THE IMPACT OF BRAND ARCHITECTURE DECISIONS ON PORTFOLIO SALES

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To my late grandfather, who instilled in me the curiousity about life at an early age, and taught me to write and think critically

Abstract: “ The Impact of Brand Architecture Decisions on Portfolio Sales”
Decisions pertaining to the organization of products under brands within the company’s portfolio are an important aspect of brand portfolio strategy with potentially serious top-and bottom-line implications. Despite the critical role brand architecture decisions play on profitability, there is little empirical evidence on how the strength of the link established among clusters of products within the company’s portfolio impacts company performance. To advance our understanding in this domain, this paper scrutinizes the effect of different brand architecture strategies (master brand with sub-brands vs stand-alone brand strategy) in moderating the impact of marketing actions (price promotion, feature, display, and new product introduction) on total portfolio sales. Using insights from diagnosticity-accessibility, similarity and derived varied behavior versus variety-seeking theories, the authors develop hypotheses as to whether and when a certain marketing action is expected to generate greater portfolio sales and how the differentiation level of products within the portfolio may interfere. The hypotheses are tested by means of a sales decomposition model, which traces demand redistribution in response to a focal brand’s marketing actions among linked (master brand with sub-brands), unlinked (stand-alone), and other brands in the category. In the empirical application, the authors use the coffee category in the IRI Academic Data Set. The results have the managerial implication that companies that use predominantly stand-alone brands benefit from price promotions more than subbrands. The reverse implication is true for line extensions.

Keywords: branding, brand architecture, brand portfolio, price promotion, innovation, econometrics, seemingly unrelated regression

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Contents

List of Tables

List of Figures

Introduction

Overall, two thirds of fast moving consumer good companies state they changed their brand architecture over the last decade (Laforet, 2015). Moreover, companies are increasingly polarized in their decision on brand architecture, either pursuing a strictly product branding or corporate branding approach (Laforet, 2015). Thus, firms do not only invest substantial resources to build, acquire and manage brands (e.g. Lodish and Mela, 2007), but they also do in discussing and executing brand architecture. However, the impact of this brand architecture for marketing managers is unclear. The few empirical studies are macro-level investigations of the impact of brand architecture strategies on firm value at the financial level (e.g. Hsu et al., 2016; Rao et al., 2004). This level is far away from the marketer's usual decision considerations and outcomes regarding e.g. promotions and new item introductions. Does having the same umbrella brand help or hurt the net revenue lift of such retail marketing mix actions for the company's portfolio? To what extent does brand architecture induce more cannibalization (undesirable) or performance spillover (desirable)? Current literature does not offer guidance on the important question of how managers with a portfolio of brands and products will use the chosen brand architecture to their advantage in marketing mix decisions.

Our research question is thus:

- Under what type of brand architecture strategy do total portfolio sales increase most with marketing mix decisions?

In this article, we decompose the sales allocation among the own-brand, brands that share the same name in the porfolio (hereafter linked brands), stand-alone brands that do not share the same name (hereafter unlinked brands) and competitor brands following an external shock to the brand system such as price promotion and line extension. Following the methodology by Van Heerde et al. (2004), we split up total category sales into own brand sales, linked brand sales, unlinked brand sales and competitor sales (see Figure 1). Either the undesirable process of cannibalization or the desirable process of performance spillover dominates in each hypothesized situation, resulting in net positive or negative sales. Therefore, the net sales effects we find for each group of brands is indicative of cannibalization or performance spillover.

Figure 1

There is a rich literature that has looked at the cannibalization (e.g. Srinivasan et al., 2005, Sullivan, 1990) and spillover (Balachander & Ghose, 2003; Erdem, 1998; Erdem & Sun, 2002) effects related to brands and brand extensions, but no work that has theoretically and empirically integrated the two outcomes within the context of the sales reallocation within a brand portfolio following a marketing mix action. This research addresses this gap and contributes to the literature on brand architecture by first developing theoretical expectations that discuss how different branding strategies impact net sales. We take into consideration the level of similarity and differentiation within the portfolio which cause the opposing forces of cannibalization and spillover. Further, this paper is the first study to apply accessibility-diagnosticity theory within the brand architecture literature.

The rest of the article is organized as follows. We begin by surveying the existing literature on brand architecture and discuss the various brand architecture types. Then, we discuss accessibility-diagnosticity theory (Feldman and Lynch, 1988) and discuss the implications of this theory for our research question. Next, we develop hypotheses concerning the interaction of brand architecture, similarity of attributes and the specific marketing mix action. We next describe our data and the methodology used to test these predictions. We conclude with a discussion of implications of our findings for brand management theory and practice.

What is brand architecture?

Multi-brand firms face the challenge of maximizing brand equity across all the different brand, products and services they offer. Their brand architecture "determines which brand elements they apply across all their new and existing products and services and is the means by which they help consumers understand those products and services and organize them in their minds" (Keller, 2012, p.386).

Brand architecture has been described as «an organizing structure of the brand portfolio that specifies brand roles and the nature of relationships between brands.» (Aaker and Joachimsthaler, 2000, p.8). Concerning the the division of companies into brand architecture st categories, Kapferer (2012) has created an operationalization that follows a hierarchical specification relating to (1) the number of levels of brands used, (2) the grouping of product brands and how strongly they are linked, and finally, (3) the dominance and role of the corporate brand.

There are various conceptual pieces that have discussed the advantages and disadvantages of different brand architecture strategies, most prominently Aaker and Joachimstahler (2000) which has introduced the term “brand architecture.” Other works also discuss under what conditions each brand architecture may be optimal and provide rich examples of brand architecture best practices and failures (Aaker, 1991; Aaker, 1996; Aaker, 2004). However, an empirical examination of most of the theory and conceptualization made in these works remains conspicously missing in the literature.

The empirical evidence which does exist deals with macro, financial marketing level studies, such as the impact of brand architecture strategy employed on firm value (Rao et.al., 2004; Hsu et al., 2016). In addition, there are studies that also look at the impact on firm value but do not concern brand architecture strategy decisions per se, but more broad independent variables such as certain characteristics of brand portfolio including the number of brands owned, the number of segments in which brands are marketed, and the degree to which brands compete with each other (Bahadir et al., 2008; Bharadwaj et al., 2011; Morgan and Rego, 2009; Rego et al., 2009; Wiles et al., 2012). However, there are no more micro-level empirical studies that look at the interaction of brand architecture strategies with daily marketing mix actions.

Experimental evidence exists for particular brand architecture strategies, such as the work of Sood and Keller (2012) which examines the ability of sub-branding to extend brands farther than they would normally be extendable. Other experimental studies include work done on brand leveraging which support the benefits of isolated brand architecture (Dacin and Smith, 1994; Roedder-John et al., 1998; Sheinin and Biehal, 1999). We emphasize that no work, experimental or secondary data based, compares the effects of different brand architecture in bringing about behavioral or market outcomes.

Different Brand Architectures and Related Literature

In a seminal article, Aaker and Joachimsthaler (2000) introduce the concept of the “brand relationship spectrum”, depicting firms that exist along the spectrum, and the advantages and disadvantages of certain positions along the spectrum (see Figure 2).

Figure 2

House-of-Brands

On one side of the brand relationship spectrum is the “House of Brands” strategy, which involves seperate product brands that are distanced from the corporate brand and from each other. The disadvantages of this strategy are that the companies lose efficiencies in marketing costs that could be potentially spread over a broad range of products, but that remain confined to one product group. As expensive as it is manage a large group of brands, this strategy is widespread in the packaged consumer goods sector where the hypercompetition draws the need for very niche-targeted products (Laforet, 2015; Aaker and Joachimstahler, 2000). The prime advantage of the House-of-Brands strategy, therefore, is its ability to micro-target and position precisely, without being worried about the positioning of other products that are associated with the brand.

As an example, if Procter & Gamble were not to market three different shampoos with three brand names, but to market them under the joint P&G shampoo name, with descriptors such as P&G Dandruff Control, P&G Combo and P&G Healthy Hair, there could be a confusion of potentially-conflicting brand associations. Each benefit segment requires its own brand associations, which are not optimally targeted using one brand name.

Further, Aaker and Joachimstahler (2000) state additional reasons for using the House-of-Brand strategy. They include signaling breakthrough advantages of new offerings, owning a new product class association by using a name which symbolizes a key benefit and avoiding or minimizing channel conflict.

Endorsed Brands

Endorsed brands (such as Simply Home from Campbell's, or Polo Jeans by Ralph Lauren) also involve independent brands, however they get support from another brand, usually the corporate brand. This endorsement adds credibility to the offering and plays only a supporting role in the decisionmaking of the consumer. Saunders and Guoqun's (1996) study of UK confectionary brands showed the endorsement strategy to be successful in the marketplace.

Subbrands

Subbrands are brands that are placed next to the master or parent brand and that enhance or alter the master brand associations. The master brand is the primary sender of information about the brand, but the subbrand works to add additional associations to the product that enable the master brand to be stretched into a new segment.

Subbrands are closer to the master brand than endorsers are to the endorsed brands, with implications of transfer of associations in both directions. This can enhance risk in the case of negative spillover between the brands, but it can also create an opportunity for subbrands and masterbrands to help each other. Additionally, a master brand within a subbranding scheme will have a more prominent role than an endorser in an endorsement scheme, which can give less freedom to the subbrand to create a differentiated brand image.

Branded House

In the Branded House strategy, the corporate brand covers all product offerings. This strategy moves the master brand to being the primary (and in some cases, the only) driver of the consumer buying decision. The subbrand loses its modest driver role and becomes a descriptor with little or no driver role. The Branded House strategy maximizes clarity, which is the major advantage from the consumer point of view. On the supply side, the other major advantage of the Branded House strategy is that it spreads the marketing costs of the brand across multiple products, increasing efficiencies in marketing. The major disadvantage of the strategy is that it is risky to put the reputations of all products under the same name. The different products' performances could dilute or worse, spillover negatively to the master brand. Alternatively, it could be difficult to maintain a consistent image across all products. Aaker and Joachimsthaler (2000) give examples of Levi's, Nike and Kodak, which have found it difficult to maintain a certain image or a quality position across a wide product line. In addition, a Branded House strategy can curtail a company's ability to address different consumer segments.

