The Demand Effects of Joint Product Advertising in Online Videos

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Abstract

Joint product display in videos may help customers to not only evaluate the attributes of products that can influence their individual demands (direct effect) but also learn about the complementarity between them that may cause additional correlation in their demands (spillover effect). To estimate the demand effects, we introduced videos displaying apparel with matching accessories for few randomly selected apparel on a fashion retailer's website. We found that introducing a video resulted in a 14.5 percent increase in apparel sales and a 28.3 percent increase in accessories sales. The estimated increase in accessories sales was largely attributed to the spillover effect of videos. Moreover, introducing videos with other product promotions resulted in a significantly higher effect of videos on product demands. Overall, we show how video display of related products can increase their demands in an online product network.

Key Words: *Electronic commerce; product advertising; online product networks; virtual product experience; complementary products; demand spillovers; randomized field experiment; value of IT; average treatment effect*

1.0 Introduction

Customers are aware of the inherent (latent) relationship between repeatedly consumed related products, such as cake mix and cake frosting, and purchase them together for this reason. However, in many product categories, such as fashion apparel and accessories, books, music, and movies, customers do not consume the same product repeatedly, and they have a large number of options of different interrelated products to choose from. In such product categories, customers are less likely to be completely aware of the relationship between products. Thus, revealing this relationship to them could result in additional sales of such products and higher revenues for the retailers. E-retailers exploit this basic premise in recommending related products by explicitly displaying their pictures (with hyperlinks) on the webpages of the focal products, thereby creating a visible network of related products on their websites. On such websites, the relationship between products is revealed to customers via the preferences (co-purchases) of other customers or recommendations from experts. Notable examples are the co-purchase product network at Amazon.com and the movie recommendation networks at Netflix.com.

Many ecommerce websites have recently begun displaying focal products with their complementary accessories in online product videos. Retailers such as J. Crew and Forever 21 present brief high-definition videos of models wearing dresses with matching purses, jewelry, and sunglasses; travel and hotel websites, such as www.ichotelsgroup.com, provide a concierge-guided video tour showcasing their rooms and other attractions of their hotel and city; automotive company websites, such as www.mbusa.com, present videos that allow consumers a virtual driving experience with complementary accessories; and real estate websites, such as www.zillow.com, offer video walk-throughs displaying their properties with matching furnishings.

Online product videos have become widely popular among customers, but their true economic value is unclear.[1] A few practitioners' studies show a positive correlation between online videos and sales

[1] As per Comscore Inc., 181 million (84.5% of the total) US Internet users watched nearly 37 billion online videos in April 2012 http://www.comscore.com/Press_Events/Press_Releases/2012/5/comScore_Releases_April_2012_U.S._Online_Video_Rankings

conversion rates (Meacham 2008, Marketing Chart 2007 & 2013), but they lack the rigor to claim a causal relationship between the two. How do product videos affect the demands of the displayed products? Do such videos additionally reveal complementarity between displayed products to customers and thus cause additional correlation in their demands? How does the effect of videos on product demand vary when they are used with other product promotions? The answers to these questions allow us to infer the true value of product videos in online product networks, which is the primary goal of this paper.

Compared to their display in still pictures, product displays in videos provide a more vivid (high definition, dynamic, and 360 degree) presentation of product attributes, accompanied by background music that stimulates customers' multiple sensory channels. Moreover, videos offer interactive features, such as zoom in/out and pause/replay/forward, that allow customers to inspect different product attributes at a desired pace. Prior experimental studies have shown that vivid product displays with interactive features provide customers with a virtual product experience, which helps them evaluate product attributes in a manner similar to that of a direct shopping experience in a real-life setting (Jiang and Benbasat 2005 & 2007, Li et al. 2001, Suh and Lee 2005, Klein 2003). Such virtual product experience via joint product display in videos should allow customers to better evaluate, and thus learn about, the attributes of the individual products and how they complement one another. Thus, joint display of products in videos can influence not only their individual demands independently due to consumers learning about their individual attributes (*direct effect*) but also the correlation in their demands due to consumers' additionally discovering about their complementarity (*spillover effect*). We conduct a randomized field experiment on the live website of a mid-sized apparel retailer in the US to estimate the direct and spillover effects of introducing product videos.[2]

Estimating demand spillovers due to an intervention across a product network poses several identification challenges because a variety of unobserved factors can simultaneously affect the demands of interrelated products and thus cause bias in spillover estimates (details of these challenges are provided

[2] The identity of the retailer is not disclosed due to a non-disclosure agreement.

in section 4.3 of this paper). We resolve these issues in our setup by experimentally layering the joint display of products in videos for a few randomly selected products over their display in the normal website settings. In the normal website settings, the focal products are jointly displayed with their matching coordinating (complementary) products in still pictures on the focal products' webpages.[3] For the first few weeks of the experiment, referred as pre-treatment period, product sales took place in the normal website settings. Then, videos for a few randomly selected focal products were introduced on their webpages for another few weeks, referred to as the treatment switch-on period. In these videos, a human model walks around to dynamically present the focal product and its matching coordinating products. The videos were removed from the website in the last few weeks of the experiment, referred to as the treatment switch-off period.

We employed a difference-in-difference design to estimate the switch-on and switch-off effects of product videos on the focal and coordinating product sales separately. We found that while sales increased during the videos' switch-on period, this increase disappeared when the videos were switched off, which shows that the observed effect on sales is caused by the videos. Specifically, we found that introducing a video on the focal product's page resulted in an average 14.5 percent increase in its sales and 28.3 percent increase in the sales of its associated coordinating products. We further found that this increased sales of video-treated products did not cannibalize the sales of products not treated with videos.

After controlling for other factors that may cause correlation in the sales of focal and coordinating products, we found a positive and significant estimate for the spillover effect of videos, which indicates an additional correlation in the sales of two products due to video. Specifically, the spillover effect of videos accounted for 40 percent of the total correlation between the two products during video switch-on period. We also found that videos caused an insignificant direct effect on the coordinating product sales but a positive and significant direct effect on the focal product sales.

[3] As is common in the retail industry, we refer to the complementary products or accessories as coordinating products.

We further examined the variation in the effect of videos when they were used with other product promotions. Although promotions may be endogenously chosen by the retailer, the random assignment of videos in our setup allowed us to estimate the unbiased coefficients for the interaction of video with other product promotions. We found that introducing videos with focal product promotions significantly increased the effect of the videos on focal product sales. We also conducted a cost-benefit analysis in our field setup and found that the retailer earned an additional profit of approximately six times the cost of introducing the videos.

Our study makes several contributions to the emerging literature on online product networks. To the best of our knowledge, this is the first large-scale randomized field experiment on an online product network that estimates the causal effect of introducing product videos on the sales of displayed interrelated products. In addition to estimating the effect of product video, we further estimate how this effect varies with the application of other product promotions, which provides guidance to managers on how to allocate other elements of the marketing mix with product videos to maximize product sales. A prior study on Amazon's book co-purchase network shows that the explicit display of still pictures of co-purchased books on a focal book's page affects the correlation in their sales (Oestreicher-Singer and Sunderarajan 2012). Our study extends this finding in two ways. First, we estimate how the joint display of related products in videos affects the sales of individual products (direct effect) as well as the correlation in their sales (spillover effect). Second, through our layered experimental setup, we estimate the additional spillover effect of the joint display of products in videos over and above the effect of their joint display in still pictures and their latent complementarity. Moreover, whereas co-purchased products by other customers can reveal any type of relationship between such products, the joint display of apparel with their matching accessories essentially reveals their complementarity. Therefore, the present study shows how the joint display of related products in videos influences customers' perception about their complementarity and thus causes additional correlation in their demands.

