Part F
Innovation and New Products

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Kersi Antia, Western University
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Innovation Processes and Outcomes

An Empirical Investigation of Composite Product Choice
Kalpesh Desai, Dinesh Gauri, Yu Ma

The Effect of Superstar Software in the Video Game Industry: The Moderating Role of Product Generation Lifecycles
Richard Gretz, Suman Basuroy

The Mitigating Effect of Personal Agency on Escalation of Commitment
Sunil Contractor

An Exploratory Study of Antecedents and Consequences of Radical Product Innovation Capability
Sanjit Sengupta, Stanley F. Slater, Jakki J. Mohr

Open, Low-Cost Innovation

Avoiding a Babylonian Confusion: A Systematic Review on Low-Cost Innovation
Ronny Reinhardt

Development of Successful Really New Products: The “Over-Collaboration” Effect at Different Stages of the New Product Development Process
Johannes S. Deker, Monika C. Schuhmacher, Sabine Kuester

Sustainability, Open Innovation, and New Product Program Success
Shuili Du, Ludwig Bstieler, Goksel Yalcinkaya

It’s All Your Fault! Attributing Blame for Co-Created New Product Failures in B2B Relationships
B.J. Allen
An Empirical Investigation of Composite Product Choice

Kalpesh Desai, University of Missouri
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ABSTRACT
Prior ingredient branding research has examined the influence of “stated” factors such as fit between partner brands on composite product (e.g., Tide with Downy fabric softener) attitudes. This research focuses on choice of composite products, and addresses three managerially relevant questions: Which consumer segments are more likely to adopt the composite product? Will the choice of the composite product have positive or negative reciprocal effects on partner brands? Will the introduction of the composite product benefit the primary or the secondary brand more? The authors use a brand choice model to investigate the “revealed” choice of complements-based composite products. Study results indicate that (i) despite high fit between the composite product and the primary brand, consumer segments have different choice likelihoods for these products, whereas prior research suggests equal likelihood; (ii) the choice of a composite product may not provide a positive reciprocal effect to the secondary brand; and (iii) the introduction of a composite product may benefit the primary brand more than the secondary brand, whereas prior research suggests a symmetrical benefit for the partner brands. Finally, the finding that introducing a composite product may not cannibalize the sale of the primary brand extends the ingredient branding literature, which has been silent on this issue.

Keywords: composite product, ingredient branding, choice models, scanner panel data

Introduction
A currently popular marketing strategy for increasing brands’ attractiveness to consumers is the introduction of composite products comprising complementary branded components. Examples include Downy fabric softener in Tide laundry detergent, Cascade automatic dishwashing detergent with Dawn dishwashing liquid, Andes candy in Perry’s ice cream, and Lays potato chips with KC Masterpiece vinegar. This composite product strategy uses one brand from each of the two complementary product categories as a component in the composite product. As an example to clarify our terminology, the product incorporating Downy fabric softener in Tide laundry detergent is referred to as the composite product, Tide is the primary brand, laundry detergent is the primary category, Downy is the secondary brand,1 and fabric softener is the secondary category. Tide and Downy are jointly referred to as partner brands, and reciprocal effects refer to the influence of the choice of composite product on the boost in attitudes toward primary and secondary brands. The strategies of ingredient branding and composite products differ slightly. In ingredient branding, one brand is a component or part of the final product that is sold under a different brand name (e.g., Intel in an HP computer, Nutrasweet in Diet Coke). In the case of composite products, two brands (primary and secondary) from complementary categories act as components in the composite product. However, we rely on the ingredient branding literature to guide our theorizing, because the literature regarding ingredient branding is well established and the difference between these two strategies is minor.

Prior research in ingredient branding has investigated the distinct roles that a secondary brand plays in the primary category. For example, experimental data showed how an ingredient co-brand (Godiva) can help a primary brand (Slim-Fast) overcome a limitation (poor taste) and improve

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1An alternate terminology could be host brand for the primary brand and ingredient brand for the secondary brand, but for clarity, we use primary and secondary brand. We thank an anonymous reviewer for this suggestion.

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its evaluation when extending into a new category (SlimFast cake mix) (Park, Jun, and Shocker 1996). Similarly, the role of the secondary brand may be to lend a specific characteristic to the primary brand (e.g., Irish Spring bath soap lending its scent to Tide laundry detergent) or to provide the primary brand with a new attribute (e.g., Dayquil adding cough relief to Life Savers candy) (Desai and Keller 2002).

While prior research has enhanced understanding of the ingredient branding, these earlier studies focused primarily on stated factors (e.g., reported brand attitude and stated brand familiarity) that influence attitudes toward the ingredient product and partner brands. Controlled lab experiments may not necessarily reflect actual consumer behavior and hence may limit the external validity of the findings (Geylani, Hofstede, and Inman 2008). Although many new products combining complementary offerings have appeared on the market, the market structure literature contains little research on these products (Elrod et al. 2002). This exploratory study investigates consumers’ revealed choice of these products by employing scanner panel data to examine important questions of interest to retailers and brand managers. The results not only fill key gaps but also answer recent calls for more research on ingredient branding (Keller and Lehmann 2006) and multiple-category decision making (Russell et al. 1999).

Our research addresses three interrelated managerially relevant questions. First, which segments of consumers are more likely to choose composite products (that combine primary and secondary brands) and thus be targeted by marketers? Theoretically, might any factors hold back a consumer from choosing the composite product despite currently using (and liking) either or both partner brands? Second, will choosing this composite product positively or adversely change the adopter’s evaluation of either or both partner brands? Theoretically, will the consumer’s evaluation of the secondary brand, post-choice of the composite product, go up because it is the only brand in the secondary category that partners with the high-equity primary brand, or will it go down because the performance of the secondary brand is now less visible as part of the performance of the composite product? Third, will the introduction of the composite product benefit the primary brand more than the secondary brand? Theoretically, in addition to changes in market share because of the composite product’s likely cannibalization of the choice of individual partner brands, will the introduction of the composite product increase the competitive clout or vulnerability of partner brands?

**Data Description**

The data for our study come from a suburban grocery market of a mid-sized city in the northeastern U.S. For this study, we obtained access to a dominant local retail chain’s daily transactions data, which provide information about the date of the transactions and bonus card holder information (whether a shopper card was used), as well as dollar volume, unit price, quantity, category, and coupon use for every UPC sold. For product stimuli, we selected two composite products according to the following considerations. First, the composite product should have been introduced somewhere in the middle of the three years for which we have the data to facilitate the comparison of pre- versus post-introduction periods. Second, the composite product should have a reasonable level of penetration (we selected only composite products that were bought by at least 1,000 households after the introduction). Third, since unbiased identification of the effects on the primary and secondary brands is important, the composite product should be a combination of only one primary brand and one secondary brand. Fourth, the primary brand should have a prior history of marketing without the secondary brand to facilitate the comparison of performances of the primary brand in pre- versus post-composite product introduction scenarios. Similar criteria applied to the secondary brand. Fifth, the secondary brand should be an ingredient in only one product, which should facilitate a “cleaner” attribution of changes in the choice of the secondary brand post-introduction of the composite product. Similarly, the primary brand should have only one secondary brand and should not feature distinct ingredients in different line extensions of the primary brand.