Another risk of the Branded House strategy is the risk of cannibalization, due to products not having clearly differentiated identities from each other. This risk of cannibalization has been expressed by Hsu et al. (2016) most recently, but not quantified. We argue that this risk of cannibalization applies to all other architecture types which contain some kind of linkage between the master brand and the subbrand, occurring at a decreasing rate when going from the Branded House to the House-of-Brands.

Brand architectures that do not fit into the four categories proposed by Aaker and Joachimsthahler (2000), i.e. House of Brands, Branded House, Subbranding and Endorsed Branding, have been discussed in several works (Kotler and Keller, 2007; Rajagopal and Sanchez, 2004). Indeed, not all brand architectures fit into a neat pattern, being the result of history, mergers and acquisitions as well as strategic reasons (Franzen, 2007).

To empirically validate our hypotheses, we use data from the coffee category. Within this category, the dominant players have mixed brand architectures. Specifically, within their portfolios, during the period of our data, Procter & Gamble, then Kraft (now Kraft Mondelez) and Segafredo Zanetti have both subbrands (for example the Folgers line under Procter & Gamble includes Folgers Lite and Folgers Coffee House) and standalone brands (such as Home Coffee and Millstone).

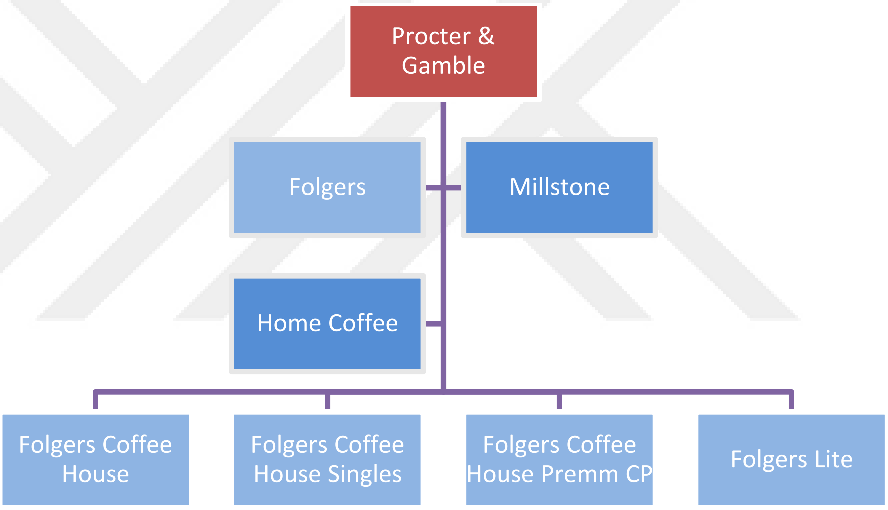

Figure 3

Hypotheses Development

In this study, we are primarily interested in comparing the effects of different brand architectures on market outcomes, considering the portfolio of products as a whole. We include product attribute similarity in our model as a means of controlling this aspect which is likely to influence consumers' decisions between products in a brand portfolio and their competitors. Different marketing interventions are used as the shocks to the system of brands to observe the brand architecture which has a more benefical reallocation of sales within the category following the shock for a particular brand portfolio. Different brand architectures are conceptualized as either having complete brand name similarity between the products, in which case a "linked" branding strategy is in place, or as having zero brand name similarity between the products, in which case an "unlinked" branding strategy is in place.

Accessibility-diagnosticity framework

Spillover effects and brand extension feedback effects (e.g. Ahluwalia and Gürhan-Canlı, 2000) have been explained in the brand extension literature by means of Feldman and Lynch's (1988) accessibility-diagnosticity theory. Feldman and Lynch's theory (1988, p.421) "... supports the general proposition that momentarily activated cognitions have disproportionate influence over judgments made about an object or on related behaviors performed shortly after their activation." Indeed, they conceptualize events in everyday life (such as seeing a product in a store) as altering the salience of potential inputs to decisions about behavior in the future. Therefore, certain events or objects may act as primes or retrieval cues to make accessible previous information.

The accessibility-diagnosticity framework holds that the likelihood that an input will be seen relevant as a base of judgment for another subsequent construct is determined by (1) the accessibility of the input in memory, (2) the perceived diagnosticity of the input for the judgment, and (3) the accessibility of other inputs in memory.

Accessibility is explained by spreading activation theory, which holds that concepts, such as brands, their product attributes, and categories in which they belong, are linked together in a network and can activate one another when the links between them are strong. (Anderson,1983; Collins and Loftus, 1975). Alternatively, Feldman and Lynch (1988) state that accessibility is a function of similarity and the time lapse between two events. Diagnosticity refers to the extent to which one object or event is informative about the other. An object is considered diagnostic if it helps categorize the target to a category of high or low quality (Herr, Kardes and Kim, 1991). A stimulus needs to be accessible before it can be diagnostic, and the more accessible it is, the more diagnostic it is due to the economies of cognition (Feldman and Lynch, 1988). Therefore, in the context of a marketing mix action such as price promotion or line extension which primes a brand and its product attributes, that brand and its product attributes are accessible and therefore diagnostic of the linked/unlinked brand to the extent that they are similar.

The priming quality of marketing mix actions

Past research has demonstrated that consumers use available information such as marketing mix stimuli as a signal about how to interpret brand name and product attributes (e.g. Boulding and Kirmani, 1993). In the context of marketing mix actions, Bridges et al. (2000) have shown how communication strategies enhance perceived fit for brand extensions by establishing explanatory links. We argue that marketing mix actions act to direct attention to the brand and product attributes of that brand within the store. With this particular brand as a frame of reference, the consumer compares the brand with other linked/unlinked brands. Our proposition is that this initial frame of reference influences which other brands and product attributes become salient.

Diagnostic role of the target brand

The diagnosticity of the target brand for other linked or unlinked brands form the other base of our predictions. The more similar is the target brand to other brands, the more diagnostic it is of that brand. Similarity can be defined in various ways (Medin et al., 1993). We have operationalized similarity in terms of the brand name similarity and/or product attribute similarity. Product attributes in our definition include (regular) price and other product feature attributes. Therefore, we argue that the more similar are two brands in name and product attributes, the more diagnostic is the target brand for the other brand. This diagnosticity implies that there is a transfer of perception and sales between the two brands. We argue that the direction of this transfer is determined by the nature of the marketing mix action. Because price promotions accelerate purchases in favor of the brand on promotion, there is likely to be a cannibalization effect that transfers sales from the brand that is diagnostic to the target brand. This transfer is likely to increase the more similar (diagnostic) are the two brands to each other. This leads us to make the following hypothesis:

H1) As product attribute similarity increases, the more that linked branding generates net negative sales compared to unlinked branding in the event of a price promotion.

Figure 4

On the other hand, established, strong line extensions have been found to benefit the parent brand more than the extension (Carter and Curry, 2013). Established parent brands that are similar in attributes to the line extension are also likely to increase sales of the parent brand more than the line extension because of the line extension acting as a cue to recall the similar parent. Therefore, we expect a feedback (reciprocal spillover) effect back to the brand that is diagnostic of the target brand. For example, if the brand Folgers were to introduce Folgers Breakfast Blend, the older and more established product Folgers House Blend (which is similar in name and product attributes) would get a transfer of sales (feedback effects) from Folgers Breakfast Blend. Folgers Breakfast Blend, in turn, would get a transfer of sales (cannibalization) from Millstone Breakfast Blend, which is not similar in brand name but is close enough in product attributes to be seen as a substitute. This leads to the following hypothesis:

H2) As product attribute similarity increases, the more that linked branding generates net positive sales compared to unlinked branding in the event of a line extension.

Figure 5

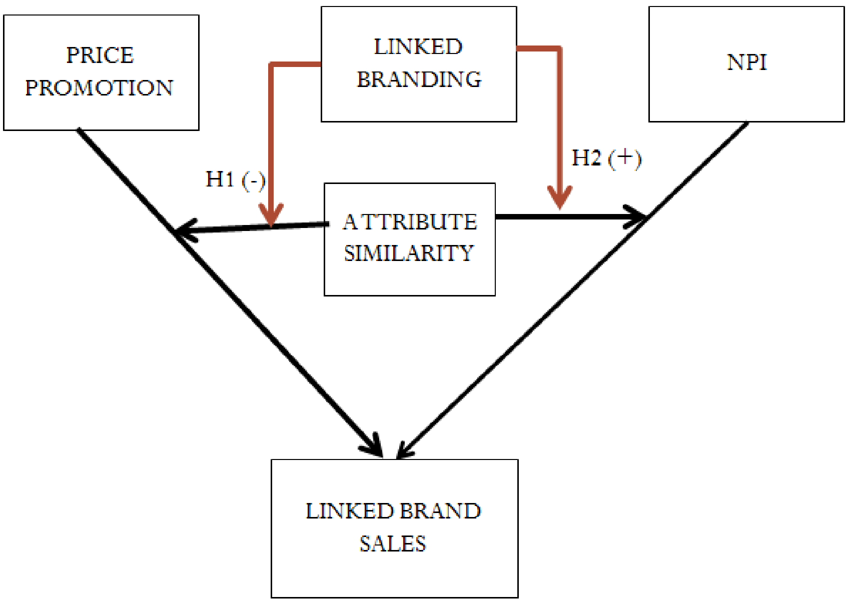

Figure 6

Therefore, we argue that (1) a particular marketing mix action focus the attention on the brand which is its target (make it accessible), and depending on the diagnosticity relationships of the brands in the consideration set cause a specific behavioral outcome.

