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Research Note

Interbrand Variant Overlap: Impact on Brand Preference and Portfolio Profit

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Firms often carry a portfolio of multiple brands within a product category to target different quality tiers in the market. Furthermore, to satisfy heterogeneous consumer preferences within each quality tier, these firms also offer several variants for each brand. A natural outcome of this practice is interbrand variant overlap that could occur across tiers or within a tier. In this paper, we show that across-tier variant overlap is likely to diminish the preference of an upper-tier brand and enhance the preference of a lower-tier brand. We also find that variant overlap within a tier is likely to increase preferences of a brand belonging to the tier. Such variant overlap effects have important brand portfolio management implications for a multibrand firm. Specifically, we demonstrate that such a firm can enhance its portfolio profit under certain conditions by pruning its variants to reduce variant overlap. Because our paper relies on aggregate data, future research should investigate variant overlap at the individual level using panel or experimental data.

Key words: brand portfolio management; variant overlap; product line pruning; multibrand firm; Bayesian

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Introduction

Firms often carry a portfolio of brands that belong to different quality tiers within a product category. For example, Procter & Gamble (P&G) offers Crest and Gleem in the toothpaste category and Pampers and Luvs in the diaper category to serve different quality segments. Similarly, Kraft offers Maxwell House and General Foods International Coffees (GFIC) in the coffee category and DiGiorno, Tombstone, and Jack's in the frozen pizza category. In addition to different brands, these firms also offer multiple variants (e.g., crust and topping determine variants of frozen pizza) for each brand to satisfy consumers' heterogeneous preferences and their desire for variety seeking (Lancaster 1990). In this paper, we examine the impact of overlap between variants on brand preference and portfolio profit.

To establish terminology, we begin by defining *interbrand variant overlap* as the degree to which two brands in a product category offer variants with the same product features.¹ For simplicity, consider the

following product portfolio structure of a multibrand firm (M). To attract consumers in different quality segments, firm M carries an upper-tier (MU) and a lower-tier brand (ML) in its portfolio. Competitive brands CU and CL compete directly with MU and ML, respectively. To satisfy consumers within each segment, firms offer multiple variants for the four brands. In this simple setup, a given brand may overlap with another brand in the category in two different ways: First, overlap can occur between brands belonging to different tiers (i.e., MU and ML, MU and CL, CU and ML, CU and CL). We refer to such an overlap as *interbrand across-tier variant overlap*. Second, overlap can also occur between brands in the same quality tier (i.e., MU and CU, ML and CL). This we refer to as *interbrand within-tier variant overlap*.

The presence of such across- and within-tier variant overlap raises two specific research questions: What is the impact of variant overlap on preference of each brand in a multibrand firm's portfolio? How does it affect the firm's portfolio profit? In order to answer these questions, we propose a modeling framework that links variant overlap, brand preference, and portfolio profit; we show that a firm can improve its portfolio profit by carefully managing variant overlap.

¹ In the remainder of the paper, we use the terms *interbrand variant overlap* and *variant overlap* interchangeably.

Our research is distinct from existing research because of its focus on interbrand variant overlap. Broadly speaking, prior research related to this paper could be broken down into two streams: (a) branding and (b) product portfolio management. In the first stream, Randall et al. (1998) assess how the extent of quality levels of products offered by a brand affects the brand's equity. Hui (2004) studies the potential link between brand preference and perceived similarity of variants offered by that brand. Unlike those two papers that focus on a single brand, we propose that variant overlap across multiple brands may also affect preferences for the brands.

In the second stream, Bordley (2003) develops a model that quantifies the advantages and disadvantages of product proliferation to determine the depth and breadth of a product portfolio. Bayus and Putsis (1999), Draganska and Jain (2005), and Kekre and Srinivasan (1990) investigate how portfolio profit relates to product line length. Desai (2001) studies how cannibalization across quality tiers affects product line design. Ramdas (2003) provides an excellent review of existing research on operational, financial, and marketing issues associated with variety creation and implementation. Previous research (Bayus and Putsis 1999, Bordley 2003, Shugan 1989, Ramdas and Sawhney 2001) attributes high cost of maintaining a long product line and cannibalization as the primary reasons to consider product line pruning. A unique aspect of our research is that we show how pruning could potentially improve a firm's portfolio profit via a different mechanism—brand preference shifts because of changes in variant overlap.

Our proposed framework links variant overlap, brand preference, and portfolio profits using theories from psychology and consumer behavior, a nested logit demand model, and Bayesian statistics. We first hypothesize the impact of variant overlap—both across and within tier—on brand preference. Then we relate such impact to aggregate consumer demand and capture heterogeneity in the marketplace at the store level using a hierarchical Bayes approach. Finally, we embed the demand model in a multibrand firm's profit function. We calibrate the aggregate demand model on store-level sales data for the frozen pizza category. Empirical results provide support for the hypotheses. Using store-specific parameter estimates obtained from the demand model and actual cost information obtained from a multibrand firm, we conduct a counterfactual experiment to demonstrate how variant pruning can possibly improve the firm's portfolio profit. A comparison between the proposed model and a restricted model that ignores variant overlap demonstrates that the latter may incorrectly suggest that carrying a large number of brand variants enhances a firm's portfolio profit.

A limitation of this paper is that, while the relationship between variant overlap and brand preference is hypothesized at the individual level, it is tested using aggregate data at the store level. Our empirical findings therefore are conditional on the assumptions implicit in the demand model used. In particular, while derived from the principle of individual utility maximization, a weakness of our aggregate demand model is that it ignores preference heterogeneity at the individual level. In addition, the model cannot capture nuances in consumer behavior observable or inferable at the individual level, such as multiple-unit purchases and individual reliance on consideration sets. A possible criticism is that our aggregate variant overlap estimates could potentially be spurious or biased due to a confound between the estimates and heterogeneous consumer preferences for variants or attributes. Therefore, it becomes necessary to further validate our findings using disaggregate data and models that allow for preference heterogeneity. We will discuss alternative approaches that future research can employ to study variant overlap effects in greater detail in Discussion at the end of the paper.

We divide this paper into three main sections. The first section provides a theoretical background for the paper and proposes specific hypotheses pertaining to the effects of variant overlap on brand preference. It also describes how we develop an empirical approach to connect variant overlap, brand preference, and portfolio profit. The second section presents analyses to test the hypotheses and assess profit implications. The last section discusses contributions and limitations of this research and outlines avenues for future research.

Conceptual Development and Model Specification

Prior research on the topic of product portfolio management focuses almost exclusively on decisions concerning quality levels of products (Desai 2001, Katz 1984, Moorthy 1984) and product line length (Bayus and Putsis 1999, Bordley 2003, Shugan 1989). With regard to quality levels of products, existing research suggests that a multibrand firm should ensure that consumers in a higher-quality segment do not purchase variants of another brand intended for consumers in a lower-quality segment. It is argued that cannibalization across tiers is likely to hurt firm profitability. In addition, Randall et al. (1998) suggest that a firm should control quality levels offered by a certain brand to maintain the brand's equity. Leclerc et al. (2005) suggest that, in certain conditions, consumers may favor the highest quality variant of a less-prestigious brand over the lowest-quality variant of a more-prestigious brand.

With regard to product line length, previous research asserts that cost structure plays a critical role in how product line length should be managed. Specifically, a firm has to ensure that incremental revenues generated from a product line extension exceed incremental costs. Recent research has begun to focus more on the impact of assortment characteristics of a brand portfolio on consumer demand. Hui (2004) examines how perceived similarity of variants offered by a brand affects the brand's preference. Gourville and Soman (2005) argue that an assortment that requires consumers to make a trade-off between attributes (nonalignable assortment) vis-à-vis between levels of an attribute (alignable assortment) may increase consumers' cognitive effort and potential regrets, thereby reducing brand share.

Notwithstanding these insights, existing literature does not recognize the potential impact of interbrand variant overlap on brand preference. Strategic management of brand equity (Keller 1993) or preference² has become increasingly important, as is evident from its impact on critical business decisions pertaining to brand extensions, subbranding, and cobranding. While much has been written on the topic of brand equity, the marketing field is silent on how to think about brand preference when a firm owns a portfolio of brands in the same product category.

The Impact of Across-Tier Variant Overlap on Brand Preference

Past literature (Keller 1993) suggests that a multi-brand firm can build and maintain equity of its multiple brands by creating favorable and unique brand associations for its upper-tier brands as opposed to its lower-tier brands. Sources of such favorable and unique brand associations include promotion and advertising (Boulding et al. 1994), packaging (Aaker 1991), and price (Rao and Monroe 1989). In addition, product features associated with a brand may also be a source of unique associations (Aaker and Keller 1990, Carpenter et al. 1994, Keller 1993). Therefore, overlap of product features across brands is likely to influence brand preference³ in a systematic manner.

Tversky (1977) conceptualizes feature-based similarity (i.e., shared tangible features between objects) as the basis for transfer of knowledge and affect. Based on this conceptualization, variant overlap between upper- and lower-tier brands is likely to trigger transfer of brand associations between brands. Specifically,

we expect a transfer of positive brand associations from an upper-tier brand to a lower-tier brand and negative brand associations from a lower-tier brand to an upper-tier brand. Previous brand equity literature (Aaker and Keller 1990, Boush and Loken 1991) also uses feature-based similarity to explain how similarity of product features across two product categories can facilitate the transfer of preference of a parent brand in a product category to an extension in a different product category. Unlike this research, we focus on transfers of brand associations across different brands in the same product category.

