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# Aggregate Impact of Different Brand Development Strategies

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Current branding literature investigates the spillover effects and extension effects due to the introduction of product extensions. However, no study so far has evaluated the aggregate market impact of these effects across different brand development strategies or accounted for the strategic decision to introduce the extension. It is important to examine the above given the significant investments and the high failure rates associated with the introduction of new product extensions. In this study, we develop an analytical framework that derives revenue outcome due to an extension introduction as a function of spillover and extension effects. We empirically estimate the above effects through a Bayesian endogenous switching model that jointly models market shares of the extension and its parent brand along with the strategic decision to introduce the extension and the endogeneity in prices. By using a data set that covers 155 extensions introduced across 20 U.S. geographic markets, we obtain several new generalizable empirical insights. Our results show that spillover effects are higher for brand extensions, whereas line extensions benefit through larger extension effects. We find that vertically differentiating a line extension in terms of increased quality mitigates its negative spillover effects. The addition of a new brand name (i.e., sub-branding) lowers spillover effects for line extensions, whereas it increases the market performance for brand extensions. Our findings provide several strategic implications for manufacturers to successfully introduce and manage product extensions.

Data, as supplemental material, are available at http://dx.doi.org/10.1287/mnsc.2014.1900.

*Keywords*: branding; brand extensions; line extensions; cobranding; new products; brand development strategy; spillover effects; extension performance; Bayesian endogenous switching model; empirical generalization
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> For years, consumer goods companies excelled at innovation: the steady introduction of profitable, convenient, high-quality products—ranging from disposable diapers to frozen dinners—that changed the daily lives of consumers. (Roth and Sneader 2006, p. 1)

## 1. Introduction

Every year sees a proliferation of new products in the consumer packaged goods (CPG) market. CPG manufacturers in the United States have introduced more than 150,000 new products in 2010 alone (Gallagher 2011). Typically, more than 90% of new products are extensions (i.e., line extensions or brand extensions) of existing brand names (SymphonyIRI 2011).[1] In the case of a *line extension*, the new product is introduced using the current brand name in the existing product class, e.g., Pepsi Lime. On the other hand, *brand extension* utilizes the current brand name to enter a different product class, e.g., Crest, a leading brand in the toothpaste category, introducing its mouthwash product. A comprehensive analysis of the most successful CPG product launches over the past 15 years by SymphonyIRI shows that firms have frequently chosen extensions over new brands as a means of bringing new products to the market. Leveraging an existing brand name has been perceived as a key mechanism to strategic success (Aaker 1996).

When an existing brand name is used to introduce an extension, the brand experiences the following two aggregate effects: *spillover effects* and *extension effects*. Spillover effects are the effects of the extension introduction on the success of the parent brand.[2] For example, when Crest introduces a new mouthwash, the

[1] This is in contrast to new brands (e.g., Vault, a carbonated beverage, launched by Coca-Cola) that do not leverage an existing brand name. Such new products are not the focus of this study.

[2] The existing brand used to create the new extension is referred to as the *parent brand* (Aaker and Keller 1990, Roedder-John et al. 1998).

change in the market performance of Crest toothpaste is known as the spillover effect. Extension effects refer to the market performance of the extension (e.g., Crest mouthwash) after its introduction. Given the significant investments and the high failure rates associated with extension introductions, CPG managers naturally have a great interest in obtaining deeper insight into the market impact of different brand development strategies.

In this study, we empirically evaluate different brand development strategies in terms of their spillover and extension effects. There is a significant stream of research in the marketing literature that examines spillover effects (e.g., Keller and Aaker 1992, Roedder-John et al. 1998), extension effects (e.g., Aaker and Keller 1990, Desai and Keller 2002), or both (e.g., Kirmani et al. 1999, Reddy et al. 1994, Swaminathan et al. 2001). We contribute to this stream of literature in the following ways. First, we use a unified analysis framework to shed insight into the aggregate market impact of extension introductions using different brand development strategies. We integrate relevant streams of literature to first formulate a taxonomy that classifies extensions into distinct brand development strategies and use it to develop theoretical expectations about spillover and extension effects. Next, we build an analytical framework to compare different brand development strategies in terms of their overall revenue outcomes, which are subsequently decomposed into underlying spillover and extension effects. Such systematic comparison has significant academic and managerial value (Reddy et al. 1994, Sullivan 1992). For instance, one can assess whether findings from existing studies, which are predominantly based on attitudinal data, hold at the market level. Managers can use our empirical model as a decision support tool for evaluating the magnitude of potential spillover and extension effects before an extension is introduced.

Second, we model the strategic aspect of the extension introduction while measuring spillover effects. Existing studies have measured spillover effects as the difference between the market shares of the parent brand before and after the extension's introduction (e.g., Reddy et al. 1994, Swaminathan et al. 2001). However, managers could *strategically* select a parent brand that is conducive for launching the relevant extension (Aaker and Keller 1990, Desai and Keller 2002). As a consequence, simply comparing the market shares of the parent brand before and after extension introduction may not be appropriate. This is because it is not possible to observe what the market share of the parent brand would have been sans the introduction of the (strategically chosen) extension. In other words, existing research has not accounted for the *endogenous switching* of the parent brand's market share due to the introduction of the extension. Toward this end, we develop a *Bayesian endogenous switching model* to simultaneously model market shares of the extension and its parent brand along with the strategic decision to introduce the extension. Modeling the decision to introduce the extension also helps us understand the factors that affect the attractiveness of introducing an extension.

Third, we account for the endogeneity in price for both the extension and its parent brand. Except for Kadiyali et al. (1999), other studies that measure spillover or extension effects have not modeled this endogeneity. Failure to account for such endogeneity may bias estimated effects (Chintagunta et al. 2005), specifically the spillover and extension effects in the context of our study.

Finally, our study uses a data set consisting of 155 extensions spanning 40 categories introduced in 20 U.S. geographic markets. Existing studies that investigate spillover effects and/or extension effects have done so only across very few extensions, product categories, and markets. The scope of our data, coupled with our analysis approach, allows our study to provide several new generalizable empirical insights that can enable manufacturers to better introduce and manage new product extensions. For instance, to assess the likely market share and revenue outcomes of a new extension, a manufacturer will find our unified analysis framework especially useful and well grounded in underlying empirical realities of the marketplace.

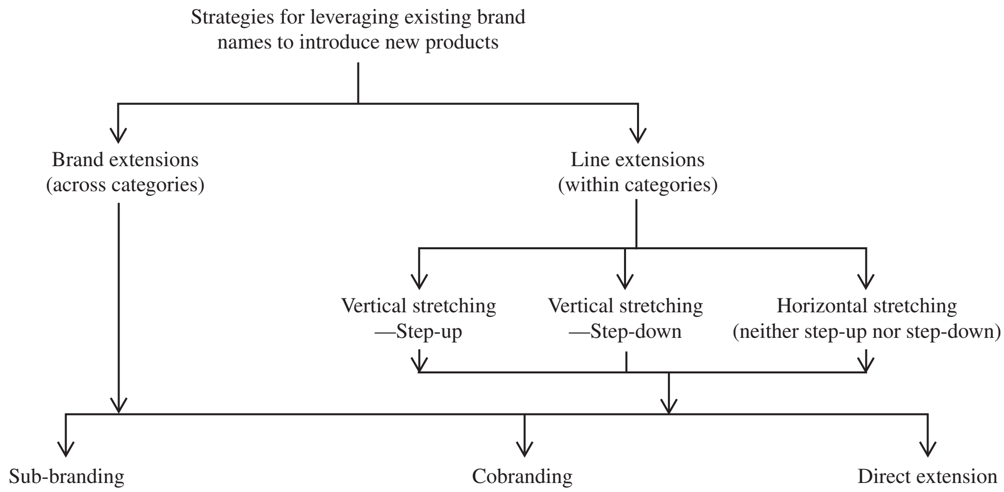
## 2. Conceptual Framework

In this section, we first outline the different brand development strategies. We then formulate expectations about the nature of spillover and extension effects across those strategies. Most prior literature (e.g., Aaker and Keller 1990, Desai and Keller 2002, Kirmani et al. 1999) has focused on attitudinal drivers of spillover and extension effects for a specific brand development strategy. In contrast, we describe how these factors may shape the aggregate market impact across various brand development strategies. However, the focus of this article is not theory development. Rather, we pursue an empirical approach by extending and generalizing prior findings. We do this using an empirical framework that accounts for the strategic aspects of entry decision and pricing.

### 2.1. Classifying Product Extensions

Based on prior branding literature (e.g., Aaker 1996, Desai and Keller 2002, Kirmani et al. 1999, Milberg et al. 1997, Park et al. 1996), we classify new product extensions as follows. We broadly group extensions into two primary brand development strategies based on whether they are introduced in the same or in a different product category as that of the parent brand: line extensions and brand extensions. While

**Figure 1** **Classifying Product Extensions Into Different Brand Development Strategies**




introducing a line extension, the brand may choose to differentiate the extension from the parent brand in terms of quality, typically signaled through price. Line extensions that extend the parent brand name at different price/quality points are termed *vertical line extensions*. Vertical line extensions can either be a *step-up*, an increase in price/quality, or a *step-down*, a decrease in price/quality (Kirmani et al. 1999). Line extensions that are neither step-up nor step-down are denoted as *horizontal line extensions*.

Both line and brand extensions pursue one of the following naming strategies: *sub-branding*, *cobranding*, or *direct extension*. Sub-branding is a strategy in which a new brand name is used in conjunction with the parent brand name to introduce an extension, e.g., Gillette Mach3. It is typically used to help consumers distinguish the extension from the parent brand (Milberg et al. 1997). Cobranding is a strategy where the name of another brand (denoted as the modifier brand) is added to the parent brand name to introduce the extension, e.g., Tide with Febreze (Desai and Keller 2002, Park et al. 1996). The objective of cobranding is to combine the strengths of two brands by, for instance, either incorporating an ingredient of another brand (e.g., Diet Coke with Splenda) or combining marketing efforts (e.g., Kellogg's Disney cereals). Direct extension is introducing the extension without the addition of a new brand name, e.g., Cherry Vanilla Dr. Pepper (Park et al. 1993).[3] Figure 1 illustrates the classification of different brand development strategies.

[3] In the case of direct extension, the extension name describes the new attribute present in the extension. However, the attribute is neither registered as a new brand name (sub-branded) nor incorporated from another brand (cobranded).