Model

We use a net sales decomposition system to decompose the sales reallocation effect of total category sales after the marketing intervention, as changing the focal (own-brand) brand sales, sales for linked and unlinked brands within the same company portfolio as well as changing competitor sales (see Van Heerde et al., 2004 for details).

The system uses a net (unit sales approach) rather than a gross (elasticity based) approach to answer the question: If the promoted brand gains 100 units, how many units do linked brand lose, how many units do unlinked brands lose and how many units do the competing companies lose? The most important difference of the gross approach (introduced by Gupta, 1988, and used by Chiang, 1991; Chintagunta, 1993; Bucklin et al., 1998; Bell et al., 1999) from the net approach (introduced by Van Heerde et al., 2003) is that the net approach accounts for the increase in purchase incidence that benefits all brands in the category (category expansion) as well as cross-period effects. In this study, we are not concerned with measuring the amount of category expansion and cross-period effect on their own, but rather use these effects as controls to be certain that the effects are net.

Van Heerde et al. (2004) has shown mathematically how current own-brand sales can be split into various decomposition components. The approach consists of specifying a separate criterion variable for the own-brand effect and for each decomposition effect. We use a slightly modified version of the decomposition of Van Heerde et al. (2004), decomposing Total Category Sales (TCS_{jt} into Own Brand Sales (OBS_{jt}, Linked Brand SalesLBS_{jt}, Unlinked Brand Sales$ULBS_{jt}$ and Competitor Brand Sales(CBS_{jt}.)

$$TCS_{jt} = OBS_{jt} + LBS_{jt} + ULBS_{jt} + CBS_{jt} (1)$$

The marketing action of interest interacted with its similarity to the focal brand is regressed linearly on each of the different criterion variables. The same covariates are used across all of the equations. The only different aspect across all equations is the inclusion of the interaction of the marketing mix variable with the relevant similarity measure compared to the focal brand. Specifically, there is no similarity measure included in the first, own-brand effects equation because its similarity to itself is 1. For the linked brand effects equation, the average similarity of the linked brands to that focal brand is included in an interaction with the marketing mix variable to answer the question, "What is the effect of the marketing intervention on sales of the linked brands the more similar they are to the focal brand?" Likewise, for the unlinked and competitor brand effects equations, the relevant similarity measures are interacted with the marketing mix action.

$$OBS_{jt=} \beta'_{ob,1} PI_{jt} + \beta'_2 FD_{jt} + \sum_{j=1}^{J} \beta'_{3j} PI_{jt} SIM_{jj'} + \sum_{j=1}^{J} \beta'_{4j} FD_{jt} SIM_{jj'}$$
$$+ \sum_{s=1}^{S} \gamma_{1s} RP_{sjt} + \sum_{s=1}^{3} \gamma_{2s} CPI_{sjt} + \sum_{s=1}^{3} \gamma_{3s} FD_{sjt} + \sum_{\tau=1}^{T+T*} \gamma_{4\tau} PI_{jt+\tau}$$
$$+ \sum_{\tau=1}^{T+T*} \gamma_{5\tau} PI_{jt-\tau} + \sum_{\tau=1}^{T+T*} \gamma_{6\tau} CPI_{jt-\tau} + \sum_{\tau=1}^{T+T*} \gamma_{7\tau} CPI_{jt+\tau}$$
$$+ \mathrm{Sin}(2\pi t/52) + \cos(2\pi t/52) + \varepsilon_{jt}$$

(2)

$$CBS_{jt}{}^{L},\ j \in L = \beta''_{cbl,1} PI_{jt} + \beta''_{2} FD_{jt} + \sum_{j=1}^{J} \beta''_{3j} PI_{jt} SIM_{jj'} + \sum_{j=1}^{J} \beta''_{4j} FD_{jt} SIM_{jj'}$$
$$+ \sum_{s=1}^{S} \gamma''_{1s} RP_{sjt} + \sum_{s=1}^{3} \gamma''_{2s} CPI_{sjt} + \sum_{s=1}^{3} \gamma''_{3s} FD_{sjt} + \sum_{\tau=1}^{T+T*} \gamma''_{4\tau} PI_{jt+\tau}$$
$$+ \sum_{\tau=1}^{T+T*} \gamma''_{5\tau} PI_{jt-\tau} + \sum_{\tau=1}^{T+T*} \gamma''_{6\tau} CPI_{jt-\tau} + \sum_{\tau=1}^{T+T*} \gamma''_{7\tau} CPI_{jt+\tau}$$
$$+ \mathrm{Sin}(2\pi t/52) + \cos(2\pi t/52) + \varepsilon''_{jt}$$

(3)

$$CBS_{jt}{}^{L},\ j \in C = \beta''''_{cbc,1} PI''''_{jt} + \beta''''_{2} FD_{jt} + \sum_{j=1}^{J} \beta''''_{3j} PI_{jt} SIM_{jj'} + \sum_{j=1}^{J} \beta''''_{4j} D_{jt} SIM_{jj'}$$
$$+ \sum_{s=1}^{S} \gamma''''_{1s} RP_{sjt} + \sum_{s=1}^{3} \gamma''''_{2s} CPI_{sjt} + \sum_{s=1}^{3} \gamma''''_{3s} FD_{sjt}$$
$$+ \sum_{\tau=1}^{T+T*} \gamma''''_{4\tau} PI_{jt+\tau} + \sum_{\tau=1}^{T+T*} \gamma''''_{5\tau} PI_{jt-\tau} + \sum_{\tau=1}^{T+T*} \gamma''''_{6\tau} CPI_{jt-\tau} + \sum_{\tau=1}^{T+T*} \gamma''''_{7\tau} CPI_{jt+\tau}$$
$$+ \mathrm{Sin}(2\pi t/52) + \cos(2\pi t/52) + \varepsilon''''_{jt}$$

(4)

$$CBS_{jt}{}^{L},\ j \in C = \beta''''_{cbc,1} PI''''_{jt} + \beta''''_{2} FD_{jt} + \sum_{j=1}^{J} \beta''''_{3j} PI_{jt} SIM_{jj'} + \sum_{j=1}^{J} \beta''''_{4j} D_{jt} SIM_{jj'}$$
$$+ \sum_{s=1}^{S} \gamma''''_{1s} RP_{sjt} + \sum_{s=1}^{3} \gamma''''_{2s} CPI_{sjt} + \sum_{s=1}^{3} \gamma''''_{3s} FD_{sjt}$$
$$+ \sum_{\tau=1}^{T+T*} \gamma''''_{4\tau} PI_{jt+\tau} + \sum_{\tau=1}^{T+T*} \gamma''''_{5\tau} PI_{jt-\tau} + \sum_{\tau=1}^{T+T*} \gamma''''_{6\tau} CPI_{jt-\tau} + \sum_{\tau=1}^{T+T*} \gamma''''_{7\tau} CPI_{jt+\tau}$$
$$+ \mathrm{Sin}(2\pi t/52) + \cos(2\pi t/52) + \varepsilon''''_{jt}$$

(5)

for j=1,….,J (brands), t=T+T*+1,…..,$T_{max} - T - T$ (weeks), L=*linked brands*, UL=*unlinked brands*, C=*competitor brands*, S=L+UL+C, where PI_{jt}=price index for brand j in week t;$PI_{jt} equals 1 - \frac{d}{100} if there is a d percent discount for brand j \in week t, \wedge$ $1 otherwise.$

CPI_{sjt}= average price index across *s=1 linked brands, s=2 unlinked brands, s=3 competitor brands.*

FD_{jt}=share-weighted average of dummy for non-price promotion (feature or display)

RP_{sjt}=regular price for brand *j* in week *t*, belonging to brand group *s*=1,2,3 (*s=1 linked brands, s=2 unlinked brands, s=3 competitor brands*) across brands *k, k=1,…..,J, k≠j*

$PI_{jt} \quad _{jj'}$= similarity of each brand *j=1,….,J* with all other brands *j=1,…,j,* multiplied by the price promotion of brand *j* at time *t*.

$FD_{jt} \quad _{jj'}$ = similarity of each brand *j=1,….,J* with all other brands *j=1,…,j*, multiplied by the non-price promotion (feature/display) of brand *j* at time *t*.

Sin(2πt/52),cos(2πt/52)= Fourier series variables used to control for seasonality.

$$\varepsilon_{jt} = disturbancetermsforbrandj \in weekt \in Equations(2) - (5).$$

T* is the numer of leads, T is the number of lags, and $T_{max}$is the total number of weeks

The parameter $\beta'_{ob,1}$in (2) is the effect on own-brand sales of the price index for brand j, $\beta'_{cbl,1}$ in (3) is the effect on cross-brand sales of linked brands of the price index for brand j,$\beta'_{cbul,1}$ in (4) is the effect on cross-brand sales of unlinked brands of the price index for brand j,and $\beta'_{cbc,1}$ in (5) is the effect on cross-brand sales of competitor brands of the price index for brand j.

The decomposition is carried out through these paramater estimates, using the identity in (1).

Variables

As per Van Heerde et al. (2004), we use a price index variable to make a distinction between promotional and regular price effects. This price index variable is composed of the division of the actual price by the regular price (non-promoted price). It is equal to one in non-promotional weeks and is less than one if the actual price is less than the regular price because there is a promotion. In the case that the regular price changes, the price index changes in relation to the regular price.

Regular price is calculated by going back in time and searching for a non-promotional week for that sku so that regular price can be assumed to be equal to that price. The process runs such that when a regular price candidate is found, a check is conducted to make sure that is higher than the actual price. In the case that it is lower than the actual price, the actual price is multiplied to be equal to 5% higher than the regular price. The search continues for six weeks prior, six weeks forward. If no non-promotional price is found for that sku in that time period, we check in other stores for the same sku's non-promotional regular price candidate.