Categorization literature can also help shed light on the potential impact of variant overlap. In this literature, representativeness of a member (Barsalou 1985) is determined by its similarity to other members in the same category and dissimilarity to members of contrast categories. In the context of a multibrand firm, we view different-quality tiers (e.g., upper tier versus lower tier) within a product category as separate subcategories (Rosch 1988). Because category boundaries tend to be fluid and a brand may be considered belonging to different categories but by different degrees (Cohen and Basu 1987, Viswanathan and Childers 1999), overlap across tiers is likely to make the upper-tier brand less representative and the lower-tier brand more representative of the upper-tier subcategory. Therefore, variant overlap between upper- and lower-tier brands is likely to downgrade the status of the upper-tier brand and upgrade the status of the lower-tier brand. Based on the above theoretical arguments, we hypothesize the impact of across-tier variant overlap on brand preference as follows:

HYPOTHESIS 1 (H1). *As the degree of variant overlap between an upper-tier brand and a lower-tier brand increases, (a) the upper-tier brand's preference tends to decrease, and (b) the lower-tier brand's preference tends to increase.*

The Impact of Within-Tier Variant Overlap on Brand Preference

The impact of within-tier variant overlap on brand preference can be predicted based on the points of parity concept proposed by Keller (1998). Specifically, for a brand to be desired by a consumer requires that it include basic features offered by other brands. Parity, therefore, becomes a necessary condition for a brand to be perceived strongly by consumers. Keller et al. (2002) offer an example of a bank that is not perceived as a bank if it does not offer basic services such as savings, checking, money market accounts, and safety deposit boxes. They refer to such consumer expectations as a *frame of reference*. It is reasonable to expect that competitive offerings are likely to shape such a frame of reference. If a given brand falls short

² We use the terms *brand preference* and *equity* interchangeably. Others have used the term *brand value* (Hui 2004).

³ Across-tier variant overlap can occur between (a) a firm's own brands, and (b) a firm's own brand and a competitive brand. In this paper we do not distinguish between (a) and (b) because most firms do not actively inform consumers about their multibrand offerings (e.g., Crest and Gleem by P&G).

of a consumer's frame of reference, the corresponding impact of such a deficiency on brand preference can be severe. The points-of-parity argument is also in line with the categorization literature, where the term *typicality* describes the degree to which each category member is a good representative of the category (Rosch and Mervis 1975). Loken and Ward (1990) propose that typicality of a member in a category positively affects the consumer's attitude toward the member.

Within-tier variant overlap is distinct from the uniqueness construct. Existing literature on differentiation (e.g., Dickson and Ginter 1987) suggests that, all else equal, brands with unique features are likely to be preferred. Attribute-based product differentiation typically requires distinguishing a brand from other competing brands through introduction of a single unique attribute or attribute level (Carpenter et al. 1994, Nowlis and Simonson 1996). However, uniqueness alone does not guarantee higher brand preference. The points-of-parity argument still operates as a necessary condition. Benefits of uniqueness accrue only after the brand meets the category frame of reference. For example, an automobile with a unique exterior (e.g., a PT Cruiser) is still expected to meet consumer frame of reference with regard to attributes such as horsepower, gas mileage, antilock brakes, etc. Variant overlap and uniqueness, therefore, tap into different aspects of how consumers perceive brands. Given our research focus on variant overlap, we propose the following hypothesis.

HYPOTHESIS 2 (H2). *As the degree of variant overlap between a given brand and other brands in the same quality tier increases, its brand preference increases.*

Model Specification

We construct a nested logit demand model (Berry 1994, Cardell 1997, McFadden 1978) to characterize aggregate demand at the brand-variant level. Such a model is more desirable than a brand-level model because it incorporates product feature effects on demand. By using brand variant as the unit of analysis, we obtain estimates of brand preference that are nonconfounding with preference for product features. The model also provides additional flexibility to capture differences in price and promotions across variants of a given brand. Importantly, a brand-variant-level model allows us to simultaneously capture cannibalization effects among brand variants and effects of variant overlap on brand preferences. As a result, we can separately account for these two sources of demand shifts.

Consider a product category that consists of brands $b = 1, \dots, B$, and a multibrand firm that owns more than one of these brands. Each of the firm's brand belongs to a quality tier $g = 1, \dots, G$. All brands in

the market can be classified into G mutually exclusive quality tiers. To satisfy heterogeneous preferences within each quality tier, the firm also offers multiple variants for each of its brands. Possible variants $j = 1, \dots, J$ are determined by product features associated with the product category. Each brand variant could be viewed as a composite of brand and features (e.g., DiGiorno oven-rising-crust pepperoni pizza), and the number of variants offered by each brand may differ. The conditional indirect utility consumer i obtains from consuming brand b variant j in week t is given by

$$u_{ibjt} = \eta_{bt} + \sum_k \beta_k x_{jk} + \alpha^p p_{bjt} + \alpha^f f_{bjt} + \alpha^d d_{bjt} + \xi_{bjt} + \varepsilon_{ibjt}, \quad (1)$$

where x_{jk} specifies observable product feature k constituting variant j , p_{bjt} denotes the price of brand b variant j in week t , ξ_{bjt} represents a mean-zero demand shock (e.g., advertising) common to all consumers, and ε_{ibjt} is an idiosyncratic mean-zero demand shock varying across consumers. We also include the presence of feature f_{bjt} and display d_{bjt} to capture in-store promotion effects.

The parameter η_{bt} captures consumer preference for brand b in week t and β_k their preference for product feature k . Parameters α^p , α^f , and α^d capture consumer sensitivity to price and in-store promotions. Because consumer preference for brand b (η_{bt}) is estimated by factoring out the effects of price, in-store promotions, and product features, some previous research argues that it captures equity of brand b (Na et al. 1999, Kamakura and Russell 1993, Park and Srinivasan 1994). By linking η_{bt} with interbrand variant overlap, as seen later, we are able to study how variant overlap affects brand sales. The brand preference parameter η_{bt} therefore provides a convenient mechanism to link variant overlap with demand.

The utility of consumer i for brand b variant j that belongs to quality tier g is

$$u_{ibjt} = \delta_{bjt} + \zeta_{ig} + (1 - \sigma)\varepsilon_{ibjt}, \quad \text{where} \\ \delta_{bjt} = \eta_{bt} + \sum_k \beta_k x_{jk} + \alpha^p p_{bjt} + \alpha^f f_{bjt} + \alpha^d d_{bjt} + \xi_{bjt}. \quad (2)$$

The variable δ_{bjt} is regarded as the mean utility of brand b variant j in week t . For consumer i , the variable ζ_{ig} is common to all brand variants that belong to quality tier g and has a distribution function that depends on σ where $0 \leq \sigma < 1$. The magnitude of σ indicates the extent to which consumers view brand variants in a given quality tier to be similar.

It is assumed that each consumer chooses the brand variant that maximizes his utility and ε_{ibjt} is distributed independent and identically distributed (iid)

extreme-value. Under these assumptions, it can be shown that $\zeta_{ig} + (1 - \sigma)\varepsilon_{ibjt}$ is also distributed as iid extreme value (Cardell 1991, McFadden 1978) and the share of brand b variant j in week t is

$$s_{bjt} = s_{bj|g,t} s_{gt} = \frac{e^{\delta_{bjt}/(1-\sigma)}}{D_g} \frac{D_g^{(1-\sigma)}}{\sum_g D_g^{(1-\sigma)}}, \quad \text{where} \\ D_g = \sum_{b \in V_g} \sum_{j \in V_b} e^{\delta_{bjt}/(1-\sigma)}. \quad (3)$$

The term $s_{bj|g,t}$ represents share of brand b variant j within tier g , and s_{gt} represents share of all brand variants that belong to tier g in the category. V_g denotes the set of brands that belong to tier g , and V_b denotes the set of variants offered by brand b .

The nested logit demand specification includes an outside good as an alternative offered in the market. The outside good is interpreted as an option of not purchasing any product offered in the product category (Besanko et al. 1998). With the inclusion of the outside good, sales of brand b variant j in week t can be calculated as

$$\text{sales}_{bjt} = s_{bj|g,t} s_{gt} \times \text{market size}, \quad (4)$$

where the market size can be interpreted as the potential consumption or, in the current context, the number of consumers in the market who consider any brand variant in the product category as a part of their consumption (Nevo 2001).

Treating the mean utility of the outside good δ_o as a parameter to be estimated, we can obtain the following model specification to characterize consumer demand for different brand variants.

$$\ln(s_{bjt}) - \ln(s_{ot}) = \mu + \eta_{bt} + \sum_k \beta_k x_{jk} + \alpha^p p_{bjt} + \alpha^f f_{bjt} \\ + \alpha^d d_{bjt} + \sigma \ln(s_{bj|g,t}) + \xi_{bjt}, \quad (5)$$

where $\mu = -\delta_o$ and $s_{bj|g,t}$ is a within-tier share of brand b variant j . Specifying ξ_{bjt} to be a mean-zero iid normal error with a common variance σ^2 , Equation (4) takes a standard linear regression form. Given the definitions of the outside good and the market size, Equation (5) can also be rewritten as

$$\ln(s_{bjt}) - \ln\left(\frac{\text{market size} - \sum_{a=1}^B \sum_{l \in V_a} \text{Sales}_{alt}}{\text{market size}}\right) \\ = \mu + \eta_{bt} + \sum_k \beta_k x_{jk} + \alpha^p p_{bjt} + \alpha^f f_{bjt} \\ + \alpha^d d_{bjt} + \sigma \ln(s_{bj|g,t}) + \xi_{bjt}. \quad (6)$$

Specification of an outside good in (6) allows the nested logit demand model to capture category

shrinkage and expansion effects over time. This is seen by observing that the term

$$\left(\frac{\text{market size} - \sum_{a=1}^B \sum_{l \in V_a} \text{Sales}_{alt}}{\text{market size}}\right)$$

is the share of the outside good. The market size captures the maximum possible sales in the category and the larger the term

$$\sum_{a=1}^B \sum_{l \in V_a} \text{Sales}_{alt},$$

the smaller the share of the outside good. A price increase should shrink category sales (and expand the outside good); similarly, presence of a feature or display should expand category sales (and shrink the outside good).

