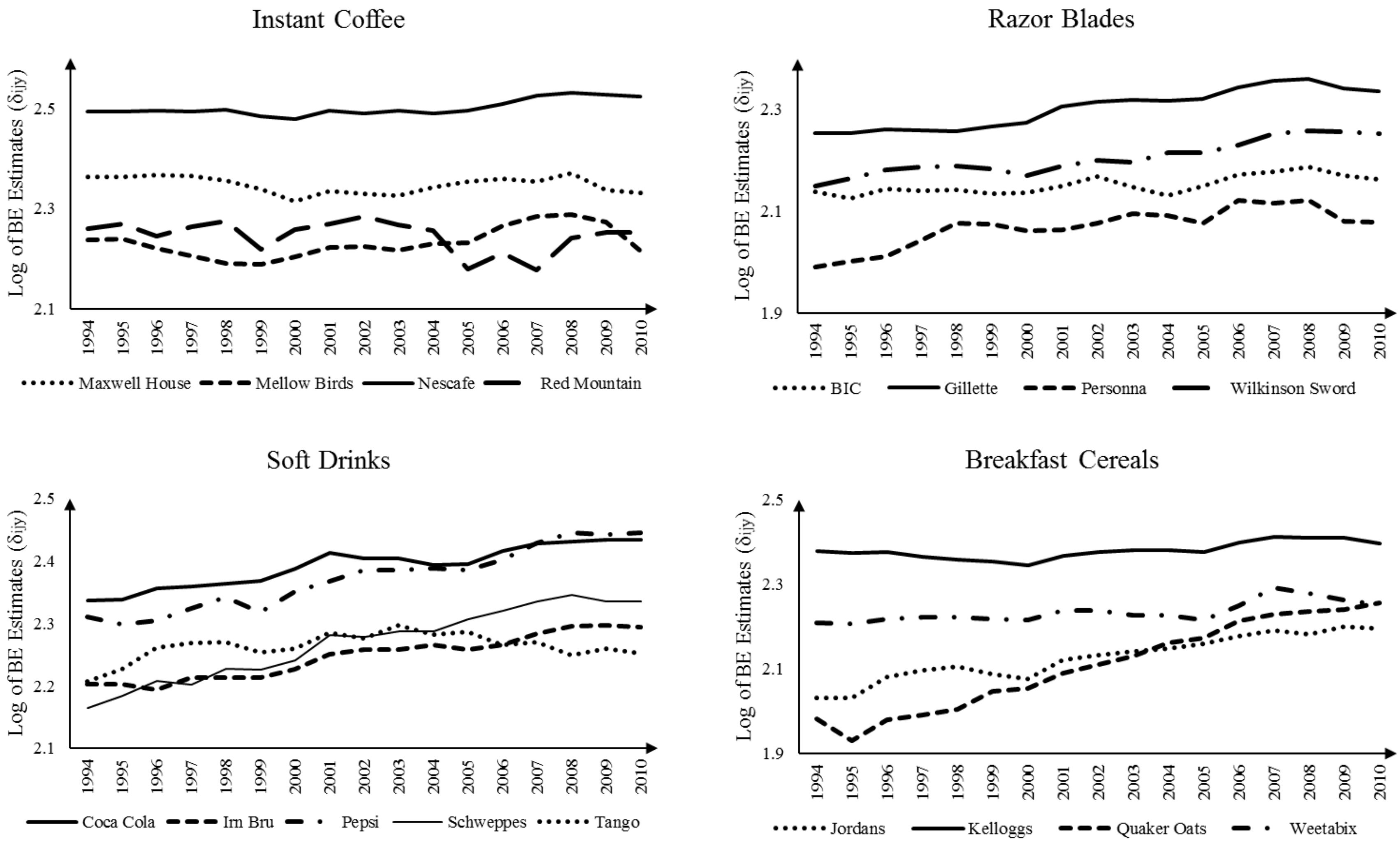
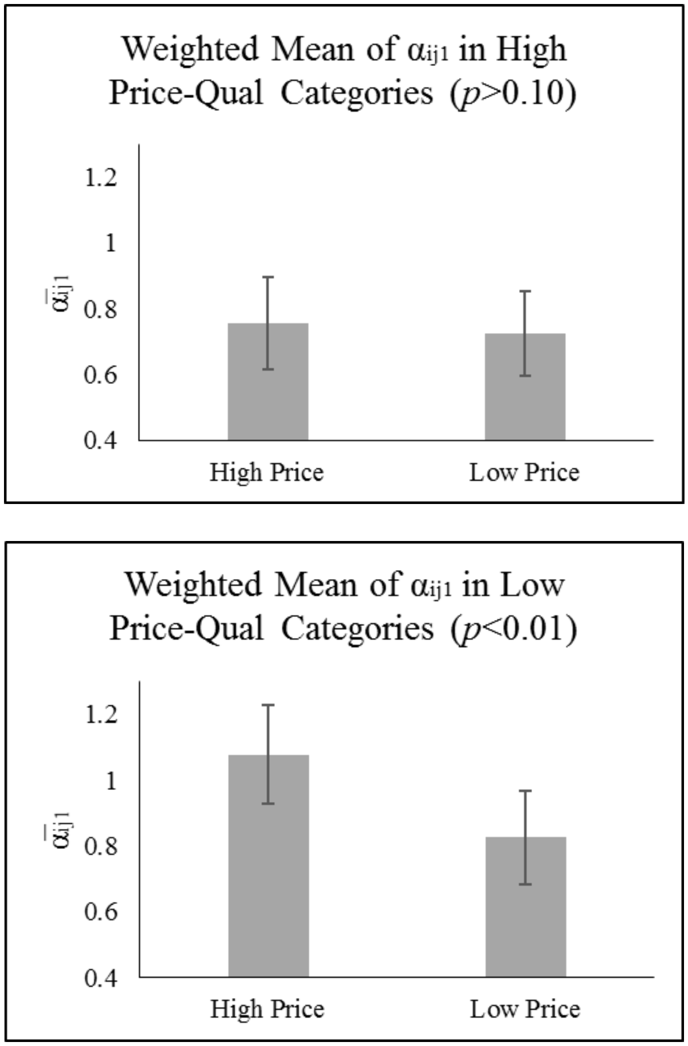


FIGURE 3.3: Compared to low priced brands, high priced brands are more strongly affected by business cycle fluctuations in categories low on price-quality relationship vis-à-vis categories high on price-quality relationship



* Bars represent meta-analytic standard errors.

CHAPTER 4: RECOVERING FROM PRODUCT-HARM CRISIS: HOW RISK FACTORS IMPACT EFFECTIVENESS OF PRICE PROMOTIONS?

Abstract

Over the past decade, number of product-harm crises has increased dramatically. Sales drop, costly lawsuits, and decline in financial value of firms are some of the negative consequences of product recalls. Oftentimes, recalled brands offer price promotions to regain their lost position. However, it is not clear whether price promotions help the recalled brands or add to consumers' suspicions regarding post-recall safety and quality of the brand. In this paper, we study post-recall price promotions as well as investigate country, category, and recall characteristics that influence price promotion effectiveness after recall. We use large multi-country household-scanner panels to empirically examine impact of 143 packaged food recalls in 12 European nations between 2010 and 2013. Findings suggest that the price promotion effectiveness in general increases after recall. However, post-recall price promotions are less effective when recall is associated with severe health concerns, or is in high risk product categories, or occurs in countries high on uncertainty avoidance cultural value. We also discuss the implications for practitioners.

Keywords: Product-harm crisis, Product recalls, Price promotion, Perceived risk, Product category risk, Uncertainty avoidance, Recall severity

Introduction

Product-harm crises are one of the worst nightmares for any manager and can cause serious problems for the affected firms (Cleeren, Van Heerde, and Dekimpe 2013). Product-harm crises are ubiquitous and can happen to any brand, anywhere. Samsung's recent global recall of Galaxy Note 7 phones due to battery explosions, Johnson & Johnson recalling cyanide-laced Tylenol capsules, and Toyota's infamous case of worldwide recall of more than nine million automobiles between 2009 and 2011 are just a few publicized instances of product recalls around the world (Inquisitr 2016).[19]

It is safe to say that no manager wants their brand to be recalled. Unfortunately, in many instances, managers and their firms have limited control over the cause of the recall due to the significant role that external factors – such as suppliers – play in a company's business operations. Thus, recalls are sometimes unavoidable. However, marketing managers can mitigate the negative impact of recalls using tools at their disposal. Marketing managers frequently use marketing mix instruments to discourage brand switching and regain consumer trust (Van Heerde, Helsen, and Dekimpe 2007). In this study, we examine role of price promotion in overcoming negative impact of product-harm crises.

Price promotions are among the most effective demand-stimulating marketing mix instruments, whose effect is evident in the short run. Bell, Chiang, and Padmanabhan (1999, p. 504) summarize it succinctly "Price promotions are used extensively in marketing for one simple reason – consumers respond". Price promotions are specifically attractive in the CPG industry,

[19] Chen, Ganesan, and Liu (2009; p.214) argue that: "Often, the consequence of product-harm crises involves product recalls, in which the implicated firm must retrieve recalled products from all distribution channels and from the end consumer." Since our empirical set up exclusively involves only recalled products, consistent with past research in this domain (see Van Heerde, Helsen, and Dekimpe 2007; Chen, Ganesan, and Liu 2009; Cleeren, Van Heerde, and Dekimpe 2013), we use the terms product-harm crisis(es) and product recall(s) interchangeably.

the empirical setting of this paper. Nowadays, CPG manufacturers spend approximately 75% of their marketing expenditures on sales promotions (Van Heerde and Neslin 2017) with price promotions accounting for half of that spending (Cadent Consulting Group 2017). This is because while advertising elasticity is estimated to be between 0.12 (short-term) and 0.24 (long-term), price promotion elasticity ranges from -3.63 in the short-run to -3.17 in the long-run (Bijmolt, Van Heerde, and Pieters 2005; Sethuraman, Tellis, and Briesch 2011).

Price promotions seem to be especially attractive after recall because they do not require huge up-front investments and, instantly impact brand sales by offering monetary incentives to the price sensitive consumers (Blattberg and Neslin 1990). Despite their attractiveness to the managers of recalled brands, the extant literature has not addressed the impact of price promotions in the context of product-harm crises. In this research, we focus on price promotions and study their impact on brand performance after recall.

Some studies have found evidence for increased price sensitivity after recall due to lower perceived value and utility of the recalled brands (Van Heerde, Helsen, and Dekimpe 2007; Cleeren, Van Heerde, and Dekimpe 2013). However, others have found evidence for decreased price sensitivity because of heightened risk aversion and quality sensitivity after recall (Zhao, Zhao, and Helsen 2011). We reconcile the contradictory findings from previous research by studying moderating role of risk on effectiveness of price promotion after product-harm crises. We take an expansive view on risk in that we investigate the risk associated with the recall event itself (recall severity), risk inherent in the product category (category risk), and the prevailing cultural attitude towards risk in the country where the recall took place (uncertainty avoidance).

We develop hypotheses regarding systematic differences in effectiveness of post-recall price promotions based on severity of recall, product category's risk, and country's uncertainty avoidance. We test our hypotheses using a combination of proprietary as well as publicly available data on several consumer packaged food categories, capturing 143 product recall instances that occurred in 12 European countries over a span of four years (2010-2013). The proprietary dataset has purchases observed in weekly consumer panel across the 12 nations. The countries in our sample are part of the European Union's *General Food Law Regulation* effort which ensures that safety standards and their implementation are uniform across all member nations and all consumer packaged food categories, thereby permitting us to disentangle heterogeneous impact of moderators on the extent of recall impact. We test the effect of product recall on brand market share over a post-recall period of 52 weeks, resulting in 24,025 observations.

We find that the recalled brands experience greater decline in market share when recall is severe, or occurs in categories with high risk or countries high on uncertainty avoidance. We also find that price promotions in general become more effective after recall vis-à-vis pre-recall price promotions. However, while this overall positive effect is weak, we find that there is significant heterogeneity in effectiveness of price promotions depending upon the level of risk. Price promotions are much more effective in clawing back market share if the recall is less severe, involve a product in a low risk category, and in countries low on uncertainty avoidance. Conversely, price promotions are considerably less effective when recall severity is high or recall occurs in high risk categories or in a country high on uncertainty avoidance.

The paper is organized as follows. In the next section we propose our theoretical framework and discuss the research hypotheses. Subsequently, we describe data and methodology followed by our findings. We conclude by discussing theoretical and managerial implications of our research as well as outlining study limitations.

Research Hypotheses

The adverse effect of product-harm crises on firm performance is by now well established. It can cause major losses in brand sales (Van Heerde, Helsen, and Dekimpe 2007), financial value (Chen, Ganesan, and Liu 2009), market share (Rhee and Haunschild 2006; Cleeren, Van Heerde, and Dekimpe 2013), and brand equity (Dawar and Pillutla 2000). Table 3.1 provides an overview of the most pertinent studies (See Table 4.1).

In order to mitigate the fallout of a product recall and avoid excessive damage, firms rely on their marketing mix instruments. Advertising, pricing, and price promotions are among the most accessible marketing mix instruments that a marketing manager can utilize shortly after recall. Previous work has found that heavy post-crisis advertising helps to gain back market share (Cleeren, Van Heerde, and Dekimpe 2013), with advertising being especially effective for stronger brands (Cleeren, Dekimpe, and Helsen 2008). Unfortunately, this is an expensive solution as the effectiveness of advertising is lower post-crisis than pre-crisis (Van Heerde, Helsen, and Dekimpe 2007). There is some evidence in previous research suggesting that customers become more price sensitive towards a recalled brand and as such, lowering price could be helpful to recalled brands (Van Heerde, Helsen, and Dekimpe 2007). However, many firms are reluctant to reduce prices permanently because of the strong adverse effect on profit (Marn, Roegner, and Zawada 2003). Accordingly, anecdotal evidence suggests that managers turn to price promotions - temporary and short-term reductions in price - to encourage customers to retry products after the recall. For example, after the Volkswagen emission scandal, the German auto manufacturer offered large discounts to avoid losing customers (Bloomberg 2015). However, it is not clear whether such discounts help the recalled brands or make customers even more suspicious about the recalled brand's intentions. Hence, we extend this burgeoning stream of research on post-recall marketing effectiveness by focusing on price promotions.

Price Promotion

There has been a rich body of literature in marketing on the effects of price promotions on consumer attention, purchase reinforcement, consumer loyalty, and consequently on brand performance (Blattberg and Neslin 1990). Primary demand effects (category purchase timing acceleration and increase in purchase quantity) and secondary demand effects (brand switching) are the two main mechanisms by which price promotions improve brand sales during regular purchase occasions (Van Heerde, Gupta, and Wittink 2003).

After recall, price promotions create awareness about the recalled brand's comeback (Van Heerde, Helsen, and Dekimpe 2007). It has further been argued that when consumers are exposed to negative information about a brand, the brand's perceived utility and credibility is reduced (Ahluwalia, Burnkrant, and Unnava 2000; Van Heerde, Helsen, and Dekimpe 2007), thereby causing consumers to become more price and discount sensitive (Boulding, Lee, and Staelin 1994; Erdem, Swait, and Louviere 2002). Accordingly, Cleeren, Van Heerde, and Dekimpe (2013) argued that consumers become more price-sensitive towards a recalled product and Van Heerde, Helsen, and Dekimpe (2007) found evidence for increased price elasticity of some recalled products. As a result of increased price sensitivity, post-recall price promotions will be more effective in increasing market share vis-à-vis price promotions offered before recall.