Two composite products, Tide laundry detergent with Downy fabric softener and Cascade automatic dishwasher soap with Dawn dishwashing liquid, satisfied our criteria. Tide (primary brand) belongs to the laundry detergent category, while Downy (secondary brand) belongs to the fabric softener category. Tide with Downy represents a complementary composite product because consumers use these products together to wash and dry clothes. Similarly, Cascade (primary brand) belongs to the automatic dishwashing detergent category while Dawn (secondary brand) belongs to the manual dishwashing liquid category, and both could be used together for the same occasion (pre-wash dishes manually with Dawn before putting into the dishwasher and cleaning with Cascade). We also empirically verify the functional relationship between these two sets of product categories.

Since consumers buy composite products less frequently, our analyses included purchase data for 45 weeks before introduction and 45 weeks after introduction of the composite product (2003–2005). We selected only consumers who...
had made at least one purchase in the primary and secondary categories before the introduction of the composite product (Swaminathan, Fox, and Reddy 2001). Using this criterion, we were able to have 5,215 and 2,604 households in the Tide and Cascade composite product samples, respectively.

We considered all the brands in the corresponding categories. Tables 1 provide some descriptive statistics about the data in the period before the introduction of the composite product. It shows that Tide and Downy are market leaders in their respective categories and that each brand has the highest price (in cents per ounce) in its category. Arm & Hammer receives the maximum feature and display support in laundry detergent category. Tide and Downy have the largest number of SKUs and receive the largest advertising spending in their respective categories. Availability of manufacturer coupons is also the highest for both Tide and Downy.

3The estimated weekly national advertising expenditures of the brands were obtained from TNS Media Intelligence for the corresponding period of the data.
4Manufacturer coupons are coded as 1 if available for selected market at a given week and 0 otherwise.

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**Table 1.** Descriptive Statistics of Brands in Detergents and Fabric Softener Categories Before the Introduction of Composite Brand

<table>
<thead>
<tr>
<th>Brand</th>
<th>Market Share</th>
<th>Price (cents/oz)</th>
<th>Feature</th>
<th>Display</th>
<th>Coupon Availability</th>
<th>Avg. # of UPCs in a week</th>
<th>Log (weekly advt. spending)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Laundry detergents</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tide</td>
<td>30.14</td>
<td>6.81</td>
<td>.70</td>
<td>.31</td>
<td>.30</td>
<td>.12</td>
<td>.26</td>
</tr>
<tr>
<td>Arm &amp; Hammer</td>
<td>18.90</td>
<td>4.12</td>
<td>.84</td>
<td>.81</td>
<td>.30</td>
<td>.75</td>
<td>.36</td>
</tr>
<tr>
<td>Era</td>
<td>15.08</td>
<td>4.63</td>
<td>.93</td>
<td>.35</td>
<td>.44</td>
<td>.16</td>
<td>.35</td>
</tr>
<tr>
<td>All</td>
<td>10.50</td>
<td>4.62</td>
<td>.49</td>
<td>.43</td>
<td></td>
<td>.11</td>
<td>.29</td>
</tr>
<tr>
<td>Purex</td>
<td>7.51</td>
<td>4.05</td>
<td>.70</td>
<td>.40</td>
<td>.42</td>
<td>.32</td>
<td>.42</td>
</tr>
<tr>
<td>Wisk</td>
<td>6.57</td>
<td>5.38</td>
<td>.58</td>
<td>.46</td>
<td>.40</td>
<td>.21</td>
<td>.34</td>
</tr>
<tr>
<td>Xtra</td>
<td>5.88</td>
<td>2.10</td>
<td>.22</td>
<td>.38</td>
<td>.44</td>
<td>.24</td>
<td>.40</td>
</tr>
<tr>
<td>Cheer</td>
<td>3.47</td>
<td>6.58</td>
<td>.46</td>
<td>.15</td>
<td>.33</td>
<td>.13</td>
<td>.31</td>
</tr>
<tr>
<td>Private Label</td>
<td>3.26</td>
<td>2.31</td>
<td>.52</td>
<td>.37</td>
<td>.43</td>
<td>.02</td>
<td>.13</td>
</tr>
<tr>
<td><strong>Fabric softeners</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Downy</td>
<td>36.64</td>
<td>8.95</td>
<td>1.11</td>
<td>.29</td>
<td>.35</td>
<td>.13</td>
<td>.29</td>
</tr>
<tr>
<td>Private Label</td>
<td>19.81</td>
<td>3.69</td>
<td>.68</td>
<td>.46</td>
<td>.33</td>
<td>.10</td>
<td>.24</td>
</tr>
<tr>
<td>Snuggle</td>
<td>13.99</td>
<td>6.62</td>
<td>.46</td>
<td>.48</td>
<td>.37</td>
<td>.14</td>
<td>.28</td>
</tr>
<tr>
<td>Bounce</td>
<td>14.25</td>
<td>4.80</td>
<td>.17</td>
<td>.24</td>
<td>.32</td>
<td>.00</td>
<td>.05</td>
</tr>
<tr>
<td>Arm &amp; Hammer</td>
<td>6.73</td>
<td>4.59</td>
<td>.37</td>
<td>.34</td>
<td>.43</td>
<td>.20</td>
<td>.39</td>
</tr>
<tr>
<td>All</td>
<td>3.41</td>
<td>4.19</td>
<td>.12</td>
<td>.43</td>
<td>.40</td>
<td>.11</td>
<td>.27</td>
</tr>
<tr>
<td>Cling Free</td>
<td>5.17</td>
<td>3.05</td>
<td>.23</td>
<td>.38</td>
<td>.42</td>
<td>.16</td>
<td>.33</td>
</tr>
</tbody>
</table>
brand experience is customer-specific. PBE (SBE) of 1 suggests a loyal user of the primary (secondary) brand, whereas PBE (SBE) of 0 suggests the household is a non-user of the primary (secondary) brand. A value of PBE (SBE) between 0 and 1 implies that the household is a familiar user who switches between the primary (secondary) brand and other brands in the primary (secondary) category.

Tables 2a and 2b show the percentage of users in various segments, classified on the basis of their experience with the primary and secondary brands. Of all the households in our detergent composite product sample, 12.04% and 11.85% constitute loyal users of the primary brand (Tide) and the secondary brand (Downy), respectively, while the percentage of users that are loyal to both Tide and Downy is relatively small (2.42%). Of the households in the dishwashing composite product sample, 23.85% and 24.58% are loyal users of the primary brand (Cascade) and the secondary brand (Dawn), respectively. The percentage of users that are loyal to both Cascade and Dawn is small here also (7.07%), although a bit larger than in the other case.

Model Specification
Our goal is to estimate a shift in consumers’ brand preference after introduction of the composite product. To isolate the change in brand preference owing to changes in marketing activities, we employ brand choice models (Guadagni and Little 1983; Krishnamurthi and Raj 1988; Lattin and Bucklin 1989) in the primary and secondary categories, estimated simultaneously and incorporating household-level heterogeneity.