The rest of this paper is organized as follows. The next section discusses the related literature. Section 3 describes the research setting and data. Section 4 outlines our empirical strategy, specifications, results, and robustness checks. Section 5 concludes with the managerial implications of the results and an outline of future research directions.

2.0 Related Literature

We draw from several streams of the literature to understand how the joint display of complementary products in videos affects their individual demands and the interrelation between those demands. Consumers require realistic product information to make informed choices (O'Keefe and McEachern 1998). This information requirement is particularly acute in experience goods, whose true quality can best be determined after direct consumption experience (Nelson 1970, 1974). For this reason, firms adopt a variety of measures to inform consumers about the quality of their experience goods, such as providing products reviews by other consumers, experts or critics, and allowing free product sampling. Fashion apparel is an example of experience goods that consumers can evaluate only by physically trying it on. Prior studies on product sampling of experience goods, such as movies and music, suggest that sampling can help consumers learn about product quality and thus influence its demand (Bawa and Shoemaker 2004, Oberholzer-Gee and Strumpf 2007, Kumar et al. 2013).

In a fashion apparel video, a human model provides a dynamic, high definition, 360-degree presentation of the garment, complete with accessories and accompanied by background music. With the zoom in/out and pause/replay/forward options, product videos also allow customers the ability to see the apparel from different perspectives and at the customer's desired pace. Thus, videos offer a vivid and interactive display of products to customers, where vividness refers to the richness of product information conveyed to customers and interactivity refers to providing customers with the flexibility to manipulate the form or content of product information in a display. Prior studies show that vivid and interactive displays reveal product information in a more realistic manner that provides customers a virtual product experience (VPE) similar to that of a direct purchase experience in a physical shopping environment

(Jiang and Benbasat 2005 & 2007, Li et al. 2001, Suh and Lee 2005, Klein 2003). Product displays in VPE formats have been shown to result in higher customer learning about products and thus higher purchase intentions (Daugherty et al. 2008, Li et al. 2003, Jiang and Benbasat 2007).

The correlation in demands of related products has been extensively studied by marketers in traditional retail settings. For instance, competing brands may benefit from a cross-brand word-of-mouth effect (Libai et al. 2009), demand for a sub-brand can affect the demands for other members of the brand portfolio (Aaker 2004), and the existence of software may affect the demand for hardware and vice versa (Binker and Stremersch 2009). Unlike studies on demand spillovers across products, there are few studies that examine spillovers across a network of things, other than products, on a website. For instance, Susarla et al. (2012) examine a network of YouTube videos, Mayzlin and Yoganarasimhan (2012) examine a network of blogs, and Dellarocas (2009) study a network of news reports.

The economics literature has examined how information spillovers across related products can lead to the correlation in their demands. For instance, Goeree (2008) shows that a strong reputation of existing products increases the demand for new products sold under the same brand name (forward spillover), and a high-quality new product can improve the brand's image and thus boost the sales of existing products (backward spillover) (Choi 1998, Cabral 2000). Similarly, Hendricks and Sorensen (2009) find an increase in sales of an artist's catalogue albums (backward spillover) due to their discovery during the release of her follow-up album.

The correlation between demands for related products in a network occurs naturally due to their latent relationship. Any shock to the demand of one product due to its promotion would spill over to the demands for its related products, stemming from their latent relationship. Carmi et al (2009) show that shocks to the information about a focal book spills over to the demands of its neighboring books in the network. However, explicit visibility of the network of related products can additionally reveal their relationship to the customers. Oestreicher-Singer and Sunderarajan (2012) estimate the additional correlation in sales of a focal book and its visible hyperlinked neighbors on the focal book's webpage after controlling for their latent relationship. They suggest that consumers observationally learn about the relationship between a focal book and its neighbors via the explicit display of other consumers' co-purchases.

Different methods may be more suitable for revealing different nature of relationships across constituent products in product networks. Other consumers' preferences or recommendations from experts can reveal different types of relationships (similarity, complementarity or other relationships) between different options in a product category, such as books and movies. The joint display of interrelated products that fit/function together as complements may be more appropriate for revealing complementarity between them, such as fashion apparel and its accessories. We conduct a randomized field experiment on a fashion retailer's apparel-and-accessories network to identify the effect of joint display of apparel with its accessories in videos on their demands. In this study, we identify a possible mechanism – virtual product experience – through which product display in videos can reveal complementarity between apparel items and their related accessories to customers and thus add to the literature on online product networks.

3.0 Research Setting and Data Description

We conducted a field study at a publicly traded, fast-growing women's apparel retailer in the U.S. The retailer sells its products through more than 300 specialty stores, a catalog channel, and a website. The retailer has annual revenues of over US $300 million. We examine the retailer's online sales in the present study.

The retailer sells products on its website in the spring and fall collections corresponding to the two main seasons of the year. The retailer's products are classified into five categories: tops, dresses, bottoms, footwear, and accessories. Tops, dresses, and bottoms are called principal products. Accessories and footwear are called auxiliary products, as they largely complete the looks of the principal products. For instance, accessories such as jewelry, hats, sunglasses, and belts are worn with tops, bottoms, and dresses. Each category is further classified into subcategories, such as (a) tops into shirts, tees, sweaters, blazers, cardigans, and vests, and (b) bottoms into pants, capris, shorts, skirts, and leggings.

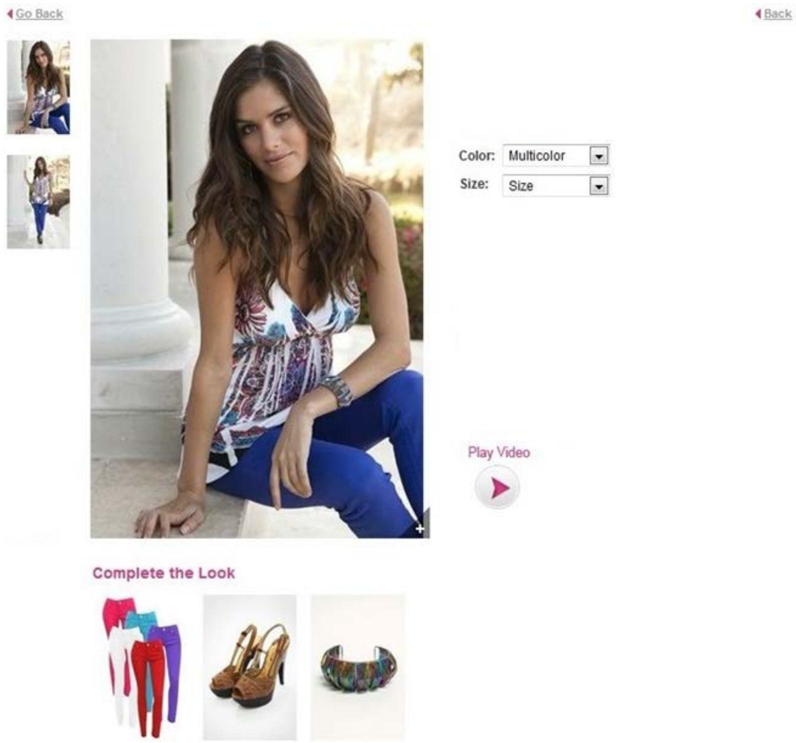

Figure 1: Focal product's page with coordinating products and video icon

The retailer promotes some of the products by hosting products' pictures on the home page of the website. The home page also hosts links to the five product categories. By clicking on a category link, a customer can navigate to the front page of that product category. The center of a category front page hosts a large picture of a model wearing the featured product surrounded by several thumbnail-sized pictures of models wearing other products in that category.[4] Apart from the front page, products in a category are displayed on several pages, with each such page hosting several thumbnail-sized pictures of the products. Customers can click on a thumbnail picture of a product on its category page to go to its product page.