Conversely, another stream of research has suggested that price promotions might adversely impact consumer learning and brand performance. As Blattberg and Neslin (1989, p. 86) pointed out, "promotion may result in negative attribution regarding the reasons the company is promoting the brand". Hence, price promotions might make consumers suspicious about intentions of the promoted brand. This might be especially true in the post-recall period when consumers are uncertain about the recalled brands and their intentions. Consumers might presume that the brand is trying to get rid of its unwanted products by offering discounts. Consistent with this argument, Zhao, Zhao, and Helsen (2011) theorized and found that consumers become more risk averse and quality sensitive, and less price sensitive after recall. Therefore, consumers are less likely to be receptive to price promotions offered by the recalled brand. As such, according to the risk aversion perspective, post-recall price promotions will be less effective in increasing market share vis-à-vis price promotions offered in pre-recall periods. We therefore test competing hypotheses suggested by each argument:

> *H1a: Price promotion for the recalled brand is more effective in the post-recall period than in the pre-recall period. (Increased price sensitivity argument)*
>
> *H1b: Price promotion for the recalled brand is less effective in the post-recall period than in the pre-recall period. (Increased risk aversion argument)*

<u>The Role of Risk Perception</u>

Previous research suggests that post-recall brand performance and post-recall effectiveness of marketing mix instruments vary considerably depending on the nature of the recall and the context in which the product was recalled (Chen, Ganesan, and Liu 2009; Cleeren, Van Heerde, and Dekimpe 2013). Product recalls are associated with heightened ambiguity and uncertainty for consumers. Consumers feel uncertain about post-recall safety and quality of a recalled brand. They might also have doubts regarding possible reoccurrence of similar failures in the future. Accordingly, an important factor that influences consumer behavior after recall is the degree of perceived risk, defined as “a combination of uncertainty plus seriousness of outcome involved” (Bauer 1967, p. 391).

Not all recalls are similar with respect to the uncertainty and seriousness of their possible outcomes. Listeria contamination in dairy products that result in illness and death, or recalls in product categories with higher perceived risk (e.g., baby food) are associated with considerable outcome uncertainty and seriousness. Such recalls generate significant risk for consumers. This might in turn result in a more severe consumer reaction towards the recalled brand and resistance towards its promotional activities. Moreover, cultural factors influence the way a consumer processes information and perceives uncertainty and ambiguity (Hofstede, Hofstede, and Minkov 2010). As such, post-recall brand performance and marketing effectiveness is likely to vary across different recalls, categories, and countries. Our conceptualization recognizes all three forms of perceived risk, to which we now turn. We discuss the role of perceived risk at the recall level (severity of recall), category level (product category risk), and country level (uncertainty avoidance) in shaping post-recall brand performance and the effectiveness of price promotions to mitigate the adverse consequences of the recall.

Recall Severity

There is considerable heterogeneity in the degree of risk that different recalls create for consumers. Some recalls are associated with illnesses, injuries, and even deaths. Tylenol's infamous painkiller recall due to cyanide-laced capsules in 1982, faulty acceleration pedals that resulted in extensive Toyota recalls in between 2009 and 2011, and salmonella outbreak that led to recall of products containing peanut and subsequently bankruptcy of Peanut Corporation of America are all examples of product recalls that were associated with numerous severe illnesses and deaths (Time 2009). Other recalls do not present such direct health risks for consumers. For example, in 2013, numerous brands had to recall frozen ready meals and frozen hamburgers across multiple European countries because several suppliers sold manufacturers horsemeat instead of beef (BBC 2013). Eating horsemeat is a taboo in some cultures but is not harmful for consumers. Similarly, in many recall instances, products are recalled because of wrong labeling or presence of undeclared ingredients.

Consumers are generally risk averse (Erdem, Zhao, and Valenzuela 2004) and are more likely to avoid a brand if it is associated with a severe recall. As a result, such brands are expected to experience stronger decline in sales after recall. This by itself is not surprising. More interesting is how severity of the recall affects the effectiveness of price promotions after recall to mitigate the fallout. Risk averse consumers are also likely to ignore marketing activities and promotional efforts of brands associated with recalls involving severe health concerns. Even if brand involved in a severe recall is offering considerable price discounts after recall, consumers might feel that the possible negative outcomes (i.e., death, illness) outweighs the utility that they get from purchasing and consuming a product on promotion. Some may even be suspicious about the brand's intentions, and interpret heavy promotion as a sign of desperation (see Kirmani and Wright 1989 for a similar argument in the context of advertising). Hence, post-recalls price promotions are expected to be less effective when recall severity is high:

H2: Post-recall market share of recalled brands will decline more (less) when recall is severe (not severe).

H3: Post-recall price promotions will be less (more) effective at regaining lost market share when recall is severe (not severe).

<u>Product Category Risk</u>

Product category risk has been defined as "customers' perceptions of uncertainty and adverse consequences of buying a good" (Dowling and Staelin 1994, p. 119). Jacoby and Kaplan (1972), Bettman (1973), Kaplan, Szybillo, and Jacoby (1974), and Laurent and Kapferer (1985) were amongst the first to study product category risk. These studies showed that product categories differ in the degree of perceived risk. For example, toothpaste is seen as less risky than deodorant (Kaplan, Szybillo, and Jacoby 1974), and detergents as less risky than yogurt (Laurent and

Kapferer 1985). Other studies have extensively looked at the consequences of product category risk. It has been found that product category risk influences consumers' information search (Dowling and Staelin 1994), willingness to pay (Tsiros and Heilman 2005), new product adoption (Ostlund 1974), and transaction channel adoption (Kushwaha and Shankar 2013).

When a product-harm crisis erupts, there is a lot of uncertainty associated with the recalled product. Consumers might have doubts regarding product safety and possibility of similar failure in future. In categories with low risk, product failure is not associated with great losses for consumers. For example, if a pen fails to perform to expected standard, the performance consequence, financial loss, possibility of physical harm, or risk to psychological and social image of the buyer is low. As a result, the limited uncertainty and seriousness associated with failure of a low risk product after its recall will only disturb consumers to a small extent. In that case, if consumers are faced with price promotions offered by the recalled brand, since the additional financial benefit is likely to outweigh the small negative loss due to possible product malfunction, consumers might buy the recalled brand on promotion. However, a possible product failure in categories with high risk might result in significant losses for consumers. For instance, if a baby food product is damaged, it might have catastrophic outcomes. In such scenarios, the risk averse consumers are more likely to avoid the recalled product because the expected losses associated with product failure are enormous. Similarly, in high risk categories, the financial benefits of purchasing a brand on discount is unlikely to outweigh the possible expected losses. As such, post-recall price promotions are expected to be less effective in product categories with higher risk than in categories with low risk:

H4: Post-recall market share of recalled brands will decline more (less) when product category risk is high (low).

H5: Post-recall price promotions will be more (less) effective at regaining lost market share when product category risk is lower (higher).

Uncertainty Avoidance

It is well-established in the marketing literature that consumer behavior varies systematically across different countries as a function of their national cultural values (De Mooij and Hofstede 2011). For the purposes of this paper, our interest is in cross-cultural differences in perceptions regarding risk and uncertainty, and the inherent motivation to avoid ambiguity, called uncertainty avoidance in the literature. Uncertainty avoidance is defined as "the extent to which people feel threatened by uncertainty and ambiguity and try to avoid these situations" (Hofstede 1991, p. 113). High uncertainty avoidance cultures embrace predictability and stability. In contrast, cultures with low uncertainty avoidance accept uncertainty more readily and are more willing to take risks. Latin American countries, as well as Eastern European countries score high on uncertainty avoidance whereas Nordic countries score low on this cultural dimension. Uncertainty avoidance has been shown to influence information exchange behavior (Dawar, Parker, and Price 1996), consumer innovativeness (Steenkamp, Hofstede, and Wedel 1999), brand image success (Roth 1995), advertising appeals (Albers-Miller and Gelb 1996), consumption of processed food (De Mooij and Hofstede 2002), and willingness to use credit (Petersen, Kushwaha, and Kumar 2015).

What does uncertainty avoidance suggest in the context of product recalls? Cultures high on uncertainty avoidance embrace predictability and avoid risk and ambiguity. Consumers in these countries are motivated to reduce risks in their purchase decision making process. Hence, they are more likely to avoid a recalled brand as it is associated with risk and uncertainty. Similarly, in high uncertainty avoidance countries, even if a recalled brand offers price promotions, consumers will have a greater tendency to avoid the recalled brand as the financial benefit is likely to be less than the expected utility associated with purchasing a recalled product.

Conversely, consumers in cultures with low uncertainty avoidance are less risk averse and more likely to accept uncertainty. Hence, in these countries, consumers have lower proclivity to avoid the uncertainty associated with purchasing a recalled product. Moreover, since the expected loss of purchasing a recalled product is weighed less heavily, the utility that consumers derive from purchasing the recalled product on price promotion is likely to outweigh the expected loss of purchasing a recalled product. As such, post-recall price promotions are expected to be more effective in low uncertainty avoidance countries than in high uncertainty avoidance countries:

H6: Post-recall market share of recalled brands will decline more (less) in countries high (low) on cultural uncertainty avoidance (UA).

H7: Post-recall price promotions will be more (less) effective at regaining lost market share in countries low (high) on cultural uncertainty avoidance (UA).

Data

Our hypotheses are tested in the context of brand recalls in consumer packaged food industry in Europe. We acquired three types of data from multiple sources - recall instances, country/category specific variables, and sales data.

Identifying Recall Instances

As for the recall instances, we primarily used the Rapid Alert System for Food and Feed (RASFF) database. RASFF provides information about all food related notifications in the EU countries. RASFF was created in 1979 to share information between European nations. The RASFF database has historic information about any notification issued with regards to food safety in European countries. The database provides information on the exact date of notification, country which notified the database, countries where affected products were distributed in, countries from where affected products were sourced, specific reason for concern, and subsequent recommended actions. Specifically, we selected instances where the affected products were recalled from consumers. These constitute events with most significant concern since the affected products have already reached the store shelves and are being purchased by consumers. Such instances require the firm to issue recall notices to consumers and retailers which sell their products. We used recall notifications issued between January 2010 and December 2013.

It is worth noting that under EU regulations (EC No 178/2002 referred to as the *General Food Law Regulation*), the recall criterion is unified across all EU members (European Commission 2017). RASFF provides a system for immediate exchange of information between member countries in cases of risks to human health deriving from food and feed, in order to facilitate a coordinated response to food safety threats. Responsible individuals (i.e., national contact points) that are identified by RASFF have to contact RASFF headquarters if they become aware that a product does not comply with the EU food safety regulation. If needed, RASFF officials will then contact all countries in which the affected products were distributed (RASFF 2009). Hence, the same product defect would result in recall in all the countries under the RASFF system, irrespective of the country-specific characteristics (e.g., effectiveness of a country's regulative system).[20] This characteristic ensures that our recall instances are exogenous with regards to the country specific characteristics.

The RASFF database does not name the affected firms and brands. To identify the affected brands we used an independent database "Red24" and did extensive search in Lexis-Nexis,

[20] It should be noted that if brand X is recalled in country A, and is at the same time distributed in other European countries such as country B, recall in country A does not necessarily imply recall in country B, even though the criteria for recall is the same across both countries. There could be several reasons for this. First, the recalled product SKUs might not be distributed in country B. Second, even if the exact SKU exists in country B, it is possible that it is not affected by the same problem because of the supply chain differences across countries.

Factiva, and Google.[21] These searches were conducted in the local language of the nations in which the recalls had occurred. After matching with sales data, 81 distinct voluntary food recall instances across 12 European countries were retained.[22] However, some recalls affected more than one brand, category, or country (e.g., the horsemeat scandal in 2013 affected multiple brands in different categories such as pasta, frozen burgers, frozen ready meals across 13 European countries). Resultantly, our dataset covers 143 brand-category-country recall instances.[23] The 143 recall instances occurred in 24 distinct food categories such as beer, frozen pizza, baby food, cheese, candy bars, juice, pasta, and yogurt. In Table 4.2, we describe some recall instances covered in our dataset (See Table 4.2).

<u>Brand Performance and Price Promotion</u>

To test our hypotheses we obtained household panel data from Europanel in 12 European countries (Austria, Belgium, Denmark, France, Germany, Hungary, the Netherlands, Poland, Portugal, Spain, Sweden, and the UK). For most countries, the sales data covered the 2010-2013 period (France and Denmark were missing the 2013 data, and for Poland, and Hungary data started at the beginning of 2011). The data was available in 71 category-country combinations (i.e., an average of about six food categories per country). Sales data were obtained from the household panels Europanel operates in these countries. Panelists used a handheld scanner to scan each UPC and enter the price they paid for the item. Therefore, we observe household id, UPC, number of items bought, and price paid by the panelist.

[21] Red24 is a London based independent risk assessment agency, which tracks events, which can impact risk borne by corporations such as product recalls, identity thefts, and impact of political crisis.

[22] As noted by Chen, Ganesan, and Liu (2009, p. 216) and Cleeren, Van Heerde, and Dekimpe (2013, p. 72) almost all recalls in the CPG industry are voluntary recalls.

[23] Hereinafter, we refer to 143 brand-category-country recall combinations as the 143 recall instances.

We constructed weekly market share, price per volume, and price promotion variables for each SKU and subsequently each brand. Using list price and volume of each SKU, we calculated its weekly price per volume. Following Gielens (2012), if SKU *i*'s observed price at week *t* was at least half a standard deviation lower than its average list price (defined over a one-year moving window), we defined that there was a price promotion for SKU *i* in that week. In such cases, price promotion was calculated by dividing average weekly promotional price of SKU *i* by its average list price. We aggregated data to the brand level (see Cleeren, Van Heerde, and Dekimpe 2013; Van Heerde, Helsen, and Dekimpe 2007 for similar practice).

Recall Severity

Food recalls happen for various reasons. Some of them are associated with severe health concerns, but others do not pose risk for human health. The U.S. Food and Drug Administration (FDA) categorizes recalls into three categories based on their likelihood of causing adverse health consequences (FDA 2009). An equivalent standardized categorization does not exist across European countries (Varallo 2016). Similar to the FDA categorization, we distinguished between recalls that are associated with severe health problems and recalls that are unlikely to cause any adverse health reactions. The former group consists of recalls associated with listeria, salmonella, E.coli, and other bacteria and allergens. The latter category consists of recalls due to the presence of safe undeclared ingredients, container/package defects, and wrong labeling. In our data, 41% of the recall instances (58 out of 143) are categorized as severe recalls (See Figure 4.1). This is comparable to the FDA statistics that show about half of recalls are not associated with severe health concerns (Gendel 2016).

Product Category Risk

We obtained perception measures on category risk for the product categories in our study from the global research agencies GfK and Kantar Worldpanel. Category risk was measured *before* all recall instances in our data and was operationalized using three items (See Table 4.3). The survey data was collected in each country in our sample. The questionnaire was developed in English and back-translated into local languages of the corresponding countries. Respondents were responsible for grocery purchases in their household. Each respondent answered questions regarding up to four product categories in which they had made at least one purchase during the six months before the survey was conducted. The samples in each country were drawn to be representative of country's education and age. On average, in each country, 52 respondents completed survey for each product category. It is also worth noting that product category risk varies not just by category but also across countries, i.e. same product category could have different risk across different countries.

