Brand Alliances: Growing Your Pie or Stealing Your Slice? Examining Field Evidence Using Causal Methods

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This research examines whether brand alliances increase the brand equity of the primary brand. The decision to enter a brand alliance is observed, but not entering is unobserved (i.e., self-selection of one outcome). Propensity score matching brand alliances with non-brand alliances allows causal inference of whether entering a brand alliance increases brand equity. The data uses aggregate consumer panel purchases over a fourteen-year period to examine 1,757 brand alliances across 138 primary brands in 83 consumer packaged goods categories. On average, brand alliances result in decreased brand equity of the primary brand, counter to the conventional wisdom.

INTRODUCTION

Brand alliances represent two brands in one product offering (Keller, 2013). While brand managers have emphasized exporting brand equity through line extensions, brand alliances seek to import the brand equity of a secondary brand into the existing primary brand. Two brands in one offering signals quality (Rao, Qu, & Ruekert, 1999) and additional value from the increased brand equity (Desai & Keller, 2002). This strategy has become an increasing part of the manager's strategic toolkit, growing from 3.5% to 6% of all new product launches in the U.S. (Schultz, 2014).

While brand alliances (or synonymously named co-brands) have become more common, an unexamined aspect is how well these strategic relationships grow the primary brand. In particular, brand managers are worried that choosing the wrong secondary brand as a partner might create negative spillover effects (Simonin & Ruth, 1998), harming the brand equity of the primary brand. The market impact of brand alliances has been previously viewed through either the lens of case study approaches (Desai, Gauri, & Ma, 2014; Swaminathan, Reddy, & Dommer, 2012) or examined outcomes like revenues and market share (Koschmann & Bowman, 2016). However, one cannot observe the market outcome had the brand *not* decided to enter a brand alliance. In one sense, the brand manager utilizes the brand alliance as an attempt to grow the brand. On the other hand, putting the brand alliance into the market may cannibalize the original primary brand.

This research addresses these considerations by making several contributions. First, this research contributes to our understanding of brands by exploring large-scale evidence of changes in brand equity through brand alliances. While impacts to market share and revenues are a going concern to managers in brand alliances (e.g., Koschmann & Bowman, 2016), the impact of brand alliances on brand equity has remained largely unexplored.

The second contribution is the use of large-scale data, which covers fourteen years of national consumer panel purchases by Information Resources Inc. (IRI). A total of 1,757 brand alliance products in the marketplace were found across 83 categories of consumer packaged goods. Whereas prior research has explored the brand alliance performance through a case study approach (Desai, Gauri, & Ma, 2014; Swaminathan, Reddy, & Dommer, 2012), this research covers market performance data of 138 primary brands to add to generalizability.

The third contribution is that in analyzing the changes to brand equity, this research makes use of causal methodology techniques to secondary data. Brand alliances do not happen at random since primary and secondary brands self-select to enter the relationship. In fields such as medicine, for instance, patients may self-select into experimental treatments (e.g., Austin 2011; Austin & Stewart, 2015). Causal methods such as propensity scoring are prevalent in these areas, yet relatively under-used in marketing. In fact, the Marketing Science Institute has noted causal research remains a high priority for the field (MSI, 2016). This research uses such methods to examine changes in brand equity, adding to our understanding of how these methodological tools can be used by managers and academics alike.

The fourth contribution is that the findings present a result contrary to expectations by managers. If managers are indeed relying more on brand alliances as a product tool, then this would suggest that brand alliances help the brand. However, the results show that on average, the decision to enter into a brand alliance – when accounted for due to self-selection bias – leads to a decrease in brand equity. On average, this decrease is $78 per 1,000 households that purchased the brand based on the data from IRI.

This research is structured as follows. First, brand alliances are provided as a conceptual framework given extant research. Next, the methodology and data are presented. The results section explains the modeling results. Finally, the discussion outlines the impact for marketing managers and academics and future research directions.