Promotional variables such as discount, display and feature can be correlated in analyses (Gupta, 1988; Chiang, 1991). It is therefore crucial to seperate them out in a way that they are uncorrelated. We accomplish this by defining them in a way that they are by their nature uncorrelated. We define our two different promotion variables as: (1) price index without display/feature support, (2) display/feature without price cut. We do not include all seven possible varieties used in Van Heerde et al. (2004) because we are more interested in the effects of different brand architectures than on the different promotion types. In addition, some of the seven possible varieties have inadequate variance in the data.

The focal variables, whose coefficients are used for the decomposition, are thus the promotion variables and the product line length variable, interacted with the relevant similarity variable to the dependent variable in each equation. For example, in the Linked Brand Sales equation, the important independent variables are the focal brand's promotion variables, product line length variable interacted with the similarity variable of the linked brands to the focal variable. Similarly, in the Unlinked Brand Sales equation, the important independent variables are the focal brand's promotion variables, product line length variable interacted with the similarity variable of the unlinked brands to the focal variable.

The numerous covariates act to minimize the possible occurrence of biased parameter estimates due to omitted variable bias. The covariates' effects are not used for the decomposition. We control for linked, unlinked and competitor (all three hereafter referred to as cross-brands) brands' price promotion (via CPI_{sljt}) and own-brand and cross-brands' display or feature activity without price discounts ($D_{sljt} \wedge CD_{sljt}$, and for own and cross-brands' regular price effects (RP_{sjt} and CRP_{sjt}).
In addition, we trigonometric seasonality variables to control for seasonality and as a proxy for missing brand level variables such as advertising, with the following variables:sin((2*π*week)/52) and cos((2* π*week)/52).

Data

The data that we use come from the Academic IRI Dataset which cover store sales and consumer panel data in 47 US markets for 30 product categories. The store sales data consist of 11 years of product sales, pricing and promotion data for all items sold (of which we took the first six years). Of this data, we use the coffee category for the 2001-2006 period for the Chicago and surrounding cities. The coffee category was picked because 1) it had a wide variety of brand architectures of the dominant companies, 2) because it is a low-involvement, hedonic category with small differences between products, which fit our theory and allow us to test our hypotheses (See Footnote 1). Data are pooled across 20 stores in Chicago and surrounding cities. We tried to reduce heterogeneity in our data that could arise due to different retail chains and geographic markets, therefore we used a chain which has a large number of stores in the same market and neighboring markets.

Store-level scanner data is used because of our goal of using a parsimonious but managerially meaningful model. In addition, store data have been shown to be more representative than household panel data (e.g.Gupta et al., 1996; Bucklin and Gupta, 1999)

Aggregation from the sku level to the brand level is carried out as follows. First, the Sku share of brand sales is calculated by dividing each sku's sales for each week by the total sales of all the skus of that brand. Then, a constant average we term "Sku weight" is calculated of the Sku share of brand sales and multiplied by the sku presence dummy.

Feature, display, price reduction, discount depth, feature and display without discount are aggregated to the brand level by considering a brand the highest occurring value of the skus that are within that brand and multiplied with the sku weight to produce their share weighted averages.

In order to operationalize linked brands, brands that share a parent brand are taken; for unlinked brands, brands that belong to the same company but have different parent brands; for all other competing brands, brands of other companies are taken.

In the calculation of linked, unlinked and competitive regular price, discount depth, feature or display without discount, number of skus of the brand, each brand is weighted by its average market share.

In order to observe all linked, unlinked, and competing brands alongside the focal brand and to be able to study how demand gets redistributed in the face a marketing intervention, cases where total category sales are zero, number of skus are zero, linked skus are zero and unlinked skus are zero are removed from the data. Essentially we are looking only at mixed brand architectures for companies that include in their portfolio both linked and unlinked brands. Consequently, our analysis covers three major companies and their portfolio of 21 brands.

Product feature similarity is calculated at the sku level. First, the number of distinct levels is reduced. Initially, in the raw data, there are five attributes: flavorscent, product type, brewing method, form and packaging. An additional attribute by the name of country of origin of bean is coded from the available information in lavorscent. Flavor and packaging are categorized seperately into reduced number of attribute levels. Product type, brewing method and form are combined to categorize large clusters of occurring instances.

Each sku's attribute levels are compared against the attribute levels of other skus' attribute levels. In the case that two skus are the same on that attribute, (see Rooderkerk et al., 2013 for details), a similarity level is calculated taking into consideration the frequency of occurrence of that attribute level. The approach looks first at whether two items share the same level of a nominal attribute (eg flavor of coffee.) If they do share the same level of that nominal attribute, "their perceived similarity should be stronger when their shared attribute level occurs less frequently." (Goodall,1966 as cited in Rooderkerk et al.,2013,p.703)

This is accomplished by defining

$$SIM_{kk\prime lti}\text{=I}\{A_{kl=}\ \ A_{k\prime l}\}.(1\text{-}\frac{1}{N_{ti}}.\sum_{\substack{k''=1 \\ X_{k''ti=1}}}^{K} I(A_{k\prime\prime l}\text{=}A_{ki})\ )$$

where

I(.)=an indicator function that is 1 if its argument holds and is 0 otherwise.

A_{kl}= the level attained by a sku on attribute *l* such that $A_{kl} = m <> A_{klm} = 1$

and

N_{ti} = the number of skus present in week t in store i.

All but one of the five product feature attributes are nominal and calculated according to the formula above. The fifth product feature attribute, price, is metric and calculated according to the following approach. The definition of similarity should again, as with the nominal attribute, take into consideration the extent to which the same attribute level is unique. In addition, frequency theory predicts that two skus that have fewer skus with attribute values in betweeen the focal skus' attribute values would be perceived as more similar (Parducci, 1965; Parducci and Wedel,1986)

In order to fulfill both of these requirements, we define

$$SIM_{kk'lti}\text{= 1-(}\frac{1}{N_{ti}} * \sum_{\substack{k''=1 \\ X_{k'ti}}}^{K} I(\min\{A_{kl}, A_{k'l}\} \leq\ A_{k''l} \leq \max\{A_{kl}, A_{k\prime l}\}\ )$$

İf attribute *l* is metric.

Finally, using the Nearest Neighbor approach, the mean of the similarities across each sku for all attributes and across each brand for all skus is calculated.

Descriptive Statistics Table of Focal Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Own-Brand Sales	46910	79.56197	188.3547	0	5662.1
Cross-Brand Sales, Linked	46910	188.1679	319.8061	0	5662.1
Cross-Brand Sales, Unlinked	46910	60.53921	79.06304	0	2216.3
Cross-Brand Sales, Competitive	46910	823.3833	595.0795	0	6628.3
Product Line Length	46910	4.669772	4.723102	1	45
Discount Depth	46910	.0629449	.102232	0	.64116
Feature or Display	46910	.2291471	.3846272	0	1
Regular Price	46910	4.998211	4.748832	1.4145	22.236
Similarity, linked	46910	.4306237	.1117229	.05614	.6625002
Similarity,unlinked	46910	.448822	.1485093	.067742	.760306
Similarlity,Competitive	46910	.4794694	.1321827	.129412	.7737513

Table 1

Estimation of seemingly unrelated regression (SUR)

Seemingly Unrelated Regression was used for estimation since the error terms of the four different equations are correlated. In this case, Ordinary Least Squares estimators would not be efficient. In this study, the different equations correspond to the demand function for the different components of Total Portfolio Sales, and their errors would be by definition correlated. The optimum lag length is found through the Bayes Information Criterion (BIC) and Schwarz Information Criterion (SIC) (See the appendix for the model with all of the regeressors).

We report the standard decomposition of the own-brand sales effect into Cross-Brand Linked, Cross-Brand Unlinked and Cross-Brand Competition effects in Table 1. The R-square for the whole SUR system (Judge et al.1985) varies between 0.42 and 0.57. Of all the brands of the four different dependent variables, 70% of all own-brand effects, 73.5% of all linked-brand effects, 79% of all unlinked brand effects, and 70.4% of all competitive effects are statistically significant ($p<0.05$,one tailed). The parameter estimates show the effect of the different independent variables on the criterion variable of choice.

	Own-Brand Effect	**CBSlinked**	**CBS unlinked**	**CBS competitor**
Dd	340.93	457.28	-86.16	-194.30**
Noskus	13.92	-0.97	1.89	-51.43***
Simdd	-	-1682.06	255.64***	-284.51
Simnoskus	-	3.09	-5.16***	56.17***

Table 2

Discount-depth-similarity interaction

The results suggest that, controlling for similarity, discount depth has a positive impact ($p<0.001$) on Sales of Linked Brands (CBSlinked). However, when looking at the coefficient for similarity interaction with discount depth, we see that it is negative and higher in magnitude than the coefficient for discount depth. For Cross-Brand Sales of Unlinked Brands (CBSUnlinked), discount depth has a negative impact ($p<0.001$). Again, as with CBSlinked, the coefficient for similarity interaction with discount depth causes the net result to change signs because it is positive and higher in magnitude than the coefficient for discount depth.

Conducting the Wald Test for statistical difference between the coefficients for similarity*discount depth between the equations for CBSlinked and CBSunlinked, shows that they are statistically different from each other (See Table 3). Therefore, we can conclude that the net effect of discount depth while similarity increases is more negative. This finding confirms *H1*, which stated that increase in similarity causes the net effect of discount depth to be more negative for linked branding compared to unlinked branding.

(	1)	[cbslinked]simlmattdd - [cbsunlinked]simulmattdd = 0		
(	2)	[cbslinked]simlmattnsku - [cbsunlinked]simulmattnsku	=	0
	chi2(2) = 120.56			
	Prob > chi2 = 0.0000			

Table 3

a) *Line extension-similarity interaction*

The results suggest that, controlling for similarity, product line length has a negative impact (p<0.001) on Sales of Linked Brands (CBSlinked). Examining the coefficient for similarity interaction with product line length, we see that it is positive and higher in magnitude than the coefficient for product line length. For Cross-Brand Sales of Unlinked Brands (CBSUnlinked), product line length has a positive impact but insignificant. The coefficient for similarity interaction with product line length causes the net result to change signs because it is negative and higher in magnitude than the coefficient for discount depth.