In cross-national research, it is necessary to establish measurement invariance across countries (Steenkamp and Baumgartner 1998). We assessed metric invariance of product category risk across the 12 countries in our dataset.[24] The fit of the metric invariance model was good ($\chi^2_{(22)} = 272.8$, $p < 0.001$; RMSEA = 0.057; CFI = 0.990; TLI = 0.984). Therefore, we averaged scale items to obtain a composite score for product category risk.

Uncertainty Avoidance

Country scores on uncertainty avoidance were taken from Hofstede, Hofstede, and Minkov (2010). Scores are on a scale from 0 (low uncertainty avoidance) to 100 (high uncertainty

[24] Since we mean-center product category risk within countries, scalar invariance is not required (Steenkamp and Baumgartner 1998).

avoidance).[25] Figure 4.2 illustrates that we have considerable variation in uncertainty avoidance scores across the 12 countries in our sample (See Figure 4.2).

Control Variables

We include several control variables to account for heterogeneity across brands and product categories. Private labels have been traditionally regarded as products with lower quality and worse brand performance vis-à-vis national brands but a recent trend is a major growth in market share of private labels across the world and specifically in European countries (Steenkamp and Geyskens 2014). In some countries such as Switzerland, Spain or the UK, private label sales account for more than 40% of overall category sales. We use a dummy variable to control for the effect of private labels. Brand price and line length were included as brand-specific controls. Increase in price per volume of a brand is most likely to result in market share decline whereas offering more SKUs will increase a brand's market share (Dhar, Hoch, and Kumar 2001). Line length was measured at the yearly level and captures the total number of different SKUs the brand sold during that year. We normalize brand price and line length by dividing price (line length) of the recalled brand by the average price (line length) of all the non-recalled brands in the category (Cleeren, Van Heerde, and Dekimpe 2013). To account for heterogeneous brand performance due to competitive intensity we used the Hirschman-Herfindahl Index. It was measured at the weekly level by squaring the volume market share of all the brands in a category (multiplied by -1 so that higher values indicate more competition). We also control for the number of brands in a category and promotional activity by other brands in the category. We also distinguish between whether a recall affected one or multiple countries. Consistent with previous

[25] Some countries might rate higher than 100 or lower than 0 because they were measured after the original scale was defined.

research (Cleeren, Van Heerde, and Dekimpe 2013), we control for differences between beverages and other product categories. Variables, their operationalization and summary statistics are reported in Table 4.3 (See Table 4.3).

Model and Estimation

We use a panel data regression framework to assess the impact of promotion and moderating role of recall severity, product category risk, and uncertainty avoidance on the effect of price promotion on market share of recalled brand *i* in category *j* in country *k* at week *t*. Our random-effects model specification follows:

$$
\begin{aligned}
(1)\ MS^{*}_{ijkt} = {} & \gamma_0 + \gamma_1 REC_{ijkt} + \gamma_2 REC_{ijkt} \times PROM_{ijkt} + \gamma_3 REC_{ijkt} \times SVR_{ijk} \\
& + \gamma_4 REC_{ijkt} \times CATRISK_{jk} + \gamma_5 REC_{ijkt} \times UA_k + \gamma_6 REC_{ijkt} \times SVR_{ijk} \times PROM_{ijkt} \\
& + \gamma_7 REC_{ijkt} \times CATRISK_{jk} \times PROM_{ijkt} + \gamma_8 REC_{ijkt} \times UA_k \times PROM_{ijkt} + \gamma_9 PROM_{ijkt} \\
& + \gamma_{10} CATRISK_{jk} + \gamma_{11} UA_k + \gamma_{12} CATRISK_{jk} \times PROM_{ijkt} + \gamma_{13} UA_k \times PROM_{ijkt} \\
& + \gamma_{14} PRICE_{ijkt} + \gamma_{15} SKU_{ijkt} + \gamma_{16} PL_{ijk} + \gamma_{17} BRNUM_{jkt} + \gamma_{18} COMP_{jkt} \\
& + \gamma_{19} OPROM_{ijkt} + \gamma_{20} MULT_{ijk} + \gamma_{21} BVRG_j + \sum_{q=22}^{24} \gamma_q\, QTR_t + \widehat{Copula}_{ijkt} + u_{ijk} + \varepsilon_{ijkt}
\end{aligned}
$$

where MS_{ijkt}^{*} is logit-transformed volume market share of brand *i* in category *j* in country *k* at week *t*.[26] *REC* is a dummy variable indicating whether the brand is recalled and it takes a value of one for 52 weeks (1 year) after the recall happens, otherwise it gets a value of zero. Therefore, γ_1 is the main effect of product recall on market share, averaged across 52 post-recall weeks, after controlling for other effects. The choice of a one year recall window is consistent with previous product recall research and allows us to capture short-term as well as long-term effects of recall (Cleeren, Van Heerde, and Dekimpe 2013). γ_2 represent the difference in price

[26] Since market share values are bounded by 0 and 1, we applied logit transformation on *MS*. The logit transformation yields the following dependent variable: $MS_{ijkt}^{*} = ln(MS_{ijkt} / 1\text{-}MS_{ijkt})$. We add a small positive constant to market share to avoid taking log of 0.

promotion effectiveness after recall vis-à-vis before recall. Thus, γ_2 tests the competing hypotheses H1a and H1b. γ_3, γ_4, and γ_5 respectively represent the moderating impact of recall severity, product category risk, and uncertainty avoidance on recall's impact on market share. Thereby, γ_3, γ_4, and γ_5 test H2, H4, and H6, respectively. γ_6, γ_7 and γ_8 represent the moderating effect of risk factors (recall severity, product category risk, and uncertainty avoidance) on the impact of price promotion on brand market share after recall. Therefore, γ_6, γ_7 and γ_8 test H3, H5, and H7 respectively. The main effects of price promotion (*PROM*), product category risk (*CATRISK*), and uncertainty avoidance (*UA*) are captured via γ_9, γ_{10}, and γ_{11}, respectively.[27] Note that there is no conceptual reason to include the main effects of product category risk or uncertainty avoidance as it tests whether the market share of a brand before the recall is higher or lower dependent on *CATRISK* and *UA*. We only include them for proper interpretation of the interaction terms (Cohen et al. 2003), and thus, they should be considered as control variables. *PL* is a dummy variable indicating whether the focal brand is a private label or a national brand. *BRNUM* captures number of brands and *COMP* represents the level of competition density in the category which the recalled brand belongs to. We also control for the level of promotional activity carried out by other category members by including *OPROM* in our model. *MULT* indicates whether the recall affected one (*MULT* = 0) or more countries (*MULT* = 1). To account for potential sales trends (i.e., seasonality) we include quarterly (*QTR*) dummies in our model (Van Heerde, Leeflang, and Wittink 2001). ε_{ijkt} is normally distributed random error component. Unobserved recall-specific heterogeneity is controlled by the random effect u_{ijk}.

In our dataset we have 143 brand-category-country recall instances and 24,025 observations. This provides us enough degrees of freedom to test our hypotheses. We mean-center the

[27] Note that we did not include the variable recall severity (SVR) as standalone term as it adds no information since it is perfectly correlated with *REC**SVR*. In other words, *REC**SVR* captures the main effect of severity.

continuous variables within countries and grand mean-center uncertainty avoidance for ease of interpretation of the interactions (Cohen et al. 2003). We use STATA 14.0 for model estimation.

Empirical Challenges

Price promotion activity of a brand is not set randomly. Strategic considerations, related to brand's performance, could influence a manager's decision to set brand's price promotion level. For example, common demand shocks such as seasonality effects might simultaneously affect the level of price discount offered by a brand as well as its performance. We account for such demand shocks by including quarterly fixed effects (*QTR*). However, shorter (daily, weekly, or monthly) demand shocks might not be captured by quarterly fixed effects. Demand shocks could also vary across categories and countries. Moreover, without accounting for endogeneity, our estimates might be biased due to omission of other variables. For example, if advertising – which is now a part of the error term – is correlated with price promotion, then our estimates for price promotion (and its interactions) are possibly biased.

In order to account for endogeneity of price promotion and partial out the exogenous variation in *PROM*, we implement Gaussian copulas. In this approach, we directly model the joint distribution of the error term and the endogenous variable (*PROM*) through a control function variable (Park and Gupta 2012). Hence, this method does not require instrumental variables, and has been used extensively in marketing to resolve endogeneity issues (see Burmester et al. 2015; Datta, Foubert, and Van Heerde 2015; Datta, Ailawadi, and Van Heerde 2017). In this approach, it is assumed that the potentially endogenous variable consists of an exogenous part (that is non-normally distributed) and an endogenous part (that is normally distributed). Therefore, this method only works if the endogenous variable is not normally distributed. We checked for normality of *PROM* using the Shapiro-Wilk test. Normality of

PROM was strongly rejected ($W_{PROM} = 0.69$, $p < 0.001$). We estimated the copula term by calculating inverse of the cumulative normal distribution function of *PROM*, and added the copula correction term ($\widehat{Copula}_{ijkt}$) to the main model as control function.

In time-series panel data sets, serial autocorrelation might lead to biased standard errors. Consistent with prior research (Mizik and Jacobson 2009; Rego, Billett, and Morgan 2009), we address possible heteroskedasticity and serial auto-correlation in our panel data by estimating cluster-adjusted robust standard errors at brand level which relaxes the assumption of error independence and allows for correlation between observations belonging to the same brand (Wooldridge 2003; Hoechle 2007). Multicollinearity is another possible empirical concern that could lead to wrong estimates. However, all variance inflation factors (VIFs) in our final model are below 10 (average VIF is equal to 2.3).

Results

Model Fit

We apply an incremental model building approach (See Table 4.4). We start with a simple model with only unobserved heterogeneity controls: quarterly and beverage fixed effects, and recall-specific random effects (M1). We then add all the substantive control variables to our model (M2), which yields a significant improvement in model fit ($\Delta Dev_{(12)} = 3{,}868.8$, $p < 0.01$). Next, recall's main effect and its two-way interactions are added to the model (M3: $\Delta Dev_{(6)} = 351.6$, $p < 0.01$) indicating that recall and its interactions explain the variation in brand market share. To build the model specified by equation 1, three-way recall interactions are then added to the model (M4: $\Delta Dev_{(3)} = 84.4$, $p < 0.01$) indicating that recall severity, product category risk, and uncertainty avoidance explain the variation in post-recall price promotion effectiveness. As it can be seen in Table 4.4, comparing AIC and BIC between models leads to the same conclusion that the blocks of variables added to the model contribute to its explanatory power.

Hypothesis Testing

Parameter estimates for M4 are reported in Table 4.5 (See Table 4.5). The main effect of recall is γ_1 = -0.129 ($p < 0.01$). It shows that after controlling for brand, category, and country level main effects and interactions, market share of recalled brands is on average 0.42 percentage points lower during the 52 weeks following the recall incidence.[28] Understanding and interpreting two-way and three-way interaction coefficients can be challenging. In order to enhance the interpretability of results, we use interaction plots. Unless stated otherwise, we plot predicted market shares for the mid 80 percentile values of our focal variables (excluding top and bottom 10 percentile values) while setting all other variables to their mean values.

H1a and H1b concern the effectiveness of price promotion after recall and its comparison with the effectiveness of promotions at regular (pre-recall) times. The coefficient for *REC*PROM* is positive and significant (γ_2 = 1.350; $p < 0.10$), which provides support for H1a (argument that product-harm crisis increases price sensitivity). We find that after controlling for the risk-related factors, price promotion effectiveness increases in the post-recall period vis-à-vis pre-recall. Figure 4.3 indicates that if the recalled brand offers heavy price promotion, it can reach its pre-recall market share level (See Figure 4.3). As such, price promotions can help recalled products overcome negative consequences of the crisis.

The coefficient for *REC*SVR* (γ_3 = -0.189; $p < 0.01$) indicates that severe recalls lead to larger drop in brand market share compared to non-severe recalls. Figure 4.4a further elaborates

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[28] We use reverse logit transformation to get market share numbers. $MS^*_{ijkt} = \exp\left(\widehat{MS}^*_{ijkt}\right)/(1+\exp\left(\widehat{MS}^*_{ijkt}\right))$, where MS^*_{ijkt} is predicted logit transformed market share. Unless indicated otherwise, market share predictions are made at the mean level of predictors.

this point (See Figure 4.4). The average predicted market share of a recalled brand in our data set before recall is 3.62%, whereas post-recall predicted market share of a brand embroiled in a severe recall is 2.90% (i.e., 0.72% drop in market share during the 52-weeks after recall). Conversely, predicted post-recall market share of brands associated with a non-severe recall is only 0.15 percentage points lower than the pre-recall period. This supports H2.

The coefficients for *REC***CATRISK* (γ_4 = -0.107; $p < 0.05$) and *REC***UA* (γ_5 = -0.003; $p < 0.01$) are both negative and significant. This suggests that post-recalled brand market share is lower when recall occurs in a category with high risk or in a country high on uncertainty avoidance. Hence, H4 and H6 are supported. As it can be seen in Figure 4.4b, post-recall predicted market share of recalled brands in categories with high risk is 0.24 percentage points lower than recalled brands in low risk categories. Similarly, Figure 4.4c shows that post-recall predicted market share of brands recalled in high uncertainty avoidance countries is 0.40 percentage points lower than that of brands recalled in low uncertainty avoidance countries.

While in general price promotion effectiveness increases after recall, not all recalled brands benefit from increased price promotion effectiveness after recall. The three coefficient estimates for *REC***SVR***PROM* (γ_6 = -1.531; $p < 0.05$), *REC***CATRISK***PROM* (γ_7 = -2.761; $p < 0.05$), and *REC***UA***PROM* (γ_8 = -0.020; $p < 0.10$) are all negative and significant. Figure 4.5 further elaborates this finding (See Figure 4.5). In Figure 4.5a, we compare post-recall price promotion effectiveness for severe and non-severe recalls. In Figure 4.5b, post-recall price promotion effectiveness in low risk categories (i.e., one standard deviation below the mean of *CATRISK*) and post-recall price promotion effectiveness in high risk categories (i.e., one standard deviation above the mean of *CATRISK*) are compared. Finally, in Figure 4.5c, we compare post-recall price promotion effectiveness in low uncertainty avoidance countries (i.e., one standard deviation below the mean of *UA*) and post-recall price promotion effectiveness in high uncertainty avoidance countries (i.e., one standard deviation above the mean of *UA*). As it can be seen across the three scenarios, post-recall price promotions for non-severe recalls, recalls in low risk categories, and recalls in low uncertainty avoidance countries have steeper slopes and therefore are more effective in recapturing market share vis-à-vis post-recall price promotions for severe recalls, recalls in high risk categories, and recalls in high uncertainty avoidance countries, respectively. Hence, H3, H5, and H7 are supported. We will subsequently discuss the implications of the effect sizes in the managerial implications section.