CONCEPTUAL DEVELOPMENT

Brand Alliances

Brand alliances represent two brands positioned in a single product offering (Keller, 2013). These arrangements are typically classified as two types: fundamentally altering the product composition as an ingredient brand alliance, or licensing/sponsoring the name without fundamentally changing the product. For instance, Klondike with Oreo is an ingredient brand alliance because it fundamentally changes the Klondike ice cream treat by including Oreo cookie bits in the ice cream. A licensed arrangement example would be Crest toothpaste feature cartoon characters like Batman or SpongeBob SquarePants on the package. Licensing of human brands also falls into this category, such as Gatorade featuring golfer Tiger Woods on its bottles. In these latter cases, the product does not fundamentally change.

Unlike brand extensions, where the brand *exports* its brand equity to a new product category, brand alliances *import* the brand equity of a second brand to aid the primary brand in its existing category space. Continuing the Klondike with Oreo example, Klondike exists as its own branded offering. By including Oreo in its product and displaying the Oreo brand name on its packaging, the joint product seeks to leverage Oreo's brand equity. Product innovations, such as brand alliances, are used by brand managers to stabilize market share for national brands and provide a point of differentiation against private label offerings (Gielens, 2012).

Several reasons explain how the secondary brand may be useful to the primary brand. The inclusion of a secondary brand creates a point of differentiation and signals an assurance of the primary brand's quality (Rao, Qu, & Ruekert, 1999). The secondary brand also provides increased brand equity (Desai & Keller, 2002). Furthermore, the secondary brand can expand markets by appealing to consumers who normally do not purchase in the product category. In this case, familiarity with the secondary brand may induce consumers to consider purchasing the brand alliance. By enhancing the value proposition, consumers are more likely to purchase the brand alliance product, thus leading to positive sales performance.

Brand Equity

Underlying brands (and brand alliances) is the value that brands have to consumers. Indeed, without the name and likeness that represents what the brand stands for, it would otherwise function as a replaceable product in the marketplace (i.e., a private label offering). Brand equity has typically been approached as two variations: consumer-based brand equity (CBBE) driven by how consumers perceive the brand (Keller, 2001), or sales-based brand equity (SBBE) which is an outcome of the brand's ability to generate revenue premiums above an unbranded (private label) offering (Ailawadi, Lehmann, & Neslin, 2003).

Although the inclusion of a secondary brand should benefit the primary brand, prior research suggests this may not always be the case. Previous consumer research has shown that impressions are influenced by how long the secondary brand has existed (Desai & Keller, 2002), as well as the favorability between the primary and secondary brands (Park, Jun, & Shocker, 1996). Furthermore, a secondary brand that is viewed by consumers as weak (or possibly even negative) may create a negative spillover, harming the brand equity of the primary brand (Cunha, Forehand, & Angle, 2015; Geylani, Inman, & Ter Hofstede, 2008; Lafferty & Goldsmith, 2005; Simonin & Ruth, 1998; Votolato & Unnava, 2006).

Brand Alliances and Brand Equity

Since brand alliances are designed to import the brand equity of a secondary brand to increase the value proposition of the primary brand, at face value this should have a positive impact on the primary brand. By increasing the primary brand's value proposition, this might enable the brand to either charge a price premium or add incremental volume. Both are drivers of brand equity, which may explain why brand alliances have become an increasingly common tool for brand managers to grow the brand.

In practice, however, the market performance of brand alliances remains minimal. Prior research into the market shares of ingredient brand alliances, for instances, has found median market share of 0.72% (Koschmann & Bowman, 2016). These products may attract consumers as a new or novel product, as well as offer two brands in one package. Yet, the brand alliance still competes alongside the primary brand offering and may cannibalize sales.

In practice, retail shelf space is largely fixed; for a brand manager to acquire distribution on shelves would mean either acquiring new shelf space from an existing competitor, or replacing an existing shelf facing with the new product. The removal of an existing shelf facing will increase the likelihood of stockouts. Although consumers might purchase the brand alliance product in case of a stockout, consumers might not purchase at all. If the brand has many varieties to choose from, an additional variant may become too much to consider, frustrating consumers to the point of thinking too much but ultimately not purchasing (e.g., Iyengar & Lepper, 2000). As such, the consideration here is that brand alliances, rather than growing the brand, may actually have a negative effect on brand equity.