Conducting the Wald Test for statistical difference between the coefficients for similarity*discount depth in Equations (3-4) (between CBSlinked and CBSunlinked), shows that they are statistically different from each other (See Table 3 above). Therefore, we can conclude that the net effect of product line length (or the effect of new line extensions) while similarity increases is more negative. This finding confirms *H2*, which stated that increase in similarity causes the net effect of line extensions to be more negative for linked branding than for unlinked branding.

Analysis of Low and High Levels of Similarity for the Interaction Effect

In order to graphically display the moderation of levels of similarity on discount depth and on product line length, the 25 percentile and 75 percentiles of similarity of linked versus unlinked brands were used with the coefficients. The following are the figures that show the moderation effect of the different levels of similarity on discount depth and product line length impact on net sales, respectively.

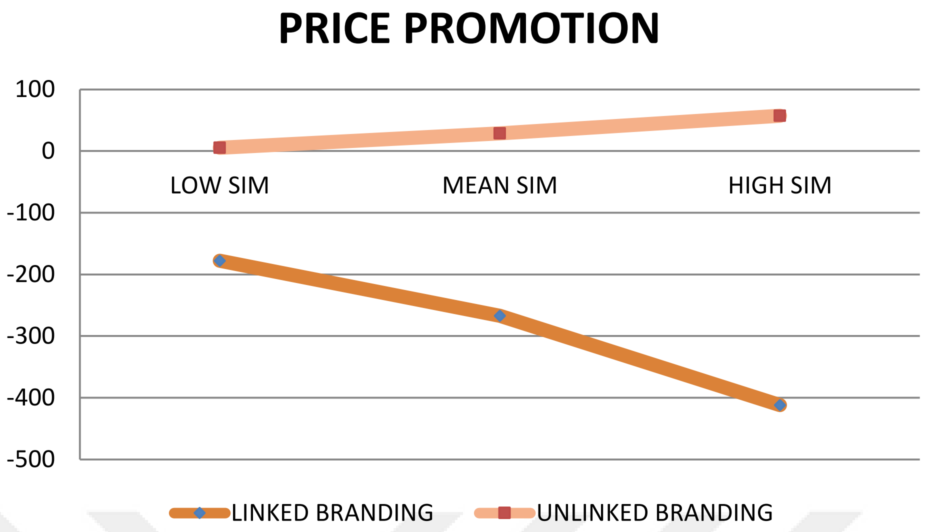
PRICE PROMOTION
100
0
-100
-200
-300
-400
-500
LOW SIM
MEAN SIM
HIGH SIM
LINKED BRANDING
UNLINKED BRANDING

Figure 7

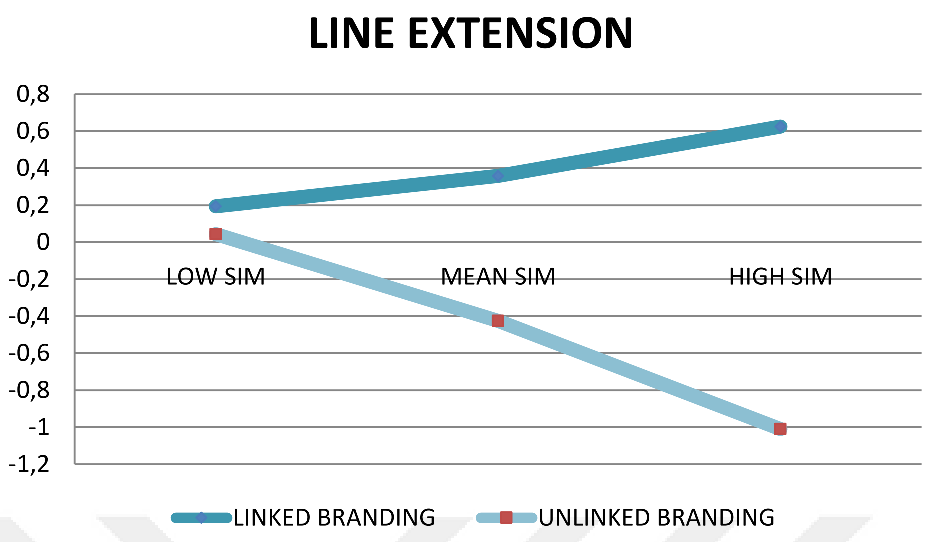

Figure 8

Therefore, the outcomes of estimation support 1) H1 that price promotions interacts with similarity within the linked brands to produce more negative sales impact than for unlinked brands 2) H2 that line extensions interact with similarity within linked brands to produce a more positive sales impact than for unlinked brands. The sign flips between coefficients for figures further imply that price promotions and line extensions have differential effects on sales displacement for the company portfolio brands (both linked and unlinked). This finding is a valuable contribution to the literature on sales decomposition effects of different marketing mix actions as well as the literature on branding.

Descriptive Statistics of Key Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
dd	46910	.0629449	.102232	0	.64116
ldd	46910	.0810578	.0999424	0	.64116
uldd	46910	.0555994	.0833459	0	.48833
cdd	46910	.0743123	.0485392	0	.26709

noskus	46910	4.669772	4.723102	1	45
lnoskus	46910	11.07455	7.783536	1	45
ulnoskus	46910	20.53298	18.82005	1	60
cnoskus	46910	136.8068	47.92295	30	289
simlmattdd	46910	.0292856	.0483028	0	.2968545
simulmattdd	46910	.031344	.0513074	0	.3124729
simcmattdd	46910	.0321576	.0516473	0	.3209099
simlmattnsku	46910	2.108554	2.346796	.05614	26.62841
simulmattn~u	46910	2.454452	2.997656	.086538	27.54135
simcmattnsku	46910	2.625365	3.141187	.147944	32.14285

Table 4

Pairwise Correlations of Key Variables

	dd	ldd	uldd	cdd	noskus	Lnoskus	Ulnoskus
dd	1.0000						
ldd	0.6544	1.0000					
uldd	0.4321	0.5326	1.0000				
cdd	0.0267	0.0505	0.0293	1.0000			
noskus	0.0632	-0.0129	-0.0428	0.0349	1.0000		
lnoskus	-0.2479	-0.0829	-0.0660	0.0826	-0.3437	1.0000	
ulnoskus	-0.1621	-0.0807	-0.0135	0.1276	0.1797	0.6004	1.0000
cnoskus	0.1778	0.1252	0.1394	0.0224	-0.1278	-0.4127	-0.4897
simlmattdd	0.9874	0.6584	0.4684	0.0288	0.0695	-0.2452	-0.1379
simulmattdd	0.9698	0.6632	0.4754	0.0298	0.1358	-0.2819	-0.1136
simcmattdd	0.9723	0.6582	0.4465	0.0327	0.1641	-0.2737	-0.1259
simlmattnsku	0.0829	-0.0064	-0.0215	0.0373	0.9757	-0.3301	0.2054
simulmattn~u	0.0809	-0.0063	-0.0262	0.0361	0.9788	-0.3460	0.2250
simcmattnsku	0.0777	-0.0074	-0.0336	0.0342	0.9902	-0.3566	0.1702
	cnoskus	simlm~dd	simu~tdd	simcm~dd	simlma~u	simulm~u	simcma~u

cnoskus	1.0000						
simlmattdd	0.1990	1.0000					
simulmattdd	0.1795	0.9796	1.0000				
simcmattdd	0.1772	0.9763	0.9834	1.0000			
simlmattnsku	-0.1019	0.1024	0.1596	0.1855	1.0000		
simulmattn~u	-0.1265	0.0928	0.1631	0.1794	0.9791	1.0000	
simcmattnsku	-0.0912	0.0883	0.1515	0.1808	0.9851	0.9835	1.0000

Table 5

Discussion

This article provides empirical evidence of the cannibalization and spillover impacts within the company portfolio of different brand architectures for different marketing mix actions. Consistent with the theory of diagnosticity-accessibility (Feldman and Lynch, 1988),marketing mix actions act as stimuli that make certain linked and unlinked brands accessible and their similarity levels lead to certain products more diagnostic for the product purchase decision and therefore likely to be included in the consideration set. What determines which product will ultimately be chosen is explained by the nature of the marketing mix action through derived varied behavior and variety-seeking.

Similarity theory provide extra support for the idea that different marketing mix actions have differential impacts on sales reallocation within the portfolio. It has been proposed and empirically validated (e.g. Gati & Tversky, 1984; Tversky, 1977) that similarity is not constant or static, but is defined contextually. Context is expected to influence similarity by activating or making salient context-related properties. To the extent that these context-related properties are shared by the two objects under comparison, their similarity is increased (Medin et al., 1993). Murphy & Medin (1985) noted that “the relative weighting of a feature (as well as the relative importance of common and distinctive features) varies with the stimulus context and task so that there is no unique answer to the question of how similar is one object to another” (p.296). On a similar vein, Barsalou (1983) demonstrated that as snake and a raccoon were judged much more similar when no explicit context was given than when the context of pets was provided.

This flexibility of similarity, is not however, random, and is governed by systematic changes with context (Medin et al., 1993). Hiatt & Trafton (2013) has concretized the abstract notions of salience (Tversky, 1977) and prototypicality (Rosch, 1975) as translating to familiarity and priming within a cognitive model. Although substitution and income theory from economics (e.g. Ashenfelter and Heckman, 1974) would predict that similarity induces substitution both for price promotions and line extensions, we find and assert that different marketing mix actions have a different interaction with observed similarity for different branding strategies. Derived varied behavior and variety-seeking helps us explain this effect. A complementary insight could be that as compared to observed similarity, perceived similarity changes as a function of branding strategy. This could explain the exact mechanism behind the impacts of marketing mix actions and similarity on net sales effects within the portfolio.