We illustrate the model specification using the example of a detergent and softener composite product. For both categories, we assume that households derive utility from the purchase and consumption of a brand. Computation feasibility leads to analysis at the brand level (e.g., Erdem 1998; Mehta 2007) instead of the SKU level (Fader and Hardie

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5Note that our segmentation of consumers is based on their initial purchases. This way of segmenting, while facilitating managerial interpretations, may introduce two potential biases owing to the “regression to the mean” (RTM) phenomenon and ceiling effect. For example, some consumers may be classified into the loyalty segment by pure chance, even if their choice probability of the focal brand is less than 100%. As a result, the introduction of the composite brand may seem to reduce these customers’ choice probability of the focal brand owing to RTM. The ceiling effect might also occur—the consumers with the highest probability of buying the focal brand would have less room to improve.

Table 2a. Segmentation of Users Based on Prior Primary and Secondary Brand Experience for Laundry Detergent and Fabric Softener Categories

<table>
<thead>
<tr>
<th>Secondary Brand (Downy) Experience</th>
<th>Non-users</th>
<th>Familiar Users</th>
<th>Loyal Users</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Primary brand (Tide) experience</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-users</td>
<td>47.02</td>
<td>7.88</td>
<td>6.12</td>
<td>61.02</td>
</tr>
<tr>
<td>Familiar users</td>
<td>18.43</td>
<td>5.20</td>
<td>3.32</td>
<td>26.94</td>
</tr>
<tr>
<td>Loyal users</td>
<td>7.56</td>
<td>2.07</td>
<td>2.42</td>
<td>12.04</td>
</tr>
<tr>
<td>Total</td>
<td>73.00</td>
<td>15.15</td>
<td>11.85</td>
<td>100.00</td>
</tr>
</tbody>
</table>

Table 2b. Segmentation of Users Based on Prior Primary and Secondary Brand Experience for Automatic and Hand Dishwashing Detergent Categories

<table>
<thead>
<tr>
<th>Secondary Brand (Dawn) Experience</th>
<th>Non-users</th>
<th>Familiar Users</th>
<th>Loyal Users</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Primary brand (Cascade) experience</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-users</td>
<td>20.85</td>
<td>16.82</td>
<td>10.02</td>
<td>47.70</td>
</tr>
<tr>
<td>Familiar users</td>
<td>13.06</td>
<td>7.91</td>
<td>7.49</td>
<td>28.46</td>
</tr>
<tr>
<td>Loyal users</td>
<td>10.91</td>
<td>5.88</td>
<td>7.07</td>
<td>23.85</td>
</tr>
<tr>
<td>Total</td>
<td>44.82</td>
<td>30.61</td>
<td>24.58</td>
<td>100.00</td>
</tr>
</tbody>
</table>
Although examining SKU-level choice would reveal additional substitution patterns among SKUs on attributes such as size and scent, this approach would not enhance our research focus on brand alliance. In addition, we isolate the composite product from the primary brand and treat it as a separate alternative in the primary category so that we can calculate potential cannibalization within the primary category without losing tractability.

The utility is composed of a deterministic part and a random error with certain distribution assumptions. We assume that the deterministic part can be written as a linear function of the brand preference, price, and other marketing mix variables. Households choose the brand that offers the most utility within the choice set. Formally, let $h$ denote a household, $t$ denote time, $X$ denote a vector of marketing mix variables (including price, feature, display, number of UPCs, coupon availability, state dependence, and advertising spending), and $t_0$ denote the time when the composite product was launched. Let $P$ denote the primary category, $S$ denote the secondary category. Let $j$ denote a brand in the primary category, where $j = 1,...,J$. Let $k$ denote a brand in the secondary category, where $k = 1,...,K$. Furthermore, let $cp$ and $pb$ denote the composite product and the primary brand in the primary category, respectively, and let $sb$ denote the secondary brand in the secondary category.

Before the launch of the composite product ($t < t_0$), the utility of choosing a particular brand in the laundry detergent (fabric softener) is given by:

$$u_{hjt}^p = b_{hjt}^p + X_{hjt}^p \beta_{hjt}^p + e_{hjt}^p, \forall j \in P, t < t_0$$

(1)

$$u_{hskt}^s = b_{hskt}^s + X_{hskt}^s \beta_{hskt}^s + e_{hskt}^s, \forall k \in S, t < t_0$$

(2)

where $u_{hjt}^p$ is the utility of buying brand $j$ in the primary category at time $t$ by household $h$, $b_{hjt}^p$ is the brand dummy for brand $j$, and $X_{hjt}^p \beta_{hjt}^p$ captures the effect of marketing mixes. Equation 2 represents the corresponding utility of buying brand $k$ in the secondary category. However, owing to the introduction of the composite product ($t > t_0$), we would expect two changes. First, the number of alternatives increases in the primary category (detergent). Second, brand experience effects occur (from the primary/secondary brand to the composite product) as well as reciprocal effects (from the composite product to the primary/secondary brand). For the composite product, the primary brand, and the remaining brands in the primary category, we specify the utility functions below.

**Utility of Composite Product**

(3)  
$$u_{h,cpt}^p = b_{h,cpt}^p + \alpha_{h}^{PL} I \left\{ PBE_{h,t} = 1 \right\} + \alpha_{h}^{PF} PBE_{h,t} I \left\{ PBE_{h,t} \in (0,1) \right\} + \alpha_{h}^{SP} SBE_{h,t} I \left\{ SBE_{h,t} \in (0,1) \right\} + \alpha_{h}^{SR} I \left\{ PBE_{h,t} = 1 \right\} I \left\{ SBE_{h,t} \in (0,1) \right\} + X_{h,cpt}^p \beta_{h,cpt}^p + \epsilon_{h,cpt}^p, t \geq t_0$$

First, we assume the utility of the composite product in the above equation depends upon the brand effect $b_{h,cpt}^p$ and marketing mix effect $X_{h,cpt}^p \beta_{h,cpt}^p$. In addition, we introduce $\alpha_{h}^{PL}$, $\alpha_{h}^{PF}$, and $\alpha_{h}^{SP}$ to represent the segment-specific brand-experience effects, where $L$ denotes loyal users and $F$ denotes familiar users. Therefore, $PL$ represents the loyal users of the primary brand, $SL$ means the loyal users of the secondary brand, and so on. The terms $\alpha_{h}^{PL}$ and $\alpha_{h}^{SP}$ capture the impact of a customer’s previous familiarity with the primary brand and the secondary brand, respectively, on the value of the composite product, when the customer is a familiar user. On the other hand, $\alpha_{h}^{PF}$ and $\alpha_{h}^{SR}$ represent the brand experience effect on the composite product when the customer is a loyal user of the primary or secondary brand, respectively. Since we normalize the non-user as the baseline, we implicitly assume no brand experience effect occurs if the customer has no prior experience with the primary or the secondary brand. Finally, we also model the potential interaction effects for those customers who are loyal to both the primary and the secondary brands. Let $BL$ denote the loyal users of both the primary brand and the secondary brand. Therefore, $\alpha_{h}^{BL}$ captures the interaction effects of being loyal users of both categories.