METHODOLOGY

Model

Given that there are two views to measure brand equity, of interest is which model to choose. CBBE methods typically rely on consumer surveys to gauge perceptions of the brand. Examples of this include EquityTrend by Harris Polling, Brand Asset Valuator by Young & Rubicam, and the brand contribution of the BrandZ rating by Millward Brown.

While these measures indeed gauge consumer perceptions of brands, another view is that consumer perceptions manifest in consumer actions, namely to purchase the brand or not. Recent research has estimated SBBE as a function of CBBE (Datta, Ailawadi, & van Heerde, 2017). The SBBE belief is that brand equity reflects the ability of the brand to be chosen by consumers over unbranded (private label) offerings. This outcome measure of brand equity is described as revenue premium (Ailawadi, Lehmann, & Neslin, 2003), which considers two related aspects of the brand: price and volume. The brand should be able to achieve a price premium if it is perceived as offering superior qualities. Yet, an excessive price will turn off consumers, reducing its sales volume. Ideally, strong brands can achieve both a price and volume premium. Equation 1 presents the brand equity (BE) for any brand b relative to private label offering pl:

$$BE_b = (volume_b)(price_b) - (volume_{pl})(price_{pl}) \tag{1}$$

From Equation 1, the brand achieves positive brand equity if it indeed has a higher price and sells more volume than the private label offering. Conversely, the brand sees negative equity (but still positive revenues) if the private label has a higher price and sells more volume. If the brand exceeds the private label along just one of the two dimensions (either higher price or higher volume), its brand equity may be positive or negative, depending on the private label's volume and pricing. The change in brand equity, then, that the brand sees in brand equity at time t is the difference between the current and prior periods:

$$\Delta BE_{bt} = BE_{bt} - BE_{bt-1} \tag{2}$$

Previous research in brand equity examined the brand's actions, such as advertising, promotion, and category size in revenues (Ailawadi, Lehmann, & Neslin, 2003). Competition should influence the decision to enter a brand alliance (Koschmann & Bowman, 2016) and affect brand equity. Building from this prior research, changes in brand equity become:

$$\Delta BE_{bt} = \beta_0 + \beta_1 Alliance\_Yes_{bt} + \beta_2 Category\_Competition_{bt} + \beta_3 Brand\_AnyDeal\_Index_{bt} + \beta_4 Brand\_Adv\_Share_{bt} + \beta_5 Category\_Revenue_{bt} + u_{bt} \tag{3}$$

where *Alliance_Yes* is an indicator of whether brand b engaged in a brand alliance in year t and is the variable of particular interest. The variable *Category_Competition* represents the number of competing products in the brand's category space. *Brand_AnyDeal_Index* is the ratio of the brand's volume sold on promotion relative to the category average and *Brand_Adv_Share* is the share of advertising dollars spent in the category. Finally, *Category_Revenue* is the size of the category in dollars and u is the error term. Other items such as whether a category is perceived as hedonic in nature or stockpileable are often treated as time invariant and are excluded here.

There are two considerations before Equation 3 can be estimated. First, the error terms are likely correlated across observations, either within the brand (such as autocorrelation across years) or between brands by operating in the same or similar product categories. To account for this, a generalized estimation equation (GEE) relaxes the assumption of independent error terms and uses a working covariance structure with a Hubert sandwich estimator (White, 1980) that is robust to heteroskedasticity and serially correlated errors. That is, brand b and brand d do not have a predefined correlation, let alone independence:

$$Corr(u_{bt}, u_{dt}) = \{\, 1 \text{ if } b=d,\ \alpha_{bd} \text{ if } b \neq d \,\} \tag{4}$$

The second consideration is that brand alliances do not happen randomly. Brands self-select to enter into a brand alliance; some brands are more likely to enter into brand alliances than others. To address this issue, propensity scoring methods are used to create a synthetic control group, to which treatment effects (brand alliance decisions) are compared. The methodology has been used in medicine, such as patients choosing to enter treatments or not (e.g., Austin, 2011; Austin & Stewart, 2015).