### 2.2. Expected Spillover Effects Across Different Brand Development Strategies

At the aggregate level, spillover effects capture both the reciprocal effects due to consumers' experience with the extension (Keller and Aaker 1992) as well as the amount of substitution (cannibalization) from the parent brand (Reddy et al. 1994). Line extensions typically cannibalize sales from their parent brands because they are introduced within the same category. Hence, we expect negative spillover effects due to line extension introductions. Parent brands of brand extensions do not face cannibalization since they extend their brand names to different categories. However, the reciprocal effects on the parent brands due to brand extension introductions could be either positive or negative depending on market reactions and consumer experiences (Keller and Aaker 1992, Roedder-John et al. 1998, Swaminathan et al. 2001). Thus, the extent and nature of such reactions could determine whether the spillover effects from brand extensions are higher or lower than those from line extensions.

In the case of vertical line extensions, the introduction of a step-up extension is perceived as a signal of the parent brand's higher quality (Wernerfelt 1988). However, a step-down extension offering plain services at lower prices makes the brand more "downstream" (Lei et al. 2008). This may induce the feeling that the brand is stepping down from its original "class" and therefore may influence the parent brand negatively (Randall et al. 1998). Hence, compared to a horizontal line extension, we expect a step-up line extension and a step-down line extension to have higher (less negative) and lower (more negative) spillover effects, respectively.

Since the naming strategies apply to both brand and line extensions, we compare sub-branded and cobranded extensions to the respective direct extensions. Sub-branding a brand extension lets consumers transfer

**Table 1 Expected and Estimated Spillover and Extension Effects for Different Brand Development Strategies**

| Aggregate impact | Brand development strategy | Compared to | Expected effects | Estimated effects | Relevant literature |
|---|---|---|---|---|---|
| Spillover effects | Brand extension | Line extension | ± | 0.116 | Keller and Aaker (1992), Roedder-John et al. (1998), Swaminathan et al. (2001) |
| | Step-up vertical line extension | Horizontal line extension | + | 0.059 | Wernerfelt (1988), Randall et al. (1998), Lei et al. (2008) |
| | Step-down vertical line extension | | − | −0.069 | |
| | Sub-branded brand extension | Direct brand extension | + | N.S. | Park et al. (1993), Milberg et al. (1997) |
| | Cobranded brand extension | | + | N.S. | Park et al. (1996) |
| | Sub-branded line extension | Direct line extension | ± | −0.057 | Milberg et al. (1997), Kirmani et al. (1999) |
| | Cobranded line extension | | + | N.S. | Rao et al. (1999), Voss and Gammoh (2004) |
| Extension effects | Brand extension | Line extension | − | −0.229 | Aaker and Keller (1990), Reddy et al. (1994) |
| | Step-up vertical line extension | Horizontal line extension | − | −0.267 | Lei et al. (2008) |
| | Step-down vertical line extension | | + | 0.627 | |
| | Sub-branded brand extension | Direct brand extension | + | 0.271 | Park et al. (1993), Milberg et al. (1997) |
| | Cobranded brand extension | | + | N.S. | Park et al. (1996) |
| | Sub-branded line extension | Direct line extension | + | N.S. | Milberg et al. (1997) |
| | Cobranded line extension | | − | −0.171 | Desai and Keller (2002) |

*Note*. N.S., not significant; for all other reported parameters, the 95% posterior probability interval excludes zero.

positive affects and beliefs associated with the parent brand to the extension while differentiating it from the family of products under the brand (Milberg et al. 1997). Similarly, cobranding a brand extension helps the parent brand to borrow strong and favorable attribute perceptions from the modifier brand (Park et al. 1996). Hence, we expect higher spillover effects for both sub-branded and cobranded brand extensions than for a direct brand extension (a brand extension that is neither sub-branded nor cobranded).

Compared to a direct line extension, a sub-branded line extension is likely to signal to consumers a limited association with its parent brand. In other words, consumers are expected to see a greater "distance" between the extension and its parent brand in case of a sub-branded line extension than in case of a direct line extension (Milberg et al. 1997). On the one hand, this greater distance may better shield the parent brand from potentially unfavorable consumer reactions to the extension (Kirmani et al. 1999). This will result in less negative spillover effects for sub-branded line extensions compared to those for direct line extensions. On the other hand, the greater distance between the extension and its parent brand is likely to accentuate range and categorization effects, because of which consumers may perceive the extant products of the parent brand as being more similar (Pan and Lehmann 1993). This will lead to potentially greater customer substitution (i.e., more negative spillover effects) of the parent brand in the case of sub-branded line extension. Accordingly, a priori, it is not clear whether the spillover effects from sub-branded line extensions will be higher (more negative) or lower (less negative) than those from direct line extensions. However, cobranding a line extension improves the perceived quality and attitude toward the parent brand when a well-known, reputable ally is present (Rao et al. 1999, Voss and Gammoh 2004). Hence, we expect higher (less negative) spillover effects for a cobranded line extension than for a direct line extension. Table 1 summarizes the expected spillover effects for each brand development strategy along with the relevant literature.

### 2.3. Expected Extension Effects Across Different Brand Development Strategies

Line extensions are often introduced to take into consideration the underlying heterogeneity in customer preferences within a given product category (Bayus and Putsis 1999). They face lower risks than brand extensions because they are introduced in same category as that of the parent brand (Aaker and Keller 1990). On the other hand, a brand extension is launched to capitalize on a market opportunity in a product category that is different from that of the parent brand. The managerial issue in a brand extension is the relative merit of extending the parent brand versus building a new brand from scratch (Sullivan 1992). Prior behavioral research (e.g., Aaker and Keller 1990, Park et al. 1993) explains the market acceptance of extensions based on how the new product fits into the schema of the parent brand's existing products in the consumers' memory structure. This framework suggests that consumers will be able to accommodate a line extension more easily than a brand extension since the latter is introduced in a different product category. Therefore, we posit that line extensions will have higher extension effects than brand extensions.

In terms of vertical line extensions, consumers perceive higher risks in a step-up extension than in a step-down extension. Consumers may question whether a formerly mainstream brand will have the knowledge and capabilities to deliver the functional and emotional benefits expected in an upscale market (Aaker 1996). This increases the perceived performance risk and, subsequently, lowers the evaluations of the extension (Lei et al. 2008). Hence, compared to horizontal line extensions, we expect step-up line extensions to have lower extension effects and step-down line extensions to have higher extension effects.

With regard to naming strategies for brand extensions, we expect that, compared to a direct brand extension, adding a new brand name (sub-branding) will more likely increase the success of the extension. A new brand name associated with the parent brand may allow a successful subcategory to be established in the consumers' mind, whereas with a direct brand extension, it may not be possible to transfer associations from the parent brand to the extension as selectively and flexibly as with a sub-branded brand extension (Park et al. 1993, Milberg et al. 1997). Although existing research provides guidance regarding expected extension performance of sub-branding strategy only for brand extensions, we expect similar effects for line extensions. In the case of cobranding, the weak attribute levels of the parent brand will be replaced by the strong and favorable attributes of the modifier brand, making the cobranded brand extension more favorable compared to a direct brand extension (Park et al. 1996). A cobranded line extension may not have similar benefits. Because the modifier brand is typically from a different product category (e.g., Tide laundry detergent with Febreze fabric softener), consumers perceive the cobranded line extension to have a lower fit with its parent brand than the direct line extension (Desai and Keller 2002). Hence, we expect cobranded line extensions to have lower extension effects when compared to direct line extensions. Table 1 summarizes the expected extension effects for each brand development strategy.

## 3. Revenue Outcomes due to Extension Introductions

We now develop an analytical framework for comparing different brand development strategies based on their revenue outcomes. Revenues have the following advantages over existing measures (e.g., attitudinal evaluations, brand choices, market shares) used to calculate the impact of new product introductions. First, revenues have high external validity because they are based on revealed market data rather than on stated responses to hypothetical scenarios or subjective judgments (Klink and Smith 2001). Second, revenue is a key performance measure that marketers and the investment community care about (Lenskold 2003). Third, revenues are easy to calculate because they do not require consumer surveys, estimates of demand elasticities, or assumptions about consumer choices (Ailawadi et al. 2003). The data required for calculating revenues are readily available from market research firms such as SymphonyIRI and ACNielsen. Therefore, they can easily be monitored for a large number of brands and categories. Finally, unlike market shares, revenues are directly comparable across diverse product categories of differing market sizes.

We denote the revenues (in dollars) generated by the brand introducing extension $i$ in market $j$ at time $t$ as

$$REV_{ijt} = \begin{cases} REV_{ijt}^{ne} & \text{if } I_{ijt} = 0, \\ REV_{ijt}^{e} & \text{if } I_{ijt} = 1, \end{cases} \tag{1}$$

where $I_{ijt}$ is an indicator variable that equals 1 if the extension $i$ is introduced in market $j$ at time $t$ and 0 otherwise; $REV_{ijt}^{ne}$ denotes the revenues generated by the brand if the extension is not introduced; and $REV_{ijt}^{e}$ denotes the revenues generated by the brand if the extension is introduced. We denote $REV_{ijt}^{ne}$ and $REV_{ijt}^{e}$ as follows:

$$\begin{aligned} REV_{ijt}^{ne} &= PBRevShare_{ijt}^{ne} \times PCR_{ijt}^{ne} \\ &= PBS_{ijt}^{ne} \times PBPr_{ijt}^{ne} \times PCR_{ijt}^{ne}, \quad \text{and} \end{aligned} \tag{2}$$

$$\begin{aligned} REV_{ijt}^{e} &= \{PBRevShare_{ijt}^{e} \times PCR_{ijt}^{e}\} \\ &\quad + \{EXRevShare_{ijt} \times ECR_{ijt}\} \\ &= \{PBS_{ijt}^{e} \times PBPr_{ijt}^{e} \times PCR_{ijt}^{e}\} \\ &\quad + \{EXS_{ijt} \times EXPr_{ijt} \times ECR_{ijt}\}, \end{aligned} \tag{3}$$

where $PBRevShare_{ijt}^{e}$ and $PBS_{ijt}^{e}$ denote revenue share and volume share of the parent brand if the extension is introduced; $PBRevShare_{ijt}^{ne}$ and $PBS_{ijt}^{ne}$ denote revenue share and volume share of the parent brand if the extension is not introduced; $PBPr_{ijt}^{e}$ and $PCR_{ijt}^{e}$ denote the relative price of the parent brand (with respect to the average price in the parent category) and the total revenues (in dollars) of the parent category, respectively, if the extension is introduced; $PBPr_{ijt}^{ne}$ and $PCR_{ijt}^{ne}$ represent the relative price of the parent brand (with respect to the average price in the parent category) and the total revenues (in dollars) of the parent category, respectively, if the extension is not introduced; $EXRevShare_{ijt}$ and $EXS_{ijt}$ denote revenue share and volume share of the extension; $EXPr_{ijt}$ denotes the relative price of the extension (with respect to the average price in the extension category); and $ECR_{ijt}$ denotes the total revenues (in dollars) of the extension category.