Control Variables

The estimates for the control variables are in the expected direction hence adding to the validity of our analysis. A recalled brand's market share is negatively affected by its price (γ_{14} = -0.046, $p < 0.01$) and by price promotion activity offered by other brands in the same category (γ_{19} = -1.720, $p < 0.01$), and positively affected by its own price promotion activity (γ_{9} = 1.492, $p < 0.01$) and line length (γ_{15} = 0.067, $p < 0.01$). Recalled private labels in our dataset have a higher market share than recalled national brands (γ_{16} = 0.524, $p < 0.01$). The number of brands and competitive intensity negatively impact the market share of recalled brands (γ_{17} = -0.003, $p < 0.01$, γ_{18} = -1.024, $p < 0.01$). Multi-country recalls compared to single country recalls are not associated with different brand performance after recall (γ_{20} = 0.004, $p > 0.10$). Our estimates for main effects of product category risk (γ_{10} = -0.091, $p > 0.10$), uncertainty avoidance (γ_{11} = -0.001, $p > 0.10$) and the two-way interactions, *CATRISK*PROM* (γ_{12} = -1.103, $p > 0.10$), and *UA*PROM* (γ_{13} = -0.001, $p > 0.10$) are not significant. Recall that we only included them in our model for accurate interpretation of the hypothesized interactions (Cohen et al. 2003).

Robustness Tests

We conducted a series of tests to assess the robustness of our substantive findings. The results are reported in Table 4.6 (See Table 4.6). First, in our main analysis, we account for differences between beverage and non-beverage food categories. However, there might still be differences between categories within beverages or non-beverages. For example, ice-cream category could be different from frozen ready meals or canned soup. We account for such differences by including 23 category fixed effects in model R1.[29] Second, there could be differences across countries with respect to the process of recalling a product. This could influence how fast a manufacturer can remove and replace the affected SKUs. Other country characteristics (e.g., consumers' economic well-being, their trust in public institutions, etc.) could influences consumer reactions towards product recalls. In R2 we introduce country fixed effects to account for country-level unobserved characteristics.[30] Different brands might face heterogeneous consumer reaction after recall. For example, Dawar and Pillutla (2000) showed that higher brand equity mitigates the negative consequences of recall. To account for brand level unobserved heterogeneity, we included 98 brand dummies in R3. As shown in Table 4.6, our findings are robust to the inclusion of category, country, and brand fixed effects.

Finally, it could also be argued that the recall impact depends on a brand's initial (pre-recall) level of market share. In R4 we accounted for such possibility by including an interaction of

[29] Product category risk scores vary across countries thereby permitting us to include category fixed effect without losing the main effect of product category risk.

[30] Since our measure for *UA* is time-invariant, we are not able to test the moderating effects of uncertainty avoidance in R2. In other robustness checks, we have included annually time-varying measures for GDP per capita, trust in public institutions, and media connectivity. Our findings do not change in terms of sign and significance. The results from those analyses are available upon request.

recall's main effect with brand's average pre-recall market share (during the 52 weeks before recall). The interaction term is not significant and our substantive findings remain the same.

General Discussion and Implications

Over the past 10 years, the number of product recall instances has dramatically increased in Europe (European Commission 2015). Such a trend has also been observed in the US (Swiss Re 2015). The increase in number of product recalls could be due to the more complex nature of supply chains and higher consumer expectations that has led to stricter safety standards around the world (Cleeren, Van Heerde, and Dekimpe 2013). Furthermore, as a result of increased globalization of production, most recalls involve multiple countries.

In this research, we used a unique cross-national dataset to investigate heterogeneous post-recall price promotion effectiveness and brand performance across multiple food categories in 12 European countries. We proposed a risk-based perspective to study brand performance and the effectiveness of the price promotion weapon to mitigate the adverse effect of the recall on brand market share. We proposed a multi-layered model for perceived risk consisting of 1) recall-specific risk (severity of recall), 2) risk perception of the category according to consumers (product category risk), and 3) cultural attitudes toward risk in the country where the recall took place (uncertainty avoidance). We developed hypotheses specifying the role of these three risk components on price promotion effectiveness and brand performance of recalled brands.

We found that on average (note: we mean-centered the data) price promotion effectiveness increases after recall. However, our moderator analyses showed that the effect of price promotion differs substantially across recalls in function of the perceived risk associated with the recall. We found that the recalled brands experienced greater decline in market share when the recall was severe. Moreover, we argued and showed that recalled brands experienced greater decline in market share in categories with high risk and countries high on uncertainty avoidance. As such, our risk-based framework enriches marketing literature by adding to our understanding of the underlying cause of brand performance variation in the wake of crisis. Most importantly, the three risk-related factors moderated the impact of price promotions after recall. Price promotion effectiveness is significantly lower when recall is severe. Similarly, post-recall price promotions were shown to be less effective in increasing market share in categories with high risk or in countries high on uncertainty avoidance.

Managerial Implications

It is safe to say that no brand manager wants a brand recall on their record. To make matters worse, there are situations where the affected firm has no control over the cause of the recall. In the horsemeat scandal in Europe, for example, numerous firms were punished for the wrongdoings of a few meat suppliers across Europe (BBC 2013). If faced with a brand recall, what can managers do to reduce the bleeding? Previous research has found that post-recall advertising can sometimes help brands regain their market share (Cleeren, Van Heerde, and Dekimpe 2013). However, post-recall advertising only appears to help stronger brands and is ineffective for weaker brands (Cleeren, Dekimpe, and Helsen 2008). Moreover, since advertising elasticity declines after recall, advertising becomes less effective and more costly for the recalled brands (Van Heerde, Helsen, and Dekimpe 2007). Finally, Van Heerde, Helsen, and Dekimpe (2007) found that the short-run post-recall advertising elasticity is insignificant (or very small). This suggests that it takes a long time for advertising to affect brand performance in a situation that time is of the essence. Permanent reduction in price might help staunch the bleeding (Van Heerde, Helsen, and Dekimpe 2007) but this is very costly (Marn, Roegner, and Zawada 2003) and it is not clear that it does the job (Zhao, Zhao, and Helsen 2011).

We propose using price promotions - short-run and temporary reductions in price – as an alternative strategy. We document that price promotion is an effective weapon to reduce the fallout fast. Moreover, we found that effectiveness of price promotion is higher post-recall vis-à-vis pre-recall. Our model predictions can be used as benchmark for price promotion effectiveness after recall. When 2SD promotion (i.e., 10.4%) is offered at regular (pre-recall) times, our model predicts a 0.55 percentage point increase in brand market share. After recall, the same level of price promotion results in 0.89 percentage point increase in brand market share, an improvement of 0.34 percentage points over pre-recall effect. This can be explained by increased price sensitivity of consumers post-recall.

While post-recall price promotions are always helpful in reducing market share decline after recall, we find that their effect varies depending on the three characteristics related to perceived risk. Offering price promotions is more effective when the recall issue is less severe (not associated with health concerns). When recall is not severe, a 2SD price promotion increases post-recall market share by 1.20 percentage points, implying a considerable increase in price promotion effectiveness of brands associated with non-severe recalls. However, when recall is severe (associated with health issues), a 2SD price promotion increases market share by 0.21 percentage points after recall. Therefore, in comparison to the pre-recall period, price promotion effectiveness decreases when recall is severe. Hence, managers should be cautious in offering price promotions if their brand was involved in a severe recall, or be prepared to spend much more than they are used to, to get the same effect.

Our model predicts that in low risk categories (1SD below the mean of *CATRISK*; e.g., cookies or mineral water in most countries), a 2SD price promotion increases post-recall brand market share by 1.09 percentage points. When product category risk is high (1SD above the mean of *CATRISK*; e.g., baby food or processed meat in most countries), a 2SD price promotion increases post-recall market share by 0.62 percentage points. Thus, even in categories with high risk (1SD above mean), price promotion effectiveness increases after recall. However, our model predicts that for categories with 2SD above the mean of *CATRISK*,[31] a 2SD post-recall price promotion increases market share by only 0.38 percentage points. Therefore, in categories with very high risk, post-recall promotion effectiveness is lower than pre-recall promotion effectiveness.

Similarly, after recall, effectiveness of price promotion is higher in countries with lower uncertainty avoidance scores. In countries with low uncertainty avoidance (1SD below the mean of *UA*; e.g., Netherlands, UK), a 2SD price promotion increases post-recall brand market share by 1.08 percentage points. In countries with high uncertainty avoidance values (1SD above the mean of *UA*; e.g., France, Poland), our model predicts a 0.68 percentage points increase in post-recall brand market share as a result of a 2SD price promotion. Even in countries that score very high on *UA* (i.e., 2SD above mean of *UA*), a 2SD price promotion increases market share by 0.55 percentage points, similar to the effect of price promotion before recall. As a result, other than countries with uncertainty avoidance higher than 2SD above mean of *UA*, price promotion effectiveness does not reduce after recall.[32] Based on our findings, brand managers can more efficiently allocate their marketing budgets to where it can be most helpful.

[31] This is an out-of-sample prediction. We do not observe such values for *RISK* in our dataset.

[32] This value (UA=108) would be out of the uncertainty avoidance range observed in our dataset. Across the world, only Greece (UA=112) scores higher than 108 on uncertainty avoidance.

Limitations and Directions for Future Research

Our study is not without limitations, which offer opportunities for future research. Our unique data-set allowed us to study numerous product recalls across Europe but in order to be able to confidently generalize the results, we recommend examining post-recall brand performance in other countries as well. Emerging markets have attracted the attention of marketing researchers as they have cultural and regulatory differences compared to high income markets (Burgess and Steenkamp 2006). Studying product crises in countries such as China, India, Mexico, and Brazil can test the generalizability of our findings to other contexts as well as helping researchers discover other interesting patterns. Additionally, it would also be helpful to analyze other industries. The automobile industry, for example, often experiences huge product recalls that costs manufactures billions of dollars. Automotive purchases have high inter-purchase times (i.e. fewer brand switching opportunities), involve high financial outlay, and are considerable physical and image risk, thereby are significantly more risky purchases than packaged goods. Future research can also analyze the impact of product recalls on abnormal stock returns across countries and categories. One study which has focused on stock price variation after recall is the study by Chen, Ganesan, and Liu (2009). Interestingly, their results suggested that passive strategies always work better than proactive strategies. It would be insightful to replicate the results of this study using stock prices to see if shareholders' reactions are similar to consumers' reactions. It would also be of great managerial relevance to test the effect of firm strategy at the time of recall in different countries and see if firms' actions have different results across countries.

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TABLE 4.1: Review of relevant literature from the domain of product-harm crises

Paper	Research Questions	Role of Price Promotions?	Role of Recall Severity?	Role of Product Category Risk?	Role of Uncertainty Avoidance?	Key Findings
Siomkos and Kurzbard 1994	- How do firm's reputation, response strategy, and the media coverage affect consumer's future purchases?	No	No	No	No	- Consumer's perception of danger, firm's reputation, and its response to the crisis affects consumers' purchase intentions
Dawar and Pillutla 2000	- How does consumer's prior expectation and firm's strategy affect brand equity?	No	No	No	No	- Firms with weak consumer expectations should support their brands aggressively
Van Heerde, Helsen, and Dekimpe 2007	- How does the crisis affect firm and brand's sales, effectiveness of marketing activities?	No	No	No	No	- Marketing effectiveness decreases - Cross sensitivity to rival firms' marketing-mix activities increases
Chen, Ganesan, and Liu 2009	- How well do proactive strategies perform when crisis happens? - Who is more likely to adopt a proactive strategy?	No	Yes	No	No	- Proactive strategies always have a more negative effect on firm value than positive ones - Reputable firms use proactive strategy less often
Cleeren, Van Heerde, and Dekimpe 2013	- How do advertising and price adjustments consumers' brand share and category purchases? - How does negative publicity and taking blame moderate effectiveness of recalled brands' marketing mix?	No	Yes	No	No	- Taking blame doesn't have significant effect on brand share but helps the category - Extent of negative publicity has no effect on change in brand share or category purchases - Post-crisis advertising has positive effect on brand's share
This Study	- Do price promotions help recalled products? - Can factors related to consumers' perceived risk explain post-recall heterogeneity in brand performance and price promotion effectiveness?	Yes	Yes	Yes	Yes	- Post-recall price promotion effectiveness is in general higher than that of pre-recall. - However, post-recall price promotion effectiveness is lower for severe recalls, recalls in high-risk product categories, and recalls in countries high on uncertainty avoidance.

TABLE 4.2: Some examples of product recalls in our study

Brand	Date	Product	Reason for Recall	Countries Affected
Bledina	Apr. 2010	Baby Food	Presence of undeclared attribute	PT,BE
Nescafé	May 2010	Instant Coffee	Glass contamination	NL,FR,DE,DK
Ilmenau	Nov. 2010	Processed Meat	Salmonella contamination	DE
Tuborg	Nov. 2010	Beer	Glass contamination	UK
Cascine di Campagna	Apr. 2011	Cheese	Listeria contamination	DE
Loka	Jun. 2011	Mineral Water	Undeclared flavor additive	SE
Robinsons	Jul. 2012	Soft Drinks	Packaging safety issue	BE
Wagner	Dec. 2012	Frozen Pizza	Pieces of metal detected	AT, DE, NL, BE, ES, FR
Kit Kat	Mar. 2013	Candy Bar	Pieces of plastic detected	AT, DE, UK
IKEA	Mar. 2013	Sweets	Bacteria contamination	PL
Benecol	Jun. 2013	Yogurt	Yeast fermentation	UK

TABLE 4.3: Variables and descriptions

Variable	Operationalization	Source	Mean	S.D.
Market Share (*MS*)	Percentage of total weekly volume sales in a category that is accounted for by brand *i*	Europanel	3.85%	6.68%
Recall (*REC*)	Dummy variable indicating recall by getting a value of 1 up to 52 weeks after recall	RASFF, Factiva	NA	NA
Recall Severity (*SVR*)	Binary variable indicating whether a recall was associated with health concerns (=0.5) or not (=-0.5)	RASFF, Factiva	-0.09	NA
Product Category Risk (*CATRISK*) [$\bar{\alpha}$ =0.75]	Measured before all recalls using three item surveys (5-point scale): 1) There is much to lose if you make the wrong choice 2) It matters a lot when you make the wrong choice 3) There are large differences in quality between the various products in the category X	GfK and KWP	3.43	0.23
Uncertainty Avoidance (*UA*)	The degree to which the members of a society feel uncomfortable with uncertainty and ambiguity. Higher values represent higher uncertainty avoidance tendencies.	Hofstede, Hofstede, and Minkov (2010)	58.9	25.6
Brand Promotion (*PROM*)	For weeks that brand offered price promotion, promotion depth is calculated using the following formula: [1-(average weekly paid price/average list price)].	Europanel	2.95%	5.22%
Brand Price (*PRICE*)	Weighted average of weekly price per volume of brand *i*'s SKUs defined over a one-year moving window (weighted by SKU weekly sales) / average price of non-recalled brands	Europanel	0.94	0.70
Brand Line Length (*SKU*)	Brand’s yearly assortment count / assortment count of non-recalled brands in the category	Europanel	4.22	4.82
Private Label (*PL*)	Dummy variable indicating whether a brand is a private label (=1) or a national brand (=0)	Europanel	49%	NA
Number of Brands in Category (*BRNUM*)	Weekly number of brands in each category	Europanel	97.6	84.3
Category Competition (*COMP*)	Category competitiveness calculated using Herfindahl index: sum of squared market shares of all brands in the category multiplied by -1 (higher values imply more competition)	Europanel	-11.6%	7.22%
Promotion of Other Brands (*OPROM*)	Average weekly promotion offered by all the non-recalled brands in a category	Europanel	3.14%	1.41%
Recalls in Multiple Countries (*MULT*)	Dummy indicating whether the recall involved more than one country (=1) or not (=0)	RASFF, Factiva	26%	NA
Beverage (*BVRG*)	Dummy variable distinguishing between beverage products (=1) and non-beverages (=0)	Europanel	5.6%	NA