While propensity scores can be used for marketing interventions (Rubin & Waterman, 2006), the method is under-used. The method has examined brand alliances and the ability to generate abnormal stock returns (Cao & Sorescu, 2013), as well as prescriptions written by doctors as a proxy for pharmaceutical ROI (Rubin & Waterman, 2006). Propensity scoring has also been used as a sensitivity analysis to assess selection bias in whether free broadcast movies affect DVD sales and piracy (Smith & Teelang, 2009) and customer relationship management on customer knowledge (Mithas, Krishnan, & Fornell, 2005).

Since the effect of brand alliances for any brand b in time t results in only one observed outcome (either the primary brand engages in a brand alliance or it does not), the creation of the synthetic control group arises as a probability of the two outcomes. This propensity of entering a brand alliance is estimated as $\hat{y}$:

$$\hat{y} = \frac{e^{(\hat{C} + \hat{S}'X)}}{1 + e^{(\hat{C} + \hat{S}'X)}} \tag{5}$$

where $\hat{C}$ represents an estimated intercept and $\hat{S}$ represents an estimated vector of coefficients for covariates, X. The covariates are items that could affect the decision to enter a brand alliance or not, as observed prior to the decision. The observables in the prior time period used here are brand equity, category competition, brand deal index, and category revenue.

Once propensity estimates are created, inverse probability of treatment weights (IPTW) weights the propensity scores from the distribution of covariates, which is assumed independent of the outcome to enter a brand alliance. This is assumed here. An additional assumption is the stable unit treatment value assumption (SUTVA), which says that outcomes for one subject are unrelated to the treatment of other subjects (e.g., Rubin, 1990). With the synthetic control group created, Equation 3 can be estimated without the self-selection bias.

Data

Brand alliance market data comes from the *Marketing Fact Book*, distributed by Information Resources Inc. (IRI). The annual data provides aggregate measures of consumer purchases from a panel of approximately 55,000 consumers for nearly 300 product categories of consumer packaged goods. Line item breakouts occur at three levels: category (e.g., soft drinks), category type (e.g., low calorie soft drinks), and product (e.g., Caffeine-Free Diet Coke). The data present single-point measures of aggregate consumer activity during the course of the calendar year. To minimize survivor bias, products purchased by at least 0.5% of households at any point during the year are published by IRI.

The data set covers fourteen years of annual data, from 1998-2011, the last and most recent full year of the *Marketing Fact Book*. A total of 1,757 brand alliance products were identified across product categories and years. This comprised 138 primary brands across 83 product categories. Very few brand alliance products lasted all 14 years; more typical was several years of data. Identifying a brand alliance product was usually apparent: 'Tide with Febreze' or 'Klondike with Oreo' are two typical examples. To validate the data, two judges were given the same random sample of 20% of the IRI data to determine whether a line item should be classified as a brand alliance or not. The inter-coder reliability of the sample was 99%, with the difference resolved through discussion. For consideration as a brand alliance, the brand had to exist as a standalone product (e.g., a brand such as Pillsbury's Funfetti sprinkles are sold only within boxes of Pillsbury cake mixes, and are not available on its own so it has no chance to form brand alliances).

The advertising data is the primary brand's advertising expenditures as a share of total category advertising dollars, or share of voice. The data comes from Kantar Media's Ad$pender program. Prior to Ad$pender, the data was annually published as *Ad $ Summary* (1998-2006).

Table 1 presents descriptive statistics of brand revenues and brand equity. It designates the 'solo brand' as market performance related to the non-alliance variants of the brand. Mean brand revenues are higher ($1,745 per 1,000 households) during years in which brands enter brand alliances than not ($1,612). However, brand equity during brand alliance years is lower, on average (-$1,586) than years in which brands do not engage in brand alliances (-$1,371).