The expected revenue gain generated by introducing extension $i$ in market $j$ is given as the difference between Equations (3) and (2) over a planning horizon:

$$
\begin{aligned}
RG_{ij} &= \mathrm{E}_t(REV^{e}_{ijt} - REV^{ne}_{ijt})\\
&= \mathrm{E}_t\begin{bmatrix}(PBS^{e}_{ijt} \times PBPr^{e}_{ijt} \times PCR^{e}_{ijt})\\ -(PBS^{ne}_{ijt} \times PBPr^{ne}_{ijt} \times PCR^{ne}_{ijt})\\ +(EXS_{ijt} \times EXPr_{ijt} \times ECR_{ijt})\end{bmatrix}. \qquad (4)
\end{aligned}
$$

Category revenues and relative prices (with respect to the average category price) are typically stable at the aggregate level for CPG products (Dekimpe et al. 1999, Raju 1992). In addition, the extensions considered in our study may not create category expansion since they are not breakthrough innovations (e.g., Ataman et al. 2008).[4] Thus, Equation (4) can be written as

$$
\begin{aligned}
RG_{ij} = PCR_{ij} \times PBPr_{ij} \times [&SpillEff_{ij} + (RevRatio_{ij}\\
&\times PriceRatio_{ij} \times ExtEff_{ij})], \qquad (5)
\end{aligned}
$$

where $SpillEff_{ij}$ denotes spillover effects and is given by the mean difference between the parent brand's market share if the extension is introduced and the parent brand's market share if the extension is not introduced, i.e., $SpillEff_{ij} = \mathrm{E}_t(PBS^{e}_{ijt} - PBS^{ne}_{ijt})$; $ExtEff_{ij}$ denotes extension effects and is captured through the mean market share of the extension, i.e., $ExtEff_{ij} = \mathrm{E}_t(EXS_{ijt})$; $RevRatio_{ij} = ECR_{ij}/PCR_{ij}$ is the ratio of revenues of the extension category to that of the parent category; and $PriceRatio_{ij} = EXPr_{ijt}/PBPr_{ij}$ denotes the ratio of the relative price of the extension to that of the parent brand. Since line extensions are introduced in the same category as that of the parent brand, $RevRatio_{ij}$ is equal to 1 for all line extensions. For brand extensions, $RevRatio_{ij}$ can be either greater or less than 1 and denotes the relative size of the extension category with respect to that of the parent category. In case of line extensions, $PriceRatio_{ij}$ can be used to indicate if the extension is a step-up ($PriceRatio_{ij} \gg 1$), step-down ($PriceRatio_{ij} \ll 1$), or horizontal ($PriceRatio_{ij} \cong 1$) line extension.

In the next section, we outline the empirical model that we use to estimate spillover and extension effects. We plug the estimated spillover and extension effects back into Equation (5) to obtain the revenue outcomes for different brand development strategies.

## 4. Empirical Model

### 4.1. General Modeling Approach

There are several challenges in modeling spillover and extension effects. First, although spillover effects can be measured as the difference between the market shares of the parent brand before and after the extension's introduction (e.g., Reddy et al. 1994, Swaminathan et al. 2001), such a measure may not be appropriate. This is because firms can strategically select a particular brand that may a priori be deemed to be more suitable for parenting the extension. Moreover, we observe the parent brand's market share either when the extension is introduced or when it is not, but never simultaneously. Consequently, it would not be possible to determine the postintroduction market share of the parent brand if there was no extension. Thus, there arises an endogenous switching of the parent brand's market share due to the introduction of the extension. Second, the decision to introduce the extension not only changes the market share of the parent brand, but also generates market share in the same or a different category through the extension. In addition, the market share captured by the extension will be correlated with that of the parent brand since both have the same underlying brand (Wernerfelt 1988). Third, the introduction of an extension can lead to strategic price-setting behavior from the extending brand (Kadiyali et al. 1999). Therefore, the prices for both the parent brand and the extension may be endogenously determined. In essence, our objective is to simultaneously model the prices and market shares both for the parent brand and the extension and the decision to introduce the extension,[5] where the latter creates an endogenous switching of the parent brand's market share and the prices are endogenous for both the extension and its parent brand. Toward this end, we develop a Bayesian endogenous switching model to account for the endogenous switching of parent brand's market share due to the extension introduction. Endogenous switching models are generally used to capture the phenomenon of a continuous variable undergoing an endogenous binary treatment (Chib 2007, Gugler and Siebert 2007).[6]

[4] We validated these claims for the extensions in our sample. Specifically, we used unit-root tests to assess whether category revenues and relative prices for both the parent brand and the extension are stable over time (Dekimpe et al. 1999). In addition, we used structural break tests to assess whether category revenues and relative prices face any shifts due to extension introduction. Except for a very few cases, we found that category revenues and relative prices are stable around their means and do not face any structural shifts due to the extension introduction. Detailed results are available from the authors upon request.

[5] Although the choice of the specific brand development strategy could be endogenous, we do not model it for the following reasons. First, our proposed modeling framework can be used to obtain similar insights into spillover and extension effects as well as on the relative attractiveness of introducing extensions using various brand development strategies. Second, incorporating the endogenous choice of each brand development strategy would increase the parameter space, resulting in not enough degrees of freedom across markets at the specific extension level to reliably identify the model parameters.

[6] Refer to Lee (1978) for a classical discussion of this problem of binary treatment and continuous response.

The following is our solution to the aforementioned methodological challenges. First, we specify a joint distribution for the prices and market shares of the parent brand and the extension as well as for the introduction decision. Second, we address the endogenous switching of the parent brand's market share by disentangling the prices, market shares, and extension introduction decision such that the marginal distribution of the extension introduction decision is the same both before and after the introduction (Chib 2007). Third, we incorporate doubling in the number of observations for the prices of the parent brand and the extension obtained through the corresponding market share distributions (Rossi et al. 2005). Finally, we explain the heterogeneity in spillover and extension effects across different brand development strategies after controlling for category and market variations. Our solution methodology contributes to the literature on endogenous switching models (e.g., Chib 2007, Gugler and Siebert 2007, Lee 1978) by simultaneously modeling four continuous variables (i.e., prices and market shares of the parent brand and the extension) and a binary variable (i.e., the decision to introduce the extension) that are endogenous to each other. The model specification and estimation steps are given below.

### 4.2. Modeling Spillover and Extension Effects

The market share of the parent brand introducing extension $i$ in market $j$ at time $t$ is given by the following *switching equation*:

$$PBS_{ijt} = PBS_{ijt}^{ne} + I_{ijt}(PBS_{ijt}^{e} - PBS_{ijt}^{ne}). \tag{6}$$

Note that, in the context of endogenous switching models, $I_{ijt}$ is the treatment variable, and $PBS_{ijt}$ is the response variable (Chib 2007). Two important features of this equation should be noted. First, for every extension $i$, market $j$, and time period $t$, either $PBS_{ijt}^{ne}$ or $PBS_{ijt}^{e}$ will be realized. Hence, the other potential outcome is referred to as the "missing counterfactual" (Koop and Poirier 1997, Gugler and Siebert 2007). This feature implies that the joint distribution of the potential outcomes is not identified. Second, the introduction decision $I_{ijt}$ is endogenous because both the parent brand's market share and the extension introduction decision can be driven by unobservable brand, category, or market characteristics. Hence, we jointly model the potential outcomes $PBS_{ijt}^{ne}$ and $PBS_{ijt}^{e}$ (denoted in logistic form as $pbs_{ijt}^{ne}$ and $pbs_{ijt}^{e}$, respectively) and the treatment $I_{ijt}$ as follows:

$$\begin{aligned} pbs_{ijt}^{ne} = {} & \beta_{0ij} + \beta_{1ij} pbpr_{ijt} + \beta_{2ij} pbdisp_{ijt} + \beta_{3ij} pbfeature_{ijt} \\ & + \beta_{4ij} pbcompr_{ijt} + \beta_{5ij} pbcomdisp_{ijt} \\ & + \beta_{6ij} pbcomfeature_{ijt} + \beta_{7ij} pbs_{i,j,t-1} + \varepsilon_{ijt}^{ne}, \end{aligned} \tag{7}$$

$$\begin{aligned} pbs_{ijt}^{e} = {} & \beta_{0ij} + \delta_{0ij} I_{ijt} + \beta_{1ij} pbpr_{ijt} + \delta_{1ij} I_{ijt} pbpr_{ijt} \\ & + \beta_{2ij} pbdisp_{ijt} + \beta_{3ij} pbfeature_{ijt} + \beta_{4ij} pbcompr_{ijt} \\ & + \beta_{5ij} pbcomdisp_{ijt} + \beta_{6ij} pbcomfeature_{ijt} \\ & + \beta_{7ij} pbs_{i,j,t-1} + \varepsilon_{ijt}^{e}, \quad \text{and} \end{aligned} \tag{8}$$

$$I_{ijt} = \begin{cases} 1 & Attr_{ijt} \geq 0, \\ 0 & Attr_{ijt} < 0, \end{cases}$$
$$\text{where } Attr_{ijt} = \gamma_{0ij} + \sum_{r=1}^{R} \gamma_{rij} AttrIV_{rijt} + \varphi_{ijt}. \tag{9}$$

Since the values of market shares ($PBS_{ijt}^{ne}$ and $PBS_{ijt}^{e}$) are bound between 0 and 1, we use logistic transformations as the dependent variables (Vanhonacker et al. 2000), i.e., $pbs_{ijt}^{ne} = \log(PBS_{ijt}^{ne}/(1 - PBS_{ijt}^{ne}))$ and $pbs_{ijt}^{e} = \log(PBS_{ijt}^{e}/(1 - PBS_{ijt}^{e}))$. In Equations (7) and (8), $pbpr_{ijt}$ denotes the price of the parent brand (in log form); $pbdisp_{ijt}$ and $pbfeature_{ijt}$ are display and feature promotion of the parent brand, respectively; $pbcompr_{ijt}$, $pbcomdisp_{ijt}$ and $pbcomfeature_{ijt}$ denote the average price (in log form), display, and feature promotion of all other brands in the parent category; $pbs_{i,j,t-1}$ denotes the lagged market share of the parent brand;[7] and $\varepsilon_{ijt}^{ne}$ and $\varepsilon_{ijt}^{e}$ are the error terms of Equations (7) and (8), respectively, which correspond to the residual market shares of the parent brand before and after the extension introduction. Since we mean center the explanatory variables in Equations (7) and (8) across time periods for each extension–market combination, $\beta_{0ij}$ captures the average market share of the parent brand introducing extension $i$ in market $j$. The parameter $\delta_{0ij}$ captures the shift in average market share of the parent brand due to the extension introduction, which we denote as spillover effects, whereas $\delta_{1ij}$ captures the shift in price sensitivity.[8] We model the parameters (including spillover effects) of Equations (7) and (8) at the extension-market level for the following reason. Existing literature (e.g., Bronnenberg et al. 2007) documents that geographic variation is the predominant source of disparity in market shares of CPG brands across markets. Thus the effect of any marketing strategy, including extension introductions, will have significant variation across markets.