Each product has a separate product page on which it appears as a focal product. The product page hosts an enlarged picture of a model wearing the focal product, such as the picture of the model wearing a top in Figure 1. In some cases, the product's page also hosts pictures of the matching

[4] In some weeks, a category's front page may have no featured products with the large picture.

complementary products that complete its look. These matching products are the coordinating products. For instance, in Figure 1, the top is the focal product, while its matching pants, bracelet, and sandals are the coordinating products. All of the coordinating products have their own product pages on which they appear as focal products. For instance, the pants, bracelet, and sandals in Figure 1 have their own product pages.

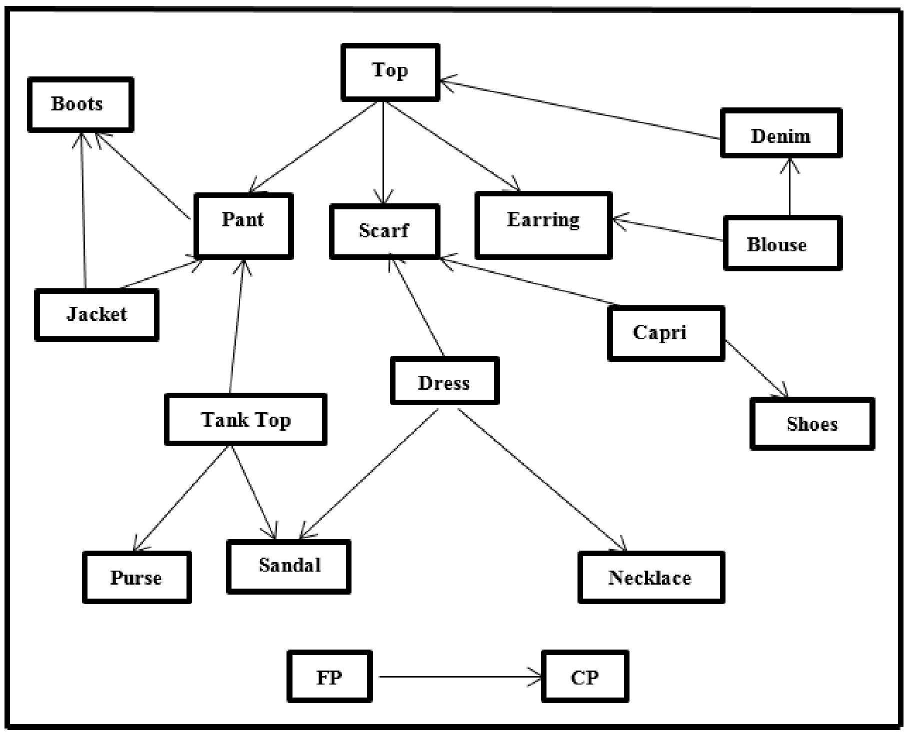

Figure 2: Focal – coordinating product network on the retailer's website [5]

Although all products appear as focal products on their product pages, not all of them appear as coordinating products on another product's page. The top in Figure 1 may not appear as a coordinating product on any other product's page. Moreover, not all focal products have matching coordinating products on their product pages. Most auxiliary products have no coordinating products on their product pages. A customer can navigate to the product page of a coordinating product by clicking on its picture on its focal product's page. For instance, a customer can navigate to the bracelet's product page by clicking on its image on the top's product page, as shown in Figure 1. Thus, by pairing the focal products with

[5] For brevity, focal and coordinating products are, respectively, referred to as FP and CP in all diagrams in the paper

their matching coordinating products on the product pages, the retailer creates a network of related products. Figure 2 exhibits an example of this network. The breakup of products in this network is displayed in Figure 3. Out of 571 focal products, only 216 appear as coordinating products for other focal products, and only 347 focal products have associated coordinating products on their product pages.

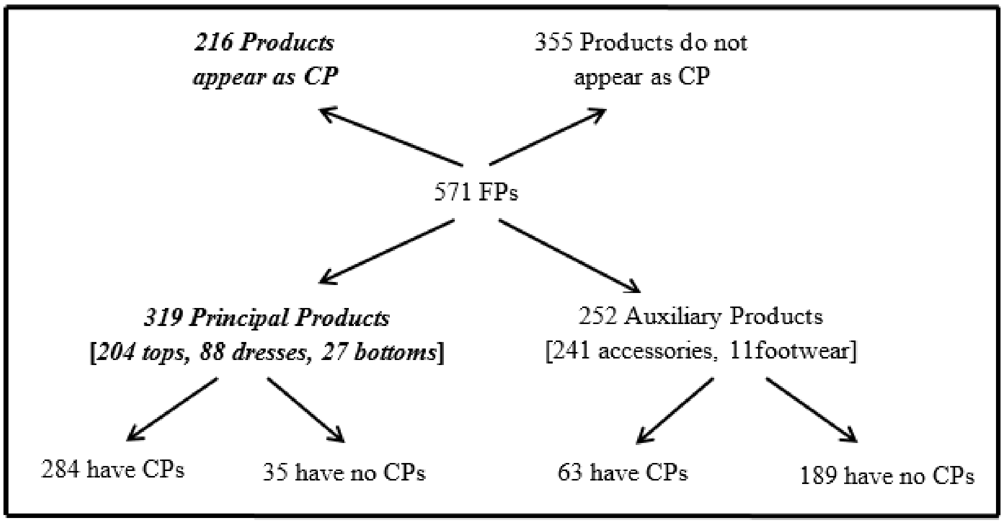

Figure 3: Focal and coordinating products breakup at the retailer's website

To effectively advertise its products online, the retailer introduced videos for 66 randomly selected principal products (42 tops, 8 bottoms, and 16 dresses) out of the total of 319 principal products. These product videos were introduced in three phases: 25 on February 17, 2012, 30 on March 23, 2012, and 11 on May 18, 2012.[6] The videos could be played by clicking on an icon next to an enlarged picture of the focal product on its product page, as shown in Figure 1.[7] In these videos, a human model displays a 360-degree view of the focal product with its matching coordinating products. As is evident from Figure 1, the combination of focal and coordinating products was already shown in still pictures on the focal product's page. With the introduction of a video, the retailer additionally provides its customers a dynamic, 360-degree presentation of the focal product with its coordinating products. Special care was taken to shoot the videos with a limited number of similar models and similar background settings so that

[6] The retailer did not introduce videos for auxiliary products because most of these products have pictures without a model on their product pages. For example, the bracelet product page has a picture of only a bracelet.
[7] Videos were introduced on the focal product's page and are thus referred to here as focal product videos.

any heterogeneity in product videos was mainly due to differences in product characteristics. After being hosted on the website for over two months, these videos were removed in three phases: on May 4, 2012, June 6, 2012, and July 18, 2012.