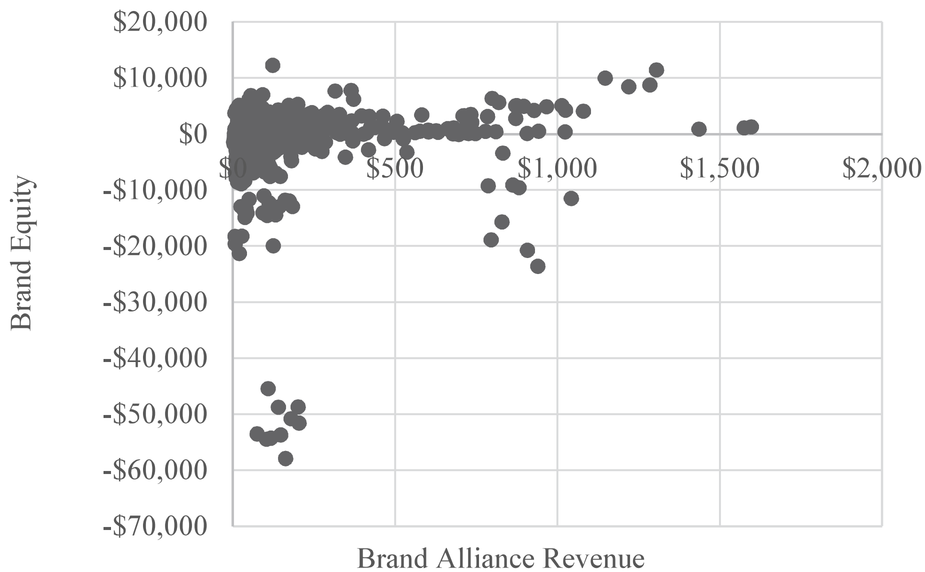
TABLE 1
DESCRIPTIVE STATISTICS OF BRAND REVENUES AND EQUITY

Measure	N	Mean	Median	SD	Min	Max
Brand Alliance Revenue	730	$145	$53	$237	$3	$1,598
Solo Brand Revenue		$1,600	$622	$2,345	$0	$19,612
Total Brand Revenue		$1,745	$845	$2,451	$3	$19,736
Brand Equity		-$1,586	-$142	$7,142	-$57,911	$12,234
Solo Brand Revenue	1,065	$1,612	$599	$3,389	$1	$32,625
Brand Equity		-$1,371	-$384	$4,886	-$56,592	$22,092

Note: $ are per 1,000 households and rounded to the nearest $.

The relationship between revenues of brand alliance products and brand equity is presented in Figure 1 as model-free evidence. The cluster in the lower left – exhibiting highly negative brand equity and smaller brand alliance revenues – primarily consists of milk, bread, and cheese products. Brand alliance products with high revenues and high brand equity are some brands of fruit snacks and yogurt.