The proposed nested logit demand model provides several advantages in estimating aggregate sales data. First, the model assumes a reasonable substitution pattern among brand-variants belonging to different quality tiers (i.e., relaxes the independence from irrelevant alternatives assumption) in a parsimonious fashion. That is, higher similarity between brands within a tier translates into higher own-price effect and higher within-tier cross-price effects.⁴ Second, it accommodates a large number of products (e.g., brand variants) better than other aggregate demand models, such as sales models, that are widely used in marketing (e.g., Blattberg and Wisniewski 1989, Montgomery 1997). A typical sales model requires P^2 price-effect parameters to capture both own and cross-price effects among all $p = 1, \dots, P$ products under investigation. This specification results in a prohibitively large number of parameters to be estimated in the case of brand-variant-level model. Third, the nested logit demand model is derived on the basis of consumer utility maximization. A policy simulation (i.e., counterfactual experiment) to demonstrate the impact of variant overlap on portfolio profit is argued to be more meaningful when a demand model is structural, that is, when derived from consumer utility (Bronnenberg et al. 2005, Franses 2005).

The Incorporation of Variant Overlap

Earlier in the paper we defined *interbrand variant overlap* as the degree to which two brands offer variants that share the same product features. To investigate the impact of interbrand variant overlap on brand preference, it is important to construct a measure of overlap. We propose two possible measures of variant overlap: (a) variant based and (b) attribute based.

⁴ We provide algebraic proofs in the technical appendix available at the *Marketing Science* website <http://mktsci.journal.informs.com>.

These measures are conceptually analogous to the two existing measures of variety of assortment. The variant-based measure of variant overlap is analogous to the product-based measure of variety of assortment (Herpen and Pieters 2002), and the attribute-based measure of variant overlap is analogous to the attribute-based measure of variety assortment (Hoch et al. 1999). Unlike the assortment measures, however, we focus on similarity of objects that belong to different groups and not the same group. That is, we focus on interbrand similarity and not intrabrand similarity.

For both measures, we need to first identify attributes k (e.g., crust and topping for frozen pizza) that characterize different variants. Then, we define different levels ℓ (e.g., oven rising is a level of the crust attribute) of each attribute k . Operationalization of the variant- and attribute-based measures of variant overlap is described next.

Variant-Based Measure of Variant Overlap (VO).

Given K attributes and L_1, L_2, \dots, L_K levels, we identify distinct variants $j = 1, 2, \dots, J$ offered by Brand A. For instance, given different levels of crust and topping, examples of distinct variants include oven-rising-crust pepperoni pizza and regular-crust sausage pizza. The variant-based measure of variant overlap between Brands A and B is specified as

$$VO_{A,B} = \frac{1}{(n_A + n_B)/2} \sum_{j=1}^J I_j(A, B), \quad (7)$$

where $I_j(A, B)$ is an indicator function which takes a value of 1 when both Brands A and B offer variant j , and 0 otherwise. That is, variant overlap between a pair of brands is measured as the number of similar variants divided by the average number of variants.

Attribute-Based Measure of Variant Overlap.

Using the same notation of attributes and attribute levels, we specify the attribute-based measure as

$$VO_{A,B} = \sum_{k=1}^K \gamma_k \sum_{l=1}^{L_k} \left[\frac{n_{kl,A} + n_{kl,B}}{n_A + n_B} \right] I_{kl}(A, B), \quad (8)$$

where $n_{kl,A}$ and $n_{kl,B}$ denote numbers of variants that have level ℓ of attribute k for Brands A and B, respectively. $I_{kl}(A, B)$ is an indicator function that takes a value of 1 when both Brands A and B offer level ℓ of attribute k , and 0 otherwise. The parameter γ_k is a weight assigned to attribute k , $0 < \gamma_k < 1$, and $\sum_k \gamma_k = 1$. In the simplest and most restrictive case, the weight γ_k for all k attributes could be assumed to be the same. A more flexible approach would be to treat γ_k as a model parameter that is estimated from the data.

Another approach, given that there are multiple pairs of brands under consideration, is to calculate weight γ_k based on variances of variant overlap across all nonredundant brand pairs. Specifically, given that $\sigma_k^2 = \sum (\text{VO}_{A,B}^k - \bar{\text{VO}}_k)^2 / P$ is the variance, $\text{VO}_{A,B}^k$ is the measure of variant overlap between Brands A and B, based on attribute k , and $\bar{\text{VO}}_k$ is the mean of overlap based on attribute k computed across all P nonredundant pairs of Brands A and B, we can compute the weight for attribute k as $\gamma_k = \sigma_k^2 / \sum_m \sigma_m^2$. The intuition behind such an approach is that an attribute exhibiting higher variance of overlap across brand pairs should be given more weight in determining variant overlap because consumers should find it more informative in judging the extent of variant overlap. For example, if crust overlap is relatively unchanged across all pairs of brands, consumers may shift their attention to overlap based on another attribute, such as toppings.

Table 1 provides a simple illustration of how variant overlap measures are calculated. The primary distinction between the attribute- and variant-based measure is that the former relies on a count involving the attributes and the latter involves counting attribute combinations (i.e., variants). Using the criteria established by Bonacich (1972), both attribute- and variant-based measures have two desirable properties for a membership overlap measure: (a) the minimum and maximum values of the measures lie between zero and one, and (b) measures account for different number of variants offered by each brand. In addi-

Table 1 Illustration of Variant Overlap Measure Calculation

Brand	Number of variants	Variant description based on crust and topping	Variant overlap measures			
			Crust overlap	Topping overlap	Attribute-based (equal weights)	Variant based
Tombstone	5	Oven-rising cheese Oven-rising supreme Regular cheese Regular pepperoni Regular sausage	8/8 = 1.0	6/8 = 0.75	= (crust overlap + topping overlap)/2 = (1.0 + 0.75)/2 = 0.875	
Red Baron	3	Oven-rising cheese Regular cheese Regular supreme				

tion, these measures are constructed in the spirit of a contrast model (Tversky 1977), which expresses similarity between objects as a function of common and distinctive features.⁵

Next, we rewrite η_{bt} as

$$\eta_{bt} = \bar{\eta}_b + \sum_{a \neq b} \phi_{b,a} \text{VO}_{a,b}^t, \quad (9)$$

where $\bar{\eta}_b$ represents baseline preference for brand b , and $\phi_{b,a}$ captures its shift because of variant overlap with brand a . Variant overlap, in Equation (9), could be viewed as a demand shifter for a given brand with the expected pattern of the shift to be consistent with (H1) and (H2).⁶ Although the way variant overlap is calculated ((7) and (8)) $\text{VO}_{b,a}^t$ is equal to $\text{VO}_{a,b}^t$, $\phi_{b,a}$ in (9) is not necessarily equal to $\phi_{a,b}$. In fact, we hypothesize $\phi_{b,a}$ and $\phi_{a,b}$ to have opposite signs when brands a and b are in different tiers (H1a and H1b). Substituting (9) in (5), we obtain

$$\begin{aligned} \ln(s_{bjt}) - \ln(s_{ot}) \\ = \mu + \bar{\eta}_b + \sum_{a \neq b} \phi_{a,b} \text{VO}_{a,b}^t + \sum_k \beta_k x_{jk} + \alpha^p p_{bjt} \\ + \alpha^f f_{bjt} + \alpha^d d_{bjt} + \sigma \ln(s_{bj|g,t}) + \xi_{bjt}. \end{aligned} \quad (10)$$

In the above specification, variant overlap between a pair of brands affects shares of all associated variants of both brands. Therefore, the variant overlap effect between two brands is over and above the cannibalization effect between two brand variants, which is naturally captured by the nested logit structure of the model.

Heterogeneity and the Hierarchical Bayes Structure

Previous research has demonstrated the existence of parameter heterogeneity at the store level (Hoch et al. 1995, Montgomery 1997). To ensure that the impact of variant overlap is not confounded with store-level heterogeneity, we model price and promotion effects, brand preferences, and preferences for product features at the store level. Such store-level heterogeneity is expected to be driven by differences in characteristics of customers who shop at different stores. For example, preferences for an upper-tier brand may be higher and sensitivities to price and in-store promotions may be lower in stores in more-affluent neighborhoods. Nonmeat pizza toppings may be preferred in stores serving ethnic neighborhoods in which the majority are vegetarians. To account for the parameter heterogeneity across stores, we impose

a hierarchical Bayes (HB) structure to the nested logit demand model. This approach provides parameter estimates at the store level that play an important role in subsequent portfolio profit analysis. To impose the HB structure to the nested logit demand model, we rewrite (11) at the level of store s :

$$\begin{aligned} \ln(s_{bjts}) - \ln(s_{ots}) \\ = \mu_s + \bar{\eta}_{bs} + \sum_{a \neq b} \phi_{b,a} \text{VO}_{b,a}^{ts} + \sum_k \beta_{ks} x_{jk} + \alpha_s^p p_{bjts} \\ + \alpha_s^f f_{bjts} + \alpha_s^d d_{bjts} + \sigma_s \ln(s_{bj|g,ts}) + \xi_{bjts}, \end{aligned} \quad (11)$$

where $\xi_{bjts} \sim N(0, \sigma_s^2)$.