**Utility of Primary Brand**

(4)  
$$u_{h,pb,t}^p = b_{h,pb,t}^p + \lambda_{h}^{CPE} CPE_{h,t} + X_{h,pb,t}^p \beta_{h,pb,t}^p + \epsilon_{h,pb,t}^p, t \geq t_0$$

where $CPE$ denotes a household’s experience with the composite product. Following the prior definition of “reciprocal effect indicator” (Swaminathan, Fox, and Reddy 2001), we set $CPE$ to 1 if the household has tried the composite product at time $t$, and 0 otherwise. Therefore, $\lambda_{h}^{CPE}$ captures the reciprocal effect of adopting the composite product on the primary brand. We expect $\lambda_{h}^{CPE}$ to be positive and significant if a reciprocal effect occurs as we hypothesize.

The utility of the remaining brands in the primary category stay the same (equation 1) as before the composite product.

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We aggregated SKUs’ marketing mixes to brand level using market share as weights.
We assume that the brand value, marketing mix coefficients, and brand experience and reciprocal effect coefficients follow a multivariate normal distribution across households and across both categories. The mean and the variance of the normal distributions are estimated from the data. Let \( b_{ph} \) be the vertical stack of all brand value parameters in the primary category, \( b_{ph} = (b_{ph1}, b_{ph2}, \ldots, b_{phJ}) \), and let \( b_{Sh} \) denote the same brand value vector in the secondary category. Let \( \theta_h \) be the vertical stack of all brand experience and spillover effects in both categories, \( \theta_h = (\alpha_{ph}, \beta_{ph}, \alpha_{Sp}, \beta_{Sp}, \alpha_{SF}, \beta_{SF}) \). We assume that \( \theta_h \sim N(\Theta_0, \Sigma_\theta) \), \( b_{ph} \sim N(b_{Ph0}, \Sigma_{bP}) \), \( b_{Sh} \sim N(b_{Sh0}, \Sigma_{bS}) \), \( \beta_{ph} \sim N(\beta_{Ph0}, \Sigma_{\beta P}), \beta_{Sh} \sim N(\beta_{Sh0}, \Sigma_{\beta S}) \). The joint log likelihood of both categories can be computed by integrating over the heterogeneity distribution. Let \( \Theta_h = \{b_{ph}, b_{Sh}, \beta_{ph}, \beta_{Sh}, \theta_h\} \), and let \( f(\Theta) \) denote the joint distribution of all parameters in \( \Theta_h \). The log likelihood can be written as \( LL = \sum_{h=1}^{H} \log \left( \int L_h(\Theta_h) f(\Theta_h) d\Theta_h \right) \).

We use simulated maximum likelihood to estimate the above model (see Hajivassiliou and Ruud 1994 for properties of simulated likelihood estimator). The integration can be approximated by simulation as follows:

\[
LL = \sum_{h=1}^{H} \log \left( \frac{1}{NS} \sum_{n=1}^{NS} L_h(\Theta_{nh}) \right)
\]

where \( NS \) is the total number of simulated draws and \( \Theta_{nh} \) are random draws from the distribution \( f(\Theta) \). We can then obtain estimates by maximizing the above equation.

**Estimation Results**

We describe below the estimation results of our proposed model for each of the two product category pairs and then discuss the implications. We estimated the full model and a baseline model assuming no brand experience and reciprocal effects. The full model outperforms the baseline model according to the Bayesian Information Criterion BIC (69643 vs. 70198 for detergent and softeners; and 37300 vs. 37412 for automatic and manual dishwashing detergents).

**Results for Laundry Detergent and Softener Categories**

Table 3 lists results of laundry detergent and softener. The coefficient for price is negative and significant for both categories, suggesting that as price increases, consumer choice likelihood goes down. In addition, feature, display, and coupon availability have a positive and significant effect on consumer choice, as expected. State dependence coefficient is positive and significant, indicating a strong inertia in brand choice. The effect of advertisement spending is significant for laundry detergent but is insignificant for fabric.

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Footnote: Households’ past purchases could influence future decisions. State dependence captures this effect and is coded as 1 if this brand is bought at the last purchase occasion and 0 otherwise.

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7Households’ past purchases could influence future decisions. State dependence captures this effect and is coded as 1 if this brand is bought at the last purchase occasion and 0 otherwise.

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softener. The brand intercepts represent the relative preference in choice with respect to a base brand (which we selected as Arm & Hammer in both categories) after controlling for various marketing mix variables. The coefficient of the number of SKUs in a category is positive and significant for the laundry detergent category, implying that consumers tend to choose brands with more SKUs available. However, this is not applicable to the fabric softener category.

For the utility of the composite product, we find that the coefficients of the primary brand loyal user (0.57, \( p = .34 \)) and the secondary brand loyal user (-.31, \( p = .72 \)) are insignificant. These two coefficients represent the brand-experience effects of a loyal user of the primary brand and the secondary brand, respectively, on the value of the composite product. Recall that these segment-specific results are with respect to the baseline segment of non-users of the primary and secondary brands. Therefore, we find no difference in the adoption likelihood of composite products between loyal users and non-users of the primary as well as the secondary brands. The coefficient (2.17, \( p < .01 \)) of primary brand experience (PBE) is positive and significant, while the coefficient (-.08, \( p = .91 \)) of secondary brand experience (SBE) is insignificant. These two coefficients capture the impact of a customer’s previous experience or familiarity with the primary and secondary brand, respectively, on the value of the composite product, when the customer is a familiar user. Thus, the adoption likelihood of the composite product is greater among familiar users than among non-users of the primary brand, but not of the secondary brand. The coefficient (-2.19, \( p < .10 \)) of the interaction between the primary brand loyal user and the secondary brand loyal user is negative and marginally significant, showing that adoption likelihood of the composite product among loyal users of both the primary and the secondary brands is lower compared to that of either the primary or the secondary brand. The coefficient (3.15, \( p < .01 \)) of the reciprocal effect of the composite product on the primary brand is positive and significant, showing that adoption of the composite product results in a positive reciprocal effect on the primary brand. We also find that the coefficient (1.70, \( p = .16 \)) of the reciprocal effect of the composite product on the secondary brand is positive but not significant, which suggests no reciprocal effect occurs with respect to the secondary brand. This finding is consistent with our expectation that the reciprocal effect on the secondary brand should be either non-existent or weaker than that for the primary brand.

**Conclusions**

Drawing on scanner panel data, the current research found that relative to the low likelihood that non-users of the primary brand would choose the composite product, familiar users of the primary brand were more likely to adopt the composite product but loyal users of the primary brand were not. In contrast, the buying likelihood of the composite product was not different between non-users, familiar users, and loyal users of the secondary brand.\(^9\) Moreover, loyal users of both the primary and secondary brands have lower likelihood of choosing the composite product compared to non-users of either of the two partner brands. Regarding other findings, the choice of the composite product resulted in a positive reciprocal effect for the primary brand but did not generate either a positive or negative reciprocal effect for the secondary brand and did not cannibalize host brand sales. We believe that these results make a stronger contribution than those related to adoption likelihood of composite products. In addition, the introduction of the composite product helped both partner brands in several ways, including improving their competitive clouts, but in terms of market share gain, it helped the primary brand more than it helped the secondary brand. Finally, results of the supplementary analysis revealed that the introduction of the composite product affected the close competitors of both the primary and secondary brands in their respective categories, although the effect was not uniform. The findings were consistent across both composite products (Tide and Downy; Cascade and Dawn), attesting to the potential generalizability of our findings. Next, we discuss implications of our findings for brand managers, retailers, and theory.