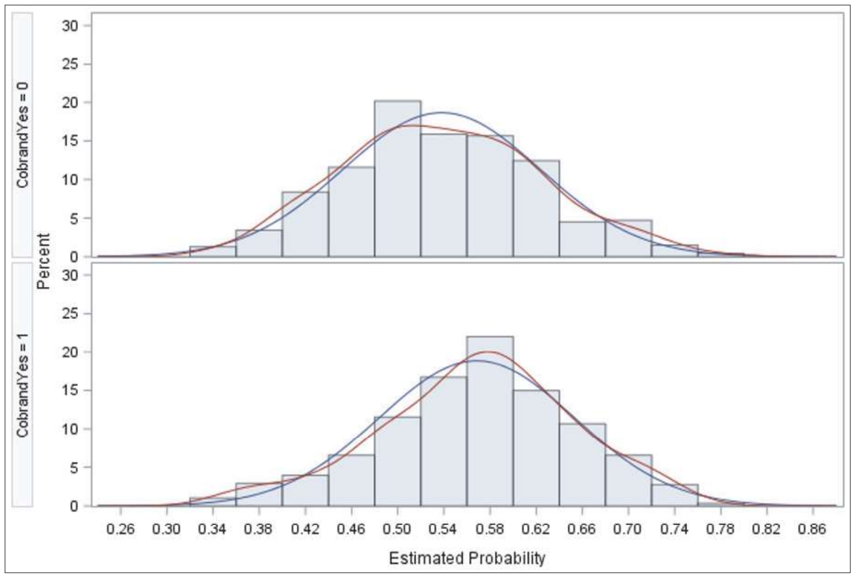
FIGURE 1
MODEL-FREE EVIDENCE OF BRAND ALLIANCE REVENUE AND BRAND EQUITY



RESULTS

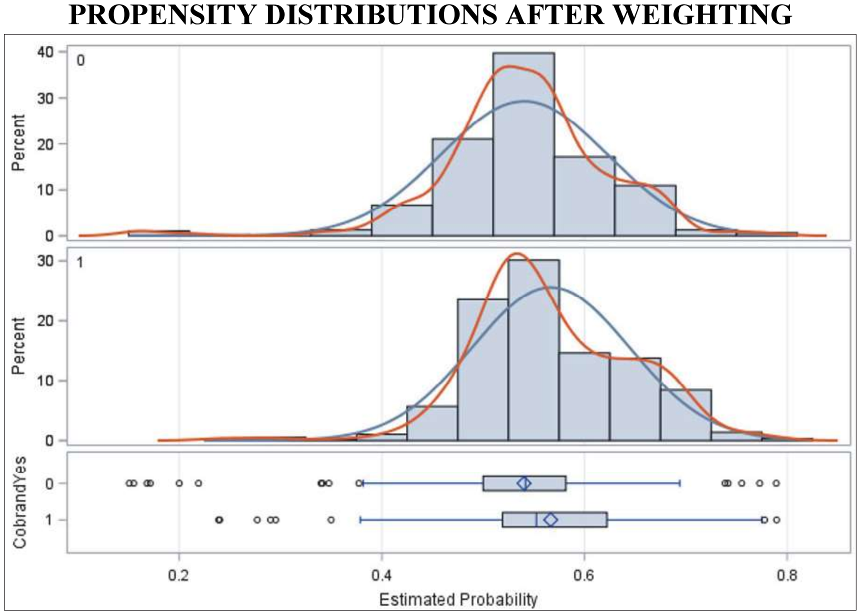
To determine whether or not the propensity scoring has created an appropriate control synthetic group, the results of the propensity score weighting need assessing. One check is to compare the propensity distributions before and after the weighting. Figures 2 shows the propensity scoring before weighting, which shows the decision to enter a brand alliance in the lower distribution (‘CoBrand=1’) and the decision not to enter a brand alliance in the upper distribution (‘CoBrand=0’). The decision not to enter a brand alliance appears to have a mean less than that of the decision to enter a brand alliance. This makes some sense: the decision should be closer to an outcome of 0 rather than 1. In medicine, for instance, this distribution is often more pronounced as a group that has never been sick (or never engages in behavior that is related to being sick) should skew heavily towards the control side, while those individuals who are sick or diagnosed should have a distribution that skews heavily towards the opposite treated side. Although appearances alone are not enough, a *t*-test comparing the means does show that the distributions are significantly different ($p < .01$).

FIGURE 2
PROPENSITY DISTRIBUTIONS BEFORE WEIGHTING



The post-propensity weighted distributions are presented in Figure 3, similarly set up like Figure 2 ('CoBrand=0' is the upper distribution to denote the synthetic control group). While the distributions appear closer in means, a *t*-test indicates there is no significant difference between the two means ($p >$ .10).

FIGURE 3
PROPENSITY DISTRIBUTIONS AFTER WEIGHTING



Although not of primary interest, Appendix A lists the results of the propensity score logistic regression in Equation 5. Instead, the focus returns to the original aim of this research: Do brand alliances lead to a positive change in brand equity? With the synthetic control group and observed outcomes of brand alliances, Equation 3 can be estimated. As a point of comparison and highlighting the effect of propensity scoring, Table 2 presents the estimated results before and after propensity scoring.