Weekly numbers of products sold on the website for the spring collection were collected over a 28-week period from January 13, 2012 to July 26, 2012. It is pertinent to note that the retailer sells different product assortments on the website and in retail stores, and there are no product reviews on the retailer's website. Therefore, the possibility of these factors confounding our study is absent.[8]

We collected information on all price and non-price promotions run by the retailer during the study. The retailer periodically mails product catalogues to its customers. Six different catalogues for the spring collection were mailed during the study period: 1.5 million copies on January, 25, 2.2 million on February, 15, 2.7 million on March, 7, 3 million on April 2, 2.7 million on May, 3 and 1.8 million on June 6, 2012. Although a catalogue contains pictures of a large number of products in the spring collection, those featured on the front and back covers of the catalogue are presumed to catch greater customer attention and thus may have higher sales than those displayed in the interior. From discussions with the retailer's representatives, we learned that it takes approximately seven to 10 days for the mailed catalogues to reach their intended recipients, and the effect of the catalogues on product sales is seen for a two-week period after that. During the study period, a total of 31 spring collection products featured in the catalogues. Therefore, the catalogue drop would influence sales for 62 product-weeks.[9]

In addition to catalogues, the retailer sends mass e-mails to its customers promoting specific products. We collected details of all e-mail-featured products, along with the dates on which the mass e-mails were sent. The retailer also promoted its products by placing them as featured products on the website's home page and the categories' front pages. During the time a product is featured on the website's home page or as a large picture on a category front page, it is likely to attract more customer attention and thus may have higher sales. Accordingly, we collected details of all products and the

[8] We excluded from our analysis four products that are offered for sale in both physical stores and on the website.
[9] Product-weeks are computed by summing the number of weeks each product appears as a featured product.

duration for which they appear as featured products on the home page or as a large picture on the front page of each product category. During the period of study, 58 products appeared on the home page for 112 product-weeks, and 72 products featured on the front page of the product categories for 124 product-weeks.

The retailer also offered several across-the-board promotions, such as free shipping for all orders over $75 on Mother's Day (May 13) or tax-filing days (April 16 – 18) and a summer sale of $10 off on orders of $75 and above in the month of June. Because such promotions apply equally to all products in a specific time period, we account for them with the time fixed effects in our econometric specifications. Apart from the price promotions applicable to all products, the retailer offered product-specific price markdowns to boost the sales of its products. Because product sales are expected to be higher during a price markdown, we also collected data on price markdowns and their duration. In all, 300 products (70 tops, 14 bottoms, 18 dresses, 8 pairs of shoes, and 190 accessories) received a price markdown for 1,072 product-weeks. Of these 300 products, prices for 279 were marked down during July 2012, that is, the last four weeks of our 28-week study period.

We also observed that some fast-moving products were sold out or stocked-out toward the end of the study period. Products are removed from the website when their inventory is exhausted. We collected information on all products that sold out in the middle of the study period to account for this fact in our analysis.

4.0 Econometric Specifications and Results

4.1 Focal Product Analysis

In this section, we estimate the effect of introducing videos on the products' pages on focal products' sales. We estimate this effect by comparing the sales of focal products treated with a video with the untreated focal products after controlling for other factors that may influence sales. Because videos were randomly assigned to 66 principal products, we treated the remaining principal products as control products. Because the sales of focal products that also appear as coordinating products for other focal products with videos may be influenced by those videos, we dropped such products from our focal product analysis. The selection of treatment and control products for focal product analysis is shown in Figure 4.

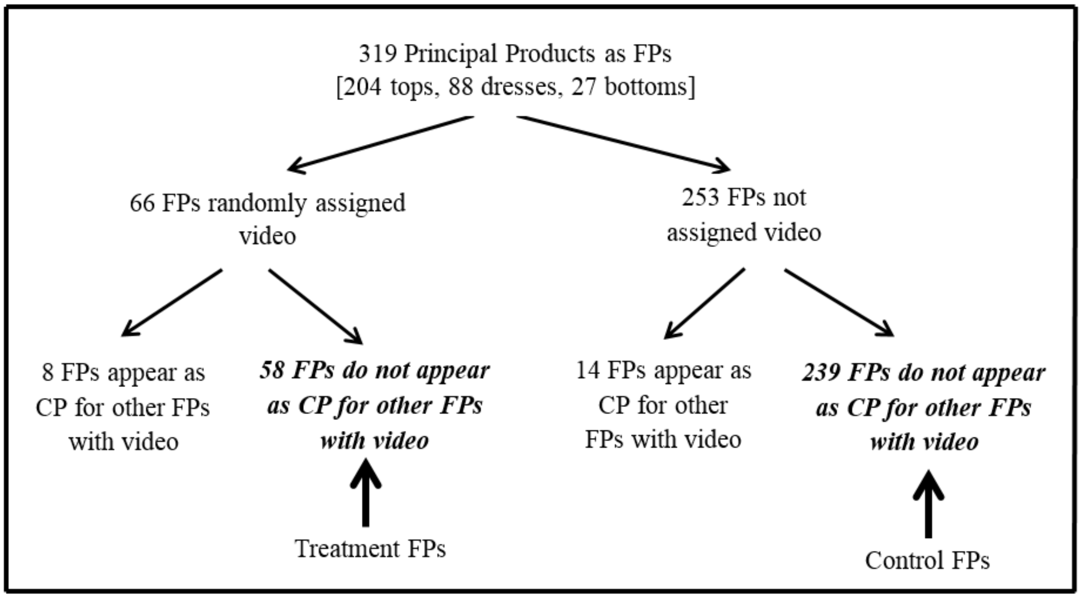

Figure 4: Selection of treatment and control products in focal product analysis

Weekly online sales were gathered for the treatment products for a few weeks before, during, and after their videos were hosted on the website. We refer to these as the pre-treatment, treatment switch-on, and switch-off periods, respectively.[10] Because the videos were introduced on three different dates and thereafter removed on three different dates, the pre-treatment, treatment switch-on, and treatment switch-off periods were different for the three groups of treatment products. We also gathered data on the weekly online sales of the 239 control products. Figure 5 illustrates the difference-in-difference experimental setup.[11]

We employed specification (1) to estimate the effect of introducing product videos on the online sales of focal products after controlling for other factors that may influence sales

[10] The treatment switch-on and then switch-off design is utilized to show that the treatment effect dissipates once the treatment is switched off (Puhani and Sonderhof 2009).
[11] The difference-in-difference design is widely used to estimate the average treatment effect (Angrist and Krueger 1999).

$$Sales_{it} = \alpha_i + \alpha_t + \delta\, Vidwk_{it} + \boldsymbol{\beta}\, \boldsymbol{X_{it}} + \varepsilon_{it} \ , \tag{1}$$

where $i \epsilon \{1, 2, 3, \ldots \ldots 297\}$ denotes the 297 focal products and $t \epsilon \{1, 2, 3, \ldots \ldots . . T_i\}$ denotes the total number of weeks product *i* remains in our analysis of the total 28 weeks of our study period. We dropped observations about focal products for those weeks when they were stocked out (instead of showing zero sales in stocked-out weeks). We conducted detailed checks in Appendix C to show that there is no systematic difference in the attrition rates of treated and control focal products.