TABLE 4.4: Model fit

Model	**M1**	**M2**	**M3**	**M4**
Description	Unobserved Heterogeneity Controls Only (Quarterly Dummies, Beverage Dummies, and Brand Random Effects)	(M1) + All Non-Hypothesized Variables and Copula Correction Term	(M2) + Main Effect of Recall and Two-way Recall Interactions	(M3) + Three-way Recall Interactions
Log Likelihood	-7,852.5	-5,918.1	-5,742.3	-5,700.1
Deviance (-2LL)	15,705.0	11,836.2	11,484.6	11,400.2
Δ Dev	-	3,868.8***	351.6***	84.4***
Δ df	-	12	6	3
AIC	15,719.1	11,874.2	11,534.1	11,456.2
BIC	15,775.7	12,027.8	11,736.2	11,682.7

*$p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

TABLE 4.5: Results: effect on logit transformed market share

Covariate	Parameter	Expected Sign	Estimate	Standard Error
Effect of Recall and its Moderators				
Main Recall Effect (*REC*)	γ_1		-0.129***	0.047
*REC*PROM*	γ_2	H1a,b:(+/-)	1.350*	0.693
*REC*SVR*	γ_3	H2:(-)	-0.189***	0.054
*REC*CATRISK*	γ_4	H4:(-)	-0.107**	0.054
*REC*UA*	γ_5	H6:(-)	-0.003***	0.001
*REC*SVR*PROM*	γ_6	H3: (-)	-1.531**	0.747
*REC*CATRISK*PROM*	γ_7	H5: (-)	-2.761**	1.303
*REC*UA*PROM*	γ_8	H7: (-)	-0.020*	0.011
Control variables				
Brand Promotion (*PROM*)	γ_9		1.492***	0.552
Product Category Risk (*CATRISK*)	γ_{10}		-0.091	0.404
Uncertainty Avoidance (*UA*)	γ_{11}		-0.001	0.003
*CATRISK*PROM*	γ_{12}		-1.103	0.845
*UA*PROM*	γ_{13}		-0.001	0.008
Brand price (*PRICE*)	γ_{14}		-0.046**	0.020
Brand Line Length (*SKU*)	γ_{15}		0.067***	0.016
Private Label (*PL*)	γ_{16}		0.524***	0.109
Number of Brands in Category (*BRNUM*)	γ_{17}		-0.003***	0.001
Category Competition (*COMP*)	γ_{18}		-1.024***	0.283
Promotion of other brands (*OPROM*)	γ_{19}		-1.720***	0.393
Recalls in Multiple Countries (*MULT*)	γ_{20}		0.004	0.033
Unobserved Heterogeneity				
Beverage Fixed Effect (*BVRG*)	γ_{21}		Included	
Quarterly Fixed Effects (*QTR*)	γ_{22}-γ_{24}		Included	
Recall-specific Random Effect	u_{ijk}		Included	
Copula Correction	$\widehat{Copula}_{ijkt}$		0.049***	0.013
Intercept	γ_0		-3.794***	0.122
Number of Observations			24,025	
Number of Recalls			143	

Note: Dependent variable is logit-transformed market share (*$p < 0.10$; ** $p < 0.05$; *** $p < 0.01$)

TABLE 4.6: Robustness checks and additional analyses

Covariate	**(R1) Including Category Fixed Effects**	**(R2) Including Country Fixed Effects**	**(R3) Including Brand Fixed Effects**	**(R4) Including Interaction of REC and Average Pre-Recall MS**
	Estimate	**Estimate**	**Estimate**	**Estimate**
REC	-0.129***	-0.130***	-0.128***	-0.129***
*REC*PROM*	1.350*	1.348*	1.354*	1.346*
*REC*SVR*	-0.188***	-0.189***	-0.187***	-0.191***
*REC*CATRISK*	-0.107**	-0.107**	-0.107*	-0.106**
*REC*UA*	-0.003***		-0.003***	-0.003***
*REC*SVR*PROM*	-1.531**	-1.528**	-1.538**	-1.535**
*REC*CATRISK*PROM*	-2.753**	-2.763**	-2.746**	-2.817**
*REC*UA*PROM*	-0.020*		-0.020*	-0.020*
Control variables	Included	Included	Included	Included
BVRG, *QTR*, u_{ijk}	Included	Included	Included	Included
$\boldsymbol{\widehat{Copula}_{ijkt}}$	Included	Included	Included	Included
Category Fixed Effects	Included			
Country Fixed Effects		Included		
Brand Fixed Effects			Included	
*REC**(Mean Pre-recall *MS*)				-0.058
Number of Observations	24,025	24,025	24,025	24,025

Note: Dependent variable is logit-transformed market share (*$p < 0.10$; ** $p < 0.05$; *** $p < 0.01$)

FIGURE 4.1: Number of recall instances by year and severity type

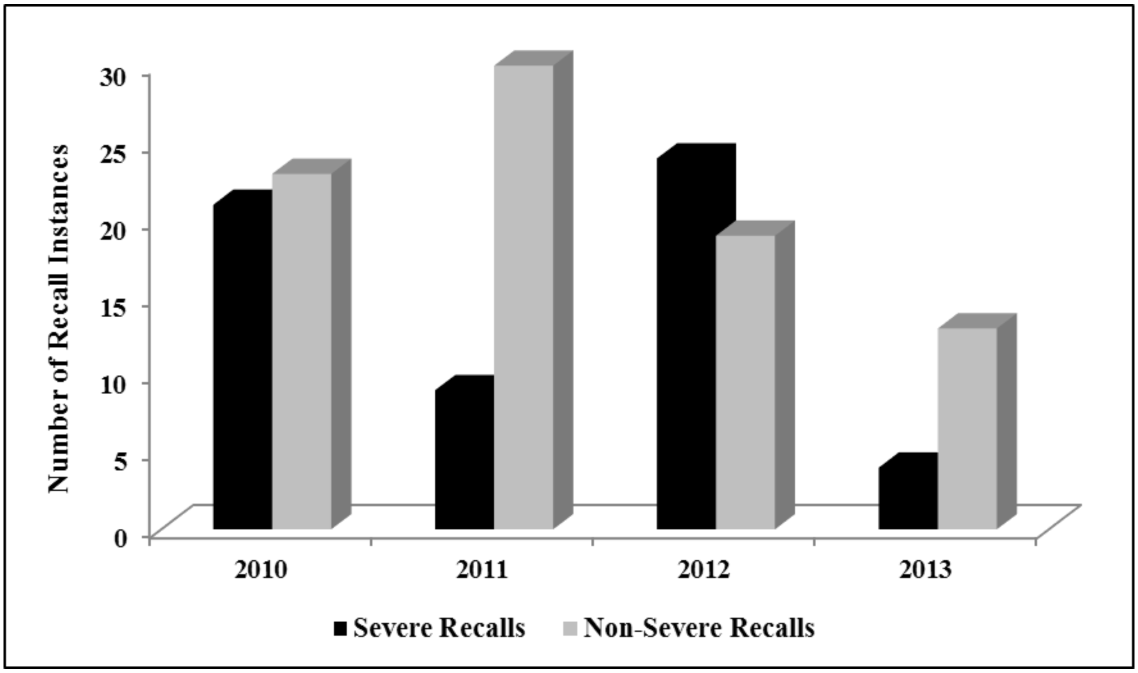


FIGURE 4.2: Distribution of uncertainty avoidance across countries in our dataset

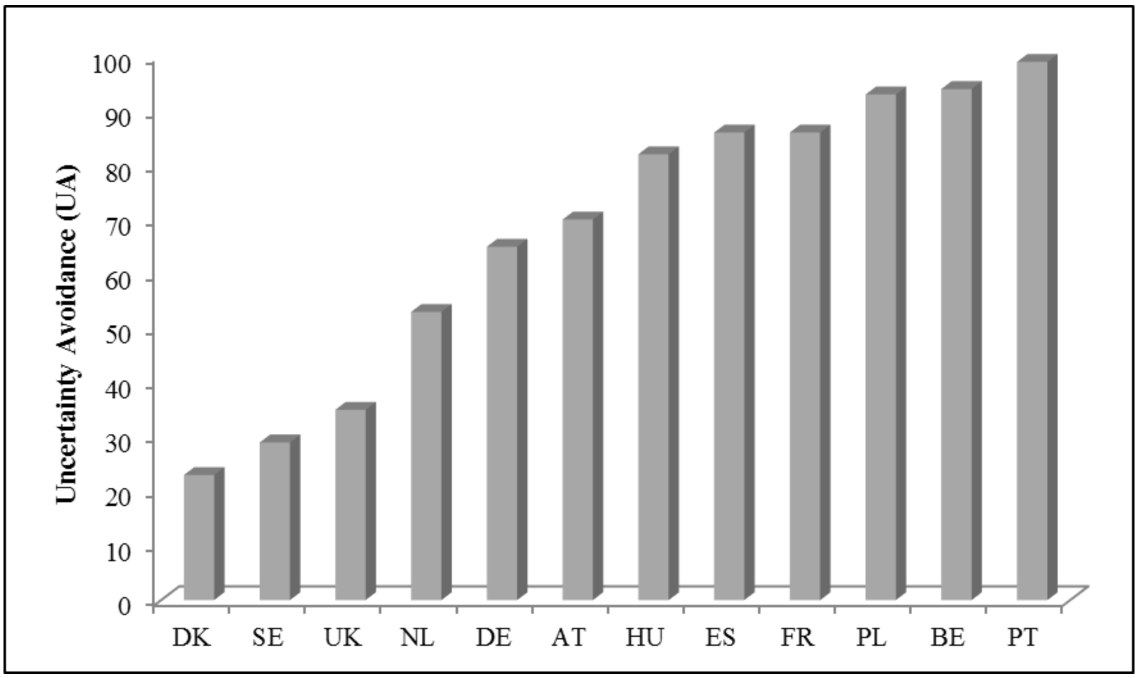


FIGURE 4.3: Comparing price promotion effectiveness before and after recall (H1)

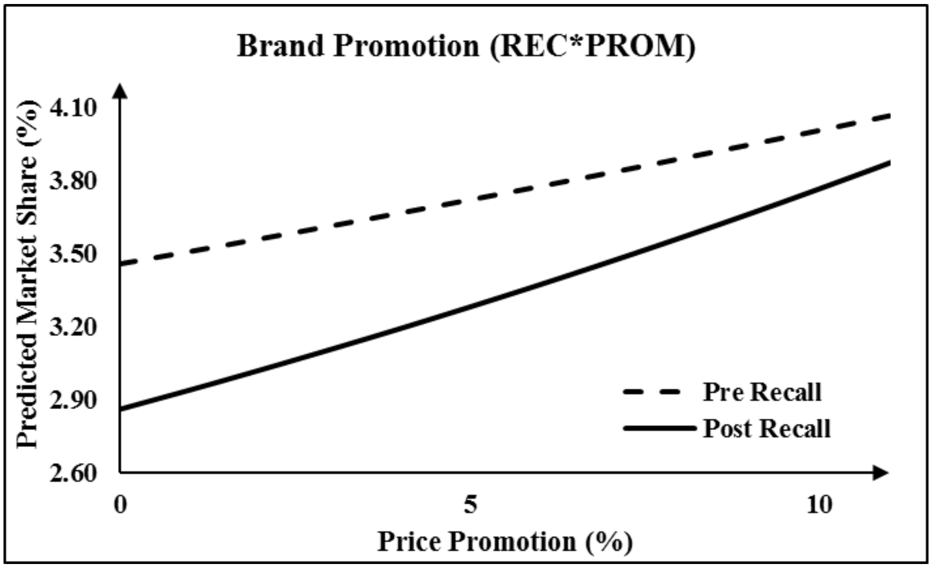


FIGURE 4.4: Impact of focal variables on predicted brand market share after recall (H2, H4, and H6)