**Theoretical Implications**

Our findings extend the ingredient branding literature, which has shown that positive equity of partner brands influences consumers’ stated attitude toward composite product (Simonin and Ruth 1998). However, as our findings reveal, this does not necessarily influence consumers’ revealed choice behaviors. For example, primary brand loyal consumers, secondary brand loyal consumers, and secondary brand familiar users, despite holding a positive attitude toward the primary and secondary brands, have very low likelihood of adopting the complements-based composite product. Thus, while brand equity and good fit between partner brands and categories might be adequate to influence composite brand attitude, among these segments other factors seem to override these influences on buying the composite product. As we don’t have access to thought processes of consumers in these segments, we speculate on these factors on the basis of our theoretical arguments. For example, primary brand loyal consumers are less likely to buy complements-based composite products because their exclusive use of the primary brand might make them believe that adding the secondary brand to the primary brand will interfere with the core functionality of the product (Kirmani, 2015 AMA Winter Educators’ Proceedings

\(^9\)We do not assume a full covariance matrix over all the parameters due to computation consideration.
<table>
<thead>
<tr>
<th></th>
<th>Coefficient Mean</th>
<th>Coefficient Std Error</th>
<th>Sigma Mean</th>
<th>Sigma Std Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>PB Loyal User</td>
<td>.57</td>
<td>.60</td>
<td>.11</td>
<td>.48</td>
</tr>
<tr>
<td>SB Loyal User</td>
<td>-.31</td>
<td>.87</td>
<td>.31</td>
<td>.30</td>
</tr>
<tr>
<td>PB Loyal X SB Loyal</td>
<td>-2.19*</td>
<td>1.24</td>
<td>1.23</td>
<td>1.72</td>
</tr>
<tr>
<td>PBE</td>
<td>2.17***</td>
<td>.44</td>
<td>1.09</td>
<td>.45</td>
</tr>
<tr>
<td>SBE</td>
<td>-0.08</td>
<td>.72</td>
<td>.64</td>
<td>.60</td>
</tr>
<tr>
<td>Reciprocal effect of composite product on primary brand (CP2PB)</td>
<td>3.15***</td>
<td>1.14</td>
<td>3.09</td>
<td>2.79</td>
</tr>
<tr>
<td>Reciprocal effect of composite product on secondary brand (CP2SB)</td>
<td>1.70</td>
<td>1.20</td>
<td>6.61</td>
<td>1.87</td>
</tr>
</tbody>
</table>

**Laundry Detergent**

- Arm & Hammer: Base
- Composite product: 10.48***
- All: 3.42***
- Cheer: 9.95***
- Era: 3.73***
- Private Label: -4.87***
- Purex: 1.44***
- Tide: 6.21***
- Wisk: 6.22***
- Xtra: -6.36***
- Price: -3.99***
- Feature: 2.34***
- Display: .94***
- Coupon availability: 1.82***
- State dependence: 12.55***
- Ln (advt. spending): .05***
- UPC count: .28***

**Fabric Softener**

- Arm & Hammer: Base
- All: -.99***
- Bounce: -.96***
- Cling Free: -.46
- Downy: 3.76***
- Private Label: -1.64***
- Snuggle: 1.26***
- Price: -1.00***
- Feature: 3.54***
- Display: .86***
- Coupon availability: 1.49***
- State dependence: 12.75***
- Ln (advt. spending): -.00
- UPC count: .00

**Note:** 1. We also controlled for new product introductions by incorporating dummy variables in both laundry detergent and softener categories.

2. *** p < .01; ** p < .05; * p < .1
Familiar users of the secondary brand might be less willing to buy the composite product because to adopt it, they would have to give up their current brand in the primary category.

Our research has a few limitations. While strengthening internal validity, the extensive criteria used in selecting composite products limited us to two replicates. These selection criteria severely restricted the number of composite product replicates we could work with, but they allowed us to be more confident in attributing our findings to posited theoretical arguments (e.g., attributing choice of the composite product to users familiar with the primary and secondary brands or attributing reciprocal effect on choices of primary and secondary brands). Future research can relax these criteria to see whether our findings extend to more composite products. Moreover, our research used consumers’ choices to test the hypotheses, but without access to consumers’ thought process, we can only speculate about theoretical reasons underlining our findings. Another limitation is that the complements-based composite products selected were “same” use situation products—that is, neither partner brand could be used outside of the common use situation of washing clothes or cleaning dishes. An interesting investigation would explore how our findings would change if this assumption of common use is relaxed by investigating composite products such as the El Fudge sandwich cookie with Nestle’s Butter Finger candy, in which consumers use or consume the primary and secondary brands in distinct situations. Since we have used data from two sets of complementary categories belonging to a single chain located in a particular market area, future research could use data from multiple stores, categories, and market areas to generalize our findings and attribute the influence of any of these characteristics on consumer choice. An interesting avenue of research would be the study of the moderating influence of various factors, such as the quality of the composite product or the perceived value, on composite product choice. We also acknowledge that this study lacks information about manufacturing costs, which could help investigate the impact of composite products on profitability of various brands (George, Kumar, and Grewal 2013). Finally, future research can use multi- and cross-category models (Russell et al. 1999; Pancras, Gauri and Talukdar 2013) to model both primary and secondary categories to yield more insights into the substitution patterns induced by composite products.

Figure 1 Conceptual Framework
References
The Effect of Superstar Software in the Video Game Industry: The Moderating Role of Product Generation Lifecycles

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Keywords: indirect network effect, superstars, software, hardware, new product introductions, product generation lifecycle, video games

EXTENDED ABSTRACT

Superstars in general seem to dominate many industries. Superstar individuals or products “possess unique and superior attributes or skills” and command a disproportionately large payoff (Binken and Stremersch 2009; Rosen 1981). Examples of such superstars abound in most industries—Tiger Woods in golf, Steven Levitt among economists, Microsoft Word in word processing, IBM in consulting. In the entertainment industry especially, superstars appear to dominate product segments—Grand Theft Auto in video games, Da Vinci Code in fiction, Brad Pitt among actors, Game of Thrones on cable television, Howard Stern on radio, Angry Birds among mobile phone apps, Harry Potter among movies, etc. Binken and Stremersch (2009), in a seminal article in the marketing literature, discuss the importance of superstar video games in the context of the video game industry and show that the introduction of game superstars affects the sales of hardware (console) significantly positively.

Our data set is provided by the NPD Group, and includes monthly point-of-sale data on prices and quantities for video game consoles from January 1995 through October 2007 from roughly 65% of US retailers. In total, the data set contains average price and quantity data for 15 consoles over 4 distinct product generations.