In Equation (9), the latent variable $Attr_{ijt}$ denotes the attractiveness of introducing extension $i$ in market $j$ at

[7] We include lagged dependent variables to account for serial correlation. In addition, to determine whether the serial correlation in error terms is an issue in our analysis, we calculated the Durbin–Watson statistic. Since the Durbin–Watson statistics are close to two for all equations, we conclude that serial correlation is not a cause for concern. The complete results of the serial correlation tests are available from the authors upon request.

[8] Our overall substantive results are similar when we model the shifts in other slope parameters. However, we retain the above specification in the interest of parsimony.

time $t$ (Bronnenberg and Mela 2004); $\gamma_{0ij}$ is the intrinsic preference to introduce the extension; $AttrIV_{rijt}$ denotes instrumental variables that affect the attractiveness of introducing the extension, but not the market share of the parent brand; and $\varphi_{ijt}$ is the error term of Equation (9). We model the parameters of Equation (9) at the extension-market level and represent them as a function of different brand development strategies, category characteristics, and market variations. The hierarchy on the intercept in Equation (9) indicates how the intrinsic attractiveness ($\gamma_{0ij}$) varies across brand development strategies, categories, and geographical markets. The hierarchy on the other variables of the extension introduction equation shows the relationship between the instrumental variables and the entry decision. We capture the effect of instruments at the extension-market level ($\gamma_{rij}$) because this allows different brands to use input factors differently across markets when deciding to introduce the extension.

It is important to note the following characteristics of our entry decision model. First, we postulate a descriptive model that focuses on the factors affecting the firm's decision to introduce an extension.[9] Such a model for entry decision has been used in prior research in both marketing and economics to account for the endogenous switching of a demand outcome (e.g., parent brand's market share) and/or to explain the factors that affect a firm's strategic choice (e.g., extension introduction decision; e.g., Bronnenberg and Mela 2004, Gugler and Siebert 2007). Second, we note that even though Equations (7)–(9) resemble a Tobit-type (limited dependent variable) model, the truncation in this case is more complicated. In a Tobit model, the continuous variable (in our case, the parent brand's market share) will not be observed when there is no treatment (i.e., if the extension is not introduced; Lee 1978). In contrast, in endogenous switching models, the continuous variable is observed both with and without the treatment. In addition, the censoring of the outcome variables (i.e., parent brand's market share) in our model occurs because of strategic (thus, endogenous) choice to introduce the extension.

We model the extension's market share (in logistic form) as follows:

$$\begin{aligned} exs_{ijt} = \theta_{0ij} &+ \theta_{1ij} expr_{ijt} + \theta_{2ij} extdisp_{ijt} + \theta_{3ij} extfeature_{ijt} \\ &+ \theta_{4ij} extcompr_{ijt} + \theta_{5ij} extcomdisp_{ijt} \\ &+ \theta_{6ij} extcomfeature_{ijt} + \theta_{7ij} exs_{i,j,t-1} + \eta_{ijt}, \end{aligned} \tag{10}$$

where $exs_{ijt} = \log(EXS_{ijt}/(1-EXS_{ijt}))$; $expr_{ijt}$, $extdisp_{ijt}$, and $extfeature_{ijt}$ denote price (in log form), display, and feature promotion for the extension, respectively; $extcompr_{ijt}$, $extcomdisp_{ijt}$, and $extcomfeature_{ijt}$ denote the average price (in log form), display, and feature promotion of all other brands in the extension category; $exs_{i,j,t-1}$ denotes lagged market share of the extension; and $\eta_{ijt}$ is the error term of Equation (10). Since we mean center the explanatory variables in Equation (10) across time periods for each extension–market combination, the parameter $\theta_{0ij}$ captures the average market share of extension $i$ in market $j$, which we denote as extension effects. Similar to spillover effects, we capture extension effects at the extension-market level.

### 4.3. Modeling Price Endogeneity

We specify an additional equation for both the parent brand and the extension to control for price endogeneity, and we follow an instrumental variable approach to account for it.[10] We model the prices of the parent brand and the extension as follows:

$$\begin{aligned} pbpr_{ijt} = \tau_{0ij} &+ \sum_{p=1}^{P} \tau_{pij} PbIV_{pijt} \\ &+ \tau_{P+1,i,j} pbpr_{i,j,t-1} + \omega_{ijt}, \quad \text{and} \end{aligned} \tag{11}$$

$$\begin{aligned} expr_{ijt} = \lambda_{0ij} &+ \sum_{q=1}^{Q} \lambda_{qij} ExIV_{qijt} \\ &+ \lambda_{Q+1,i,j} expr_{i,j,t-1} + \xi_{ijt}, \end{aligned} \tag{12}$$

where $PbIV_{pijt}$ and $ExIV_{qijt}$ are the instrumental variables (in log form) that affect the prices but not the unobserved drivers of the corresponding market shares; $pbpr_{i,j,t-1}$ and $expr_{i,j,t-1}$ denote lagged prices (in log form) of the parent brand and the extension, respectively; and $\omega_{ijt}$ and $\xi_{ijt}$ denote the error terms of Equations (11) and (12). We capture the effect of instruments at the extension-market level ($\tau_{pij}$ and $\lambda_{qij}$) because this allows different extensions to use input cost factors differently across markets while setting prices (Chen et al. 2010).

### 4.4. Error Structure

The next vital step is to specify the required distributions of the market shares $pbs^{ne}_{ijt}$, $pbs^{e}_{ijt}$, and $exs_{ijt}$; the decision to introduce the extension $I_{ijt}$; and prices

[9] In contrast, a normative model of entry decision would maximize long-term (expected) profits with respect to the timing of entry. However, obtaining relevant data to model the above may be hard, especially across multiple categories and extensions. Therefore, in line with Bronnenberg and Mela (2004), we believe that, given the complexity of this problem, our econometric representation of the strategic behavior of firms as a set of manufacturing and cost factors is a likely acceptable representation of what firms do in practice.

[10] We tested whether competitors' prices, displays, and feature promotions are endogenous to the market shares of the parent brand and the extension. Specifically, we checked for the correlation between the residuals of the market share equations (Equations (7), (8), and (10)) and each competitive variable (Stock et al. 2002). All correlations are either equal to or very close to zero, which indicates that endogeneity of competitors' variables is not a cause for concern. The complete results of the endogeneity tests are available from the authors upon request.

$pbpr_{ijt}$ and $expr_{ijt}$. In formulating these distributions, we have to acknowledge the fact that the joint distribution of $pbs_{ijt}^{ne}$ and $pbs_{ijt}^{e}$ is unidentified because the parent brand's market shares before and after the introduction cannot be observed simultaneously. In addition, distributions for the price and the market share of the extension are available only after the extension introduction. We resolve these difficulties by specifying joint distributions for the error terms before the extension introduction ($\varphi_{ijt}, \varepsilon_{ijt}^{ne}, \omega_{ijt}$) and after ($\varphi_{ijt}, \varepsilon_{ijt}^{e}, \omega_{ijt}, \eta_{ijt}, \xi_{ijt}$) as follows:

$$\begin{bmatrix} \varphi_{ijt} \\ \varepsilon_{ijt}^{ne} \\ \omega_{ijt} \end{bmatrix} \sim N(0, \Omega_{ne}), \quad \text{where}$$

$$\Omega_{ne} = \begin{bmatrix} 1 & \sigma_{\varphi,ne} & \sigma_{\varphi,\omega} \\ \sigma_{\varphi,ne} & \sigma_{ne}^2 & \sigma_{ne,\omega} \\ \sigma_{\varphi,\omega} & \sigma_{ne,\omega} & \sigma_{\omega}^2 \end{bmatrix}, \quad \text{and} \tag{13}$$

$$\begin{bmatrix} \varphi_{ijt} \\ \varepsilon_{ijt}^{e} \\ \omega_{ijt} \\ \eta_{ijt} \\ \xi_{ijt} \end{bmatrix} \sim N(0, \Omega_{e}), \quad \text{where}$$

$$\Omega_{e} = \begin{bmatrix} 1 & \psi_{\varphi,e} & \psi_{\varphi,\omega} & \psi_{\varphi,\eta} & \psi_{\varphi,\xi} \\ \psi_{\varphi,e} & \psi_{e}^2 & \psi_{e,\omega} & \psi_{e,\eta} & \psi_{e,\xi} \\ \psi_{\varphi,\omega} & \psi_{e,\omega} & \psi_{\omega}^2 & \psi_{\omega,\eta} & \psi_{\omega,\xi} \\ \psi_{\varphi,\eta} & \psi_{e,\eta} & \psi_{\omega,\eta} & \psi_{\eta}^2 & \psi_{\eta,\xi} \\ \psi_{\varphi,\xi} & \psi_{e,\xi} & \psi_{\omega,\xi} & \psi_{\eta,\xi} & \psi_{\xi}^2 \end{bmatrix}. \tag{14}$$