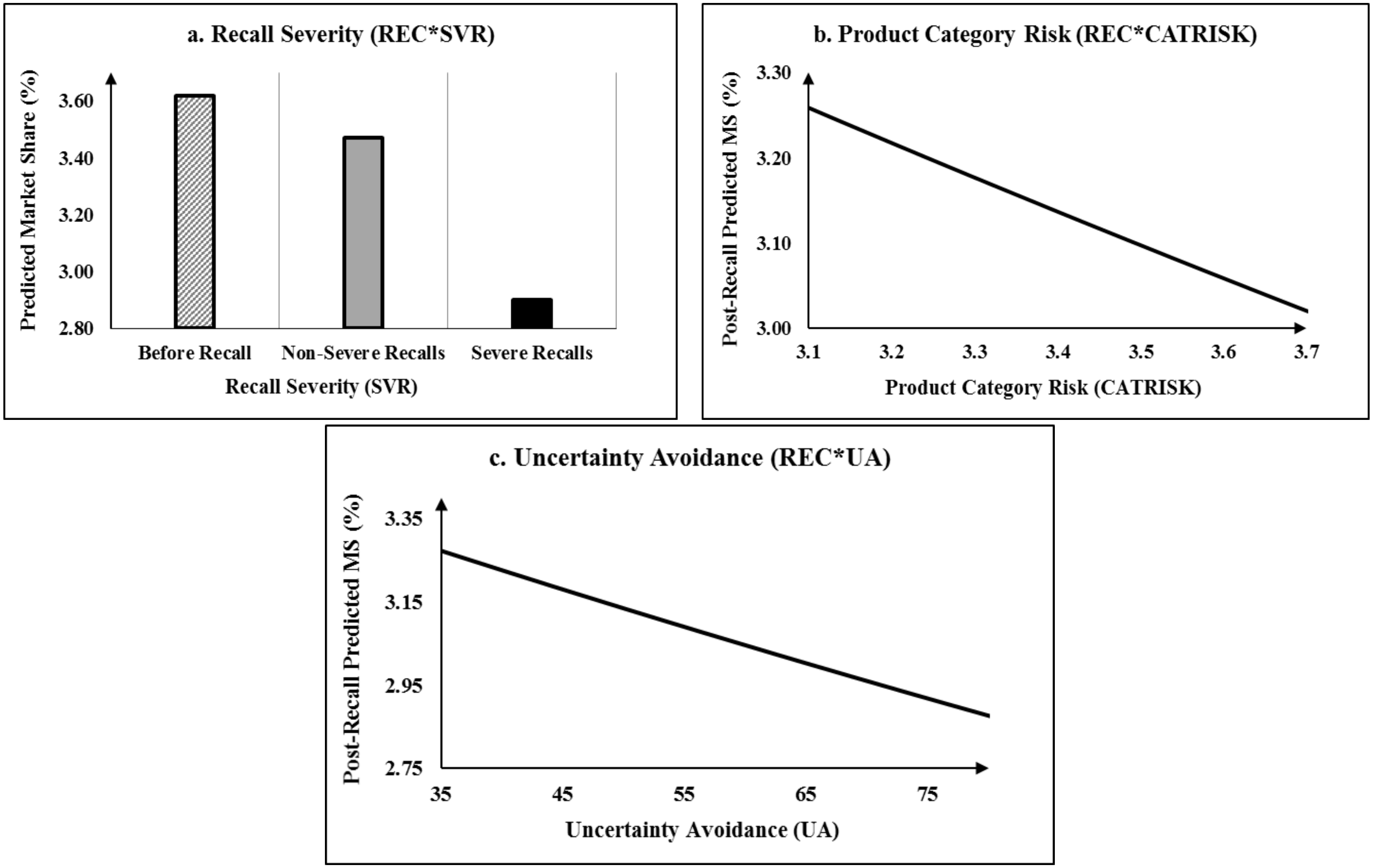
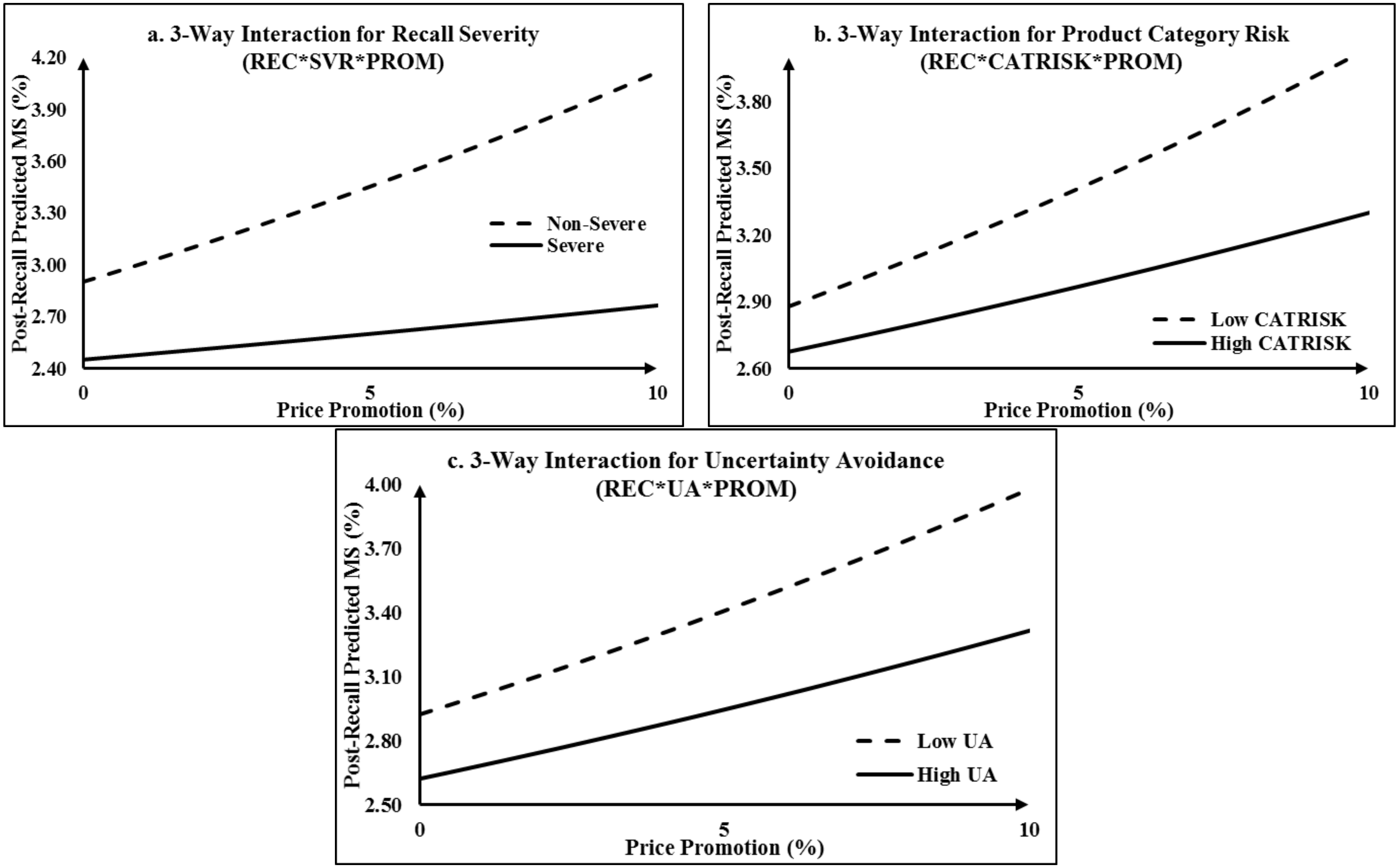


FIGURE 4.5: Moderating role of SVR, CATRISK, and UA on the post-recall impact of price promotion (H3, H5, and H7)



CHAPTER 5: CONCLUSION

The three essays in this dissertation examined different aspects of brand trust that were not thoroughly investigated in the marketing literature. In the first essay (see Chapter 2), I studied the relationships between marketing mix activities and brand trust. Using a unique data-set which consists of survey and scanner panel data on 589 leading national brands in 46 CPG categories across 13 countries, I showed that advertising intensity, new product introduction intensity, distribution intensity, and price are positively related to brand trust. However, I found that not all marketing activities have a positive influence on brand trust. Specifically, I showed that price promotion intensity is negatively linked to brand trust.

I also examined category and country level characteristics that moderate these relationships. I argued that in categories and countries where brands are important to consumers, marketing activities are more strongly related to brand trust. Subsequently, I showed that in categories with high brand relevance, countries high on secular-rational values, and countries low on self-expression values marketing mix activities are more strongly related to brand trust.

In the second essay (see Chapter 3), I focused on brand equity, which is the most important consequence of brand trust. I studied the effects of macroeconomic fluctuations on the changes in brand equity. Using longitudinal monthly data on 150 leading CPG brands in the United Kingdom across 36 product categories and 17 years, I empirically investigated how business cycle fluctuations influence brand equity. I showed that brand equity behaves cyclically; it increases (decreases) during economic upturns (downturns) and that such changes persist in the long run. Moreover, I showed that for certain brands and product categories, macroeconomic fluctuations have stronger impact on brand equity. Specifically, my findings suggested that business cycles have stronger impact on brand equity in low performance risk categories, for brands that are pricier, and brands that do not advertise a lot.

In the third essay (see Chapter 4), I examined the implications of violation of brand trust. I focused on product recalls as well-known instances in which a brand does not deliver its promises and hence violates customer trust. I examined the role that price promotions play on reducing customer risk and helping brands mitigate the negative impact of recall. I studied 143 recalls that occurred between 2010 and 2013 across 12 European countries and showed that price promotions can generally help recalled brands but their effectiveness varies considerably across different recalls. I argued that factors related to customers' perceived risk explain such heterogeneity. As such, I conceptualized that recall severity, product category risk, and national uncertainty avoidance can explain post-recall price promotion effectiveness as well as post-recall product performance. I showed that severe recalls, recalls in high risk product categories, and recalls in high uncertainty avoidance countries are associated with greater decline in market share as well as lower post-recall price promotion effectiveness.

I hope that this dissertation inspires future studies on brand trust – as well as studies on related topics such as brand equity and product recalls – and can help marketing scholars and practitioners to better understand drivers, consequences, and implications of brand trust.

APPENDIX 2.A: EXAMPLES OF LOW, MEDIUM, AND HIGH TRUSTED BRANDS

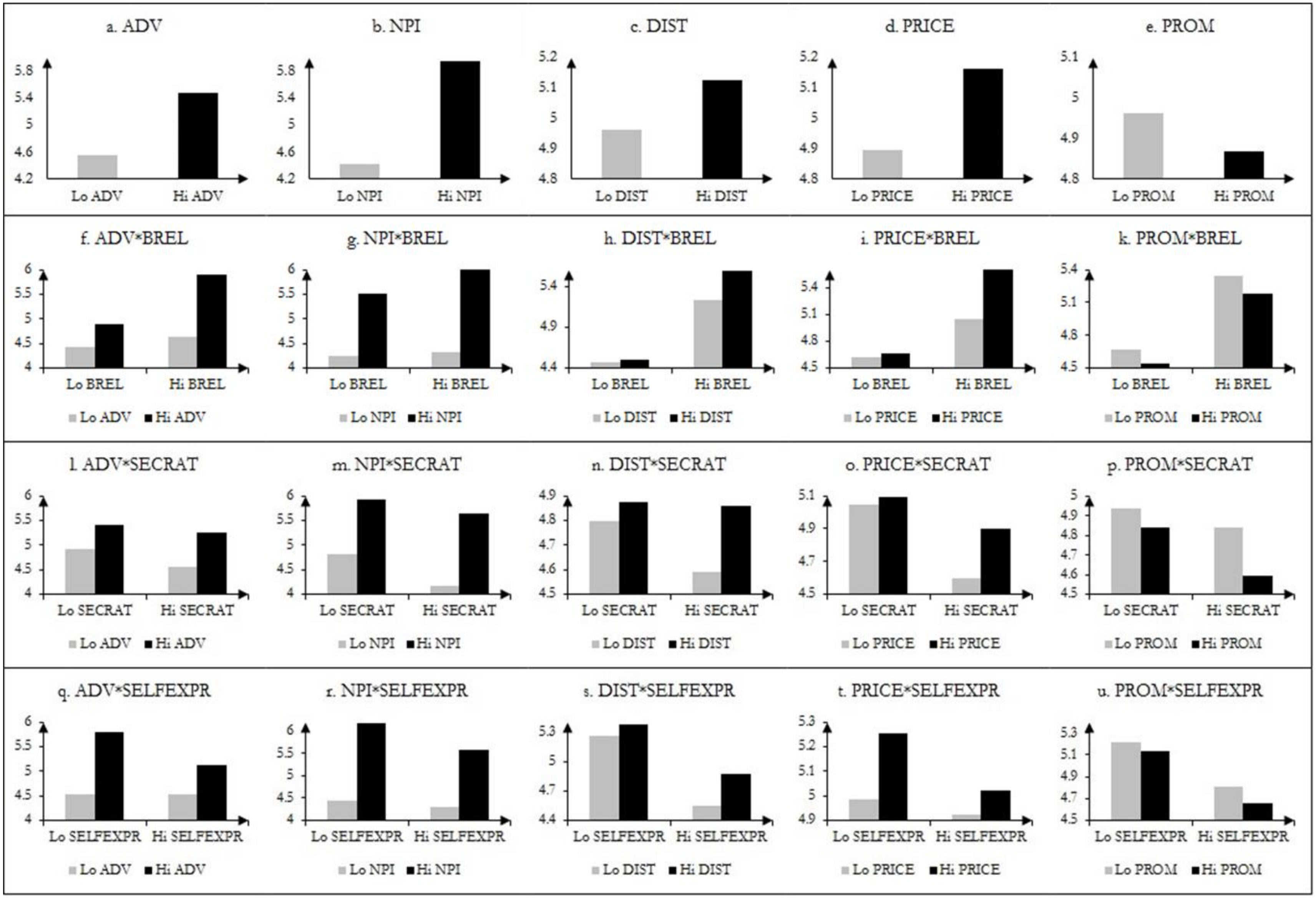
Countr	Low Brand Trust	Medium Brand Trust	High Brand Trust
BRA	Condor (*Laundry Detergent*), Tixan (*Toothbrush*), Sorriso (*Toothpaste*)	Dove (*Toilet Soap*), Soya (*Cooking Oil*), Arisco (*Coffee*)	Nescafé (*Instant Coffee*), Kibon (*Ice Cream*), Omo (*Laundry Detergent*)
CHN	Fortune (*Cooking Oil*), Yinyin (*Diaper*), Slek (*Shampoo*)	7 Up (*CSD*), Snickers (*Chocolate Tablet*), Tsingtao (*Beer*)	Dove (*Chocolate Tablet*), Mr. Muscle (*Lavatory Cleaner*), Johnson’s (*Skin Care*)
DEU	Regina (*Kitchen Paper*), Vitrex (*Mineral Water*), Pedigree (*Dog Food*)	Kraft (*Ketchup*), Palmolive (*Shaving Foam*), Thomy (*Cooking Oil*)	Dr. Oetker (*Frozen Pizza*), Gillette (*Razor Blade*), Kölln (*Breakfast Cereal*)
DNK	Aquafresh (*Toothpaste*), Frolic (*Dog Food*), Pepsi (*Cola*)	Ajax (*Household Cleaner*), Dove (*Skin Care*), Yoggi (*Yoghurt*)	Nutella (*Chocolate Spread*), Merrild (*Coffee*), Dr. Oetker (*Frozen Pizza*)
ESP	Pepsi (*Cola*), Foxy (*Kitchen Paper*), Flota (*Dish Soap*)	Coca-Cola (*Cola*), Knorr (*Cooking Sauce*), Tulipan (*Margarine/Spreads*)	Gillette (*Razor Blade*), Purina (*Cat Food*), Gallo (*Pasta*)
FRA	Kronenbourg (*Beer*), Vania (*Sanitary Pads*), DOP (*Shampoo*)	Nana (*Sanitary Pads*), Panzani (*Cooking Sauce*), Sanex (*Shower/Bath Additive*)	Coca-Cola (*Cola*), Always (*Sanitary Pads*), Evian (*Mineral Water*)
GBR	BIC (*Razor Blade*), Pantene (*Shampoo*), Yoplait (*Yogurt*)	Pepsi (*Cola*), Radox (*Bath Additive*), Whiskas (*Cat Food*)	Colgate (*Toothpaste*), Comfort (*Fabric Conditioner*), Fairy (*Dish Soap*)
IND	Tops (*Cooking Sauce*), Vi-John (*Shaving Foam*), Close-Up (*Toothpaste*)	Sunsilk (*Shampoo*), Tide (*Laundry Detergent*), Lizol (*Household Cleaner*)	Amul (*Milk*), Gillette (*Shaving Foam*), Kissan (*Jam*)
ITA	Splendid (*Coffee*), Garnier (*Skin Care*), Squibb (*Shampoo*)	Pepsi (*Cola*), Ajax (*Household Cleaner*), Infré (*Tea*)	Heinz (*Ketchup*), Coca-Cola (*Cola*), Coccolino (*Fabric Conditioner*)
NLD	Plenty (*Kitchen Towel*), Pepsi (*Cola*), Purina (*Dog Food*)	Amstel (*Beer*), Dove (*Deodorant*), Whiskas (*Cat Food*)	Gillette (*Razor Blade*), Nivea (*Shampoo*), Nutella (*Chocolate Spread*)
RUS	Avon (*Skin Care*), Schick (*Razor Blade*), Toilet Duck (*Lavatory Cleaner*)	Morozko (*Frozen Pizza*), Persil (*Laundry Detergent*), Zlato (*Cooking Oil*)	Always (*Sanitary Pad*), Lay’s (*Potato Crisp*), Gillette (*Razor Blade*)
SWE	Becel (*Margarine*), Spar (*Laundry Detergent*), Family Fresh (*Shower/Bath Additive*)	Felix (*Frozen Pizza*), Valio (*Yoghurt*), Sensodyne (*Toothpaste*)	Pripps (*Beer*), Yes (*Dish Soap*), Lipton (*Tea*)
USA	Busch (*Beer*), Suave (*Shampoo*), Suavitel (*Fabric Conditioners*)	Mr. Bubble (*Laundry Detergent*), Nestlé (*Mineral Water*), Prego (*Cooking Sauce*)	Tide (*Laundry Detergent*), Vaseline (*Shower/Bath Additive*), Pepsi (*Cola*)

Low (High) trust brands are among the bottom (top) third trusted brands in a country. Medium trust brands are among the middle third in terms of brand trust in a country.

