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Identifying Demand Effects in a Large Network of Product Categories

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Abstract

Planning marketing mix strategies requires retailers to understand within- as well as cross-category demand effects. Most retailers carry products in a large variety of categories, leading to a high number of such demand effects to be estimated. At the same time, we do not expect cross-category effects between all categories. This paper outlines a methodology to estimate a parsimonious product category network without prior constraints on its structure. To do so, sparse estimation of the Vector AutoRegressive Market Response Model is presented. We find that cross-category effects go beyond substitutes and complements, and that categories have asymmetric roles in the product category network. Destination categories are most influential for other product categories, while convenience and occasional categories are most responsive. Routine categories are moderately influential and moderately responsive.

Keywords: Cross-category demand effects; Market response model; Sparse estimation; Vector AutoRegressive model

Introduction

While within-category demand effects of the marketing mix have been studied extensively, cross-category effects are less well understood (Leeflang and Selva 2012). Nevertheless, cross-category effects might be substantial. Some categories are complements, for example bacon and eggs studied by Niraj, Padmanabhan, and Seetharaman (2008) or cake mix and cake frosting studied by Manchanda, Ansari, and Gupta (1999), while others are substitutes, for example frozen, refrigerated and shelf-stable juices (Wedel and Zhang 2004). But cross-effects also exist among categories that are not complements or substitutes for several reasons. First, as a result of brand extensions, brands are no longer limited to one category (Erdem 1998; Kamakura and Kang 2007; Ma, Seetharaman, and Narasimhan 2012). So advertising and promotion of a brand within one category might spill over to own brand sales in other categories. Second, advertising and promotions generate more store traffic and therefore more sales in other categories (Bell, Ho, and Tang 1998). And third, lower expenditures in one category alleviate the budget constraint such that consumers are able to spend more on other, seemingly unrelated, categories (Lee, Kim, and Allenby 2013; Song and Chintagunta 2007).

While cross-category effects might be substantial for these reasons, we do not expect that each category's marketing mix variables influence each and every other category. Instead, we expect some cross-category effects to be zero – or very close to zero – but we cannot a priori exclude them. Therefore, we use an exploratory modeling approach for parsimonious estimation of a product category network. The network allows us to easily identify categories that are influential for or responsive to changes in other categories. Building on a widely used category typology of destination, routine, occasional and convenience categories (Blattberg, Fox, and Purk 1995; Briesch, Dillon, and Fox 2013), we find that destination categories are most influential, convenience and occasional categories most responsive, and routine categories moderately influential and moderately responsive.

In order to estimate the cross-category network, this paper presents sparse estimation of the Vector AutoRegressive (VAR) model. The estimation is *sparse* in the sense that some of the within-and cross-category effects in the model can be estimated as exactly zero. Initiated by the work of Baghestani (1991) and Dekimpe and Hanssens (1995), the VAR Market Response Model has become a standard, flexible tool to measure own- and cross-effects of marketing actions in a competitive

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environment. The main drawback of the VAR model is the risk of overparametrization because the number of parameters increases quadratically with the number of included categories. Earlier studies using the VAR model, like for example Nijs et al. (2001), Nijs, Srinivasan, and Pauwels (2007), Pauwels, Hanssens, and Siddarth (2002), Srinivasan et al. (2000, 2004), and Steenkamp et al. (2005), were often limited by this overparametrization problem. To overcome this problem, previous research on cross-category effects has limited its attention to a small number of categories by studying substitutes or complements (Bandyopadhyay 2009; Kamakura and Kang 2007; Leeflang et al. 2008; Ma, Seetharaman, and Narasimhan 2012; Song and Chintagunta 2007). We present an estimation technique for cross-category effects in much larger product category networks. The technique allows many parameters to be estimated even with short observation periods. Short observation periods are commonplace in marketing practice since many firms discard data that are older than one year (Lodish and Mela 2007).