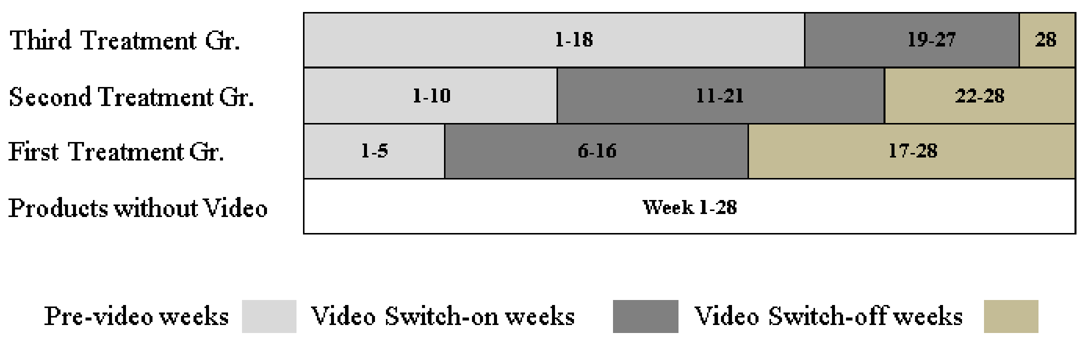

Figure 5: Difference-in-Difference experimental setup

On the left-hand side of specification (1), $Sales_{it}$ denotes the sales of product *i* in week *t*. On the right-hand side of specification (1), $Vidwk_{it}$ is an indicator variable equal to unity if product *i* has the video switched-on the firm's website in week *t* and is zero otherwise; $\boldsymbol{X_{it}}$ is a column vector of indicator variables for the different promotions carried out by the retailer for product *i* in week *t*. $\boldsymbol{X_{it}}$ includes the following: $Catwk_{it}$ is equal to unity if product *i* features on the front or back cover of the catalogue and if week *t* falls in the two-week period immediately after 7 to 10 days from the catalogue drop dates and is zero otherwise; $Pricewk_{it}$ is equal to unity if there has been a price markdown for product *i* in week *t* and is zero otherwise; $Emailwk_{it}$ is equal to unity if the retailer sends a promotional e-mail featuring product *i* in week *t* and is zero otherwise; $Homepgwk_{it}$ is equal to unity if product *i* appears on the home page of the website in week *t* and is zero otherwise; $Catpgwk_{it}$ is equal to unity if product *i* appears as a large picture on the front page of its category in week *t* and is zero otherwise, α_i and α_t denote the product and week fixed-effects, respectively.

The components of $\boldsymbol{\beta}$ account for the various product-specific observed promotions that may influence sales. We include the product fixed-effects to account for the scale differences in weekly sales of different products due to unobserved and time-invariant product-specific factors, such as quality. The week fixed-effects account for any unobserved, time-specific shocks that are equally applicable to the demands of all products, such as seasonality or across-the-board promotions at a specific time, such as the price markdowns for Mother's Day and tax-filing day.

The coefficient δ represents the average treatment effect (*ATE*) of product videos. The average treatment effect of product i in week t (ATE_{it}) = $Sales_{it}^{T} - Sales_{it}^{C}$, where $Sales_{it}^{T}$ is the weekly sales for product i with a video in week t, and $Sales_{it}^{C}$ is its weekly sales if it did not have a video in week t. Because we only observe sales of a product either with or without a video, if product i has a video on the website in week t, its counterfactual sales without a video in week t are inferred from the average sales of all products that do not have videos on the website that week. Therefore, products for which videos are introduced after week t also act as controls for those for which videos are introduced on or before that week. This further makes our specification robust to any possibility of selection of products for the creation of a video.

The *overlap assumption* for the identification of the *ATE* requires that for each week with a product-video treatment, there should be sufficient control products without videos.[12] This requirement is met in our case as a result of: (1) the presence of a large number of products (239) that are not assigned a video treatment and (2) the fact that the video-treated products also act as control products when they are without videos in their pre-video and video switch-off periods.

The *ignorability-of-treatment assumption* for the identification of the *ATE* requires that the treatment and control products have equal likelihoods of a video assignment. Because videos were randomly assigned to products, this requirement should be well met. Nonetheless, we perform further checks on the integrity of our randomization, as discussed in Appendix A, to show the following: (1) the

[12] See Wooldridge (2002) for details on the overlap and ignorability-of-treatment assumptions.

proportion of video assignments in the full sample has been proportionately transmitted to the subcategories of products (tops, dresses, bottoms, and auxiliary products); and (2) the mean characteristics of the treated and control products are statistically similar. To further ensure that our experimental setup cleanly identifies the treatment effect of a video, we show in Appendix B that the mean values of weekly sales for the treatment and control products are statistically indistinguishable in the period without the treatment. We further recognize that pre-existing sales trends of the treatment and control products can falsely lead to the treatment effect in a difference-in-difference design.[13] Appendix B discusses checks on the sales trends to ensure that our results are robust to this possibility. Moreover because the videos were introduced and then removed in phases, the possibility that the timing of a video will coincide with any unobserved events that may influence sales is further minimized.[14]

Table 1: Parameter estimates for the focal product analysis

Dependent Variable (Weekly sales in numbers)	Coefficient Estimates (Robust Cluster Corrected Std. Errors)		
	(A)	(B)	(C)
Product video	16.70^{**} (8.02)	23.55^{**} (9.81)	17.47 (10.11)
Catalogue	103.80^{**} (48.95)	106.09^{**} (53.04)	168.10^{***} (59.17)
Website home page	61.08^{***} (15.53)	62.33^{***} (16.90)	66.65^{***} (16.86)
Category front page	29.44 (20.90)	34.48^{*} (19.40)	45.53^{***} (14.32)
Price markdown	76.62^{***} (8.75)	77.13^{***} (7.99)	76.73^{***} (8.50)
Email promotion	68.91^{*} (41.75)	73.53^{*} (44.98)	86.25^{*} (49.90)
No. of product-weeks (No. of products)	6828 (297)	6487 (297)	6417 (297)
R Square	0.56	0.57	0.56

Note - ***, **, * = statistically significant at $\alpha = 0.01$, $\alpha = 0.05$, and $\alpha = 0.10$ levels (two-sided test), respectively. Columns A, B, and C, respectively, display the coefficient estimates for the full dataset, pre-treatment and switch-on-period data, and treatment switch-on and switch-off-period data only. The standard errors are cluster corrected at focal product level.

The OLS estimates of Equation (1) are obtained for three sets of data: (1) the complete dataset covering the entire 28-week period; (2) the data comprising the pre-treatment and treatment switch-on periods; and (3) the data comprising the treatment switch-on and switch-off periods. Table 1 reports the coefficient estimates for the three datasets and their robust cluster corrected standard errors.

[13] We may obtain a positive treatment effect if the sales of control-group products have a pre-existing declining trend and the treatment-group sales remain constant throughout.

[14] If some unobserved events that may influence product sales coincide with the duration of the product videos, the estimated effect on sales during the time of product videos could be partly due to such unobserved events.

First and foremost, the first row of the coefficient estimates reveals positive and similar magnitudes of the treatment-effect coefficients in all three datasets, the first two of which are statistically significant (α = 0.05) and the third of which is borderline significant (α = 0.105). This suggests that product sales increase upon introduction of a product video – the switch-on effect. This effect, however, dissipates when the video is removed – the switch-off effect. The estimated value of the treatment coefficient indicates an average increase in weekly sales of focal products of 16.7 following the introduction of their videos, which translates into a 14.5 percent increase on the mean weekly sales of 114.9 in the period without treatment or the pre-treatment and treatment switch-off periods. The comparable estimate with sales revenue as the dependent variable indicates additional weekly revenues of \$321.6 (α = 0.05) on the introduction of a product video.[15]

However, the inclusion of the promotion-related control variables in Equation (1) only leads to more precise treatment coefficients as long as these promotions are exogenous, which is not necessarily the case. For example, price markdowns may be reserved for slow-moving products, and video-treated products may be given preferential placement in the catalogue and the website. In Appendix F, we show that as long as the videos are assigned randomly, any endogeneity of promotions would not bias the $Vidwk_{it}$ coefficient, δ. In Appendix D, we further show that: (1) the probability of promotions (price as well as non-price) for the treated products during their treatment period is statistically indistinguishable from that of control products; (2) there are qualitatively similar treatment-effect estimates on a sample of only those products, both treated and control, that received no promotions; and (3) there are similar magnitudes of treatment effect estimates without the inclusion of the promotion-related variables. These results indicate that our treatment-effect estimates are robust to potential endogeneity in promotions.