Note that the variance corresponding to $\varphi_{ijt}$ is set to 1 for identification. There are two main challenges in estimating the error structures given in Equations (13) and (14). First, the parameterizations of $\Omega_{ne}$ and $\Omega_e$ are not convenient because they must satisfy the positive-definiteness constraint. Second, the most common inverse-Wishart distribution cannot be used to draw the variance–covariance structures given in Equations (13) and (14) since the distribution of a Wishart conditional on one element is no longer a Wishart (Koop and Poirier 1997). Therefore, it is helpful to reparameterize $\Omega_{ne}$ and $\Omega_e$. We reparameterize $\Omega_{ne}$ as

$$\Phi_{ne} = \Sigma_{ne} - \rho_{ne}\rho_{ne}', \quad \text{where}$$

$$\Sigma_{ne} = \begin{bmatrix} \sigma_{ne}^2 & \sigma_{ne,\omega} \\ \sigma_{ne,\omega} & \sigma_{\omega}^2 \end{bmatrix} \quad \text{and} \quad \rho_{ne} = [\sigma_{\varphi,ne} \;\; \sigma_{\varphi,\omega}].$$

Similarly, we reparameterize $\Omega_e$ as

$$\Phi_e = \Sigma_e - \rho_e\rho_e', \quad \text{where}$$

$$\Sigma_e = \begin{bmatrix} \psi_e^2 & \psi_{e,\omega} & \psi_{e,\eta} & \psi_{e,\xi} \\ \psi_{e,\omega} & \psi_{\omega}^2 & \psi_{\omega,\eta} & \psi_{\omega,\xi} \\ \psi_{e,\eta} & \psi_{\omega,\eta} & \psi_{\eta}^2 & \psi_{\eta,\xi} \\ \psi_{e,\xi} & \psi_{\omega,\xi} & \psi_{\eta,\xi} & \psi_{\xi}^2 \end{bmatrix} \quad \text{and}$$

$$\rho_e = [\psi_{\varphi,e} \;\; \psi_{\varphi,\omega} \;\; \psi_{\varphi,\eta} \;\; \psi_{\varphi,\xi}].$$

### 4.5. Heterogeneity

We estimate all parameters of Equations (7)–(12) (including spillover and extension effects) at the extension-market level. We then capture their mean values across different brand development strategies after accounting for category and market variations. Thus, we model the heterogeneity in parameters $\beta$, $\delta$, $\gamma$, $\theta$, $\tau$, and $\lambda$ across extensions, categories, and markets as follows:

$$\begin{aligned} f_{ij}^m = {} & \mu_0^m + \mu_1^m DBE_i + \mu_2^m SUL_i + \mu_3^m SDL_i \\ & + \mu_4^m SBL_i + \mu_5^m SBB_i + \mu_6^m CBL_i + \mu_7^m CBB_i \\ & + \mu_8^m CC_i + \varsigma_j^m + \kappa_{ij}^m, \end{aligned} \tag{15}$$

where $f_{ij}^m$ is the $m$th parameter in Equations (7)–(12). The first set of explanatory variables in this equation consists of dummies to capture the mean effects for different brand development strategies. Keeping direct horizontal line extension (a horizontal line extension that is neither sub-branded nor cobranded) as the base, we include dummies for direct brand extension ($DBE_i$), step-up line extension ($SUL_i$), step-down line extension ($SDL_i$), sub-branded line extension ($SBL_i$), sub-branded brand extension ($SBB_i$), cobranded line extension ($CBL_i$), and cobranded brand extension ($CBB_i$). We use the parameters $\mu_1^m$–$\mu_7^m$ to compare spillover and extension effects across the different brand development strategies mentioned in Table 1. For example, we compare the effects of a brand extension with those of a line extension through parameter $\mu_1^m$. Similarly, we compare the effects of a step-up vertical line extension with those of a horizontal line extension through parameter $\mu_2^m$.

Since extensions are introduced in various categories across several markets, we account for category and market variations. On the basis of previous research (e.g., Reddy et al. 1994, Srinivasan et al. 2009), we use category concentration ($CC_i$) to control for variation across categories. We capture market-specific shocks through a random effect $\varsigma_j^m$ that is jointly distributed as $N(0, S)$. Finally, the error term $\kappa_{ij}^m$ in Equation (15) is jointly distributed as $N(0, K)$.

### 4.6. Estimation

Until recently, estimating endogenous switching models was cumbersome since it required priors on the nonidentified covariance parameters of the joint distributions (Koop and Poirier 1997). Our modeling framework utilizes recent advances in econometrics (e.g., Chib 2007, Rossi et al. 2005) that do not involve either the likelihood function directly or the unobserved outcomes. Moreover, these advances are simpler not only in terms of the required prior inputs and sampling of covariance matrices, but also in the amount of computational burden and extendibility to more complex settings. Online Appendix A (online appendices available at http://ssrn.com/abstract=2363340) provides the Gibbs sampler algorithm we use to sample the posterior distributions. Following conventional practice, we assume normal-diffuse prior for all parameters. We run the Gibbs sampler algorithm for 10,000 iterations. The first 7,500 and last 2,500 of these iterations are used for burn-in draws and the posterior parameter estimates, respectively. We graphically monitor the posteriors to check for convergence.

We perform a simulation study to check whether the model is identified and if the parameters are recovered. We generate data for prices and market shares by setting the actual values of the explanatory variables. We set realistic values for the data-generating parameters similar to those obtained empirically (Bezawada et al. 2009). The parameter estimates recovered are very close to the true values and have very small standard deviations. Moreover, the correlations between the true and the recovered values are high, and the mean square errors are low. These findings suggest that the model is identified and that our estimation procedure can recover the parameters successfully. Online Appendix B provides the true and estimated values for key parameters of the simulation study.[11]

## 5. Data

### 5.1. Sample

To draw generalizable empirical results, a number of data requirements had to be met. Mainly, we needed access to retail data for several years across several markets and multiple categories for various extensions and their parent brands. We achieved the above objectives by using the IRI Marketing Data Set (Bronnenberg et al. 2008). Our data comprise of weekly store-level information on sales, prices, and promotions for all stock-keeping units (SKUs) within several product categories for a period of six years (2001–2006) across 47 U.S. markets. The markets are geographic units in the United States that are either major metropolitan areas (e.g., Chicago, Illinois) or part of a region (e.g., New England). For the purpose of this study, we extract data corresponding to the top 20 U.S. geographic markets based on dollar sales. These chosen markets comprise 63.77% of the dollar revenues of all markets in the data set. The geographical markets chosen for this study and the share of dollar revenues they represent are given in Online Appendix C.

We choose extensions for our analysis as follows. We extensively search the entire available IRI Marketing Data Set for all new products introduced by the existing brand names[12] in all categories during the six-year time period. To avoid biases in measuring spillover and extension effects, we ensure that there are no other introductions of the same brand during the period of one year before and one year after the introduction of any extension. This time window is sufficient to capture spillover and extension effects in the context of CPG industry (Swaminathan et al. 2001). In the very few cases where there is more than one extension during a two-year time period, we choose one extension at random. Using this procedure, we obtain a total of 155 extensions introduced in 40 product categories.

All chosen extensions fall into at least one of the brand development strategies defined in Figure 1. We classify extensions into line extensions or brand extensions if they are introduced in either the same or a different category as the parent brand, respectively. We classify line extensions into vertical or horizontal extensions based on the price of the extension relative to that of the parent brand. Similar to prior studies (e.g., Lei et al. 2008), we define a step-up line extension as a line extension that is priced at more than one and a half times (150%) the parent brand's price, and a step-down line extension is one that is priced at less than two-thirds (66.67%) of the parent brand's price. We classify a brand or a line extension as a cobranded extension if its name or packaging explicitly contains the name of another brand (Desai and Keller 2002). We classify a brand or a line extension as a sub-branded extension if the name of the extension is registered in the U.S. Patent and Trademark Office. The sub-brand can be either a prefix or a suffix to the parent brand name (Milberg et al. 1997). If a line or brand extension is neither cobranded nor sub-branded, we classify it as a direct extension.

We also obtain data on parent brands to measure spillover effects. As mentioned earlier, the parent brand of a line extension exists in the same category as the extension. However, in the case of a brand extension, the parent brand belongs in a different category. To determine the flagship category of the parent brand, we perform a historical analysis similar to that of Golder and Tellis (1993). Specifically, we identify from historical data the product category in which the brand was first

[11] The complete set of results of the simulation study can be obtained from the authors upon request.

[12] Since our focus is on extensions of existing brand names, we do not include new brands in our analysis.

**Table 2 Summary of Chosen Extensions**

| Primary brand development strategy | Secondary strategy | Count | Spillover effects (% share) | Extension share (% share) | Parent brand's price ratio | Extension's price ratio |
|---|---|---|---|---|---|---|
| Brand extension | Naming strategy | | | | | |
| | Sub-branding | 15 | 0.15 | 4.60 | 1.42 | 1.40 |
| | Cobranding | 3 | 1.02 | 2.59 | 1.08 | 1.23 |
| | Direct extension | 14 | 0.18 | 2.93 | 1.40 | 1.57 |
| | All brand extensions | 32 | 0.24 | 3.68 | 1.38 | 1.46 |
| Line extension | Horizontal vs. vertical | | | | | |
| | Step-up vertical | 19 | −1.56 | 1.45 | 0.89 | 2.25 |
| | Step-down vertical | 4 | −0.97 | 3.10 | 2.28 | 1.09 |
| | Horizontal | 100 | −1.34 | 2.25 | 1.18 | 1.33 |
| | Naming strategy | | | | | |
| | Sub-branding | 80 | −1.67 | 2.59 | 1.16 | 1.41 |
| | Cobranding | 22 | −0.75 | 1.31 | 1.07 | 1.67 |
| | Direct extension | 21 | −0.81 | 1.35 | 1.32 | 1.46 |
| | All line extensions | 123 | −1.36 | 2.15 | 1.17 | 1.46 |
| All extensions | | 155 | −1.03 | 2.47 | 1.21 | 1.46 |

*Notes.* We measure spillover effects as the difference between the market shares of the parent brand one year before and one year after the extension's introduction. We measure extension share as the average market share one year after its introduction. We calculate parent brand's price ratio as the average weekly ratio between the parent brand's price and the average price in the parent category. Similarly, extension's price ratio is the average price weekly ratio of the extension's price to the average price of the extension category.

launched.[13] For each brand extension in our sample, we collect information from various sources such as archived news reports, magazines, trade press, and the brand's website. Given the focus of our study, we only consider the launches in the CPG industry.[14] If the parent category identified through the above process is present in the IRI Marketing Data Set, we include it in our analysis. The data set does not contain information on the parent category of six brands corresponding to seven extensions. For these brands, we choose the parent category as the next earliest category that the brand entered for which information is available.