APPENDIX 2.B: ESTIMATION AFTER EXCLUDING ONE COUNTRY AT A TIME

Covariate	Hypothesis	Supported at 0.10	Supported at 0.05
ADV	H1a	12/13	9/13
NPI	H1b	13/13	13/13
DIST	H1c	11/13	6/13
PRICE	H1d	13/13	13/13
PROM	H1e	12/13	6/13
*BREL * ADV*	H2	13/13	13/13
*BREL * NPI*	H2	13/13	13/13
*BREL * DIST*	H2	13/13	13/13
*BREL * PRICE*	H2	13/13	13/13
*BREL * PROM*	H2	0/13	0/13
*SECRAT * ADV*	H3	0/13	0/13
*SECRAT * NPI*	H3	12/13	10/13
*SECRAT * DIST*	H3	0/13	0/13
*SECRAT * PRICE*	H3	13/13	13/13
*SECRAT * PROM*	H3	13/13	13/13
*SELFEXPR * ADV*	H4	13/13	13/13
*SELFEXPR * NPI*	H4	13/13	13/13
*SELFEXPR * DIST*	H4	0/13	0/13
*SELFEXPR * PRICE*	H4	12/13	7/13
*SELFEXPR * PROM*	H4	0/13	0/13

APPENDIX 2.C: MODEL-FREE EVIDENCE



APPENDIX 3.A: SURVEY ITEMS USED FOR CATEGORY LEVEL PERCEPTUAL MEASURES

Performance Risk [$\overline{\alpha}$ = 0.79]:

1- There is much to lose if you make the wrong choice in the category X.

2- It matters a lot when you make the wrong choice in the category X.

3- In the category X, there are large differences in quality between the various products.

Social Risk [$\overline{\alpha}$ = 0.92]:

1- You can tell a lot about a person from the brand in category X he or she buys.

2- The brand in the category X a person buys, says something about who they are.

3- The brand in the category X I buy reflects the sort of person I am.

Price-Quality Relationship [$\overline{\alpha}$ = 0.79]:

1- In the category X, higher priced products provide better quality than lower priced products.

2- In the category X, the higher the price for a product, the higher the quality of the product.

APPENDIX 3.B: HETEROGENEITY IN TEMPORARY AND PERMANENT IMPACTS OF BUSINESS CYCLE FLUCTUATIONS ON BRAND EQUITY USING CONTINUOUS MEASURES FOR BRAND AND CATEGORY LEVEL MEASURES

	DV= Temporary Effect of Business Cycle on Brand Equity (α_{ij1})			***DV= Permanent Effect of Business Cycle on Brand Equity (β_{ij1})***		
Covariates	**Estimate**	**Standard Error**	***p*-value**	**Estimate**	**Standard Error**	***p*-value**
Performance Risk	-0.6234	0.3885	<0.10	-0.5808	0.2575	<0.05
Social Risk	0.4268	0.4186	>0.10	0.4732	0.4243	>0.10
Advertising	-0.0001	0.0000	<0.10	-0.0001	0.0000	<0.05
Price	0.1805	0.0961	<0.05	0.0292	0.0278	>0.10
Intercept	1.3645	0.4735	<0.01	1.0939	0.2986	<0.01
Number of Brands		150			150	
Number of Categories		36			36	

N=150 across both regressions. Since the dependent variables are estimated variables (α_{ij1} and β_{ij1}), we adopt WLS and use inverse of standard errors of (α_{ij1} and β_{ij1}) as weights. One-sided *p*-values are reported. Robust cluster-adjusted standard errors (at the category level) are reported. Price and advertising represent brand-specific level of price and advertising averaged across 17 years. Price and advertising have been centered around category means.

APPENDIX 3.C: TEMPORARY BRAND-SPECIFIC EFFECTS OF BUSINESS CYCLE CHANGES ON BRAND EQUITY

Brand	Category	Coef. (α_{ij1})	Std. Err.	t-Val.	Brand	Category	Coef. (α_{ij1})	Std. Err.	t-Val.
Domestos	Household Cleaners	-1.83	2.07	-0.88	Pantene	Shampoo	0.47	0.94	0.49
Buitoni	Dry Pasta	-1.23	1.44	-0.85	Alberto	Conditioners	0.47	0.92	0.51
Red Mountain	Instant Coffee	-1.21	1.12	-1.08	Johnsons	Shower Products	0.48	0.22	2.16
Seabrook	Crisps	-1.06	0.74	-1.43	Kotex	Sanpro Prod.	0.50	0.53	0.93
Oxy	Cleansers	-0.84	0.56	-1.50	Palmolive	Shower Products	0.52	0.41	1.27
Highlander	Crisps	-0.68	0.31	-2.21	Morning Fresh	Washing-Up Prod.	0.56	1.32	0.42
Macrae	Frozen Fish	-0.60	1.29	-0.46	Tampax	Sanpro Prod.	0.58	0.66	0.88
Strathmore	Mineral Water	-0.36	1.57	-0.23	Bodyform	Sanpro Prod.	0.61	0.45	1.36
Yoplait	Yoghurt	-0.35	0.64	-0.55	Jordans	Breakfast Cereals	0.63	0.97	0.64
Sun-Pat	Peanut Butter	-0.26	1.09	-0.24	Daddies Sauce	Table Sauces	0.65	1.33	0.49
Kit-E-Kat	Cat Food	-0.19	1.36	-0.14	Tango	Soft-drinks	0.66	1.47	0.45
Crest	Dentifrice	-0.09	0.89	-0.10	Batchelors	Packet Soup	0.67	1.07	0.63
Velvet	Toilet Tissues	-0.07	0.34	-0.20	Flash	Household Cleaners	0.68	1.10	0.61
I C B I N B	Margarine	0.09	1.34	0.07	Lillets	Sanpro Prod.	0.68	0.46	1.50
Mentadent	Dentifrice	0.11	0.77	0.14	Palmolive	Bath Additives	0.69	0.77	0.89
Always	Sanpro Prod.	0.12	0.61	0.20	Clearasil	Cleansers	0.73	0.43	1.70
Brooke Bond	Tea	0.18	1.11	0.16	Sensodyne	Dentifrice	0.73	0.61	1.21
Pantene	Conditioners	0.20	0.65	0.31	H.P Sauces	Table Sauces	0.74	1.12	0.67
Lavazza	Ground Coffee	0.25	0.40	0.62	Whole Earth	Peanut Butter	0.77	0.84	0.91
Country Life	Butter	0.30	1.24	0.24	Kerrygold	Butter	0.77	0.84	0.91
Nouvelle	Toilet Tissues	0.31	0.26	1.17	Bic	Razor Blades	0.77	0.31	2.49
Simple	Cleansers	0.31	0.45	0.70	Butchers	Dog Food	0.78	1.27	0.61
Lyons	Ground Coffee	0.34	0.89	0.38	Homepride	Cooking Sauces	0.79	1.24	0.64
Weight Watchers	Ambient Soup	0.34	1.21	0.28	Ski	Yoghurt	0.80	1.41	0.56
Marshalls	Dry Pasta	0.34	0.87	0.39	Clean & Clear	Cleansers	0.80	0.31	2.58
Golden Wonder	Crisps	0.36	1.11	0.32	Johnsons	Bath Additives	0.83	0.86	0.97
Andrex	Toilet Tissues	0.38	0.30	1.28	Youngs	Frozen Fish	0.84	1.05	0.80
Alberto	Shampoo	0.44	0.92	0.47	St Ivel	Margarine	0.84	0.77	1.09
Wilkinson Sword	Razor Blades	0.45	0.23	1.95	Aquafresh	Dentifrice	0.85	0.91	0.93
Supersoft	Conditioners	0.46	0.99	0.46	Mackeson	Stout	0.89	1.09	0.82
Surf	Machine-Wash Prod.	0.46	1.31	0.35	Sure	Deodorants	0.90	0.92	0.97

N=17 for each regression.

Brand	Category	Coef. (α_{ij1})	Std. Err.	t-Val.	Brand	Category	Coef. (α_{ij1})	Std. Err.	t-Val.
Dolmio	Cooking Sauces	0.91	1.17	0.78	Robinsons	Fruit/Yoghurt Juice	1.18	1.63	0.72
Clover	Margarine	0.92	1.41	0.65	Typhoo	Tea	1.19	1.28	0.93
Personna	Razor Blades	0.92	0.19	4.91	Del Monte	Tinned Fruit	1.21	1.33	0.91
Yorkshire Tea	Tea	0.95	0.89	1.06	Ribena	Fruit/Yoghurt Juice	1.21	1.37	0.89
Cif	Household Cleaners	0.96	1.18	0.81	Flora	Margarine	1.23	1.52	0.81
Imperial Leather	Bath Additives	0.97	0.60	1.61	Fairy	Washing-Up Prod.	1.24	1.42	0.87
Oil Of Olay	Cleansers	0.98	0.46	2.11	Stork	Margarine	1.25	1.33	0.94
Natrel Plus	Deodorants	0.98	1.04	0.95	Tetley	Tea	1.25	1.38	0.91
Baxters	Ambient Soup	0.99	1.18	0.84	Heinz	Ambient Soup	1.26	1.49	0.85
Guinness	Stout	0.99	1.33	0.74	Muller	Yoghurt	1.26	1.52	0.83
Irn Bru	Soft-drinks	1.03	1.44	0.71	KP	Crisps	1.27	0.75	1.68
Macleans	Dentifrice	1.03	0.88	1.17	Soft & Gentle	Deodorants	1.28	0.74	1.73
Ecover	Washing-Up Prod.	1.03	0.49	2.09	Persil	Machine-Wash Prod.	1.29	1.64	0.79
Gillette	Razor Blades	1.03	0.36	2.85	Chappie	Dog Food	1.32	1.46	0.91
Danone	Yoghurt	1.04	0.86	1.22	Quaker Oats	Breakfast Cereals	1.34	1.01	1.33
Radox	Bath Additives	1.05	0.98	1.08	Timotei	Shampoo	1.35	1.05	1.28
Sweetex	Artificial Sweeteners	1.05	1.02	1.03	Mellow Birds	Instant Coffee	1.35	0.89	1.53
Jordans	Cereal Bars	1.06	0.90	1.18	Whiskas	Cat Food	1.36	1.58	0.86
Timotei	Conditioners	1.07	0.97	1.10	Nescafe	Instant Coffee	1.38	1.29	1.07
Mr Muscle	Household Cleaners	1.07	1.12	0.95	Volvic	Mineral Water	1.42	1.17	1.21
Radox	Shower Products	1.07	0.54	1.99	Pedigree	Dog Food	1.42	1.62	0.88
Rightguard	Deodorants	1.08	0.91	1.18	Pal	Dog Food	1.44	1.62	0.89
Head & Shoulders	Shampoo	1.08	0.93	1.16	P.G.Tips	Tea	1.44	1.22	1.18
Dettol	Household Cleaners	1.08	0.89	1.21	Tropicana	Fruit/Yoghurt Juice	1.46	0.96	1.52
Harvest	Cereal Bars	1.10	1.01	1.09	Coca Cola	Soft-drinks	1.46	1.65	0.89
Uncle Bens	Cooking Sauces	1.11	1.06	1.05	Pepsi	Soft-drinks	1.47	1.63	0.90
Lynx	Deodorants	1.14	0.85	1.34	Highland Spring	Mineral Water	1.47	0.94	1.57
Imperial Leather	Shower Products	1.15	0.61	1.89	Schweppes	Soft-drinks	1.50	1.32	1.13
Tracker	Cereal Bars	1.15	0.94	1.22	Finish	Washing-Up Prod.	1.50	1.17	1.29
Lynx	Shower Products	1.17	0.63	1.86	Anchor	Butter	1.53	1.32	1.16
Ocean Spray	Fruit/Yoghurt Juice	1.17	0.77	1.52	Dole	Tinned Fruit	1.53	1.26	1.22

N=17 for each regression.

Brand	Category	Coef. (α_{ij1})	Std. Err.	t-Val.	Brand	Category	Coef. (α_{ij1})	Std. Err.	t-Val.
Kelloggs	Breakfast Cereals	1.54	1.62	0.95	Knorr	Cooking Sauces	1.86	1.61	1.15
Hermesetas	Artificial Sweeteners	1.56	1.04	1.51	Weetabix	Breakfast Cereals	1.88	1.05	1.78
Ross	Frozen Fish	1.56	1.41	1.11	Murphys Beer	Stout	1.97	0.86	2.27
Maxwell House	Instant Coffee	1.57	1.18	1.32	Del Monte	Fruit/Yoghurt Juice	2.15	1.63	1.32
Douwe Egbert	Ground Coffee	1.61	0.74	2.19	Wash & Go	Shampoo	2.22	0.89	2.50
Evian	Mineral Water	1.61	1.21	1.33	Sucron	Artificial Sweeteners	2.33	0.92	2.54
Walkers	Crisps	1.65	1.11	1.48	Bold	Machine-Wash Prod.	2.39	1.37	1.74
Felix	Cat Food	1.65	1.52	1.09	Buxton	Mineral Water	2.76	1.68	1.65
Lurpak	Butter	1.72	1.17	1.48	Ariel	Machine-Wash Prod.	2.85	1.55	1.83
Canderel	Artificial Sweeteners	1.77	0.78	2.26	Daz	Machine-Wash Prod.	3.04	1.54	1.97
Princes	Tinned Fruit	1.80	1.16	1.55	Persil	Washing-Up Prod.	3.09	3.06	1.01
Winalot	Dog Food	1.83	1.39	1.31	Hammonds	Table Sauces	3.79	1.57	2.42
Birds Eye	Frozen Fish	1.86	1.41	1.31	Katkins	Cat Food	8.58	2.14	4.01

N=17 for each regression.