Endogeneity and Instruments

In Equation (11), because price and log within-segment brand-variant share, $\ln(s_{bj|g,t})$, tend to be determined endogenously with the demand for each brand variant, we account for endogeneity of both these variables in the HB nested logit demand model. Our approach follows what is suggested by Berry (1994), Berry et al. (1995), and Bresnahan et al. (1997). We use functions of product features x_{mk} as instruments for both price and $\ln(s_{bj|g,t})$. The rationale for using these instruments is that price, as well as $\ln(s_{bj|g,t})$, of a brand variant should be driven by (a) the extent to which a brand offers variants with different product characteristics, and (b) the extent to which its competing brands in the same tier offer variants with different product characteristics. For variant j of brand b , we use (a) sum of each attribute k for all variants of brand b , excluding itself ($\sum_{m \in V_b, m \neq j} x_{mk}$), and (b) sum of each attribute k for variants of other brands competing within the same tier ($\sum_{m \in V_g, m \notin V_b} x_{mk}$). Because x_{mk} is a vector of $L_k - 1$ indicator variables, (a) and (b) are essentially using counts of each level of attribute k .

A critical requirement for a valid instrument is that it should not be endogenously determined with the dependent variable in the model. Berry et al. (1995) provide extensive explanations on the exogeneity of instruments that are functions of product characteristics. In addition, Bresnahan et al. (1997) argue that, because of an operationalization of such instruments at the group level, they should not be endogenously determined with demand for members of the group. In our case, because instruments are computed across a brand tier (i.e., a group) and the dependent variable is at the brand-variant level (i.e., a member of the group), the instruments should not be endogenously determined with the dependent variable. Recent marketing applications of this approach include Hui (2004) and Nair et al. (2004).

The argument pertaining to the exogeneity of instruments suggests that our measure of variant overlap should also be exogenous. Specifically, the overlap

⁵ We provide an algebraic proof in the technical appendix available at the *Marketing Science* website <http://mktsci.journal.informs.org/>.

⁶ We thank the associate editor for this observation.

measure is operationalized as a function of product attributes and conceptualized at the brand level (i.e., group level). That is, variant overlap varies by brands and not by variants of a brand. It is therefore unlikely that overlap between a pair of brands could be endogenously determined with variant sales of one of the brands in that pair. As a result, we treat variant overlap as an exogenous variable in our model.

Concerns about endogeneity may also apply to feature and display variables in the model. However, several reasons suggest that endogeneity in in-store promotions may be less of a concern. First, the demand we observe is at the level of a store and promotion decisions are likely to be made at a more aggregate level such as a region or a retail chain. Second, we observe weekly data and promotion decisions are likely to be made more infrequently than once a week. Third, in addition to demand expectations, promotions are likely to be affected by external factors such as store specific space constraints for display, and print space constraints in Sunday flyers. Feature and display, therefore, are treated as exogenous variables in our model.

Because the nested logit demand model can be transformed into a linear Model (5), the incorporation of price and $\ln(s_{bj|g,t})$ endogeneity involves a straightforward two-stage model estimation. In the first stage, we construct an HB regression model for both endogenous variables with all exogenous variables and instruments as independent variables. This HB regression model accommodates parameter heterogeneity across stores in the first-stage estimation. In the second stage, we replace prices and $\ln(s_{bj|g,t})$ in the nested logit demand Model (12) with their respective predicted values obtained from the first-stage estimation. Unlike the two-stage least square method that uses point predictions from the first stage, in the Bayesian framework, predicted prices and $\ln(s_{bj|g,t})$ are drawn from their associated predictive posterior distribution (see the appendix). This method helps account for uncertainty of parameter estimates in both stages of model estimation.

The Multibrand Firm's Profit Function

The multibrand firm's portfolio profit includes profits generated from all brands in its portfolio. The consideration of the multibrand firm's portfolio profit versus profits from individual brands is consistent with the notion of category management vis-à-vis brand management in the retailer's context (Basuroy et al. 2001, Zenor 1994). Three main factors involved in the multibrand firm's profit function are (a) sales for different brand-variants, (b) wholesale prices (i.e., prices to retailer), and (c) costs to the firm. Given

Equation (4), the multibrand firm's profit function is given by

$$\pi = \sum_s \sum_t \sum_{b \in V_M} \sum_{j \in V_b} mc_{bjts} \times w_{bjts} \times s_{bj|g,st} s_{gst} \times \text{market size}, \quad (12)$$

where V_M denotes the set of the firm's brands, and V_b denotes the set of variants offered under each of its brands b . The $s_{bj|g,st}$ is within-tier share, w_{bjts} is wholesale price, and mc_{bjts} is the proportion of marginal profit contribution the firm gains from its wholesale price of brand b variant j in week t for store s . The s_{gst} is share of all brand variants that belong to tier g in the category. Thus, the multiplication of mc_{bjts} and w_{bjts} yields a profit margin per unit that the firm obtains from brand b variant j in week t for store s . Because $s_{bj|g,st}$ and s_{gst} are functions of store-level parameters, brand preferences, product features, prices, in-store promotions, and variant overlap (Equation (11)), the firm's portfolio profit is directly affected by these factors.

Empirical Analysis

Frozen Pizza Data

In order to conduct the empirical analysis, we looked for a product category with (a) distinct quality tiers, (b) presence of variant overlap (both within and across tier), and (c) the existence of at least one multibrand firm. Based on these characteristics, we determined that the frozen pizza category would be well suited for empirical testing of the proposed hypotheses. The data used are weekly store sales for 12" frozen pizza at the brand-variant (i.e., brand-crust-topping composite) level. We included only 12" frozen pizza in the empirical analysis in order to control for size (e.g., 9" versus 12") and form (e.g., pan pizza versus pizza roll) effects. Also, 12" frozen pizza accounts for a bulk (70%) of sales in the category.

The frozen pizza category comprises two major players: Kraft and the Schwan food company. Both are multibrand firms. Each of them owns three brands⁷ of frozen pizza targeted to different quality tiers. Kraft owns DiGiorno, Tombstone, and Jack's; Schwan owns Freschetta, Red Baron, and Tony's. Interestingly, each Schwan brand competes directly with a Kraft brand within a quality tier (*Advertising Age* 2001; *Consumer Reports* 2002; *Frozen Food Age* 1999): DiGiorno versus Freschetta in the high tier, Tombstone versus Red Baron in the medium tier, and Jack's versus Tony's in the low tier. The six brands account for about 75% share of all 12" frozen pizza.

⁷ Kraft also licenses the California Pizza Kitchen brand. Because of its limited distribution, we did not include California Pizza Kitchen in the empirical analysis.

Table 2 Summary Statistics of Tier-Based Variant Overlap

	Variant-based		Crust overlap		Topping overlap	
	Mean	Std.	Mean	Std.	Mean	Std.
Across-tier variant overlap						
DiGiorno-Medium	0.30	0.11	0.59	0.16	0.78	0.09
DiGiorno-Low	0.34	0.11	0.60	0.19	0.72	0.12
Tombstone-High	0.24	0.14	0.43	0.18	0.80	0.11
Tombstone-Low	0.63	0.11	0.95	0.07	0.76	0.09
Jack's-High	0.48	0.13	0.67	0.14	0.79	0.10
Jack's-Medium	0.71	0.12	0.97	0.08	0.87	0.08
Freschetta-Medium	0.38	0.14	0.51	0.14	0.79	0.12
Freschetta-Low	0.42	0.15	0.54	0.17	0.87	0.13
Red Baron-High	0.43	0.16	0.67	0.19	0.77	0.10
Red Baron-Low	0.76	0.13	0.94	0.09	0.92	0.10
Tony's-High	0.27	0.22	0.47	0.33	0.80	0.13
Tony's-Medium	0.68	0.14	0.93	0.10	0.81	0.11
Mean across-tier variant overlap across brands	0.47		0.69		0.81	
Range of mean across-tier variant overlap across brands	(0.25, 0.76)		(0.43, 0.97)		(0.72, 0.92)	
Within-tier variant overlap						
DiGiorno-Frechetta ^a	0.72	0.18	1.00	0.00	0.72	0.18
Tombstone-Red Baron	0.64	0.14	0.97	0.08	0.76	0.10
Jack's-Tony's	0.69	0.18	0.88	0.17	0.89	0.13
Mean within-tier variant overlap across brands	0.68		0.95		0.79	
Range of mean within-tier variant overlap across brands	(0.64, 0.72)		(0.88, 1.00)		(0.72, 0.89)	

^aFreschetta-DiGiorno = DiGiorno-Freschetta; Red Baron-Tombstone = Tombstone-Red Baron; Tony's-Jack's = Jack's-Tony's.

In our analyses, we used weekly sales data for the year 2000 from 171 stores. These stores covered three regions: Chicago, Detroit, and Minneapolis. On average, all three Kraft brands, DiGiorno (mean share = 12%), Tombstone (mean share = 27%), and Jack's (mean share = 30%) perform better than their same-tier competitors offered by Schwan, Freschetta (mean share = 5%), Red Baron (mean share = 13%), and Tony's (mean share = 13%), respectively. Kraft maintains more variants than Schwan in each tier, and its brand Tombstone has a larger number of variants than any other brand, on average, (Mean: DiGiorno = 9.37; Tombstone = 12.33; Jack's = 10.12; Freschetta = 5.11; Red Baron = 7.37; Tony's = 6.74). Average paid prices across brands appear to reflect the brand tier structure. DiGiorno and Freschetta (mean shelf prices = \$5.87 and \$6.05) are the high-priced brands, Tombstone and Red Baron (mean shelf prices = \$4.76 and \$5.07) the mid-range-priced brands, and Tony's and Jack's (mean shelf prices = \$4.08 and \$3.65) the low-priced brands.