4.2 Coordinating Product Analysis

We next consider the effect of introducing a video on the focal product's page on the demands for its associated coordinating products. To estimate this effect, we compare the sales of coordinating products

[15] Recognizing the count nature of the outcome variable, we also estimate a fixed-effect Negative Binomial regression on the data and find qualitatively similar results.

for which the associated focal products have a video (treatment products) with the sales of those for which the associated focal products do not have a video (control products). The sales of a coordinating product that also has a video on its product page may be influenced by its own video. To isolate the effect of focal products' videos on coordinating product sales, we dropped 20 such products from the total of 216 coordinating products in the coordinating product analysis. Figure 6 shows our selection process for the treatment and control products for the coordinating product analysis.

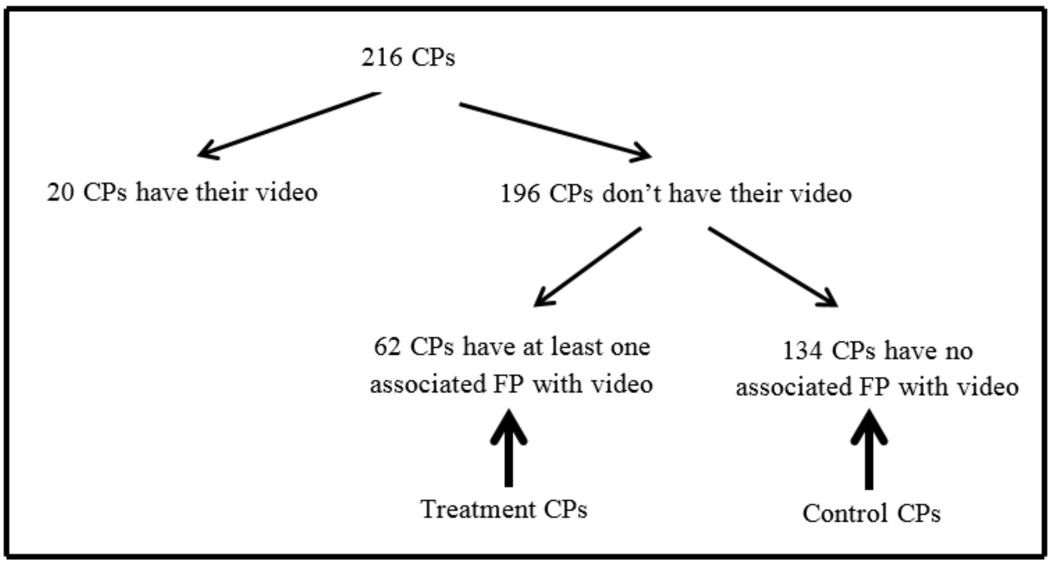

Figure 6: Selection of treatment and control products in the coordinating product analysis

A coordinating product may be associated with more than one focal product. For instance, a pair of sunglasses can appear as a coordinating product on the product pages of a top and a bottom with a video as well as on that of a set of earrings without a video. Out of a total of 807 product-weeks during which videos of focal products associated with a coordinating product were switched on, 594 product-weeks had one focal product video, 127 had two focal product videos, 32 had three focal product videos, 21 had four focal product videos, and 33 had more than four focal product videos, with a maximum of 10 videos. To accommodate such treatment of coordinating products with multiple focal product videos, we used the number of focal products with switched-on videos in a week as the treatment variable.

We used the same experimental setup shown in Figure 5 for the coordinating product analysis. We used specification (2) to estimate the effect of focal product videos on the sales of their coordinating products.

$$Sales_{jt} = \alpha_j + \alpha_t + \delta \sum Vidwk_{i_jt} + \boldsymbol{\beta}\, \boldsymbol{X_{jt}} + \boldsymbol{\gamma} \sum \boldsymbol{X}_{i_j\boldsymbol{t}} + \varepsilon_{jt}, \qquad (2)$$

where $j\epsilon\{1, 2, 3, \ldots \ldots 196\}$ denotes the 196 coordinating products (62 treatment and 134 control) and $t\epsilon\{1, 2, 3, \ldots \ldots T_j\}$ denotes the total number of weeks coordinating product *j* remains in our analysis out of the total 28 weeks of the study period.[16] Several focal products, $i_j\epsilon\{1, 2, 3, \ldots\}$, may be associated with *j*, some with videos and others without. On the left-hand side of specification (3), $Sales_{jt}$ denotes the sales of coordinating product *j* in week *t*. On the right-hand side of specification (3), $\sum Vidwk_{i_jt}$ denotes the number of focal products i_j that had their videos switched-on in week *t*. The control variable X_{jt} and the fixed-effects have the same meaning as in specification (1).

Variable X_{i_jt} includes the following: $Catwk_{i_jt}$ is equal to unity if focal product i_j features on the front or back cover of the catalogue and the week *t* falls in the two-week period immediately after 7-10 days from the catalogue drop dates and is zero otherwise; $Homepgwk_{i_jt}$ is equal to unity if focal product i_j features on the website's home page in week *t* and is zero otherwise; $Catpgwk_{i_jt}$ is equal to 1 if focal product i_j features on the category front page in week *t* and is zero otherwise; $Emailwk_{i_jt}$ is equal to unity if focal product i_j features in the e-mail in week *t* and is zero otherwise; and $Pricewk_{i_jt}$ is equal to unity if there has been a price markdown on focal product i_j in week *t* and is zero otherwise. The sum of each type of promotional indicator variable for all focal products in i_j in week *t* are computed and stacked in form of a column vector in variable $\sum \boldsymbol{X}_{i_j\boldsymbol{t}}$ in specification (2).[17]

[16] Note that a product drops out of our analysis for the period during which it is stocked out in the study period.
[17] If different promotions on focal products associated with coordinating product *j* in week *t* are - one focal product appears on catalogue front page, one focal product appears on home page, no focal product appears on category main pages or email, and two focal products are under price promotion - the column vector $\sum \boldsymbol{X}_{i_j\boldsymbol{t}}$ will be {1, 1, 0, 0, 2}.

Table 2: Parameter estimates for the coordinating product analysis

Dependent Variable (Sales in numbers)	Coefficient Estimates (Robust cluster-corrected Std. Errors)					
	(A)		(B)		(C)	
No. of focal product videos	12.34**	(5.61)	10.41**	(4.92)	11.58*	(6.12)
Coordinating product-related control variables						
Catalogue	103.05**	(50.29)	108.72**	(53.64)	123.09*	(70.77)
Website home page	64.63	(37.44)	61.29	(40.62)	71.29	(46.48)
Category front page	48.97**	(24.41)	52.68**	(24.57)	61.19*	(36.18)
Email promotion	70.97***	(28.46)	72.56***	(27.97)	76.31**	(32.54)
Price markdown	87.43***	(9.18)	87.99***	(7.25)	87.03***	(9.40)
Focal product-related control variables						
Catalogue	-9.03	(16.72)	-9.62	(11.39)	-15.21	(20.38)
Website home page	12.92	(14.71)	12.61	(17.53)	23.21	(18.83)
Category front page	2.83	(9.45)	2.85	(9.76)	8.13	(12.18)
Email promotion	7.07	(14.83)	2.73	(18.78)	29.33	(18.39)
Price markdown	-12.05	(7.85)	-10.41	(7.86)	-12.37	(7.91)
No. of product-weeks (No. of products)	4708 (196)		4370 (196)		4305 (196)	
R Square	0.70		0.69		0.68	

***, **, * = statistically significant at $\alpha = 0.01$, $\alpha = 0.05$, and $\alpha = 0.10$ levels (two-sided test), respectively. Columns A, B, and C, respectively, display the coefficient estimates for the full dataset, pre-treatment and switch-on-period data, and treatment switch-on and switch-off-period data only. The standard errors are cluster-corrected at the coordinating product level.