This paper contributes to the extant retail literature in a number of important ways. (1) Previous cross-category literature largely limits attention to categories that are directly related through substitution, complementarity or brand extensions. We provide evidence that cross-category effects go beyond such directly related categories. (2) We introduce the concepts of influence and responsiveness of a product category and position different category types (destination, routine, occasional and convenience) according to these dimensions. (3) To identify the cross-category effects, we estimate a large VAR model using an extension of the lasso approach of Tibshirani (1996).

The remainder of this article is organized as follows. Section “Cross-Category Management” positions this paper in the cross-category management literature and describes the conceptual framework that positions category types according to their influence and responsiveness. Section “Sparse Vector Auto-Regressive Modeling” discusses the methodology. We describe the sparse estimator of the VAR model, discuss how to construct impulse response functions and compare the sparse estimation technique with two Bayesian estimators. In Section “Estimation and Prediction Performance”, a simulation study shows the excellent performance of the proposed methodology in terms of estimation reliability and prediction accuracy. Section “Data and Model” presents our data and model, Section “Empirical Results” presents our findings on cross-category demand effects. We first identify which categories are most influential and which are most responsive to changes in other categories. Then, we identify the main cross-category effects based on estimated cross-price, promotion and sales elasticities.

Cross-Category Management

The importance of category management for retailers is widely acknowledged, both as a marketing tool for category performance (Basuroy, Mantrala, and Walters 2001; Dhar, Hoch, and Kumar 2001; Fader and Lodish 1990) and as an operational tool for planning and logistics (Rajagopalan and Xia 2012). Successful category management requires retailers to understand cross-category effects of prices, promotions and sales. Among these, the cross-category effects of prices on sales – which define substitutes and complements – are the most extensively studied (Bandyopadhyay 2009; Leeflang and Selva 2012; Sinistyn 2012; Song and Chintagunta 2006). Cross-category effects of promotions, for example feature and display promotions, on sales result from many brands being active in multiple categories (Erdem and Sun 2002). Brand associations carry over to products of the same brand in other categories, for example through umbrella branding (Erdem 1998) or horizontal product line extensions (Aaker and Keller 1990). Less well understood than the effects of prices and promotions, are the effects of sales in one category on sales in other categories. Such effects might exist because categories are related based on affinity in consumption (Shankar and Kannan 2014), because products from various categories are placed close to each other in the shelves (Bezawada et al. 2009; Shankar and Kannan 2014), or because of the budget constraint (Du and Kamakura 2008). If consumers spend more in a certain category they might, all else equal, spend less in other categories simply because they hit their budget constraint. As a result, cross-category effects might exist between seemingly unrelated categories.

When studying these cross-category effects of price, promotion and sales on sales, several asymmetries might arise. A first asymmetry concerns within- versus cross-category effects. We expect within-category effects to be more prevalent and larger in size than cross-category effects (e.g. Bezawada et al. 2009; Song and Chintagunta 2006). A second asymmetry concerns category influence versus category responsiveness. Influential categories are important drivers of other category’s sales, while sales of responsive categories react to changes in other categories. To identify which categories are more influential or more responsive, we build on a widely used typology of categories described in Blattberg, Fox, and Purk (1995).

Blattberg, Fox, and Purk (1995) define four category types from the consumer perspective: destination, routine, occasional and convenience. Destination categories contain goods that consumers plan to buy before they go on a shopping trip, such as soft drinks. Briesch, Dillon, and Fox (2013) show that destination categories are generally categories in which consumers spend a lot of their budget. Retailers typically use a price aggressive promotion strategy and high promotion intensity for these destination categories with the goal of increasing store traffic. Because consumers shop to buy products in the destination categories, destination categories are likely to influence sales in other categories. However, since consumers already plan to buy in the destination categories before entering the store, destination category sales will not be highly responsive (Shankar and Kannan 2014).

About 55–60% of categories are routine categories (Pradhan 2009). Routine categories are regularly and routinely purchased, such as juices and biscuits. Retailers typically use a consistent pricing strategy and average level of promotion intensity. Because purchases in routine categories can more easily be delayed than purchases in destination categories, we expect routine categories to be more responsive. But, since purchases in routine categories altogether still account for a large portion