Table 2 provides the summary and the mean descriptive statistics of the extensions used in our analysis across different brand development strategies. We note that the mean spillover effect is positive (0.24% share) for brand extensions and negative (−1.36% share) for line extensions. This indicates that, in contrast to brand extensions, an average line extension cannibalizes sales from its parent brand. We also observe that the average market share realized by brand extensions (3.68% share) is higher than that realized by line extensions (2.15% share). The descriptive data suggest that an average step-up line extension is priced at 2.53 times (=2.25/0.89) its parent brand's price, whereas an average step-down line extension is priced at 0.48 times (=1.09/2.28) its parent brand's price. This disparity in extension price ratio plausibly explains some of the differences in the relative extension shares realized by the corresponding step-up and step-down vertical extensions. In the case of naming strategies for both brand and line extensions, we notice that spillover effects are highest for cobranded extensions, followed by direct and then by sub-branded extensions. The order reverses for the extension's market share. Online Appendix D lists the chosen line extensions along with their secondary strategies (vertical versus horizontal and naming strategies). Online Appendix E lists the chosen brand extensions and their naming strategies. It includes for each brand extension both the parent category that was identified through the historical analysis and the one considered in our empirical analysis. Online Appendix F provides market share plots for selected extensions and their parent brands.

### 5.2. Dependent Variables

The dependent variables in our analysis are prices and market shares of the parent brand and the extension, and the extension introduction decision. The market share of the parent brand and the extension are measured at the market level for each extension. In each market, we only include stores in which the extension is present during a particular week. Failure to exclude the stores in which the extension is not present during a particular week would bias both spillover and

[13] We thank the associate editor for suggesting this approach. We also obtained the flagship category for each brand through a questionnaire similar to that of Roedder-John et al. (1998). Whereas the historical analysis provides the earliest category in which a brand entered, the questionnaire reveals the most popular category for each brand. In most cases, both these analyses result in the same parent category for the brand extensions in our sample. In addition, our main substantive results remain robust when we use the parent categories obtained from the questionnaire.

[14] For example, although Weight Watchers was first launched as a dieting program, the above analysis revealed frozen dinners as the parent category.

extension effects. To maintain symmetry in the sales of the parent brand before and after the introduction of the extension, we include the same set of stores in both periods. For example, if an extension is present in 20 stores during week 53, then those stores will be included in our analysis during week 53 for the extension, and during weeks 1 and 53 for the parent brand.

Data are aggregated from the SKU-store level to the brand-market level following the procedure outlined in Christen et al. (1997) to avoid any biases due to aggregation. We first aggregate the sales from SKU-store level to brand-store level in a linear fashion. Using lagged all commodity volume (ACV), we then calculate an ACV weighted average of brand-store level market share to obtain brand level data. For both the parent brand and the extension, we define the price of a brand as the regular price in a given store during a particular week. Consistent with prior studies (e.g., Ataman et al. 2008), we calculate brand-store level price as the average price of all SKUs weighted by their lagged share, and market-level price for each brand by aggregating brand-store level price using lagged store ACVs as weights. The manufacturer's decision to introduce the extension is in principle unobserved by the analyst. Nonetheless, our data set allows for good proxies for the timing of this decision. We define extension introduction as the week of first sales of the extension in any store within the focal market (Bronnenberg and Mela 2004).[15]

### 5.3. Instrumental Variables

We use the following instruments to tackle the endogeneity of the extension introduction decision and the resulting endogenous switching of the parent brand's market share. First, we include variables relating to input costs for the manufacturer to introduce the extension in each market: industrial energy rate and shipping costs. Since industrial energy is a critical input in the production process, its prices will affect production costs directly and have indirect effects on the firms' overall costs (Ghosal 2000). Shipping costs, on the other hand, reflect the amount spent transporting the finished goods from the manufacturing plant to the retail location (Zhu and Singh 2009). Although these variables may affect the firms' strategic decisions, such as new product introductions (Cooper and Kleinschmidt 1986, Ganesan et al. 2005), they are unlikely to affect unobservable shocks to the parent brand's market share (Chen et al. 2010). Second, we include market wages and grocery wages because these variables proxy for the spending potential of consumers and retailer adoption costs, respectively. Both market and grocery wages are likely to affect the entry attractiveness and therefore the decision to introduce a new product (Bronnenberg and Mela 2004, Gielens et al. 2012). However, they are unlikely to differentially affect the sales of the parent brand compared to those of other brands in the parent category. Finally, we include the spatial distribution coverage of the extension because this may impact the extension introduction decision in the focal market. For instance, it may be more likely for a firm to introduce a product in the focal market if this was already done in neighboring markets because then the firm may be able to exploit synergies related to distribution. Existing literature (e.g., Bronnenberg and Mela 2004) has shown that distribution coverage significantly affects the decision to introduce new products. However, it is unlikely that distribution coverage of the extension will be correlated with the unobserved factors affecting the parent brand's market share in a single market, especially in the case of mature product categories such as those in the CPG industry (Vanhonacker et al. 2000).

We tackle the endogeneity of prices for both the extension and its parent brand by identifying variables that are correlated with their prices but uncorrelated with the unobservable factors affecting their market shares. First, we use producer price index for the corresponding product category, which measures the average change over time in input prices (Chen et al. 2010, Dube and Manchanda 2005). We expect this to be highly correlated with shelf prices. However, we do not expect the prices in a single market to affect the nationwide wholesale price. Therefore, we assume these prices to be uncorrelated with unmeasured product attributes within a given market (Chintagunta et al. 2005). We interact the producer price indices with the parent brand and the extension dummies to allow different brands to use inputs differently (e.g., Chen et al. 2010). Second, we use market-specific manufacturing and transportation wages. These variables represent different measures of manufacturers' costs and are likely to affect prices (Dube and Manchanda 2005). Although wages are not as informative about price variation as price indices, wages are unlikely to be correlated with market shares (Chintagunta et al. 2005). Third, we use variables relating to energy costs such as gasoline prices and market-specific commercial energy rate. Gasoline prices may affect the retail prices of products because the former represent input costs for firms. Similarly, commercial energy rate is a proxy

[15] We model the firm's introduction decision at the weekly level for the following reasons. First, we do so to be consistent with the practice in prior literature on the extension introduction decision (e.g., Bronnenberg and Mela 2004). Second, aggregating the data at other levels (e.g., monthly) will limit the necessary variation and degrees of freedom to reliably estimate the model parameters. Finally, modeling the entry decision at the weekly level minimizes the resulting aggregation bias since the quantities of interest such as sales, prices, and promotions are observed at the weekly level in the IRI Marketing Data Set (Christen et al. 1997). Nevertheless, our substantive results are similar when we estimate the empirical model at the monthly level. The results are available from the authors upon request.

**Table 3 Operationalization, Sources, and Descriptive Statistics of the Instrumental Variables**

| Instrumental variable | Operationalization | Primary data source | Descriptive statistics Mean | Std. dev. | Min | Max |
|---|---|---|---|---|---|---|
| *Producer price index* (parent category) | Industry-level price index for the specific product category | Bureau of Labor Statistics | 157.64 | 28.41 | 79.4 | 242.3 |
| *Producer price index* (extension category) | | | 156.90 | 27.56 | 94.4 | 242.3 |
| *Transport wages* ($'000/week) | Weekly wages of the transportation industry in the state where the closest manufacturing plant[a] is located | | 0.74 | 0.07 | 0.5 | 0.96 |
| *Manufacturing wages* ($'000/week) | Weekly wages of the manufacturing industry in the state where the closest manufacturing plant[a] is located | | 0.94 | 0.14 | 0.55 | 1.91 |
| *Market wages* ($'000/week) | Weekly wages across all industries in the state where the market is located | | 0.85 | 0.12 | 0.60 | 1.39 |
| *Grocery wages* ($'000/week) | Weekly wages of the grocery industry across the entire U.S. | | 0.37 | 0.02 | 0.34 | 0.41 |
| *Shipping costs* ($'000/gallon) | Product of average weekly gasoline price and the distance[b] from the market to the closest manufacturing plant[a] | Energy Information Administration | 0.72 | 1.07 | 0 | 8.03 |
| *Industry energy rate* (¢/KwH) | Average price for industrial consumption in the state where the closest manufacturing plant[a] is located | | 6.56 | 2.23 | 3.95 | 17.43 |
| *Commercial energy rate* (¢/KwH) | Average price for commercial consumption in the state where the market is located | | 9.12 | 2.59 | 5.45 | 15.54 |
| *Gasoline price* ($/gallon) | Weekly price of gasoline across the entire U.S. | | 2.02 | 0.58 | 1.10 | 3.26 |
| *Distribution coverage* | Spatially weighted-average[c] of the extension entry in all other markets in the data set | IRI Marketing Data Set | 0.47 | 0.48 | 0 | 1 |

[a]We collected information on the closest manufacturing plant for each market from a myriad of sources such as company websites and government and third-party databases.
[b]Distance is measured as the driving distance between the geocenters obtained through Google API.
[c]We constructed the weight matrix as the inverse of the geographical distance from all other markets.

for the retailer's input costs to operate stores and stock products, and thus could affect product prices (Ghosal 2000). Although energy prices have always been seen as a primary determinant of consumer prices (*Wall Street Journal* 2012), they are unlikely to reflect time-varying shocks in market shares. Table 3 provides the operationalization, data sources, and descriptive statistics of the chosen instrumental variables.

### 5.4. Control Variables

We use competitors' prices as well as displays and feature promotions of the parent brand, the extension, and their competitors as independent variables in the market share equations. The feature and display variables take the value 1 if at least one SKU from the corresponding brand's product line is on promotion in a given week. The brand-market level averages for these variables are calculated across stores in a linear fashion using lagged store ACVs as weights (Ataman et al. 2008). Price, display, and feature promotion of the composite competitor in a given category are computed as the weighted average of the corresponding marketing mix variable of all other brands in that product category. We use average market share in the most recent 13 weeks ($t-1, t-2, \ldots, t-13$) as rolling weights in the aggregation. We use category concentration as the control variable at the category level. We measure category concentration in terms of the Herfindahl index, i.e., the sum of the squares of the brand market shares during the entire period of our data set.