Using this dataset, our paper extends the results of Binken and Stremersch (2009) in several ways. First, we build on their results and show that the presence of superstar software positively and significantly affects console market share. Second, and importantly, we show that such superstar effects vary dramatically over the product generation’s (console) lifecycle. Specifically we find that superstars are significant for console market share early on, especially in the Introductory and Growth phases of the product generation lifecycle but not important later on. This finding provides interesting managerial insights which we discuss later and serves as key departures from extant results. Third, we find that regular games (non-superstars) are important later on especially in the Decline phase of the generation product lifecycle but not important earlier. Thus managerial strategies regarding superstars should vary with the console generation lifecycle. Fourth, Binken and Stremersch (2009) do not consider a simultaneous equation system where both hardware and software impact each other (feedback loop). However, following Stremersch et al. (2007), we jointly estimate both the demand for hardware and the supply of regular and superstar software which make our results more robust. Including this complexity (feedback loop) has the benefit of informing managers when they can leverage their installed base to attract superstars to their console. Our results show that the effect of the installed base on the supply of superstars is significant in the Growth phase and not in the Introduction phase. Also, the installed base has a positive and significant effect on superstar supply in the Decline phase—when the effect of superstars on console demand is weakest. This interesting result and insight regarding the criticality of the network effect on the supply of superstars was ignored in prior research and would not be possible without considering the feedback loop that we model. Fifth, software and hardware sale are usually affected by omitted variables that pose endogeneity problems, an issue not addressed by Binken and Stremersch (2009). In this paper, we control for such endogeneity by using several reasonable instruments with instrumental variables regression techniques via generalized method of moments (GMM) estimations.

References are available on request.

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F-12 2015 AMA Winter Educators’ Proceedings
Research Question
Marketing managers and individuals making a variety of decisions (decision makers hereinafter) are likely to continue a failing course of action and escalate commitment if they are responsible for initiating the course (Boulding, Morgan, and Staelin 1997). However, none of the research to date shows that responsibility to initiate a course of action (hereafter personal agency) mitigates (i.e. decrease) escalation of commitment conditionally. Moreover, debate concerning the process to explain this phenomenon is thriving (Sleesman et al., 2012).

In this paper, I integrate the research on escalation of commitment and the research on regret, a negative emotion that is experienced based on cognitive evaluations of an adverse outcome (Zeelenberg, Van Dijk, and Manstead 2000a), to explicate the conditional effects of personal agency on the phenomenon. I propose that likelihood of receiving a desired final outcome (hereafter outcome reversibility) jointly with the availability of the information about superior foregone outcome moderates the effect of personal agency on escalation of commitment. I also hypothesize that regret mediates the effect of personal agency on escalation of commitment to propose regret regulation (Zeelenberg and Pieters 2007) as a theoretical rationale for the phenomenon.

Method and Data
I recruited 192 business students (mean age 21 years, male 49%, experience 4.25 years) and evaluated their escalation of commitment decision on a stock investment using a 2 (personal agency: self select vs. assigned) x 2 (probability of receiving a desired outcome subsequent to interim loss from the stock investment: 65% chance versus 25% chance) between-subjects design. At the outset of the study, I manipulated personal agency by asking half of the participants to select and justify the stock they would choose to receive as a gift (Bobocel and Meyer 1994). The other half of the participants had no choice.

Subsequently, I manipulated reversibility of the adverse outcome by reporting an interim loss from the investment and a probability (65% versus 25%) that the future outcome of the stock will deliver desired outcome. I also reported the superior performance of the foregone stock investment to all participants. Then, I measured each participant’s regret, self-attribution for the loss and perception of the superiority of the foregone option. In addition, as measures of attitudinal and behavioral escalation of commitment, I assessed each participant’s intentions to sell the stock and the actual amount of the stock they sold. Furthermore, I gave them bonus cash and measured their additional investment in the stock.

Summary of Findings
Study results suggest that personal agency mitigates perceived superiority of the foregone option when the reversibility of the received outcome is high, and amplifies it when the reversibility of the received outcome is low. On the other hand, results suggest that personal agency not only triggers self-attribution when the outcome of the foregone option is superior, but it also further amplifies self-attribution when the reversibility of the received outcome is reduced. More importantly, results show that when the outcome of the foregone option is superior, the effect of personal agency on regret and escalation of commitment is contingent upon the reversibility of the received outcome. On the one hand, when the reversibility of the received outcome is high, participants who self-choose a course of action experience less regret, which, in turn, increases their escalation of commitment. On the other hand, when the reversibility of the received outcome low, those who self-choose experience more regret, which, in turn, decreases their escalation of commitment. Accordingly, a mediation test sug-

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suggests that regret mediates the conditional effects of personal agency on escalation of commitment.

**Key Contributions**

Study results show that personal agency decreases or increases escalation of commitment when the outcome of the foregone option is superior and the reversibility of the received adverse outcome is low or high, respectively. Therefore, this is the first study to demonstrate the mitigating effect of personal agency on escalation of commitment. The results also suggest that the knowledge of the foregone option’s outcome and the reversibility of the received outcome are important characteristics of an escalation situation. While proposing self-justification theory as a rational for escalation of commitment, Staw (1976) asserts that individuals attempt to avoid self-attribution of causality when their behavior leads to negative consequences or results in personal failure. However, I find that those who are responsible for initiating a failing course of action not only engage in self-attribution for the adverse outcome, but they amplify their self-attribution when the probability of recovering from a loss decreases so that the negative consequence or the personal failure is more apparent. Moreover, while researchers have proposed several other theories to explain the amplifying effect of personal agency on escalation of commitment, none explains the mitigating effect. Therefore, my research suggests regret regulation as a theoretical rationale for the effect of personal agency on escalation.

*References are available on request.*
An Exploratory Study of Antecedents and Consequences of Radical Product Innovation Capability

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Keywords: innovation, capability, first-to-market, performance

EXTENDED ABSTRACT

Research Question
The literature in marketing, management, strategy and innovation has evolved in two important directions. One, antecedents to innovation have been studied at the organization or project level. There has not been much work on an organization-level innovation capability and the work that has been done is largely conceptual. Two, there has been a lot written about two kinds of innovation, incremental and radical innovation. However not much attention has been paid to the issue of whether the antecedents and outcomes of radical product innovation are different than those for incremental innovation. It is widely recognized that companies like Amazon, Apple, P & G, and Google are better at being pioneers and launching radical innovations whereas Dell, Microsoft and Samsung are arguably better at being followers or launching incremental innovations. This paper takes a focused look at the antecedents of an organizational capability called radical product innovation capability and explores how that results in specific consequences for new product launches such as being first to market and product performance.

Method and Data
We developed an online survey with multiple-item measures for the constructs of interest. The items were presented in scrambled order so that underlying constructs could not be identified. Some items had the wording reversed at periodic intervals. The survey questionnaire was pre-tested with 9 executives familiar with innovation processes in their company and revised for clarity. A list of 6000 email addresses was purchased from a vendor, of senior managers in US companies across many industries. An email solicitation with the link to the online survey was sent to each person addressed by name. They were requested to answer the survey if they were familiar with a major new product or service their company had launched within the past 3 years. Respondents were asked to answer the questionnaire with that product in mind. They were also asked to voluntarily provide the name of the product or a web page address where one could obtain more information about the product (81% of respondents provided this). We received 97 responses of which 95 were usable. The main industries in our sample were Computer and Electronic Product Manufacturing (34%), Publishing but not Internet (27%), Machinery Manufacturing (13%), and Professional, Scientific, and Technical Services (12%).