Variant Overlap Measures

Using (7) and (8), we operationalized the variant overlap measure based on two attributes: crust and topping. Variants in the frozen pizza category could have two types of crust (oven-rising or regular) and seven

types of toppings (cheese, pepperoni, sausage, meat combo, supreme, half-half, and special⁸). Because the impact of variant overlap on brand preference is conceptualized at the tier level, we converted pairwise measures to tier-based variant overlap measures. For example, to obtain variant overlap between DiGiorno and medium-tier brands (referred to as DiGiorno-Medium), we averaged $VO_{DiGiorno, Tombstone}$ and $VO_{DiGiorno, RedBaron}$. Recall that variant overlap equal to zero represents no overlap and variant overlap equal to one represents complete overlap.

In Table 2, based on the topping-based measure of variant overlap we notice very high across-tier variant overlap (mean = 0.81). In addition, this measure exhibits little variation across brands (range = 0.72 to 0.92). This suggests a high similarity among all brands with regard to toppings. A crust-based measure, on the other hand, reflects lower variant overlap across tiers (mean = 0.69) and its variation across brands is higher (range = 0.43 to 0.97). Because of its reliance on both attributes, the variant-based measure exhibits the lowest variant overlap (mean = 0.47), while preserving measure variation across brands (range = 0.25

⁸ A half-half topping is a combination of two toppings on one pizza. Special toppings include all other toppings not included in the first six types (e.g., Mexican, vegetable).

to 0.76). As expected, we also find that the degree of variant overlap between adjacent tiers (e.g., a high- or a low-tier brand with the medium tier) is generally higher than nonadjacent tiers (e.g., high-tier and low-tier brands). For example, based on the variant-based measure, the mean overlap across adjacent tiers is 0.52 compared to the mean of 0.38 across nonadjacent tiers (p -value from a paired t -test < 0.05).

The within-tier measures of variant overlap also exhibit interesting patterns. As expected, the variant-based measure indicates that within-tier overlap is higher (mean = 0.68) than across-tier overlap (mean = 0.47). The range for within-tier overlap is also narrower (0.64 to 0.72 for within tier versus 0.25 to 0.76 for across tier). We also notice larger within-tier crust-based overlap (mean = 0.95), as opposed to its topping-based counterpart (mean = 0.79). Overall, measures for variant overlap appear reasonable and exhibit a fair amount of variation across brands and tiers.

Variant overlap measures vary both across and within stores (across weeks) although the variation across stores is larger. Within-store variance can occur because of variant addition or deletion and out-of-stock incidents. On average, across all pairs of brands, variance of across-store variant overlap is approximately 10 times larger than that of within-store variant overlap. Despite potential heterogeneity in variant overlap effects across stores, we estimate an average effect because the primary source of variation in variant overlap in our data is across stores.

Model Estimation

In calibrating the nested logit demand model on our data, we included only those stores that carried all six brands throughout the calibration period, because we want to avoid confounding effects between the case where “there is no variant overlap between two brands but both brands are present” and the case where “one of the brands is merely not present” in a store (i.e., both cases lead to zero variant overlap). We specified the market size for each store to be the largest category sales observed over the calibration period plus one.⁹

Variant overlap parameters were constrained to correspond to our hypotheses of the across- and within-tier variant overlap effects. Specifically, to test across-tier variant overlap impact on the upper-tier brand’s preference, we constrained parameters for DiGiorno-Medium, DiGiorno-Low, Freschetta-Medium, Freschetta-Low, Tombstone-Low, and Red

Baron-Low to be the same. This parameter is hypothesized to be negative. Analogously, to test across-tier variant overlap impact on the lower-tier brand’s preference, we constrained parameters for Jack’s-High, Jack’s-Medium, Tony’s-High, Tony’s-Medium, Tombstone-High, and Red Baron-High to be the same. This parameter is hypothesized to be positive. To test within-tier variant overlap impact, we constrained parameters for all within-tier variant overlap measures (DiGiorno-Freschetta, Tombstone-Red Baron, Jack’s-Tony’s) to be the same. This parameter is hypothesized to be positive. In combining pairwise variant overlap measures, both average and share-weighted variant overlap measures were considered. Because the two measures provide similar results and the latter provides a slightly better fit, the following analyses are based on share-weighted variant overlap.

We used the Gibbs sampler (Gelfand and Smith 1990) to obtain parameter estimates from the HB nested logit demand model that takes into account price and log within-tier brand-variant share, $\ln(s_{bj|g,t})$, endogeneity (see the appendix). Generating 5,000 draws, we kept every 25th draw of the last 2,500 draws to compute posterior means of the parameters. Because we can write out full conditionals of the posterior distributions of our parameters of interests (14–31), the draws reach stationarity within the first 1,000 iterations.

Parameter Estimates

Table 3 exhibits posterior means of parameters for seven different models. We report results for the nested logit demand model with (M3, M4, M5, M6, M7) and without (M1, M2) variant overlap. For the purpose of comparison we include results for models that incorporate¹⁰ (M2, M4, M5, M6, M7) or ignore (M1, M3) endogeneity. Multiple measures for variant overlap were considered. Results in Table 3 include both variant-based measures (M3, M4) based on Equation (7) and attribute-based measures (M5, M6, M7) based on Equation (8). For the variance-weighted model M5, the weight λ_k for attribute k was obtained as described earlier in the model specification section. For the estimated weight model M6, λ_k was treated as a model parameter and estimated. These weights are store specific, thus inducing heterogeneity in variant overlap effect across stores. Because there are only two attributes (crust and topping) involved in our analysis, we estimate store-specific weights for crust (γ_s). The weight for topping = $1 - \gamma_s$ because $\sum_k \gamma_k = 1$. Finally, we incorporate uniqueness in M7 to test for the within-tier variant overlap effect in the presence of uniqueness.

⁹ We added the plus one bound to the largest category sales because log share of the outside good equal to zero (i.e., for a week that category sales are equal to market size) is not defined.

¹⁰ The instruments we use work well. For example, for model M6, we obtain R -square equal to 0.76 for the price regression model, and 0.40 for the $\ln(s_{bj|g,t})$ regression model.

Table 3 Parameter Estimates^a

	Model with no overlap		Model with variant-based measure of overlap		Model with attribute-based measure of overlap		M6 with uniqueness variable M7
	HB M1	ENDO HB M2	HB M3	ENDO HB M4	Variance weighted M5	Estimated weight M6	
Intercept	−0.828	−1.767	−1.238	−1.811	−2.168	−2.417	−2.646
DiGiorno	0.727	1.240	1.053	1.741	1.621	1.774	1.863
Tombstone	0.644	0.748	1.145	1.311	1.260	1.479	1.347
Jack's	0.569	0.783	0.565	0.809	0.796	0.738	0.731
Freschetta	0.502	0.858	0.866	1.400	1.209	1.359	1.457
Red Baron	0.629	0.666	1.192	1.278	1.193	1.431	1.349
Crust ^b : Oven rising	0.261	0.016	0.257	0.114	0.040	0.062	0.022
Toppings ^c :							
Pepperoni	−0.059	−0.064	−0.060	−0.075	−0.071	−0.058	−0.060
Sausage	−0.212	−0.332	−0.214	−0.322	−0.337	−0.316	−0.315
Meat	−0.090	−0.116	−0.093	−0.122	−0.122	−0.108	−0.114
Supreme	−0.025	−0.018	−0.028	−0.024	−0.025	−0.014	−0.015
Half-half	0.069	0.109	0.068	0.109	0.107	0.102	0.104
Special	−0.012	−0.029	−0.019	−0.030	−0.036	−0.021	−0.025
Price	−0.554	−0.564	−0.559	−0.664	−0.582	−0.567	−0.544
Feature	0.268	0.434	0.270	0.343	0.416	0.407	0.433
Display	0.435	0.632	0.427	0.568	0.615	0.597	0.617
Tier similarity	0.571	0.295	0.574	0.298	0.300	0.335	0.326
Across-tier variant overlap	n/a	n/a	−0.648	−0.535	−0.538	−0.786	−0.706
Impact on upper-tier brand							
Across-tier variant overlap	n/a	n/a	0.166	0.276	0.039	0.103	0.283
Impact on lower-tier brand							
Within-tier variant overlap	n/a	n/a	0.460	0.327	0.510	0.798	0.776
Impact							
Weight	n/a	n/a	n/a	n/a	n/a	0.816	0.748
Uniqueness	n/a	n/a	n/a	n/a	n/a	n/a	0.240
Deviance	1,172,163	1,221,030	1,171,216	1,220,258	1,220,734	1,216,610	1,213,493

ENDO = Endogeneity.

^aAll estimates are statistically different from zero (posterior probability of parameter distribution containing zero < 0.001), unless italicized.^bRegular crust is the baseline.^cCheese topping is the baseline.

We will first focus on results in M1–M6; the results generally indicate strong support for both (H1) and (H2). Specifically, the estimates suggest that across-tier variant overlap hurts upper-tier brands (H1a) and helps lower-tier brands (H1b). They also suggest that within-tier variant overlap between two brands competing within the same tier helps increase preferences of both brands. Support for the hypotheses is not sensitive to whether (M4, M5, M6) or not (M3) endogeneity is taken into account. Across different measures of variant overlap (M4, M5, M6), we observe consistent patterns of variant overlap impact on brand preference, with the exception of a non-significant effect of (H1b) in M5. However, because M5 is shown to be the model with the worst fit¹¹

among the three, we conclude that empirical support for (H1) and (H2) appears to be robust to multiple measures of variant overlap.

Several additional observations about results pertaining to M1–M6 could be made. When comparing M1 versus M3, and M2 versus M4, model fit improves when variant overlap is included in the model. Also, incorporating endogeneity causes model fit to decline (M1 versus M2, and M3 versus M4). This is not surprising, because the incorporation of endogeneity involves a trade-off between consistency and fit (Berry et al. 1995). Consistent with most previous research in economics, we find that price coefficients become more negative when endogeneity is taken into account. Incorporating endogeneity in $\ln(s_{bj|g,t})$ also leads to smaller magnitude of tier similarity coefficients. Among models that incorporate endogeneity and variant overlap, the fit statistic is the best for the attribute-based, estimated weight model (M6).