In Appendix A, we validate the random assignment of videos in our sample of coordinating products. In Appendix B, we check that the treatment effect in our experimental design is not identified solely due to differences in either the pre-existing mean weekly sales levels or the pre-existing weekly sales trends for the treatment and control products.

Table 2 reports coefficient estimates of specification (2) on the three datasets. In all three datasets, the coefficient estimates for the number of switched-on focal product videos are positive and statistically significant ($\alpha = 0.10$) in a two-tail test, which suggests that introducing an additional focal product video increases the weekly coordinating product sales by 12.34. However, the effect of focal product videos on coordinating product sales may not be linear, i.e., the effect may either increase or decrease with the introduction of more videos. To check for this possibility, we further estimated specification (2) with three ordinal indicator treatment variables for a coordinating product appearing in one, two, and more than two of its associated focal product videos in a week and found a positive estimate of 18.83 significant at ($\alpha = 0.05$) for the treatment indicator for one focal product video but insignificant estimates for other treatment indicators. This suggests that coordinating product sales increase by 18.83 (a

28.3 percent increase on the average weekly sales of 66.58 in the period without treatment) on introduction of their first focal product video but remain statistically similar on introduction of additional videos for their focal products. The comparable estimate with sales revenue as the dependent variable indicates additional weekly coordinating product sales revenues of US $ 203.63 (α = 0.01) on introduction of their first focal product video.

We acknowledge that the focal and coordinating product promotions may be endogenous in specification (2). However, we show in Appendix F that as long as the videos are assigned randomly, the endogeneity of the promotional variables does not bias the coefficient (δ) for *Vidwk* variable. We perform additional checks in Appendix D to ensure that our treatment effect estimates are robust to the possibility of endogeneity in promotions.

4.3 Direct and Spillover Effects of Video on Coordinating Product Sales

Our results thus far show that the introduction of videos results in increased focal and coordinating product sales. Because videos are hosted on the focal products' pages, customers watch them while considering purchasing the focal products. Therefore, an increase in the sales of focal products is simply the direct promotional effect of the videos. However, the estimated increase in the sales of associated coordinating products during the video switch-on period may be due to the following three reasons. First, a dynamic and more vivid display of a coordinating product in a video may allow customers to better evaluate its attributes that may result in increased sales, which is the *direct effect* of the video on coordinating product sales. Second, the joint display of a coordinating product in its associated focal product video could additionally reveal its complementarity with the focal product to customers. Such additional revealed complementarity may cause an additional correlation in the sales of focal and coordinating products and thus additional sales of coordinating products, which is the *spillover effect* of video on coordinating product sales. Third, any direct promotional effect of video during its switch-on period may increase the focal product sales and, in turn, increase the sales of associated coordinating products due to their latent complementarity. In the following paragraphs, we discuss the various factors that could lead to the correlation in sales of the two products and propose an econometric specification to tease out the additional correlation in their sales attributable to the video after controlling for the portion of the correlation that may be attributed to other factors.

The retailer selects coordinating products to jointly display in the still picture of one of its focal products (see Figure 1) based on a variety of factors, such as their matching colors/styles or similar contemporary appeal. Due to these factors, such focal and coordinating products are inherently (latently) complementary, which customers recognize even while seeing only one of the products, and therefore purchase these products together in a fixed proportion. Such co-purchase of related products due to their latent complementarity leads to a correlation in their sales. If a promotion is offered on one of the products, customers purchase higher quantities of the product on promotion and, consequently, higher quantities of its complement because of their latent complementarity. However, the correlation in sales of the related products remains unchanged on such promotions. For example, customers who, sans promotions, purchase 8 focal and 4 coordinating products would purchase 12 focal and 6 coordinating products with a promoted focal product.

The joint display of focal and coordinating products in still pictures could, however, lead to an additional correlation in their sales over the existing correlations from their latent complementarity for two reasons. First, if customers, even though aware of the complementarity between the two products, do not recall it when viewing only one of the products, the joint display of products in still pictures may help customers recall their complementarity, which may result in additional correlation in their sales. For this reason, related products, such as cake mix and cake frosting, are commonly grouped on a grocer's shelves. Second, the joint display of products in still pictures may help customers visualize how they would look in an ensemble and may additionally reveal their complementarity to customers and thus result in a higher correlation in their sales.[18]

[18] The possibility of customers recalling or learning about complementarity between related products from their joint display is more relevant in apparel-and-accessories networks, where large numbers of complementary apparel-accessories combinations are possible. The joint display of a combination from such a large number of possible combinations is likely to help customers recall

Because the joint display of focal-coordinating product combinations in still pictures remains constant throughout the study period, the effect of their latent complementarity and any recalled and/or revealed complementarity from their still pictures will apply for the whole period. In our experiment, we introduce video for a few randomly selected focal products for a portion of the total period. Thus, the effect of the additional visibility of focal and coordinating products in a video over their visibility in a still picture can be identified with specification (3).

$$Sales_{jt} = \alpha_j + \alpha_t + \delta_1 \sum Vidwk_{i_jt} + \delta_2 \sum Sales_{i_jt} + \delta_3 \sum (Vidwk_{i_jt} \times Sales_{i_jt}) + \boldsymbol{\beta} \boldsymbol{X_{jt}} + \boldsymbol{\gamma} \sum \boldsymbol{X}_{i_j\boldsymbol{t}} + \varepsilon_{jt}, \qquad \text{----- (3)}$$

where, $j\epsilon\{1, 2, 3, \dots \dots 196\}$ denotes the 196 coordinating products and i_j denotes the focal products associated with *j*. In specification (3), $Sales_{jt}$ denotes sales of *j* in week *t*. Because only a subset of focal products in i_j have videos on their product page, $Vidwk_{i_jt}$ is equal to one for only those focal products during the weeks when their videos are switched on, and $\sum Vidwk_{i_jt}$ denotes the number of switched-on videos of focal products associated with *j* in week *t*. $\sum Sales_{i_jt}$ denotes the sum of sales of all focal products associated with *j* in week *t*, but $\sum (Vidwk_{i_jt} . Sales_{i_jt})$ is the sum of sales of only those focal products associated with *j* whose videos are switched on in week *t*.

In specification (3), product fixed-effects α_j account for time-invariant unobserved product-related factors that may affect sales, and time fixed-effects account for all time-related unobserved factors that equally affect the sales of all coordinating products. The correlation in sales of the focal and coordinating products due to their latent complementarity, applicable at all times, would be captured in coefficient δ_2. If the joint display of these products in still pictures over the entire duration of the study causes any additional correlation in their sales because of recalled and revealed complementarity, it will also be captured in coefficient δ_2. Any time-varying unobserved shocks to the sales of either focal or

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the latent complementarity in the displayed combination. Moreover, because a large number of different accessories could be combined with a focal apparel, customers require visual cues to be able to visualize and thus determine the complementarity between different possible combinations.

coordinating products would increase its sales and, consequently, the sales of its complement due to their latent complementarity.[19] The sales of focal and coordinating products could be simultaneously affected due to a variety of unobserved factors other than their complementarity, such as co-incidence in their purchase cycles (Manchanda et al. 1999). Omission of such unobserved factors and demand shocks would make $\sum Sales_{i_j t}$ endogenous and thus could lead to biased estimates of coefficients in specification (3).