Summary of Findings
We have a 3-stage model and do path analysis results using OLS regression. We use two control variables at every stage, one for the environment (market uncertainty) and one for the age of the business. In Stage 1, we find that all three of our antecedents (risk tolerance, learning to explore new competencies, innovation process) are positively related to RPI capability. In Stage 2 we find that RPI Capability is positively related to being First to Market. And in Stage 3 we find that First to Market is not related to RPI Performance, however, RPI Capability is positively related to RPI Performance. We test the moderating effect of being First to Market on the positive relationship between RPI Capability and RPI Performance and find there is a positive moderating effect.

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Key Contributions

This paper makes several contributions to the literature. First, it conceptualizes measures and empirically tests the concept of radical product innovation capability, as the central construct, which enables firms to consistently bring out new to the world products every few years. Second, it provides empirical support for the antecedents to radical product innovation. In order to develop, nurture and maintain this capability firms need to take risks and tolerate failure as part of their culture of innovation. They need to encourage employees to explore and learn about new competencies (technologies, products, markets) and they also need to have internal processes in place to incubate radical ideas and convert them into big business opportunities. Third, we show that a radical product innovation capability does result in pioneering or first-mover advantage. Consistent with equivocal findings in the literature, (Tellis and Golder 1996) we find no direct relationship between being first to market and product performance. However, if a firm has RPI Capability and is first to market, we do find a positive impact on patent performance.

There are some interesting managerial implications of our findings. What separates Amazon, Apple and Google from Dell, Microsoft and Samsung, we believe, is the first three companies have had radical product innovation capability through most of their history whereas the latter three have not. Just being first to market doesn’t result in successful product performance. Being first to market together with radical product innovation capability is needed to enhance product performance.

References are available on request.
Avoiding a Babylonian Confusion: A Systematic Review on Low-Cost Innovation

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Keywords: low-cost innovation, disruptive innovation, BOP innovation, frugal innovation, systematic review

EXTENDED ABSTRACT

Research Question
Low-cost innovations, defined as new products or services that organizations direct at consumers who have a lower willingness-to-pay, enable firm growth and help drive societies’ prosperity. However, research has generated a plethora of different theories and frameworks to investigate low-cost innovation. Consequently, this study seeks answers to the following questions:

1) Which theories relate to low-cost innovation?
2) How do low-cost innovations create value for consumers?
3) How can companies capture the value they have created?

Method and Data
A systematic review was conducted to provide collective insights through theoretical synthesis into fields and sub-fields following a structured, reproducible methodology. Using the different sub-fields of low-cost innovation as inputs into the database search and systematically eliminating irrelevant papers results in a sample of 97 relevant, peer-reviewed articles. Starting from a basic structure of value creation and value capture, I used the text analysis software MaxQDA to code each of the 97 articles. Finally, a reference network analysis reveals clusters in low-cost innovation research.

Summary of Findings
The results of the network analysis imply contingencies concerning the introducer (i.e., incumbents vs. entrants) and the target market (i.e., emerging vs. developed market). Applying the contingency lens in combination with the value creation and value capture perspective in the content analysis leads to a set of consistent factors (i.e., valid across settings) and contextual factors (i.e., valid in particular settings). Consistent value creation factors for low-cost innovation include a lower price, a focus on key performance dimensions and new value combinations. Contextual value creation mechanisms in emerging markets comprise innovating financing models and creating access. Firms across different settings are more likely to capture value from low-cost innovation when they can use economies of scale and when they possess a low-cost innovation culture. In addition, incumbents benefit from creating an ambidextrous organization and firms in emerging markets need a business model orientation as well as unique low-cost innovation processes.

Key Contributions
Researchers use a multitude of different theoretical lenses to analyze products and services that organizations direct at consumers who have a lower WTP than the going rate. By highlighting overlapping theories from disruptive innovation, emerging markets, strategy and entrepreneurship, and defining low-cost innovation from a consumer point of view, this study provides a basis for further research on this issue. The systematic review reveals consistent factors for both value creation and value capture that are valid across different settings and firm types. In addition, the analysis revealed unique factors that are contingent on the setting and firm type. Consequently, low-cost innovation theory can be understood as a nested model. The proposed model offers the opportunity to combine research streams on a global level as well as on a context specific level.

References are available on request.

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Development of Successful Really New Products: The “Over-Collaboration” Effect at Different Stages of the New Product Development Process

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Keywords: collaboration breadth, really new products, new product development, process stages

EXTENDED ABSTRACT

Research Questions
Based on an extensive literature review we find that there is a lack of research (1) addressing the effectiveness of collaboration breadth for the development of successful really new products (RNPs) and (2) investigating the impact of collaboration breadth in the different stages of the new product development (NPD) process. Collaboration breadth refers to the number of different types of external collaboration partners (Laursen and Salter 2013). The deficiency of research is surprising because the various stages of the NPD process, i.e. the idea generation, research and development, design, test and evaluation, and market introduction stage, have different knowledge requirements and thus, lead to different levels of uncertainty. These knowledge requirements can be potentially addressed by various and different external collaboration partners. Thus, different levels of collaboration breadth can be an effective way to integrate the required knowledge in the NPD process and to reduce stage-specific uncertainties. Therefore, the main research questions of the paper are: (1) how does collaboration breadth impact the performance of RNPs overall and (2) how does collaboration breadth impact the performance of RNPs specifically in the various stages of the NPD process? (3) whom to collaborate with in which stage of the NPD process?

Method and Data
We used the Mannheim Innovation Panel from the Center for European Economic Research as our data source. The yearly conducted large-scale survey designed as a panel represents the German part of the Community Innovation Survey (CIS). The definitions of constructs and the methodology of the survey follow the Oslo Manual (OECD/Eurostat 2005). The CIS data have been previously used in innovation research (e.g., Van Beers and Zand 2014; Laursen and Salter 2006). Of the total sample of manufacturing and service firms (6,110 firms), 1,718 firms (28.1%) indicated that they were actively engaged in the development of RNPs, thus constituting our effective sample size.

The dependent variable ‘performance of RNPs’ is heavily left-censored as it measures the performance of RNPs in percentage of sales that ranges between 0 and 100. Because of left-censoring we applied a Tobit regression as recommended in the literature (Greene 2011).

Collaboration breadth is measured as sum of six different types of external collaboration partners (customers B2B, customer B2C, suppliers, service providers, competitors, and universities and research institutes) that ranges from 0 to 6 (Laursen and Salter 2013). We included firm size, firm age, R&D intensity, human capital, firm location and industry as control variables in the analysis.

Summary of Findings
Based on the relational view, the findings reveal evidence of a general ‘over-collaboration’ that means an inverted U-
shaped relationship between collaboration breadth and the performance of RNPs over the entire NPD process and at every stage of the NPD process. In addition, we see across the different stages of the NPD process, that the development of RNPs benefits the most from collaboration breadth in the initial idea generation stage, while the optimal number of collaboration partners decreases towards the end of the NPD process.