The objective of the present article was to be able to judge which brand architecture is overall most advantageous to companies. The article addresses the sales reallocation following a marketing mix action among a company's portfolio. The key contributions of the present article are threefold. First, it applies a parsimonious methodology which has clear implications for brand architecture theory and practice. Second, it introduces accessibility-diagnosticity, similarity theories and derived varied behavior versus (true) variety seeking to the brand architecture literature. Third, the interactions among similarity within the portfolio and branding stategy are further moderated by the third marketing mix action. We therefore understand that managing brand portfolios cannot be predicted for all marketing mix actions equally.

Limitations and Directions for Future Research

We explain our findings through Diagnosticity-Accessibility theory, however we cannot test the behavioral mechanisms. This could provide a fruitful opportunity for testing the theories through experiments in behavioral studies in the future. Although the category selection process was very discriminatory to provide an ideal testing ground for our hypotheses, it could be interesting to see our results replicated in other hedonic, low-involvement categories which have a relatively high level of similarity within the product category in research that examines the conditions for other categories. It would be particularly interesting to study how the implications change for high-involvement categories such as durables. Finally, the lack of data on advertising in our model might be biasing our coefficients

Managerial Implications and Conclusion

From a practical perspective, our findings suggests that firms that do heavy price-promoting should have a more “unlinked” (or House-of-Brands architecture), and firms that focus their budgets on innovation should have a more “linked” brand architecture. This implication has face validity through prominent cases of successful companies that tend toward one of these ends of the Brand Relationship Spectrum (Aaker & Joachimsthaler, 2000) and therefore follow a “linked” or “unlinked” branding strategy. Procter & Gamble is an example of a company that pursues linked branding. Ailawadi et al. (2001) documents Procter & Gamble’s negative experience in replacing price promotions with everyday-low prices during the 1990s. We argue that a possible reason Procter & Gamble did not perform as well under a no-price promotions strategy is because it has an unlinked brand architecture (House-of-Brands). We have shown in this study that for unlinked brand architecture, price promotions increase sales. On the other extreme are technology companies that predominantly pursue a more linked (“corporate”) branding strategies due to their role in risk-reduction (e.g. Montgomery and Wernerfelt, 1992) for these high-involvement categories. Finally, there is the implication that companies that have investment in a particular brand architecture choose their overall marketing strategy and allocate resources using tactics that would optimize their total portfolio sales.

Appendix

Table 6

Coef.	Std. Err.	z		P>z		
Own Brand Sales						
Discount Depth	340.9303	12.67469	26.9	0	316.0883	365.7722
Feature/display	9.194506	3.62341	2.54	0.011	2.092753	16.29626
Product Line Length	13.92443	2.510712	5.55	0	9.003524	18.84534
Comp.Prod.Line Length	-0.23906	0.231251	-1.03	0.301	-0.6923	0.214183
Linked Prod.Line Length	2.169639	1.319987	1.64	0.1	-0.41749	4.756766
Unlinked Prod.Line Length	2.366401	0.771515	3.07	0.002	0.854261	3.878542
Competitive Discount Depth	-230.454	19.69948	-11.7	0	-269.064	-191.844
Competitive Feature/Display	-38.5531	6.924499	-5.57	0	-52.1249	-24.9813
Regular Price	-8.22533	1.648554	-4.99	0	-11.4564	-4.99423
Competitive Regular Price	59.66945	3.310811	18.02	0	53.18038	66.15852
Linked Regular Price	-62.8122	2.955424	-21.25	0	-68.6047	-57.0197
Linked Discount Depth	416.5538	13.20699	31.54	0	390.6686	442.4391
Linked Feature/Display	41.77085	4.061746	10.28	0	33.80997	49.73172
Unlinked Regular Price	-2.99206	0.52291	-5.72	0	-4.01694	-1.96718
Unlinked Discount Depth	-76.0487	14.50207	-5.24	0	-104.472	-47.6252
Unlinked Feature/Dispaly	-8.02571	4.305183	-1.86	0.062	-16.4637	0.412297
Lagnskus	1.224528	1.546125	0.79	0.428	-1.80582	4.254877
Fnskus	-3.99426	1.811736	-2.2	0.027	-7.5452	-0.44332
Laglnskus	1.302114	0.837889	1.55	0.12	-0.34012	2.944346
Flnskus	0.06081	0.909966	0.07	0.947	-1.72269	1.84431

Lagulnskus	-1.62265	0.49062	-3.31	0.001	-2.58425	-0.66105
Fulnskus	-0.81684	0.487435	-1.68	0.094	-1.77219	0.138519
Fcnskus	0.166884	0.145569	1.15	0.252	-0.11843	0.452195
Lagcnskus	-0.1909	0.140139	-1.36	0.173	-0.46557	0.083766
Lagdd	-79.8445	14.68385	-5.44	0	-108.624	-51.0647
lag2dd	-21.7471	12.65193	-1.72	0.086	-46.5444	3.050233
Lagfd	-6.23975	3.856235	-1.62	0.106	-13.7978	1.318328
lag2fd	-2.06203	3.608125	-0.57	0.568	-9.13382	5.009766
Laglfd	7.736434	7.931758	0.98	0.329	-7.80953	23.28239
lag2lfd	-6.70299	6.761386	-0.99	0.322	-19.9551	6.549086
Lagldd	13.67156	23.3292	0.59	0.558	-32.0528	59.39595
lag2ldd	55.67044	19.46171	2.86	0.004	17.5262	93.81469
Laguldd	-58.1966	15.06478	-3.86	0	-87.7231	-28.6702
lag2uldd	-29.5003	13.18574	-2.24	0.025	-55.3438	-3.65668
Lagulfd	-1.18836	4.392881	-0.27	0.787	-9.79825	7.421526
lag2ulfd	-11.3163	4.079932	-2.77	0.006	-19.3129	-3.31982
Lagcdd	8.485063	17.38647	0.49	0.626	-25.5918	42.56193
lag2cdd	13.86543	14.54078	0.95	0.34	-14.634	42.36483
Lagcfd	10.03005	4.676488	2.14	0.032	0.864302	19.1958
lag2cfd	10.11062	4.316912	2.34	0.019	1.649624	18.57161
sin1	4.801469	0.976278	4.92	0	2.888	6.714939
cos1	-3.13704	0.988388	-3.17	0.002	-5.07424	-1.19983
br_1	55.22441	9.436667	5.85	0	36.72889	73.71994
br_2	-150.731	8.913571	-16.91	0	-168.201	-133.261
br_3	-102.726	27.07729	-3.79	0	-155.797	-49.6559
br_4	-205.077	9.58075	-21.41	0	-223.855	-186.299
br_5	-206.413	12.90574	-15.99	0	-231.708	-181.119
br_6	-128.656	7.581555	-16.97	0	-143.516	-113.796
br_7	-173.64	8.52985	-20.36	0	-190.358	-156.922
br_8	-186.447	7.489755	-24.89	0	-201.127	-171.768
br_9	-96.9637	8.527056	-11.37	0	-113.677	-80.251
br_10	-45.1463	24.4505	-1.85	0.065	-93.0684	2.775782
br_11	-156.725	7.807945	-20.07	0	-172.028	-141.421
br_12	-157.845	8.322787	-18.97	0	-174.157	-141.532
br_13	-162.086	12.39135	-13.08	0	-186.373	-137.8
br_14	-137.496	11.12284	-12.36	0	-159.296	-115.695
br_15	-88.7052	55.92477	-1.59	0.113	-198.316	20.90537
br_16	326.7497	55.75822	5.86	0	217.4656	436.0338
br_17	-118.036	7.574491	-15.58	0	-132.882	-103.191
br_18	-187.765	7.620685	-24.64	0	-202.701	-172.828
br_19	-44.8763	8.218027	-5.46	0	-60.9833	-28.7692
store_1	26.4226	5.40331	4.89	0	15.83231	37.01289

store_2	36.99568	5.442475	6.8	0	26.32862	47.66273
store_3	74.00504	5.871601	12.6	0	62.49691	85.51316
store_4	63.68143	5.464372	11.65	0	52.97145	74.3914
store_5	102.1076	7.176945	14.23	0	88.04106	116.1742
store_6	25.09912	5.556487	4.52	0	14.20861	35.98964
store_7	29.5743	5.595022	5.29	0	18.60826	40.54034
store_8	15.07157	5.536131	2.72	0.006	4.220949	25.92218
store_9	31.57079	5.495905	5.74	0	20.79901	42.34257
store_10	-15.0964	11.70835	-1.29	0.197	-38.0443	7.851586
store_11	69.89305	5.856232	11.93	0	58.41504	81.37105
store_12	38.80167	11.69812	3.32	0.001	15.87377	61.72957
store_13	13.76724	11.67887	1.18	0.238	-9.12292	36.65739
store_14	7.055132	5.905897	1.19	0.232	-4.52021	18.63048
store_15	-5.18796	7.181622	-0.72	0.47	-19.2637	8.887763
store_16	25.34511	5.464303	4.64	0	14.63527	36.05495
store_17	74.17182	6.552177	11.32	0	61.32979	87.01385
store_18	50.91592	5.867754	8.68	0	39.41533	62.4165
_cons	109.2288	11.86338	9.21	0	85.97704	132.4806
CBS linked						
Similarity linked* disc. Depth	-1682.06	179.1251	-9.39	0	-2033.14	-1330.98
Similarity linked* feat./display	-29.5752	23.85899	-1.24	0.215	-76.3379	17.18759
Similarity linked* Prod.Line Length	3.094992	3.244562	0.95	0.34	-3.26423	9.454216
Discount Depth	457.2816	83.71374	5.46	0	293.2057	621.3575
Feature/Display	2.303782	11.35583	0.2	0.839	-19.9532	24.56081
Prod.Line Length	-0.97438	4.43794	-0.22	0.826	-9.67258	7.723822
Competitive Line Length	0.416972	0.386689	1.08	0.281	-0.34093	1.174869
Linked Competitive Product Line Length	18.54001	2.210258	8.39	0	14.20799	22.87204
Unlinked Product Line Length	1.646344	1.290576	1.28	0.202	-0.88314	4.175826