TABLE 2
GEE REGRESSION SUMMARY COMPARING PRE- AND POST-PROPENSITY SCORING

	Pre-Propensity		Post-Propensity	
Variable	**Estimate**	**SE**	**Estimate**	**SE**
Intercept	-195.93	90.91**	-85.44	86.03
Alliance_Yes	-23.21	33.14	-78.36	44.12*
Category_Competition	0.34	0.27	-0.02	0.23
Brand_AnyDeal_Index	207.52	92.42**	155.21	86.52*
Brand_Adv_Share	-104.69	618.12	624.03	623.08
Category_Revenue	-0.00	0.00*	-0.01	0.00**
QIC	1,051.61		945.92	
Pseudo R^2	0.360		0.425	

* $p < .10$, ** $p < .05$, *** $p < .01$

In the pre-propensity score model (that is, estimating Equation 3 without propensity scoring), the effect of brand alliances on the change in brand equity is not statistically significant ($\beta = -23.21$, $p > .10$). However, after propensity scoring and inverse probability of treatment weights, the effect of brand alliances is negative and now marginally significant ($\beta = -78.36$, $p < .08$). As to the other control variables for promotion, advertising, competition and category size, these retain similarly significant results. The focal aspect is that during years in which a brand engages in brand alliances, its brand equity decreases $78 per thousand households, on average.

DISCUSSION

This study makes several contributions to our understanding of brand alliances on brand equity. One, this research examines the effect of strategic brand alliances (two brands in one joint product offering) on the brand equity of the primary brand. Two, this study makes use of a unique and large-scale data set that examines aggregate national purchase data of brands over a fourteen-year period. Three, the research utilizes a statistical tool (propensity scoring) that infers causality of secondary data, a tool more commonly applied to medicine than to marketing. Four, the study finds that after accounting for self-selection bias of brands, brand alliances have a negative effect on the change in brand equity of the primary brand.

Several implications from this research arise for both marketing managers and academics alike. For managers, the results show that brand alliances have a negative effect on brand equity. While the model-free evidence described an overall average increase in revenues, the brand is unable to grow its brand equity over the prior year, on average. One possibility for this is that for retailers to carry a new branded variant on shelves would require the brand obtaining more shelf space (which is costly and presumed fixed for the retailer) or replacing an existing shelf facing of the primary brand with the new product. For academics, the research adds to the brand equity literature by examining the impact of brand alliances. Of particular interest is the use of propensity scoring as a causal inference methodology to work with secondary data.

While this research makes several contributions, several limitations are worth addressing. First, assumptions are made regarding the data and model. Two, the data consists of products that met a minimum threshold of sales for inclusion in the data set. Three, the advertising data – captured at the level of the primary brand – provides no additional breakout for individual products. These latter two are natural limitations that arise when working with secondary data.

Although limitations arise, this also presents an opportunity for future research directions. Regarding the assumptions, advances in modeling techniques may address these concerns. Furthermore, other product categories may exhibit different effects stemming from brand alliances. Durable goods (such as Dell computers with Windows operating systems and Ford F-150 pickup trucks with the Harley-Davidson package) may display different characteristics. Likewise, services – like the Delta Airlines credit card by American Express – may present different mechanisms for changes to brand equity. Lastly, while this research has examined brand equity, measures of profitability would also interest managers, including the cost of maintaining the relationship due to governance and controls.

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APPENDIX A
RESULTS OF PROPENSITY LOGISTIC REGRESSION

Variable	Estimate	SE
Intercept	0.57	0.22**
Brand_Equity last year	-0.00	0.00*
Category_Competition last year	0.00	0.00***
Brand_AnyDeal_Index last year	0.04	0.16
Category_Revenue last year	-0.00	0***

Note: log-odds ratios presented as estimates
* $p < .10$, ** $p < .05$, *** $p < .01$