Furthermore, we identify which external collaboration partners should be integrated in the different stages of the NPD process. We demonstrate that B2B customers are the most important external collaboration partners as they contribute to the performance of RNPs at all stages of the NPD process. In contrast, the knowledge of suppliers seems to be very specific to the development of RNPs in the R&D/construction stage. Whereas universities and research institutes appear as important collaboration partners in the first stages of the NPD process, service providers gain importance in the later stages of the NPD process.

**Key Contributions**

First, we contribute to research on the impact of collaboration breadth on the performance of RNPs which has been called for previously (e.g., Knudsen 2007). We garner intriguing evidence for the effect of ‘over-collaboration’, a non-linear relationship between collaboration breadth and performance of RNPs across and at each and every stage of the NPD process. By exploring the influence of collaboration breadth on the performance of RNPs in the different stages of the NPD process, we address general calls for research for a stage-specific investigation of the relationship between collaboration and successful NPD (e.g., Homburg and Kuehnl 2013). Second, with the focus on RNPs, we add to the understanding on how firms can improve the development and performance of the most important and critical type of new products represented by RNPs. Third, we provide managerial implications for managers who seek to optimize the number of collaboration partners in the different stages of developing RNPs as called for previously (e.g., Di Benedetto 2012). Lastly, we make a theoretical contribution to the relational view by showing that the positive impact if collaboration with diverse external partners in NPD has its limits.

*References are available on request.*
Sustainability, Open Innovation, and New Product Program Success

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Keywords: open innovation, sustainability orientation, customer focus, new product success

EXTENDED ABSTRACT

Research Questions
Over the years, firms have been reinventing their innovation approaches, anticipating changes in society and markets. Current trends suggest that businesses are witnessing the emergence of the next big innovation wave, driven by societal and environmental needs. Increasingly, firms are looking at the impact of their operations on the environment as well as the positive or negative impact on the communities in which they operate. Understanding these impacts can drive improvements in corporate strategy, in developing new products more creatively and competitively, and ultimately determine a firm’s innovation performance. As such, this research explores how the sustainability efforts of innovating firms affect their new product program (NPP) performance, i.e., the extent to which the new product program is successful and meets its performance target. This research also attempt to understand how firms draw on and successfully utilize external ideas and knowledge in their new product development.

Method and Data
The data analyzed is drawn from the 2012 Product Development and Management Association (PDMA)’s Comparative Performance Assessment Study (CPAS), which was administered on a global scale using Global Park’s online survey tool. Emails containing a link to get a code that allowed each respondent to access the online survey were sent to PDMA members and PDMA contacts. A total of 1,167 codes were sent to key respondents for their business unit with instructions on how to fill out the survey, yielding 453 useable surveys. The final sample consists of firms from North America (198), Asia (149), Europe (61), and elsewhere (45) across multiple industries. Goods manufacturers make up 56% of the sample, with technology companies comprising 45.4% and business-to-business companies accounting for 56.4% of responding companies, while companies with less than $100 million in revenue make up 63.3% of the sample. We test our hypotheses using multiple regressions with, if necessary, relevant interactions terms.

Summary of Findings
The findings of the study suggest that sustainability can enhance firm performance through its positive impact on new product innovation, and customer focus mediates the innovation outcomes of a sustainability orientation. Furthermore, our findings suggest that this mediated link varies significantly across firms with different levels of open innovation activities. While open innovation activities aimed at gathering market insights enhances customer focus directly, open innovation activities aimed at technical problem solving accentuates the link between customer focus – NPP performance.

Key Contributions
This study advances our knowledge about the business case of sustainability by documenting the positive association between sustainability orientation and NPP performance. Since new product innovation is critical to the profitability and long-term performance of any firm, our findings suggest that sustainability can improve firm performance through its positive impact on new product innovation. More importantly, we identified a route through which sustainability orientation is related to NPP performance. Our results indicate that a firm’s sustainability orientation helps enhance its customer focus in the NPP, in turn customer focus positively affect the innovation outcomes. The mediating role of customer focus is important for two reasons. First, it extends the...
sustainability literature by uncovering a previously ignored outcome (i.e., customer focus) of sustainability orientation. Second, it extends the literature on customer focus by uncovering the antecedents (i.e., sustainability) of customer focus. Furthermore, our study highlights the importance of differentiating between two types of open innovation activities, those aimed at gathering market insights and those aimed at technical problem solving, as they function differently to enhance NPP performance. This suggests that managers should leverage these two types of open innovation activities differently in various phases of new product development program.

References are available on request.
It’s All Your Fault! Attributing Blame for Co-Created New Product Failures in B2B Relationships

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Keywords: co-creation, B2B channels, new product development, product failure

EXTENDED ABSTRACT

Research Question
The literature exploring co-creation, the process of integrating customers in the new product development process, has grown rapidly in the last decade. The extant work has established co-creation as a powerful tool for both innovation and improving customer perceptions of the firm. While co-creation is widely used within B2B markets, there is little work exploring the use of co-creation within B2B channels. Additionally, while co-creation is touted as a positive interaction for business, there may also be negative relationship outcomes of co-creation in B2B relationships. This research takes a novel approach to B2B co-creation and investigates what happens when channel partners co-create a product together and the new product performs poorly in the marketplace. This conceptual study seeks to answer three main questions. First, what effect may failure of a co-created product have on B2B channel relationships? Second, how do channel partners assess blame for the product failure and what role does blame play in explaining negative relationship outcomes. Third, what characteristics of the relationship and what characteristics of the new product moderate the effect of product failure on B2B partnerships? This paper takes a conceptual approach and offers propositions regarding the effect of new product failure on B2B relationships.

Key Contributions
This research makes some important theoretical and managerial contributions. First, the co-creation literature in the B2B space is limited and this study sheds light on issues within B2B co-creation. Although new product development is an essential aspect of B2B success, very little is understood about the dynamics that exists between channel partners resulting from the co-creation process. This research proposes that the degree to which channel manufacturers assess blame to customers for the new product failure impacts channel relationships. Second, the literature on the negative outcomes of co-creation is also limited. Much of the co-creation literature discusses the positive production and relational benefits of co-creation, but co-creation is also bound to have negative nuances that have yet to be considered. Co-creation involves new types of interactions between partners which could create new avenues for friction. This paper helps researchers develop a theoretical context for which to understand the co-creation process and how to study problems that may arise.

Summary of Findings
Using the theoretical underpinnings taken from the new product literature and the relationship marketing literature, this study proposes a conceptual model that aids future research in better understanding all the nuances of co-creation in B2B settings. Using the theory of self-serving bias, this study shows how co-created new product failures can cause B2B relationships to deteriorate. Relationship partners are likely to assess blame to each other when a co-created new product performs worse than expected. This blame causes increased volatility in relationship sentiments such as relationship continuity and performance. This paper also proposes moderators that strengthen and weaken the effect of new product failure on relationships. Specifically, this study shows how attributes of the relationship and attributes of the co-created product impact how channel partners assess blame for co-created product failure.

References are available on request.

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