Competitive Discount Depth	-535.501	32.93896	-16.26	0	-600.06	-470.942
Competitive feat/display	-81.6229	11.58019	-7.05	0	-104.32	-58.9262
Regprice	-7.32867	2.756361	-2.66	0.008	-12.731	-1.92631
Cregprice	155.8451	5.562214	28.02	0	144.9433	166.7468
Lregprice	-164.358	4.956647	-33.16	0	-174.072	-154.643
Ldd	1294.38	21.79386	59.39	0	1251.665	1337.095
Lfd	55.01709	6.723774	8.18	0	41.83873	68.19544
Ulregprice	-3.09235	0.877091	-3.53	0	-4.81141	-1.37328
Uldd	256.2725	24.48276	10.47	0	208.2871	304.2578
Ulfd	25.56126	7.194093	3.55	0	11.46109	39.66142
Lagnskus	4.771865	2.585165	1.85	0.065	-0.29496	9.838694
Fnskus	5.284323	3.029285	1.74	0.081	-0.65297	11.22161
Laglnskus	1.145023	1.401315	0.82	0.414	-1.6015	3.891551
Flnskus	-3.17802	1.522255	-2.09	0.037	-6.16158	-0.19445
Lagulnskus	-1.63271	0.820718	-1.99	0.047	-3.24129	-0.02413
Fulnskus	0.039848	0.815228	0.05	0.961	-1.55797	1.637665
Fcnskus	-0.33305	0.243396	-1.37	0.171	-0.8101	0.143993
Lagcnskus	-0.73078	0.234396	-3.12	0.002	-1.19019	-0.27137
Lagdd	-46.4199	24.53542	-1.89	0.058	-94.5085	1.668606
lag2dd	85.57934	21.16811	4.04	0	44.09061	127.0681
Lagfd	12.10794	6.453579	1.88	0.061	-0.54085	24.75672
lag2fd	-13.899	6.050817	-2.3	0.022	-25.7584	-2.03963
Laglfd	5.903857	13.26312	0.45	0.656	-20.0914	31.8991
lag2lfd	-8.82634	11.31122	-0.78	0.435	-30.9959	13.34325
Lagldd	12.75372	39.00721	0.33	0.744	-63.699	89.20645
lag2ldd	174.3763	32.54194	5.36	0	110.5953	238.1573
Laguldd	-144.706	25.11055	-5.76	0	-193.922	-95.49
lag2uldd	-90.1595	22.04698	-4.09	0	-133.371	-46.9482
Lagulfd	-5.82178	7.335124	-0.79	0.427	-20.1984	8.554795
lag2ulfd	-7.18069	6.825074	-1.05	0.293	-20.5576	6.196207
Lagcdd	-40.9846	29.0597	-1.41	0.158	-97.9406	15.97132
lag2cdd	-71.6944	24.31961	-2.95	0.003	-119.36	-24.0288
Lagcfd	24.19431	7.818582	3.09	0.002	8.870171	39.51845
lag2cfd	11.80694	7.218213	1.64	0.102	-2.3405	25.95438
sin1	11.84611	1.63364	7.25	0	8.644238	15.04799
cos1	-7.33623	1.654325	-4.43	0	-10.5787	-4.09381
br_1	-411.752	16.03579	-25.68	0	-443.182	-380.323
br_2	-294.496	15.08299	-19.53	0	-324.059	-264.934
br_3	-162.363	45.32386	-3.58	0	-251.196	-73.5299
br_4	-244.268	16.10636	-15.17	0	-275.836	-212.701

br_5	-272.775	21.63933	-12.61	0	-315.187	-230.362
br_6	-407.299	12.73244	-31.99	0	-432.254	-382.344
br_7	-357.712	14.34188	-24.94	0	-385.821	-329.602
br_8	-376.292	12.58488	-29.9	0	-400.958	-351.626
br_9	-394.498	14.35383	-27.48	0	-422.631	-366.365
br_10	-264.786	40.88824	-6.48	0	-344.925	-184.647
br_11	-320.008	13.08535	-24.46	0	-345.655	-294.361
br_12	-300.311	13.96034	-21.51	0	-327.673	-272.95
br_13	-264.225	20.76409	-12.73	0	-304.922	-223.528
br_14	-349.449	18.62219	-18.77	0	-385.948	-312.95
br_15	350.7407	94.97771	3.69	0	164.5878	536.8936
br_16	588.168	93.45263	6.29	0	405.0042	771.3318
br_17	-406.404	12.80391	-31.74	0	-431.499	-381.308
br_18	-373.655	12.83713	-29.11	0	-398.815	-348.494
br_19	-68.4473	13.78286	-4.97	0	-95.4612	-41.4334
store_1	62.56678	9.040421	6.92	0	44.84788	80.28568
store_2	91.18349	9.108941	10.01	0	73.3303	109.0367
store_3	200.9568	9.81848	20.47	0	181.7129	220.2007
store_4	149.3996	9.146364	16.33	0	131.473	167.3261
store_5	237.8425	12.00546	19.81	0	214.3122	261.3727
store_6	49.45718	9.293754	5.32	0	31.24176	67.6726
store_7	104.7236	9.358086	11.19	0	86.38205	123.0651
store_8	28.54188	9.262555	3.08	0.002	10.3876	46.69615
store_9	66.39268	9.193114	7.22	0	48.37451	84.41085
store_10	-64.7896	19.59657	-3.31	0.001	-103.198	-26.381
store_11	196.4825	9.795165	20.06	0	177.2843	215.6806
store_12	114.0369	19.5738	5.83	0	75.673	152.4009
store_13	34.90736	19.54882	1.79	0.074	-3.40763	73.22235
store_14	48.65208	9.876951	4.93	0	29.29361	68.01055
store_15	-2.43171	12.02461	-0.2	0.84	-25.9995	21.13609
store_16	60.05116	9.139745	6.57	0	42.13759	77.96473
store_17	187.6796	10.95899	17.13	0	166.2004	209.1589
store_18	151.0555	9.811659	15.4	0	131.825	170.286
_cons	183.1699	19.98873	9.16	0	143.9927	222.3471
CBSunlinked						
Similarity Unlinked* disc. Depth	255.6433	24.09273	10.61	0	208.4224	302.8642
Similarity Unlinked* feat./display	-6.05935	4.277726	-1.42	0.157	-14.4435	2.324835

Similarity Unlinked* Prod.Line Length	-5.15807	0.633134	-8.15	0	-6.39899	-3.91715
Discount Depth	-86.1581	11.93813	-7.22	0	-109.556	-62.7598
Feature/Display	6.019646	2.107307	2.86	0.004	1.889399	10.14989
Prod.Line Length	1.889749	0.983951	1.92	0.055	-0.03876	3.818257
Competitive Line Length	-0.31908	0.085112	-3.75	0	-0.4859	-0.15226
Linked Competitive Product Line Length	1.23292	0.485984	2.54	0.011	0.28041	2.18543
Unlinked Product Line Length	1.299993	0.284393	4.57	0	0.742594	1.857392
Competitive Discount Depth	-60.6482	7.250462	-8.36	0	-74.8589	-46.4376
Competitive feat/display	-9.93331	2.538979	-3.91	0	-14.9096	-4.957
Regprice	0.025094	0.604483	0.04	0.967	-1.15967	1.209859
Cregprice	6.872321	1.21766	5.64	0	4.485752	9.258891
Lregprice	-8.48439	1.074625	-7.9	0	-10.5906	-6.37817
Ldd	-1.12963	0.197116	-5.73	0	-1.51597	-0.74329
Lfd	381.3694	5.005159	76.2	0	371.5594	391.1793
Ulregprice	22.24857	1.542242	14.43	0	19.22583	25.2713
Uldd	1.48663	0.569426	2.61	0.009	0.370576	2.602683
Ulfd	1.329386	0.667159	1.99	0.046	0.021779	2.636994
Lagnskus	0.842185	0.308534	2.73	0.006	0.237469	1.446901
Fnskus	0.41166	0.335181	1.23	0.219	-0.24528	1.068602
Laglnskus	-0.39186	0.180592	-2.17	0.03	-0.74581	-0.0379
Flnskus	-0.33477	0.179427	-1.87	0.062	-0.68644	0.016901
Lagulnskus	0.137064	0.053585	2.56	0.011	0.03204	0.242088
Fulnskus	-0.0827	0.051564	-1.6	0.109	-0.18376	0.018369
Fcnskus	-4.10411	5.265288	-0.78	0.436	-14.4239	6.215662
Lagcnskus	-11.945	4.657186	-2.56	0.01	-21.0729	-2.81705
Lagdd	0.155002	1.416059	0.11	0.913	-2.62042	2.930426
lag2dd	0.618385	1.328771	0.47	0.642	-1.98596	3.222728
Lagfd	-2.69259	2.919329	-0.92	0.356	-8.41437	3.029191
lag2fd	-5.82973	2.489663	-2.34	0.019	-10.7094	-0.95008
Laglfd	-21.5882	8.585929	-2.51	0.012	-38.4163	-4.76007