¹¹ We use deviance (Gelman et al. 2004), $D(y | \theta) = -2 \log p(y | \theta)$, as the measure of model fit. The lowest expected deviance will have the highest posterior probability for large sample sizes. We compute mean deviance based on simulated draws of the posterior distribution.

Examining the results corresponding to M6 in some detail, it is evident that the estimates have good face validity. Coefficients for price, feature, and display exhibit correct signs. The tier similarity coefficient is significantly different from zero, implying the appropriateness of the nested model structure. In terms of brand preference estimates, for the purpose of identification we constrained baseline preference of Tony's to be zero ($\bar{\eta}_{\text{Tony's}} = 0$). The preferences for the three Kraft brands clearly reflect the brand-tier structure (High, Medium, Low) in the market described earlier ($\text{prob}(\bar{\eta}_{\text{DiGiorno}} > \bar{\eta}_{\text{Tombstone}}) = 1$; $\text{prob}(\bar{\eta}_{\text{Tombstone}} > \bar{\eta}_{\text{Jack's}}) = 1$). For Schwan brands, the preferences for Freschetta and Red Baron are also significantly larger than for Tony's; however, preferences for Freschetta and Red Baron are not significantly different from each other ($\text{prob}(\bar{\eta}_{\text{Freschetta}} > \bar{\eta}_{\text{Red Baron}}) = 0.14$). While we do not observe higher preference for Freschetta over Red Baron in M6, we observe this pattern in M4 ($\text{prob}(\bar{\eta}_{\text{Freschetta}} > \bar{\eta}_{\text{Red Baron}}) = 0.96$). In terms of product feature effects, the parameter estimates suggest that, at the aggregate level, oven-rising crust is as desirable as regular crust, cheese topping is more preferred than plain toppings (pepperoni, sausage, meat combo) and less preferred than half-half. The weight parameter of 0.82 also suggests crust contributes more than topping to the variant overlap effects.

Finally, we explore the impact of uniqueness on brand preference in M7. Earlier, we noted that while variant overlap is conceptualized across attributes, uniqueness operates at the attribute level, and benefits of uniqueness accrue only after the brand meets the category frame of reference. We measured uniqueness by counting, for each brand, the number of attributes the brand has that are not shared by any other brand. Overall, the frozen pizza category is characterized by little uniqueness as the average number of unique variants offered by the six brands, across stores, varied from 0.0004 (Red Baron) to 0.377 (Tombstone). In spite of little uniqueness in the category, we found a positive (coefficient = 0.24) and significant ($\text{Prob} > 0 = 1$) effect of uniqueness on brand preference. Inclusion of uniqueness, however, did not affect the pattern of variant overlap effects. All three coefficients corresponding to the within- and across-tier variant overlap were found to be significant, and in the same direction as our hypotheses.

Counterfactual Experiment

Equations (11) and (12) establish the relationship between variant overlap and portfolio profit. These equations permit an informed assessment of change in portfolio profit for a change in variant overlap ($\partial\pi/\partial\text{VO}$). Using such an approach, a multibrand firm may therefore be able to improve its portfolio profit by carefully managing variant overlap, for example,

between its upper-tier and lower-tier brands. All else equal, consideration of such across-tier effects may be particularly critical when variant overlap hurts the upper-tier brand more than it helps the lower-tier brand (i.e., the magnitude of ϕ_{hl} is larger than ϕ_{lh}). In such a situation, two possible variant overlap management strategies may be (a) reducing variant overlap while keeping the number of variants offered for both brands constant, and (b) pruning variants of the lower-tier brand. Equations (11) and (12) suggest that the effectiveness of either strategy is contingent on factors such as market share, relative margins, and magnitude of variant overlap effects. For example, it is unclear if a pruning strategy would be profitable, because the benefit of reducing variant overlap could be more than offset by market share loss.

To study the potential benefit of pruning in greater detail, we conduct a counterfactual experiment in which we regard Kraft as the multibrand firm of interest. Recall that Kraft owns three brands of frozen pizza: DiGiorno (high-tier brand), Tombstone (medium-tier brand), and Jack's (low-tier brand). Until 1997, Kraft offered only oven-rising-crust pizza for DiGiorno and only regular crust pizza for Jack's. However, in 1997 Kraft began offering oven-rising-crust pizza for Jack's. Cast in terms of variant overlap, Jack's product line extension resulted in an increase in variant overlap between Kraft's brands. In the empirical portfolio profit analysis, we ask the following hypothetical question relating to product line pruning: How would portfolio profit for Kraft have changed if Jack's oven-rising-crust pizza had not been offered?

We conducted the counterfactual experiment based on data used for the model calibration, the store-level parameter estimates obtained from M6, and cost information obtained from Kraft. Because of its confidentiality, we do not report cost information in the paper. To perform the analysis, we calculated Kraft's portfolio profit in two scenarios: (a) Jack's oven-rising-crust pizza is offered reflecting what actually happened, and (b) Jack's oven-rising-pizza is not offered reflecting what could have happened because of pruning. To account for parameter uncertainty, we computed store-specific average profits in both scenarios using draws associated with each store kept from the Gibbs sampler run. We then calculated percent change in profit for the pruning scenario as compared to the status quo scenario. An identical cost structure was used in both scenarios to tease out the confounding effect of cost on profit. We assume the absence of competitive and retailer reaction in this analysis. This assumption is not overly restrictive because competitors (who are concerned about market share) and retailers (who are concerned about

Table 4 Portfolio Profit Analysis

% profit change	All stores ($N = 21$) ^a (%)		Upper-tier dominated stores ($N = 10$) ^b (%)		Lower-tier dominated Stores ($N = 11$) ^c (%)	
	with overlap effects (R1)	no overlap effect (R2)	with overlap effects (R3)	no overlap effect (R4)	with overlap effects (R5)	no overlap effect (R6)
DiGiorno	14.9	2.7	16.8	1.4	13.2	3.8
Tombstone	5.1	2.6	5.4	1.4	4.8	3.7
Jack's	−51.5	−35.2	−56.2	−32.3	−47.3	−37.8
Portfolio profit for Kraft	−0.3	−6.0	5.4	−3.2	−5.6	−8.4

^aThere are 25 stores in Detroit but we used only 21 of them in the analysis because four of the stores in Detroit did not offer oven-rising-crust Jack's.

^bUpper-tier dominated stores are the ones in which DiGiorno has a higher share than Jack's.

^cLower-tier dominated stores are the ones in which Jack's has a higher share than DiGiorno.

shelf space allocation) are more likely to react to product line extension than to pruning. To further ensure the absence of competitive reaction, we also carried out our analysis at the store level, because pruning at this level is less prone to such a reaction.

We expect that the benefit of pruning to reduce variant overlap may be moderated by relative shares of upper- versus lower-tier brands. To examine such moderating effects, we chose to conduct our experiment based on stores in Detroit, because in roughly half of the sampled stores in this region, Kraft's high-tier brand DiGiorno had higher share than its low-tier brand Jack's, and the opposite was true in the other half of the sampled stores. For ease of exposition, we will call the former group of stores upper-tier dominated stores and the latter lower-tier dominated stores.

Table 4 presents six sets of results (R1–R6) that demonstrate the impact of pruning Jack's oven-rising-crust variants on Kraft's profit. The results in R1, R3, and R5 were derived based on M6, and the results in R2, R4, and R6 were derived based on M2, the model that ignores the variant overlap impact. First, we will focus on the results based on all the stores in R1 and R2. Across all stores, the results R1 and R2 suggest that pruning Jack's would have led to higher profits for DiGiorno and Tombstone, and lower profit for Jack's. Overall, pruning would have decreased Kraft's portfolio profit. It should be noted that ignoring the impact of variant overlap (R2) overestimates the negative impact of pruning on the portfolio profit (i.e., 0.3% profit decrease in R1 versus 6% profit decrease in R2).

Interesting results emerged when we conducted a more disaggregate analysis (R3–R6). That is, although we found that pruning would have led to a slight decrease in Kraft's portfolio profit across all the stores (R1), examining Kraft's profit changes only among upper-tier dominated stores (R3) and only among lower-tier dominated stores (R5) painted a different picture. Specifically, results suggest that for upper-tier dominated stores (R3), pruning would have

increased Kraft's portfolio profit (5.4%), whereas for lower-tier dominated stores (R5), pruning would have changed Kraft's portfolio profit in the opposite direction (−5.6%). The same conclusion of a possible benefit of pruning on a multibrand firm's bottom line cannot be drawn using a model that ignores variant overlap impact (R4 and R6). The results based on such a model suggest that pruning would have led to lower portfolio profit among upper-tier dominated stores (−3.2%) and lower-tier dominated stores (−8.4%).

The above results have important implications because they suggest that a multibrand firm can use the knowledge about variant overlap impact to help customize its brand-variant assortments. Such customization is likely to be feasible at a regional or retail-chain level. In summary, the counterfactual experiment reinforces the following: (a) In the presence of variant overlap, a multibrand firm can generate higher portfolio profits by pruning variants of its lower-tier brand, (b) the possible benefit of pruning can be moderated by factors such as relative shares of upper-versus lower-tier brands, and (c) ignoring the impact of variant overlap on brand preference in product portfolio evaluation can lead a multibrand firm to make suboptimal portfolio decisions.