## 6. Results

### 6.1. Model Fit

In a Bayesian approach, we can empirically test the assumption of endogeneity by estimating the model with and without endogeneity and then comparing the in-sample fit statistics (Chib 2007). We test our full model against alternative benchmark models that do not account for different sources of endogeneity. Based on all possible combinations of the three sources of endogeneity, we obtain seven ($=2^3-1$) benchmark models. We can obtain the Gibbs sampler algorithms for the benchmark models by imposing restrictions on our full model. We compare the in-sample fit of the alternative specifications with our full model using the log Bayes factor. In Table 4, we provide the log Bayes factors comparing the full model with the alternative specifications. All log Bayes factors are much higher than two. This indicates that our full model outperforms other models, confirming that the endogeneity of extension introduction decision and the endogeneity of prices of the parent brand and the extension are salient. We also observe that benchmark models that account for the endogeneity of parent brand's price perform better than other benchmark models. This suggests that the endogeneity of parent brand's price plays a greater role than the endogeneity of extension's price and extension introduction decision.

For computing the out-of-sample fit, we use data on all extensions from the chosen markets and designate as holdout period the second year after the

**Table 4** In-Sample Fit Measures

| Model | Sources of endogeneity modeled: Introduction decision | Parent brand price | Extension price | Log Bayes factor (compared with the full model) |
|---|---|---|---|---|
| Benchmark model 1 | | | | 63,800 |
| Benchmark model 2 | | | ✓ | 35,468 |
| Benchmark model 3 | | ✓ | | 34,008 |
| Benchmark model 4 | ✓ | | | 35,711 |
| Benchmark model 5 | ✓ | ✓ | | 19,228 |
| Benchmark model 6 | ✓ | | ✓ | 34,829 |
| Benchmark model 7 | | ✓ | ✓ | 17,761 |
| Full model | ✓ | ✓ | ✓ | Not applicable |

extension introduction. We use mean square error to compare predicted and actual market shares in the holdout period (Bezawada et al. 2009). The mean square errors obtained are 0.069 for the parent brand's market share and 0.135 for the extension's market share. This demonstrates that our full model has good predictive power.

### 6.2. Fit of the Instrumental Variables

We test the strength of the instruments for price endogeneity using first-stage $R^2$ and $F$-statistic of the price equations. The value of $R^2$ has to be close to 1 and the value of $F$-statistic has to be greater than 50 to claim that the instruments are strong (Stock et al. 2002). In the case of endogeneity of extension introduction decision, we test the strength of the instruments based on the percentage of weekly extension introduction decisions correctly predicted by the instrumental variables (Chesher 2010). Because our model captures heterogeneity across extensions and markets, we estimate the parameters at the extension-market level and pool the data to determine the overall predictive power of the instrumental variables. In line with prior research (e.g., Chen et al. 2010), we choose the number of lags for the instrumental variables as the one with the best fit. We find that one-week, two-week, and four-week lagged measures provide the best fit for the extension introduction decision, parent brand price, and extension price, respectively.

The fit measures are as follows. The combined instruments provide overall $R^2$ values of 0.973 for the parent brand price equation and 0.957 for the extension price equation. The $F$-statistic is 162 for the parent brand price equation and 212 for the extension price equation. In the case of extension introduction equation, inclusion of the instruments correctly predicts 92.5% of the extension introduction decisions. These fit measures are very high, indicating that the variables that we used to account for the three sources of endogeneity are strong instruments (Dube and Manchanda 2005, Stock et al. 2002).

We test the exogeneity of the instrumental variables through the correlation between the residual of the market share equations and each instrumental variable (Stock et al. 2002). All correlations are either equal to or very close to zero. In particular, the correlations between the instruments for extension introduction decision and the error terms of the parent brand's market share equations ($\varepsilon_{ijt}^{ne}$ and $\varepsilon_{ijt}^{e}$) range from 0.000 to 0.144, with an average of 0.050. The correlations between the instruments for parent brand price and the error terms of the parent brand's market share equations ($\varepsilon_{ijt}^{ne}$ and $\varepsilon_{ijt}^{e}$) range from 0.000 to 0.107, with an average of 0.009. The correlations between the instruments for extension price and the error term of the extension's market share equation ($\eta_{ijt}$) range from 0.000 to 0.108, with an average of 0.017. These correlation values indicate that the instruments used to account for the endogenous switching of the parent brand's market share and the price endogeneity for both the parent brand and extension are exogenous to the unobservable drivers of the corresponding market shares.

### 6.3. Spillover and Extension Effects

The fifth column of Table 1 provides the estimated spillover and extension effects, most of which are in line with our expectations. Online Appendix G provides the complete set of second layer estimates from our empirical model. We find that the average spillover effects are positive for brand extensions and are negative for line extensions. Although both extensions enhance their respective parent brands' recognition among consumers, line extensions also subject their parent brands to within-category competitive pressure as a consumption substitute (Reddy et al. 1994). In contrast, the parent brand of a brand extension gets the potential benefits from increased consumer familiarity, but without the cannibalization threat, since the extension is introduced in a different category (Swaminathan et al. 2001). The finding that brand extensions generate positive spillover effects for the parent brand is an interesting result given that most brand extension research (e.g., Keller and Aaker 1992, Milberg et al. 1997, Roedder-John et al. 1998) focuses on negative spillover effects on parent brands. The primary reasons associated with negative spillover effects are failure of the extension and low similarity between the extension and parent categories. The aforementioned studies experimentally manipulated these factors to examine the attitudinal effects on parent brands. However, using scanner panel data, Swaminathan et al. (2001) show that brand extensions create positive spillover effects in all cases except when the extension fails. Since we do not explicitly constrain the extensions in our sample in terms of extension success or category similarity, we find that the parent brand of an average brand extension does not suffer from negative spillover effects. Our results indicate that managers may already take into account factors such as category similarity and potential extension success when introducing brand extensions. We find that extension effects are higher for line extensions than for brand extensions. This is because consumers will be able to more easily accommodate a line extension when it is introduced in the same category as the parent brand. It is interesting to note that this finding differs from the one based on a simple average of extensions' market shares (Table 2). We attribute this to the several effects our model captures, such as the endogenous decision to introduce the extension, price endogeneity, and the effect of brand and category covariates. In other words, it attests to the importance of the above decisions/variables when measuring spillover and extension effects.

Among vertical line extensions, we find that a step-up line extension has higher spillover effects, and a step-down line extension has lower spillover effects compared to a horizontal line extension. Both of these results are in line with our expectations and indicate that step-up and step-down vertical line extensions signal higher and lower quality of parent brands, respectively (Randall et al. 1998, Wernerfelt 1988). Hence, managers wishing only to maximize the equity of their current brands may put a greater emphasis on offering a step-up instead of a step-down line extension. For instance, Ragu faced lower spillover effects (refer to Figure F5 in Online Appendix F), due to the launch of its premium extension, Carb Options, in the spaghetti sauce category. However, these spillover effects reverse in terms of extension effects: step-up line extension leads to lower, whereas step-down line extension leads to higher, extension effects. The higher (lower) amount of perceived risk to try a step-up (step-down) vertical line extension translates into a lower (higher) rate of extension success. For example, Crest achieved greater performance for its extension by introducing a cheaper Classic Clean toothbrush (refer to Figure F6 in Online Appendix F) targeted to value-centered consumers. Thus, managers need to consider the trade-offs while designing their future product portfolios based on their objectives (e.g., enhancing equity of their current portfolio versus incremental revenue/market share generation).

As expected, we find that sub-branded brand extensions have greater extension effects when compared to direct brand extensions. This implies that sub-branding enables consumers to selectively transfer positive associations from the parent brand to the extension (Park et al. 1993, Milberg et al. 1997). In the case of naming strategies for line extensions, we find that spillover effects for sub-branded line extensions are more negative than those for direct line extensions. This finding suggests that consumers may perceive the extent products of the parent brand to be more similar in case of a sub-branded line extension (Pan and Lehmann 1993). Hence, the cannibalization of the parent brand that stems from customer substitution is more predominant for sub-branded line extensions than for direct line extensions. We find that cobranding lowers the extension effects of a line extension. As described earlier, this is because consumers may perceive the cobranded line extension to have a poorer fit with the parent brand than a direct line extension (Desai and Keller 2002).

### 6.4. Effect of Control Variables

We find that category concentration affects spillover effects negatively and extension effects positively. (We provide the complete results including the hierarchical components for the control variables in Online Appendix G.) These findings indicate that although extensions are less successful in categories that have greater competition, introducing extensions in such categories leads to higher spillover effects. Whereas the former is intuitive, we explain the latter as follows. The intensity of promotion campaign accompanying the entry of a new extension is typically higher if the extension category is more competitive (i.e., less concentrated). Thus, when an extension is introduced in a more competitive category, more brand awareness is likely to be generated for the parent brand (Aaker and Joachimsthaler 2000). Such increased brand awareness implies more positive spillover effects for brand extensions and less negative spillover effects for line extensions.

The effects of marketing mix variables are in line with existing findings in the CPG industry. In the market share equations of both the parent brand and the extension, we find that own prices, competitors' displays, and competitors' feature promotions have negative effects, and that own displays, own feature promotions, and competitors' prices have positive effects. In addition, market shares and prices of both the parent brand and the extension are significantly dependent on their past values. We find that the parent brand's price sensitivity increases due to the introduction of a step-up line extension. Because a brand signals a higher quality by introducing a step-up line extension, its existing customers may perceive higher financial risk and become increasingly conscious of price variations (Lei et al. 2008). On the other hand, the parent brand's price sensitivity decreases due to the introduction of all other types of extensions. This implies that brands that extend to the same or lower price levels gain price-setting power (Kadiyali et al. 1999).

The parameter estimates of the extension introduction equation reveal that the intrinsic attractiveness to introduce extensions is higher in less competitive categories. In addition, we find that firms intrinsically prefer certain geographical markets to others when introducing extensions. For instance, markets comprised of smaller cities (e.g., Buffalo/Rochester, New England) are more attractive for introducing new products than markets comprised of larger cities (e.g., San Francisco, San Diego). This is consistent with anecdotal evidence that smaller cities are very good test markets for consumer products (Pride and Ferrell 2012).