lag2lfd	4.79561	7.156099	0.67	0.503	-9.23009	18.82131
Lagldd	-0.28434	4.870738	-0.06	0.953	-9.83082	9.262128
lag2ldd	1.96799	4.849994	0.41	0.685	-7.53782	11.4738
Laguldd	0.942619	1.502276	0.63	0.53	-2.00179	3.887026
lag2uldd	1.651922	1.494517	1.11	0.269	-1.27728	4.581121
Lagulfd	-24.7841	6.308551	-3.93	0	-37.1486	-12.4196
lag2ulfd	-36.506	5.351962	-6.82	0	-46.9956	-26.0163
Lagcdd	-6.21162	1.716303	-3.62	0	-9.57552	-2.84773
lag2cdd	-5.63247	1.588971	-3.54	0	-8.7468	-2.51815
Lagcfd	-2.01492	0.359314	-5.61	0	-2.71916	-1.31067
lag2cfd	1.05346	0.363924	2.89	0.004	0.340182	1.766739
sin1	-57.4555	3.5846	-16.03	0	-64.4812	-50.4298
cos1	-73.6831	3.311058	-22.25	0	-80.1727	-67.1936
br_1	-79.9078	9.907151	-8.07	0	-99.3255	-60.4902
br_2	-72.8407	3.527868	-20.65	0	-79.7551	-65.9262
br_3	-93.9704	4.739869	-19.83	0	-103.26	-84.6805
br_4	-26.9635	2.824518	-9.55	0	-32.4995	-21.4276
br_5	-44.9653	3.136048	-14.34	0	-51.1118	-38.8187
br_6	-28.2786	2.758488	-10.25	0	-33.6852	-22.8721
br_7	-45.2204	3.224646	-14.02	0	-51.5405	-38.9002
br_8	-40.3674	8.950381	-4.51	0	-57.9098	-22.825
br_9	-49.4938	2.897932	-17.08	0	-55.1736	-43.814
br_10	-47.6204	3.080062	-15.46	0	-53.6572	-41.5836
br_11	-49.5079	4.584916	-10.8	0	-58.4942	-40.5217
br_12	-48.4454	4.097053	-11.82	0	-56.4755	-40.4153
br_13	271.8652	20.68345	13.14	0	231.3264	312.404
br_14	253.2341	20.5079	12.35	0	213.0394	293.4289
br_15	-16.3528	2.824215	-5.79	0	-21.8882	-10.8174
br_16	-17.0978	2.811759	-6.08	0	-22.6088	-11.5869
br_17	-7.40671	3.097997	-2.39	0.017	-13.4787	-1.33474
br_18	9.729994	1.991371	4.89	0	5.826978	13.63301
br_19	12.80385	2.007138	6.38	0	8.869934	16.73777
store_1	94.4416	2.161667	43.69	0	90.20481	98.67839
store_2	18.37675	2.018181	9.11	0	14.42119	22.33231
store_3	134.0155	2.644831	50.67	0	128.8317	139.1993
store_4	25.12214	2.048626	12.26	0	21.1069	29.13737
store_5	30.30866	2.062962	14.69	0	26.26533	34.35199
store_6	15.62195	2.039303	7.66	0	11.62499	19.61891
store_7	16.04986	2.026889	7.92	0	12.07724	20.02249
store_8	-16.3505	4.30977	-3.79	0	-24.7975	-7.90349
store_9	94.25409	2.155991	43.72	0	90.02843	98.47976
store_10	-1.97145	4.304973	-0.46	0.647	-10.409	6.466141
store_11	-2.48061	4.302248	-0.58	0.564	-10.9129	5.95164
store_12	39.25643	2.175194	18.05	0	34.99313	43.51974

store_13	94.94676	2.642139	35.94	0	89.76826	100.1253
store_14	19.10059	2.014363	9.48	0	15.15251	23.04867
store_15	160.8018	2.410617	66.71	0	156.0771	165.5266
store_16	76.95735	2.160337	35.62	0	72.72317	81.19153
store_17	39.78396	4.361595	9.12	0	31.23539	48.33253
CBS competitive						
Similarity comp* disc. Depth	-284.507	195.5031	-1.46	0.146	-667.686	98.67166
Similarity comp* feat./display	-83.3297	35.88195	-2.32	0.02	-153.657	-13.0024
Similarity comp* Prod.Line Length	56.17066	5.872463	9.57	0	44.66084	67.68047
Discount Depth	-194.302	97.38926	-2	0.046	-385.181	-3.42208
Feature/Display	-2.49952	18.52217	-0.13	0.893	-38.8023	33.80326
Prod.Line Length	-51.4339	7.747239	-6.64	0	-66.6182	-36.2496
Competitive Line Length	0.809859	0.625137	1.3	0.195	-0.41539	2.035105
Linked Competitive Product Line Length	-15.3111	3.569701	-4.29	0	-22.3075	-8.31458
Unlinked Product Line Length	-3.33887	2.086005	-1.6	0.109	-7.42737	0.749624
Competitive Discount Depth	5993.822	53.24616	112.57	0	5889.462	6098.183
Competitive feat/display	315.529	18.64154	16.93	0	278.9922	352.0657
Regprice	24.91993	4.437955	5.62	0	16.22169	33.61816
Cregprice	-372.593	8.943393	-41.66	0	-390.122	-355.065
Lregprice	81.10128	7.915838	10.25	0	65.58652	96.61604
Ldd	-8.60496	1.414533	-6.08	0	-11.3774	-5.83252
Lfd	-192.995	36.42254	-5.3	0	-264.381	-121.608
Ulregprice	-73.7621	11.32834	-6.51	0	-95.9652	-51.5589
Uldd	-2.13621	4.181702	-0.51	0.609	-10.3322	6.059772
Ulfd	-1.75846	4.898158	-0.36	0.72	-11.3587	7.841757
Lagnskus	4.101145	2.264862	1.81	0.07	-0.3379	8.540193
Fnskus	-4.41292	2.462276	-1.79	0.073	-9.2389	0.413052

Laglnskus	1.088605	1.326308	0.82	0.412	-1.51091	3.68812
Flnskus	0.117434	1.317689	0.09	0.929	-2.46519	2.700057
Lagulnskus	1.665619	0.393499	4.23	0	0.894375	2.436863
Fulnskus	-1.23156	0.378652	-3.25	0.001	-1.9737	-0.48941
Fcnskus	164.2228	38.67783	4.25	0	88.41561	240.0299
Lagcnskus	26.46514	34.20408	0.77	0.439	-40.5736	93.50391
Lagdd	12.40047	10.40199	1.19	0.233	-7.98705	32.78799
lag2dd	-7.85604	9.757233	-0.81	0.421	-26.9799	11.26778
Lagfd	5.473951	21.43743	0.26	0.798	-36.5426	47.49053
lag2fd	-44.8044	18.27337	-2.45	0.014	-80.6195	-8.98923
Laglfd	-1326.28	63.05223	-21.03	0	-1449.86	-1202.7
lag2lfd	-447.042	52.5577	-8.51	0	-550.053	-344.031
Lagldd	-203.468	35.81944	-5.68	0	-273.673	-133.263
lag2ldd	106.7696	35.62354	3	0.003	36.94877	176.5905
Laguldd	12.59082	11.04905	1.14	0.254	-9.06493	34.24656
lag2uldd	-6.03911	10.98004	-0.55	0.582	-27.5596	15.48137
Lagulfd	68.39208	46.33512	1.48	0.14	-22.4231	159.2072
lag2ulfd	-102.968	39.30989	-2.62	0.009	-180.014	-25.9216
Lagcdd	-1.26967	12.6037	-0.1	0.92	-25.9725	23.43313
lag2cdd	-65.1007	11.66623	-5.58	0	-87.9661	-42.2353
Lagcfd	38.47338	2.640286	14.57	0	33.29852	43.64825
lag2cfd	-29.3179	2.671355	-10.97	0	-34.5537	-24.0822
sin1	219.5687	25.66778	8.55	0	169.2608	269.8766
cos1	233.5104	24.1384	9.67	0	186.2	280.8208
br_1	-98.1299	72.78643	-1.35	0.178	-240.789	44.52884
br_2	194.8782	25.78493	7.56	0	144.3406	245.4157
br_3	153.3627	34.85955	4.4	0	85.03925	221.6862
br_4	252.5114	20.51263	12.31	0	212.3074	292.7154
br_5	198.1659	23.04216	8.6	0	153.0041	243.3277
br_6	232.1584	20.23449	11.47	0	192.4995	271.8172
br_7	273.3852	23.07858	11.85	0	228.152	318.6184
br_8	-14.3511	65.67941	-0.22	0.827	-143.08	114.3782
br_9	223.0549	21.18017	10.53	0	181.5426	264.5673
br_10	188.5485	22.46278	8.39	0	144.5223	232.5748
br_11	51.6194	33.35251	1.55	0.122	-13.7503	116.9891
br_12	233.2989	30.08762	7.75	0	174.3282	292.2695
br_13	-391.238	151.9901	-2.57	0.01	-689.133	-93.3423
br_14	-473.347	150.6632	-3.14	0.002	-768.641	-178.052
br_15	254.4941	20.45052	12.44	0	214.4118	294.5763
br_16	235.6061	20.62755	11.42	0	195.1768	276.0354
br_17	50.41424	22.22412	2.27	0.023	6.855763	93.97271
br_18	134.9407	14.61824	9.23	0	106.2895	163.592

br_19	177.5286	14.72585	12.06	0	148.6665	206.3908
store_1	828.0564	15.87239	52.17	0	796.9471	859.1657
store_2	478.0127	14.77135	32.36	0	449.0614	506.964
store_3	852.9392	19.40418	43.96	0	814.9077	890.9707
store_4	686.5162	15.0201	45.71	0	657.0774	715.9551
store_5	113.5316	15.141	7.5	0	83.85582	143.2075
store_6	400.9188	14.98188	26.76	0	371.5548	430.2827
store_7	366.5274	14.85657	24.67	0	337.409	395.6457
store_8	32.91365	31.65924	1.04	0.299	-29.1373	94.96462
store_9	827.3289	15.83225	52.26	0	796.2982	858.3595
store_10	-2.46815	31.63039	-0.08	0.938	-64.4626	59.52628
store_11	23.39397	31.60523	0.74	0.459	-38.5512	85.33908
store_12	310.3029	15.96869	19.43	0	279.0049	341.601
store_13	1221.396	19.40106	62.96	0	1183.371	1259.421
store_14	340.1681	14.77093	23.03	0	311.2176	369.1186
store_15	1613.992	17.70563	91.16	0	1579.29	1648.695
store_16	642.4094	15.85983	40.51	0	611.3247	673.4941
store_17	1053.869	32.53332	32.39	0	990.1048	1117.633

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