Discussion

For a multibrand firm, a natural outcome of owning multiple brands and several variants for each brand is variant overlap. In this paper, we show that it is important for a multibrand firm to understand the role of variant overlap (both across and within tier) because of its potential impact on preferences of the firm's brands and its portfolio profit. Given that variant overlap can be managed through better product portfolio design, such understanding can be viewed as a strategic tool for the firm to manage its brand portfolio. We propose a framework that formally captures variant overlap effects and facilitates systematic investigation of how strategies such as variant pruning could

be used to improve the firm's portfolio profitability. Empirical results also indicate that if a multibrand firm disregards the impact of variant overlap on brand preference, it could overestimate portfolio profit from carrying a large number of variants.

By focusing attention on the variant overlap construct, our paper adds to two broad streams of literature within the field of marketing: product portfolio management (Bayus and Putsis 1999, Bergen et al. 1996, Bordley 2003, Draganska and Jain 2005, Guo 2006, Kadiyali et al. 1999, Mazzeo 2002, Schmalensee 1978, Shugan 1989) and brand equity (Randall et al. 1998, Loken and Roedder John 1993, Milberg et al. 1997). Previous research relating to product portfolio management attributes high costs as a primary reason for firms to prune their product lines. This research suggests that product line extensions help firms better satisfy consumers' heterogeneous preferences and desire for variety seeking, accommodate future preference uncertainty, deter market entry, and gain price-setting power. More-recent research suggests that characteristics of assortment (i.e., portfolio) of a brand such as whether or not it is alignable (Gourville and Soman 2005) and perceived similarity of variants (Hui 2004) may also have profit implications for a firm. Our research is closer in spirit to the more recent research. However, it differs because of our focus on interbrand rather than intrabrand characteristics. Our empirical evidence supports the assertion that interbrand variant overlap is an important piece of the product portfolio management puzzle that has been neglected in the past.

In the second related research stream, brand extension literature focuses on how brand extension from one category to another can lead to preference dilution for the brand. Extending this research, Randall et al. (1998) suggest that the range of product quality associated with a brand, which results from product line extension, can affect the brand's preference. Unlike this research, we show that product line extensions based on nonquality attributes of different brands in the same product category may also enhance or dilute the brands' preferences.

Although our empirical analysis was conducted on a nondurable frequently purchased product, we expect our conceptual framework to also apply to durable products and services (e.g., General Electric [GE] offers Profile and Monogram in the refrigerator category; Marriott offers Marriott, Courtyard, and Fairfield Inn in the hotel category). Consider the case of GE that offers lower-tier refrigerators under the name Profile and high-tier refrigerators under the name Monogram. In light of across-tier variant overlap effects, we expect that when variant overlap for GE Monogram with a GE Profile increases, the preference for GE Monogram is likely to decline while the preference for GE Profile is likely to increase.

The impact of within-tier variant overlap is also expected to hold for durable products because the points-of-parity argument still applies. However, we expect within-tier variant overlap to be less strong for durable products for several reasons: First, because the points-of-parity argument likely requires that consumers have expectations about what attributes or attribute levels brands in each quality tier should offer (i.e., a frame of reference). Given that some consumers may not have enough knowledge to form such a frame of reference, within-tier variant overlap may not have any effect on these particular consumers. Second, because of the large number of attributes encompassing durable products (e.g. automobiles), there is an increased opportunity to design unique product features. Third, because durable products can provide consumers with social symbols, consumers likely attach a higher value to uniqueness (e.g., luxury cars). Overall, we expect the variant overlap effects to hold for both nondurable and durable products, but expect the effect size of within-tier variant overlap to be smaller for the latter. Future research may consider a careful replication of our findings for durable goods and examination of competing effects between within-tier variant overlap and uniqueness.

Earlier in the paper, we acknowledge a limitation of this paper to be that, while the relationship between variant overlap and brand preference is hypothesized at the individual level, it is tested using aggregate data at the store level. Although our nested logit demand model is derived from the principle of individual utility maximization (i.e., the new empirical industrial organization approach), it inherently suffers from the assumption that consumer preference heterogeneity can be integrated out via the specification of the error term as extreme value. This means that the model assumes that, apart from such heterogeneity, all consumers respond to marketing variables in the same way (i.e., a representative consumer model). Although we attempt to alleviate the problem by incorporating heterogeneity at the store level, one may raise a concern that such an assumption could still lead to spurious or biased results within each store, especially in the presence of large individual preference heterogeneity. We conducted a series of simulations to alleviate concerns about the possible confound between measured variant overlap effects and consumer preference heterogeneity for particular variants or attributes. Results from these simulations reveal that the confounding issue may not be a concern under some conditions. However, the simulations cannot rule out the problem completely because we did not study all possible conditions in our simulations. As a result, the validity of our empirical findings is conditional on the assumption embedded in our demand model.

Given the above limitation, we encourage future research to address these concerns by reexamining the impact of variant overlap using SKU-level models that rely on panel data (Sinha et al. 2005, Fader and Hardie 1996). We believe that our nested logit demand models should be used to investigate the variant overlap effects at the individual level only when panel data are not available. We acknowledge that panel data dominates store-level data in every regard when it comes to examining behavior at the individual level. Future research relying on panel data should therefore also extend our current research by examining how variant overlap effects can be moderated by factors such as usage level (heavy buyers may be more susceptible to variant overlap effects) and variety seeking (high-variety seekers are likely to be more knowledgeable about the category and therefore may show stronger variant overlap effects). Given that each consumer may pay more attention to brand variants in her consideration set, it may also be possible to construct a variant overlap measure that depends on each individual's consideration set. Given Borle et al. (2005)'s finding that the negative impact of product assortment reduction on shopping frequency leads to higher loss in sales as compared to its negative impact on purchase quantity, future research may attempt to disentangle the impact of variant overlap on choice, purchase quantity, and purchase incidence.

An alternative method to study variant overlap is to conduct experiments where variant overlap is explicitly manipulated. In fact, experimental research also presents additional avenues for follow-up research in this area, because it allows us to investigate other moderating factors that are unobservable or hard to control in panel data. Examples of such factors include product involvement, consumer knowledge about the multibrand firm, types of product attributes (e.g., alignable versus nonalignable), and the order of variant introduction (i.e., the upper-tier brand or the lower-tier brand introduces overlapping variants first). Leclerc et al. (2005) coin the term *ranking effect* to describe a situation where consumers evaluate the highest-quality variant of a less prestigious brand more favorably than they evaluate the lowest-quality variant of a more prestigious brand. Future research may also examine the interplay between ranking and variant overlap effects.

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Appendix

Let $\lambda_s = [\mu_s, \bar{\eta}_s, \beta_s, \alpha_s^p, \alpha_s^f, \alpha_s^d, \sigma_s]$ be a vector of store-specific parameters in Equation (11) and ϕ a vector of variant overlap parameters to be estimated at the aggregate level. For the first-stage estimation, we specify P_s as a vector of prices, WS_s a vector of $\ln(s_{bj|g,t})$, and X_s^{ins} a matrix of independent variables for both price and $\ln(s_{bj|g,t})$ regression models, which include all exogenous variables and instruments. The likelihood functions of the regression models for price and $\ln(s_{bj|g,t})$ for each store s are $N(P_s | X_s^{ins}, \omega_s^p, \sigma_{\omega^p,s}^2)$ and $N(WS_s | X_s^{ins}, \omega_s^{ws}, \sigma_{\omega^{ws},s}^2)$, where ω_s^p and ω_s^{ws} are vectors of store-specific parameters associated with the price and $\ln(s_{bj|g,t})$ regression models, respectively. The error terms of the first-stage regression models are assumed to be $N(0, \sigma_{\omega^p,s}^2)$ and $N(0, \sigma_{\omega^{ws},s}^2)$. For the second-stage estimation, we denote Y_s a vector of dependent variable from Equation (11), \hat{P}_s a vector of predicted prices, \hat{WS}_s a vector of predicted $\ln(s_{bj|g,t})$, and X_s^Y a matrix of exogenous variables for the nested logit demand model (i.e., excluding price and $\ln(s_{bj|g,t})$). We specify separate likelihood functions for the nested logit demand model; $N(Y_s^* | \hat{P}_s, \hat{WS}_s, X_s^Y, \lambda_s, \phi, \sigma_s^2)$ for the parameters estimated at the store level and $N(\{Y_s^{**}\} | \{\hat{P}_s\}, \{\hat{WS}_s\}, \{X_s^Y\}, \{\lambda_s\}, \phi, \{\sigma_s^2\})$ for the variant overlap parameters estimated at the aggregate level. Brackets denote aggregation of all store-level observations. X_s^* is a matrix of exogenous variables including predicted prices and predicted $\ln(s_{bj|g,t})$, but excluding variant overlap variables, X_s^{**} a matrix of only variant overlap variables, $Y_s^* = Y_s - X_s^{**}\phi$, and $Y_s^{**} = Y_s - X_s^*\lambda_s$. The error term of the nested logit demand model is assumed to be $N(0, \sigma_s^2)$.