### 6.5. Revenue Outcomes

We obtain the revenue gain due to the introduction of extension $i$ in market $j$ by substituting the estimated values of spillover effects ($\delta_{0ij}$) and extension effects ($\theta_{0ij}$) in Equation (5).[16] We thus denote the revenue gain as

$$RG_{ij} = PCR_{ij} \times PBPr_{ij} \times \left[\left\{\frac{PBS_{ij}^{ne} \times (1-PBS_{ij}^{ne}) \times (1-e^{-\delta_{0ij}})}{e^{-\delta_{0ij}} + PBS_{ij}^{ne} \times (1-e^{-\delta_{0ij}})}\right\} + \left\{\frac{RevRatio_{ij} \times PriceRatio_{ij}}{1+e^{-\theta_{0ij}}}\right\}\right]. \quad (16)$$

We obtain this formulation after accounting for the endogenous decision to introduce the extension, the endogenous price-setting behavior of the parent brand and the extension, the competitors' prices, other marketing mix activities of the parent brand and extension and of their competitors; and the market- and category-specific variations. Our empirical model can be used to derive the revenue gain for a specific extension based on the characteristics of the parent brand and extension and their categories. We demonstrate this by first deriving the average revenue gain for each brand development strategy based on the extensions in our sample and then proceeding as follows.

First, to obtain the average value of spillover and the extension effects for each brand development strategy, we use the corresponding parameter(s) from the hierarchy on $\delta_{0ij}$ and $\theta_{0ij}$ in Equation (15) (see Tables G1 and G3 in Online Appendix G). These estimates of spillover and extension effects account for variation in category characteristics as well as for any market-specific shocks. Second, we assume that the market share ($PBS_{ij}^{ne}$) and relative price ($PBPr_{ij}$) of the hypothetical parent brand are equal to the average market share (17%) and average relative price (1.21) of all parent brands in our sample. Third, we set the values of $RevRatio_{ij}$ and $PriceRatio_{ij}$ in the following manner. Because line extensions are introduced in the same category as that of the parent brand, $RevRatio_{ij}$ is always equal to 1.0. We set $PriceRatio_{ij}$ to 1.0 for horizontal line extensions since they are introduced at the same price level as that of the parent brand. We set $PriceRatio_{ij}$ equal to 1.5 for step-up line extension (50% more expensive than the parent brand), and $PriceRatio_{ij}$ equal to 0.67 for step-down line extension (33% cheaper than the parent brand) in line with prior literature (e.g., Lei et al. 2008).

In the case of brand extensions, we choose the following three conditions. The first condition describes a scenario wherein the size of the extending category is the same as that of the parent category, and the extension's price ratio is identical to that of the parent brand ($RevRatio_{ij} = 1.0$ and $PriceRatio_{ij} = 1.0$). The second condition is where either the extension category is half the size of the parent category ($RevRatio_{ij} = 0.5$ and $PriceRatio_{ij} = 1.0$) or the relative price of the extension is 50% lower than that of its parent brand ($RevRatio_{ij} = 1.0$ and $PriceRatio_{ij} = 0.5$). Similarly, the third condition is when either the extension category is 50% bigger than the size of the parent category ($RevRatio_{ij} = 1.5$ and $PriceRatio_{ij} = 1.0$) or the relative price of the extension is 50% higher than that of its parent brand ($RevRatio_{ij} = 1.0$ and $PriceRatio_{ij} = 1.5$).

Table 5 lists for each of the above scenarios the revenue gain for each brand development strategy as a percentage of the parent category revenues ($PCR_{ij}$). We find that in the case of line extensions, the negative spillover effects dominate positive extension effects, thereby leading to negative overall revenues. However, brand managers can mitigate the negative spillover effects by vertically differentiating the line extensions through increased quality (price). In our illustration, we find that a step-up line extension generates positive revenues. Specifically, they gain 1.1%, 0.83%, and 0.13% of the parent category revenues when combined with direct, cobranding, and sub-branding strategies, respectively. We note that this calculation does not take into account the marketing efforts required to convince consumers about the higher prices of the line extension (Randall et al. 1998).

We find that brand extensions generate positive overall revenues across all the above conditions. This is because a newly launched brand extension generates positive revenues through extension effects, and spillover effects are positive for an average brand extension. However, our analysis does not account for

[16] Since we mean center the explanatory variables in Equations (7), (8) and (10), the representation of revenue gain in Equation (16) does not contain the parameters $\delta_{1ij}$, $\beta_{1ij}$–$\beta_{7ij}$ and $\theta_{0ij}$–$\theta_{7ij}$.

**Table 5 Revenue Outcomes**

| Primary brand development strategy | Horizontal/vertical extension | Naming strategy | Ratio of extension category revenues to parent category revenues | Ratio of relative price of the extension to relative price of the parent brand | Revenue gain as a percentage of parent category revenues |
|---|---|---|---|---|---|
| Line extension | Horizontal | Direct extension | 1.0[a] | 1.0[a] | −0.102 |
| | Vertical step-up | | | 1.5 | 1.073 |
| | Vertical step-down | | | 0.67 | −0.860 |
| | Horizontal | Sub-branded | | 1.0[a] | −1.005 |
| | Vertical step-up | | | 1.5 | 0.133 |
| | Vertical step-down | | | 0.67 | −1.720 |
| | Horizontal | Cobranded | | 1.0[a] | −0.314 |
| | Vertical step-up | | | 1.5 | 0.828 |
| | Vertical step-down | | | 0.67 | −1.121 |
| Brand extension | Not applicable | Direct extension | 1.0 | 1.0 | 1.555 |
| | | | 1.0 | 0.5 | 1.011 |
| | | | 0.5 | 1.0 | |
| | | | 1.0 | 1.5 | 2.099 |
| | | | 1.5 | 1.0 | |
| | | Sub-branded | 1.0 | 1.0 | 1.890 |
| | | | 1.0 | 0.5 | 1.179 |
| | | | 0.5 | 1.0 | |
| | | | 1.0 | 1.5 | 2.601 |
| | | | 1.5 | 1.0 | |
| | | Cobranded | 1.0 | 1.0 | 1.555 |
| | | | 1.0 | 0.5 | 1.011 |
| | | | 0.5 | 1.0 | |
| | | | 1.0 | 1.5 | 2.099 |
| | | | 1.5 | 1.0 | |

[a]The condition is applied by definition of the corresponding brand development strategy.

the potentially higher costs involved in developing and marketing a brand extension (Aaker and Keller 1990). Among the various naming strategies, we find that sub-branding generates greater revenues for a typical brand extension. Our calculation also suggests that a brand extension generates greater revenue if it enters a larger category or at a higher price level.

## 7. Conclusion

In this study, we empirically evaluate the aggregate market impact of different brand development strategies through spillover and extension effects. We develop a conceptual framework to classify extensions into different brand development strategies. Based on a comprehensive survey of the existing literature, we first posit theoretical expectations for spillover and extension effects. We then build an analytical framework to evaluate the revenue outcomes of an extension introduction, which are then denoted as a function of spillover and extension effects. Our empirical model is a Bayesian endogenous switching model in which we jointly model the prices and market shares of the extension and its parent brand, as well as the decision to introduce the extension. We account for the endogenous switching of the parent brand's market share as a result of the strategic decision to introduce the extension while measuring spillover effects, and for the endogeneity due to the prices of both the parent brand and the extension. We use a data set that covers 155 extensions introduced across 20 U.S. geographic markets. The broad scope of our data allows us to draw several new and empirically generalizable insights.

We find that brand extensions have higher spillover effects and that line extensions have higher extension effects. In the case of vertical line extensions, we find that step-up line extensions have higher spillover effects and lower extension effects, whereas the opposite holds for step-down line extensions. The addition of a new brand name (i.e., sub-branding) lowers spillover effects for line extensions, whereas it increases the market performance for brand extensions. We use the market share estimates to obtain the overall revenues generated by each brand development strategy. We find that vertically differentiating a line extension in terms of increased quality mitigates its negative spillover effects. Among the various naming strategies, we find that sub-branding generates greater revenues for a typical brand extension.

A deeper understanding of different brand development strategies is essential for CPG manufacturers because these strategies have the potential to protect and boost the firms' revenues and profits, that is, their "top and bottom lines." We believe our empirical model helps in that endeavor because our model can be used as a decision support tool for evaluating the magnitude of potential spillover and extension effects before an extension is introduced. Specifically, our market share and revenue calculations can provide useful guidance for branding new product introductions, especially for CPG firms (e.g., P&G, Unilever) operating in multiple categories and holding a portfolio of brands. However, as with any research, caution should be used in generalizing some of the findings. Although we control for brand, category, and market characteristics, the impact of an extension can be determined by other missing factors such as perceived quality of the extension, variation in parent brand equity, introduction costs, etc.[17]

Our study also has implications for the theoretical literature on brand development strategies because we develop a detailed taxonomy to classify product extensions in the context of the CPG industry and integrate existing findings across different strategies. The empirical analysis provides insights on how findings from the existing studies based on attitudinal data extend to the aggregate market level. Our modeling framework extends the literature on endogenous switching models (e.g., Chib 2007, Koop and Porier 1997) because it simultaneously models four continuous variables and a binary treatment variable that are endogenous to each other. In addition, the instrumental variables that we identify are suitable for explaining the endogenous switching of the parent brand's market share and the price endogeneity for both the parent brand and the extension. The methodological framework also captures spillover and extension effects across different brand development strategies, categories, and markets.

In conclusion, the scope of the empirical data and the estimation methodology used in our study help shed several new insights into the aggregate market impact of different brand development strategies. At the same time, our study also points to several complementary directions in need of future research within the important domain of branding strategies. One such direction would be to compare the aggregate firm-level impact of different corporate branding strategies such as "house of brands" versus "branded house" (e.g., Aaker and Joachimsthaler 2000). Another interesting direction would be to endogenize each brand development strategy to obtain insights on the supply-side factors that affect the firms' decisions to launch each of the strategies. In addition, although it will be challenging from a data collection perspective, future research could control for the effect of advertising while measuring spillover and extension effects. Finally, similar to previous studies on new product introductions, we consider products that were formally launched in the market place. This is a typical limitation present in the existing market-level studies investigating the extent and determinants of success of new product introductions. This limitation may lead to a bias in the findings toward surviving new products (Boulding and Christen 2003, Reddy et al. 1994). Although the lack of market data on failed extensions has been the main stumbling block to addressing this issue, it remains an important direction for future research to pursue.

[17] We thank the associate editor and a reviewer for this suggestion.

## Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mnsc.2014.1900.

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