APPENDIX 3.D: TEMPORARY CATEGORY-SPECIFIC META-ANALYTIC EFFECTS OF BUSINESS CYCLE CHANGES ON BRAND EQUITY

Category	Weighted Mean (α_{ij1})	Meta Std. Err.	Meta Z-Val.	Category	Weighted Mean (α_{ij1})	Meta Std. Err.	Meta Z-Val.
Dry Pasta	-0.250	2.628	-0.095	Bath Additives	0.884	0.374	2.366
Crisps	-0.019	0.013	-1.485	Tea	0.974	0.474	2.053
Toilet Tissues	0.224	0.184	1.221	Butter	1.050	0.525	2.000
Peanut Butter	0.319	0.578	0.551	Deodorants	1.087	0.403	2.697
Cleansers	0.476	0.204	2.330	Cereal Bars	1.103	0.516	2.139
Yoghurt	0.507	0.720	0.704	Shampoo	1.115	0.429	2.603
Conditioners	0.509	0.447	1.140	Cooking Sauces	1.121	0.651	1.722
Sanitary-Protection Products	0.515	0.219	2.355	Washing Up Products	1.215	0.448	2.714
Dentifrice	0.531	0.332	1.598	Soft-drinks	1.219	0.602	2.025
Household Cleaners	0.636	0.380	1.676	Breakfast Cereals	1.312	0.522	2.512
Ground/Bean Coffee	0.642	0.391	1.643	Dog Food	1.342	0.597	2.248
Packet Soup	0.671	0.957	0.701	Stout	1.357	0.561	2.419
Shower Products	0.762	0.221	3.455	Fruit/Yoghurt Juice	1.388	0.490	2.835
Razor Blades	0.777	0.151	5.132	Mineral Water	1.390	0.523	2.658
Instant Coffee	0.781	0.567	1.376	Tinned Fruit	1.527	0.695	2.199
Ambient Soup	0.837	0.682	1.226	Table Sauces	1.563	0.820	1.905
Margarine	0.853	0.519	1.641	Artificial Sweeteners	1.702	0.492	3.463
Frozen Fish	0.876	0.639	1.371	Machine Wash Products	1.970	0.659	2.992

APPENDIX 3.E: PERMANENT BRAND-SPECIFIC EFFECTS OF BUSINESS CYCLE CHANGES ON BRAND EQUITY

Brand	Category	Coef. (β_{ij1})	Std. Err.	t-Val.	Brand	Category	Coef. (β_{ij1})	Std. Err.	t-Val.
Domestos	Household Cleaners	-0.20	1.03	-0.19	Whole Earth	Peanut Butter	0.25	0.26	0.96
Highlander	Crisps	-0.16	0.18	-0.86	Lyons	Ground Coffee	0.25	0.39	0.64
Velvet	Toilet Tissues	-0.03	0.10	-0.35	Alberto	Shampoo	0.25	0.47	0.53
Oxy	Cleansers	-0.02	0.24	-0.09	Pantene	Conditioners	0.26	0.37	0.69
Seabrook	Crisps	-0.02	0.34	-0.06	Tracker	Cereal Bars	0.26	0.36	0.73
Red Mountain	Instant Coffee	0.00	0.34	0.01	Fairy	Washing-Up Prod.	0.26	0.43	0.62
Nouvelle	Toilet Tissues	0.03	0.01	2.23	Sun-Pat	Peanut Butter	0.26	0.49	0.53
Simple	Cleansers	0.05	0.07	0.66	Hammonds	Table Sauces	0.26	0.35	0.76
Andrex	Toilet Tissues	0.09	0.13	0.71	Finish	Washing Up Prod.	0.27	0.38	0.71
Wilkinson Sword	Razor Blades	0.10	0.10	0.91	Mentadent	Dentifrice	0.28	0.51	0.54
Lavazza	Ground Coffee	0.11	0.20	0.58	Timotei	Conditioners	0.28	0.23	1.22
Bic	Razor Blades	0.12	0.13	0.96	Daddies Sauce	Table Sauces	0.29	0.44	0.66
Clearasil	Cleansers	0.13	0.16	0.80	Alberto	Conditioners	0.29	0.46	0.64
Bodyform	Sanpro Prod.	0.13	0.23	0.59	Morning Fresh	Washing-Up Prod.	0.30	0.38	0.77
Supersoft	Conditioners	0.14	0.37	0.37	Johnsons	Bath Additives	0.30	0.41	0.72
Personna	Razor Blades	0.14	0.07	1.87	Harvest	Cereal Bars	0.30	0.38	0.79
Always	Sanpro Prod.	0.14	0.24	0.61	Mellow Birds	Instant Coffee	0.31	0.29	1.07
Gillette	Razor Blades	0.16	0.14	1.11	Pantene	Shampoo	0.31	0.47	0.66
Palmolive	Shower Prod.	0.16	0.23	0.72	Douwe Egbert	Ground Coffee	0.31	0.33	0.95
Oil Of Olay	Cleansers	0.17	0.14	1.20	H.P Sauces	Table Sauces	0.32	0.47	0.67
Clean & Clear	Cleansers	0.18	0.21	0.83	Aquafresh	Dentifrice	0.32	0.49	0.66
Lillets	Sanpro Prod.	0.18	0.24	0.72	Radox	Shower Prod.	0.32	0.44	0.73
Marshalls	Dry Pasta	0.18	0.30	0.59	Yoplait	Yoghurt	0.33	0.67	0.49
Ecover	Washing-Up Prod.	0.18	0.19	0.94	Mackeson	Stout	0.33	0.47	0.70
Sensodyne	Dentifrice	0.21	0.31	0.66	Nescafe	Instant Coffee	0.34	0.49	0.70
Tampax	Sanpro Prod.	0.21	0.28	0.75	Head & Shoulders	Shampoo	0.35	0.47	0.76
Crest	Dentifrice	0.21	0.53	0.40	Macleans	Dentifrice	0.36	0.53	0.68
Johnsons	Shower Prod.	0.22	0.28	0.80	Jordans	Cereal Bars	0.37	0.53	0.71
Imperial Leather	Bath Additives	0.23	0.32	0.70	Maxwell House	Instant Coffee	0.37	0.45	0.82
Kotex	Sanpro Prod.	0.23	0.27	0.87	Imperial Leather	Shower Prod.	0.38	0.52	0.73
Golden Wonder	Crisps	0.23	0.80	0.29	Wash & Go	Shampoo	0.38	0.48	0.79

N=16 for each regression.

Brand	Category	Coef. (β_{ij1})	Std. Err.	t-Val.	Brand	Category	Coef. (β_{ij1})	Std. Err.	t-Val.
Lynx	Shower Prod.	0.38	0.44	0.86	St Ivel	Margarine	0.60	0.94	0.64
Cif	Household Cleaners	0.39	0.59	0.66	Youngs	Frozen Fish	0.60	0.84	0.71
Timotei	Shampoo	0.39	0.43	0.91	Del Monte	Tinned Fruit	0.61	0.85	0.72
Brooke Bond	Tea	0.39	0.81	0.49	Uncle Bens	Cooking Sauces	0.61	0.83	0.73
Buitoni	Dry Pasta	0.40	0.73	0.54	Weetabix	Breakfast Cereals	0.61	0.79	0.78
Dettol	Household Cleaners	0.43	0.57	0.75	Homepride	Cooking Sauces	0.62	0.94	0.66
Mr Muscle	Household Cleaners	0.44	0.58	0.76	Baxters	Ambient Soup	0.63	0.81	0.78
Batchelors	Packet Soup	0.44	0.67	0.66	Hermesetas	Artificial Sweeteners	0.64	0.77	0.82
Yorkshire Tea	Tea	0.47	0.69	0.68	Chappie	Dog Food	0.64	0.94	0.68
Canderel	Artificial Sweeteners	0.47	0.48	0.98	Heinz	Ambient Soup	0.67	0.96	0.69
Tetley	Tea	0.48	0.67	0.71	I C B I N B	Margarine	0.67	1.05	0.64
Princes	Tinned Fruit	0.48	0.72	0.67	Sucron	Artificial Sweeteners	0.69	0.57	1.20
Dole	Tinned Fruit	0.49	0.60	0.81	Walkers	Crisps	0.71	0.91	0.78
Sweetex	Artificial Sweeteners	0.49	0.66	0.75	Clover	Margarine	0.71	1.00	0.71
Persil	Washing-Up Prod.	0.51	0.63	0.81	Butchers	Dog Food	0.73	1.10	0.67
Kerrygold	Butter	0.52	0.90	0.58	Jordans	Breakfast Cereals	0.75	1.04	0.72
Rightguard	Deodorants	0.53	0.68	0.78	Evian	Mineral Water	0.78	0.98	0.80
P.G.Tips	Tea	0.54	0.78	0.69	Pedigree	Dog Food	0.79	1.15	0.69
Lynx	Deodorants	0.54	0.68	0.79	Natrel Plus	Deodorants	0.80	0.75	1.06
Typhoo	Tea	0.55	0.81	0.67	Lurpak	Butter	0.80	1.01	0.79
Weight Watchers	Ambient Soup	0.55	0.83	0.66	Kelloggs	Breakfast Cereals	0.81	1.08	0.75
Soft & Gentle	Deodorants	0.55	0.65	0.84	Winalot	Dog Food	0.82	1.10	0.75
Sure	Deodorants	0.55	0.75	0.74	Danone	Yoghurt	0.83	1.02	0.82
Guinness	Stout	0.56	0.80	0.70	Volvic	Mineral Water	0.84	0.96	0.87
Country Life	Butter	0.56	0.85	0.66	Flora	Margarine	0.87	1.16	0.75
Palmolive	Bath Additives	0.56	0.61	0.91	Ski	Yoghurt	0.88	1.26	0.70
Dolmio	Cooking Sauces	0.57	0.80	0.71	Anchor	Butter	0.88	1.22	0.72
KP	Crisps	0.58	0.72	0.80	Irn Bru	Soft-drinks	0.89	1.23	0.72
Murphys Beer	Stout	0.58	0.62	0.94	Buxton	Mineral Water	0.90	1.38	0.65
Flash	Household Cleaners	0.58	0.85	0.69	Muller	Yoghurt	0.90	1.20	0.75
Radox	Bath Additives	0.59	0.78	0.77	Pal	Dog Food	0.93	1.31	0.71

N=16 for each regression.

Brand	Category	Coef. (β_{ij1})	Std. Err.	t-Val.	Brand	Category	Coef. (β_{ij1})	Std. Err.	t-Val.
Surf	Machine-Wash Prod.	0.94	1.36	0.69	Bold	Machine-Wash Prod.	1.07	1.25	0.86
Coca Cola	Soft-drinks	0.95	1.30	0.73	Daz	Machine-Wash Prod.	1.08	1.22	0.88
Quaker Oats	Breakfast Cereals	0.96	1.17	0.81	Strathmore	Mineral Water	1.09	1.45	0.75
Stork	Margarine	0.96	1.27	0.76	Ariel	Machine-Wash Prod.	1.09	1.23	0.88
Schweppes	Soft-drinks	0.97	1.26	0.77	Birds Eye	Frozen Fish	1.11	1.34	0.82
Pepsi	Soft-drinks	0.97	1.31	0.74	Kit-E-Kat	Cat Food	1.12	1.91	0.59
Tropicana	Fruit/Yoghurt Juice	0.97	1.23	0.78	Robinsons	Fruit/Yoghurt Juice	1.19	1.64	0.72
Highland Spring	Mineral Water	0.97	1.18	0.83	Felix	Cat Food	1.20	1.66	0.72
Persil	Machine-Wash Prod.	0.98	1.28	0.76	Knorr	Cooking Sauces	1.31	0.98	1.33
Ross	Frozen Fish	1.01	1.21	0.84	Whiskas	Cat Food	1.31	1.81	0.73
Ribena	Fruit/Yoghurt Juice	1.02	1.36	0.75	Ocean Spray	Fruit/Yoghurt Juice	1.59	2.09	0.76
Tango	Soft-drinks	1.02	1.40	0.73	Del Monte	Fruit/Yoghurt Juice	1.79	2.06	0.87
Macrae	Frozen Fish	1.06	1.48	0.72	Katkins	Cat Food	3.57	2.49	1.44

N=16 for each regression.

APPENDIX 3.F: PERMANENT CATEGORY-SPECIFIC META-ANALYTIC EFFECTS OF BUSINESS CYCLE CHANGES ON BRAND EQUITY

Category	Weighted Mean (β_{ij1})	Meta Std. Err.	Meta Z-Val.	Category	Weighted Mean (β_{ij1})	Meta Std. Err.	Meta Z-Val.
Toilet Tissues	0.030	0.014	2.221	Packet Soup	0.442	0.665	0.664
Crisps	0.079	0.207	0.381	Stout	0.470	0.357	1.318
Cleansers	0.094	0.064	1.467	Tea	0.484	0.333	1.454
Razor Blades	0.127	0.051	2.516	Tinned Fruit	0.521	0.411	1.267
Sanitary-Protection Products	0.176	0.113	1.567	Artificial Sweeteners	0.566	0.301	1.880
Ground/Bean Coffee	0.203	0.175	1.159	Deodorants	0.589	0.314	1.877
Dry Pasta	0.243	0.323	0.752	Ambient Soup	0.613	0.500	1.226
Conditioners	0.245	0.159	1.542	Butter	0.672	0.497	1.351
Instant Coffee	0.245	0.191	1.279	Yoghurt	0.675	0.526	1.283
Peanut Butter	0.251	0.229	1.096	Margarine	0.749	0.486	1.542
Shower Products	0.265	0.164	1.617	Cooking Sauces	0.757	0.450	1.682
Dentifrice	0.268	0.206	1.302	Breakfast Cereals	0.765	0.506	1.512
Washing Up Products	0.268	0.163	1.646	Dog Food	0.773	0.498	1.553
Table Sauces	0.287	0.238	1.208	Mineral Water	0.899	0.517	1.738
Cereal Bars	0.303	0.238	1.275	Frozen Fish	0.900	0.601	1.497
Shampoo	0.338	0.206	1.639	Soft-drinks	0.957	0.580	1.648
Household Cleaners	0.363	0.279	1.303	Machine Wash Products	1.034	0.565	1.829
Bath Additives	0.367	0.256	1.438	Fruit/Yoghurt Juice	1.247	0.736	1.695

APPENDIX 3.G: PERFORMANCE RISK, SOCIAL RISK, AND PRICE-QUALITY INFERENCE VALUES ACROSS PRODUCT CATEGORIES

Category	Perf. Risk	Soc. Risk	Price-Qual	Category	Perf. Risk	Soc. Risk	Price-Qual.
Ambient Soup	3.09	2.25	3.06	Instant Coffee	3.68	2.86	3.32
Artificial Sweeteners	2.99	2.31	3.08	Machine Wash Products	3.19	2.35	2.89
Bath Additives	3.07	2.59	2.91	Margarine	3.27	2.44	2.89
Breakfast Cereals	3.24	2.43	2.82	Mineral Water	2.70	2.43	2.61
Butter	3.27	2.59	2.97	Packet Soup	3.05	2.07	2.74
Cereal Bars	3.03	2.29	2.87	Peanut Butter	3.05	2.03	2.87
Cleansers	3.44	2.55	2.92	Razor Blades	3.51	2.43	3.19
Conditioners	3.28	2.59	3.03	Sanitary-Protection Products	3.44	2.25	3.04
Cooking Sauces	3.50	2.40	2.97	Shampoo	3.35	2.47	3.00
Crisps	3.40	2.35	3.22	Shower Products	3.07	2.59	2.91
Dentifrice	3.14	2.41	3.08	Soft-drinks	3.20	2.34	2.89
Deodorants	3.46	2.55	2.85	Stout	3.31	2.74	2.87
Dog Food	3.43	2.41	2.99	Table Sauces	3.36	2.37	3.14
Dry Pasta	3.04	2.35	3.05	Tea	3.66	2.73	3.04
Frozen Fish	3.59	2.41	3.17	Tinned Fruit	2.91	2.20	2.90
Fruit/Yoghurt Drink	3.03	2.28	2.71	Toilet Tissues	3.24	2.26	3.10
Ground/Bean Coffee	3.67	2.71	2.98	Washing Up Products	3.01	2.27	3.01
Household Cleaners	3.07	2.34	2.95	Yoghurt	3.24	2.32	2.98