We specify the distribution of heterogeneity for $\lambda_s \sim \text{Normal}(\bar{\lambda}, V_\lambda)$, $\omega_s^p \sim N(\bar{\omega}^p, V_\omega^p)$, and $\omega_s^{ws} \sim N(\bar{\omega}^{ws}, V_\omega^{ws})$. Next, we specify the prior distributions for all the parameters as follows:

$$\begin{aligned} \bar{\lambda} &\sim N(\lambda_0, \Lambda_\lambda), \quad V_\lambda \sim IW(g_\lambda, G_\lambda^{-1}), \quad \sigma_s^2 \sim IG(h, H), \\ \bar{\omega}^p &\sim N(\omega_0^p, \Lambda_\omega^p), \quad V_\omega^p \sim IW(g_\omega^p, G_\omega^{p-1}), \quad \sigma_{\omega^p,s}^2 \sim IG(f^p, F^p), \\ \bar{\omega}^{ws} &\sim N(\omega_0^{ws}, \Lambda_\omega^{ws}), \quad V_\omega^{ws} \sim IW(g_\omega^{ws}, G_\omega^{ws-1}), \\ \sigma_{\omega^{ws},s}^2 &\sim IG(f^{ws}, F^{ws}), \quad \phi \sim N(\phi_0, \Lambda_\phi). \end{aligned} \quad (13)$$

With this specification, we employ the Gibbs sampler—alternating conditional sampling—which is a Markov Chain Monte Carlo algorithm widely used to facilitate high-dimensional model estimation (Gelfand and Smith 1990). The full conditionals for all parameters associated with the first-stage estimation (i.e., estimation for the price and $\ln(s_{bj|g,t})$ regression models) are represented as follows:

$$\begin{aligned} p(\omega_s^p | P_s, X_s^{ins}, \sigma_{\omega^p,s}^2, \bar{\omega}^p, V_\omega^p) \\ \propto N(P_s | X_s^{ins}, \omega_s^p, \sigma_{\omega^p,s}^2) N(\omega_s^p | \bar{\omega}^p, V_\omega^p), \end{aligned} \quad (14)$$

$$\begin{aligned} p(\sigma_{\omega^p,s}^2 | P_s, X_s^{ins}, \omega_s^p, f^p, F^p) \\ \propto N(P_s | X_s^{ins}, \omega_s^p, \sigma_{\omega^p,s}^2) IG(\sigma_{\omega^p,s}^2 | f^p, F^p), \end{aligned} \quad (15)$$

$$\begin{aligned} p(\bar{\omega}^p | \{\omega_s^p\}, V_\omega^p, \omega_0^p, \Lambda_\omega^p) \\ \propto \prod_s p(\omega_s^p | P_s, X_s^{ins}, \sigma_{\omega^p,s}^2, \bar{\omega}^p, V_\omega^p) N(\bar{\omega}^p | \omega_0^p, \Lambda_\omega^p), \end{aligned} \quad (16)$$

$$p(V_\omega^p | \{\omega_s^p\}, \bar{\omega}^p, g_\omega^p, G_\omega^{-1}) \\ \propto \prod_s p(\omega_s^p | P_s, X_s^{ins}, \sigma_{\omega^p, s}^2, \bar{\omega}^p, V_\omega^p) IW(V_\omega^p | g_\omega^p, G_\omega^{-1}), \quad (17)$$

$$p(\omega_s^{ws} | WS_s, X_s^{ins}, \sigma_{\omega^{ws}, s}^2, \bar{\omega}^{ws}, V_\omega^{ws}) \\ \propto N(WS_s | X_s^{ins}, \omega_s^{ws}, \sigma_{\omega^{ws}, s}^2) N(\omega_s^{ws} | \bar{\omega}^{ws}, V_\omega^{ws}), \quad (18)$$

$$p(\sigma_{\omega^{ws}, s}^2 | WS_s, X_s^{ins}, \omega_s^{ws}, f^{ws}, F^{ws}) \\ \propto N(WS_s | X_s^{ins}, \omega_s^{ws}, \sigma_{\omega^{ws}, s}^2) IG(\sigma_{\omega^{ws}, s}^2 | f^{ws}, F^{ws}), \quad (19)$$

$$p(\bar{\omega}^{ws} | \{\omega_s^{ws}\}, V_\omega^{ws}, \Lambda_{\omega^{ws}}) \\ \propto \prod_s p(\omega_s^{ws} | WS_s, X_s^{ins}, \sigma_{\omega^{ws}, s}^2, \bar{\omega}^{ws}, V_\omega^{ws}) \\ \cdot N(\bar{\omega}^{ws} | \Lambda_{\omega^{ws}}), \quad (20)$$

$$p(V_{\omega^{ws}} | \{\omega_s^{ws}\}, \bar{\omega}^{ws}, g_{\omega^{ws}}, G_{\omega^{ws}}^{-1}) \\ \propto \prod_s p(\omega_s^{ws} | WS_s, X_s^{ins}, \sigma_{\omega^{ws}, s}^2, \bar{\omega}^{ws}, V_\omega^{ws}) \\ \cdot IW(V_{\omega^{ws}} | g_{\omega^{ws}}, G_{\omega^{ws}}^{-1}). \quad (21)$$

In the second-stage estimation (i.e., estimation for the nested logit demand model), the predicted values \hat{P}_s and \widehat{WS}_s are drawn from their associated posterior Predictive Distributions (22) and (23), respectively. The full conditionals for all parameters associated with the second-stage estimation are represented in (24)–(28).

$$p(\hat{P}_s | P_s, X_s^{ins}, \omega_s^p) \\ \propto N(\hat{P}_s | X_s^p, \omega_s^p) N(\omega_s^p | P_s, X_s^{ins}, \sigma_{\omega^p, s}^2, \bar{\omega}^p, V_\omega^p), \quad (22)$$

$$p(\widehat{WS}_s | WS_s, X_s^{ins}, \omega_s^{ws}) \\ \propto N(\widehat{WS}_s | X_s^{ws}, \omega_s^{ws}) N(\omega_s^{ws} | WS_s, X_s^{ins}, \sigma_{\omega^{ws}, s}^2, \bar{\omega}^{ws}, V_\omega^{ws}), \quad (23)$$

$$p(\lambda_s | Y_s, \hat{P}_s, \widehat{WS}_s, X_s^Y, \sigma_s^2, \bar{\lambda}, V_\lambda) \\ \propto N(Y_s^* | \hat{P}_s, \widehat{WS}_s, X_s^Y, \lambda_s, \phi, \sigma_s^2) N(\lambda_s | \bar{\lambda}, V_\lambda), \quad (24)$$

$$p(\sigma_s^2 | Y_s, \hat{P}_s, \widehat{WS}_s, X_s^Y, \lambda_s, h, H) \\ \propto N(Y_s | \hat{P}_s, \widehat{WS}_s, X_s^Y, \lambda_s, \phi, \sigma_s^2) IG(\sigma_s^2 | h, H), \quad (25)$$

$$p(\bar{\lambda} | \{\lambda_s\}, V_\lambda, \Lambda_\lambda) \\ \propto \prod_s p(\lambda_s | Y_s, \hat{P}_s, \widehat{WS}_s, X_s^Y, \sigma_s^2, \bar{\lambda}, V_\lambda) N(\bar{\lambda} | \Lambda_\lambda), \quad (26)$$

$$p(V_\lambda | \{\lambda_s\}, \bar{\lambda}, g_\lambda, G_\lambda^{-1}) \\ \propto \prod_s p(\lambda_s | Y_s, X_s^Y, \hat{P}_s, \widehat{WS}_s, \sigma_s^2, \bar{\lambda}, V_\lambda) IW(V_\lambda | g_\lambda, G_\lambda^{-1}), \quad (27)$$

$$p(\phi | \{Y_s\}, \{\hat{P}_s\}, \{\widehat{WS}_s\}, \{X_s^Y\}, \{\sigma_s^2\}, \{\lambda_s\}, \phi_o, \Lambda_\phi) \\ \propto N(\{Y_s^{**}\} | \{\hat{P}_s\}, \{\widehat{WS}_s\}, \{X_s^Y\}, \{\lambda_s\}, \phi, \{\sigma_s^2\}) N(\phi | \phi_o, \Lambda_\phi). \quad (28)$$

With conjugate properties, we obtain normal posterior distributions for (14), (16), (18), (20), (22), (23), (24), (26), and (28); inverse gamma posterior distributions for (15), (19), and (25); and inverse Wishart distributions for (17), (21), and (27).

To estimate store-specific weights γ_s , we assume its heterogeneity distribution and associated priors to be $\gamma_s \sim$

$N(\bar{\gamma}, V_\gamma) \bar{\gamma} \sim N(\gamma_o, \Lambda_\gamma)$ and $V_\gamma \sim IW(g_\gamma, G_\gamma^{-1})$. Then, we need to add three additional steps to the above estimation procedure:

$$p(\gamma_s | Y_s, \hat{P}_s, \widehat{WS}_s, X_s^Y, \sigma_s^2, \bar{\lambda}, V_\lambda) \\ \propto N(Y_s^{***} | \hat{P}_s, \widehat{WS}_s, X_s^Y, \gamma_s, \lambda_s, \phi, \sigma_s^2) N(\gamma_s | \bar{\gamma}, V_\gamma), \quad (29)$$

$$p(\bar{\gamma} | \{\gamma_s\}, V_\gamma, \gamma_o, \Lambda_\gamma) \\ \propto \prod_s p(\gamma_s | Y_s, \hat{P}_s, \widehat{WS}_s, X_s^Y, \sigma_s^2, \lambda_s, \phi, \bar{\gamma}, V_\gamma) N(\bar{\gamma} | \gamma_o, \Lambda_\gamma), \quad (30)$$

$$p(V_\gamma | \{\gamma_s\}, \bar{\gamma}, g_\gamma, G_\gamma^{-1}) \\ \propto \prod_s p(\gamma_s | Y_s, X_s^Y, \hat{P}_s, \widehat{WS}_s, \sigma_s^2, \lambda_s, \phi, \bar{\gamma}, V_\gamma) \\ \cdot IW(V_\gamma | g_\gamma, G_\gamma^{-1}). \quad (31)$$

Given that γ_s is estimated with respect to crust and let VO_{cs} and VO_{ts} be matrices of crust-based overlap measures and topping-based overlap measures, respectively, $Y_s^{***} = Y_s - X_s \lambda_s - VO_{ts} \phi$ and the independent variable of the linear regression model to estimate γ_s is $[VO_{cs} - VO_{ts}] \phi$. In addition to these extra steps, all the estimates from (14)–(28) have to be conditioned on γ_s . With conjugate properties, the posterior distributions of (29) and (30) are normal and (31) inverse Wishart.

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