Table 3: Direct and spillover effects of product video

Dependent Variable [Weekly CP sales in numbers]	Coefficient Estimates (Robust Cluster Corrected Std. Errors)	
	Analysis with promotional variables	Analysis without promotional variables
Number of focal product video (δ_1)	0.30 (5.92)	-1.25 (5.49)
Associated focal products weekly sales (δ_2)	0.06** (0.03)	0.07** (0.03)
Associated focal products weekly sales in video switch-on period (δ_3)	0.04** (0.02)	0.04** (0.02)
No. of product-weeks (No. of products)	4708 (196)	4708 (196)
R Square	0.72	0.71

***, **, * = statistically significant at α = 0.01, α = 0.05, and α = 0.10 levels (two-sided test), respectively.
The standard errors are cluster-corrected at the coordinating product level.

Moreover, estimation of the system of equations in specification (3) poses simultaneity issues because the dependent variable in one equation is part of an independent variable in the second equation, and the dependent variable in the second equation is part of an independent variable in the first equation. For instance, suppose a pair of pants as a coordinating product has a top as one of its associated focal products and that the top as a coordinating product, in turn, has the pair of pants as one of its associated focal products.[20] This simultaneity may lead to biased estimates for the coefficient in specification (3). We show in Appendix F that as long as videos are randomly assigned, the omitted unobserved shocks and simultaneity issues lead to a biased estimate for the coefficient of the endogenous sales variable (δ_2), but it does not lead to bias in either the coefficient of video variable (δ_1) or the coefficient of its interaction with the endogenous sales variable (δ_3) in specification (3).

[19] An example of such unobserved shock to the demand of a focal product could be a celebrity wearing the product (or a similar product) in the Oscar awards ceremony.
[20] In the present setup, none of the coordinating products have all bidirectional links with their associated focal products, i.e., at least one associated focal product does not appear as a coordinating product on the product page of the coordinating product.

In Appendix F, we further show that any endogeneity of the promotional variables would not bias the video-related coefficients. If the videos merely promote the sales of focal products and, consequently, the sales of coordinating products due to their latent complementarity, such correlation in their sales will be captured in coefficient δ_2. Therefore, after controlling for the effects of their latent complementarity, any recalled/revealed complementarity due to their display in still pictures and other unobserved factors that could promote their purchase together, coefficient δ_3 estimates the spillover effect and coefficient δ_1 estimates the direct effect of videos on coordinating product sales.

Table 3 reports the coefficient estimates for specification (3) with and without the promotional control variables. Because endogeneity of promotional variables is not expected to bias the coefficients of video-related variables, we find qualitatively similar estimates for them in the two cases in Table 3. We find a positive and significant estimate for the spillover effect and an insignificant estimate for the direct effect due to videos. The ratio of δ_3 to (δ_3+ δ_2) [0.4 / (0.4+0.6)] indicates that 40 percent of the total correlation between sales of focal and coordinating products during the video switch-on period can be attributed to the spillover effect of videos.

Because our analysis is at a product level and not a customer order level, the estimated additional correlations in sales of focal and coordinating products could come from one set of customers buying higher quantities of coordinating products and a different set of customers buying higher quantities of associated focal products during the video switch-on period. However, because we introduced and removed videos in three phases, the possibility of different sets of customers buying different categories of products in three different video switch-on periods is highly unlikely. Therefore, after controlling for and falsifying the other possible explanations for the spillover effect, a plausible cause of this effect is that joint product display in videos additionally reveals complementarity between focal and coordinating products to customers over and above what is revealed from their joint display in still pictures. To examine this possibility, we compare the display formats of videos and still pictures.

In a product video, a human model walks around and provides a dynamic, high-definition, 360 degree view of the focal product with matching coordinating products, accompanied by background music. In addition, the video provides zoom in/out, pause/replay/forward, and sound adjustment controls to customers. Thus, as discussed in Section 2, videos provide a more vivid and interactive presentation of products compared to the still pictures that could offer customers a virtual product experience similar to a physical shopping environment. Such virtual product experience may allow customers to not only better evaluate the attributes of individual products but also visualize and thus better evaluate how these products will fit, look, and function together. Thus, our estimated additional correlation in sales of focal and coordinating products during video switch-on period suggests that customers additionally learn about the complementarity between them from their joint display in videos.

Because videos are placed on the focal products' pages, customers watch them while exploring the focal products and are thus more likely to independently evaluate focal rather than coordinating products in such videos. This could be a possible reason for our estimated insignificant direct effect of product videos on coordinating product sales. If this argument is true, we should see a significant direct effect of product videos on focal product sales. To check this fact, we estimate specification (3) with focal product sales as a dependent variable and the sum of sales of their associated coordinating products as the independent variable. We find positive and significant estimates for coefficient δ_2 [0.07 significant at $\alpha = 0.01$] and δ_3 [0.01 significant at $\alpha = 0.05$] indicating a positive correlation between sales of focal and coordinating products during the period without videos and an additional correlation due to the spillover effect during the period when videos were switched on, respectively. However, we also find a positive and significant estimate for coefficient δ_1 [11.67 significant at $\alpha = 0.05$], which indicates that the introduction of video causes a substantial and significant direct effect on focal product sales.[21] This result suggests that the joint display of related products may independently affect their individual sales in addition to the correlation between their sales. Therefore, it is important to identify both direct and

[21] Note that the magnitude of the direct effect (11.7) comprises a large portion of the total effect (16.7) of video on focal product sales estimated from specification (1).

spillover effects to fully understand the impact of the joint visibility of related products in a product network.

4.4 The Moderating Effect of Promotions on Product Video Effects

The introduction of product videos results in increased focal and coordinating product sales. A related managerial question is whether combining different promotions with product videos could further increase returns on videos. To answer this question, we extend specifications (1) and (2) to include the interaction terms for product videos with their promotions and, therefore, estimate the following specifications (4) and (5).

$$Sales_{it} = \alpha_i + \alpha_t + \delta_1 \, Vidwk_{it} + \boldsymbol{\beta} \, \boldsymbol{X_{it}} + \delta_2 \, (\boldsymbol{X_{it}} \times Vidwk_{it}) + \varepsilon_{it}, \qquad \text{-------------- (4)}$$

$$Sales_{jt} = \alpha_j + \alpha_t + \delta_1 \sum Vidwk_{i_jt} + \boldsymbol{\beta} \, \boldsymbol{X_{jt}} + \boldsymbol{\gamma} \sum \boldsymbol{X_{i_jt}} + \delta_2 \, (\boldsymbol{X_{jt}} \times \sum Vidwk_{i_jt}) + \delta_3 \sum (Vidwk_{i_jt} \times \boldsymbol{X_{i_jt}}) + \varepsilon_{jt}, \qquad \text{------------- (5)}$$

where, all terms in specification (4) have the same meaning as in specification (1) except for the added terms for interactions between video ($Vidwk_{it}$) and focal product promotions ($\boldsymbol{X_{it}}$). Similarly, all terms in specification (5) have the same meaning as in specification (2) except for the added interaction terms for the number of videos ($\sum Vidwk_{i_jt}$) with focal product promotions ($\boldsymbol{X_{i_jt}}$) and with coordinating product promotions ($\boldsymbol{X_{jt}}$). Although the focal and coordinating product promotions could be endogenous in specifications (4) and (5), we show in Appendix F that as long as the videos are assigned randomly, the coefficients for the video variable and its interaction with endogenous promotions are unbiased. Therefore, coefficients δ_1 and δ_2 in specification (4), respectively, capture the unbiased effects of only videos and videos with focal product promotions on the focal product sales. Similarly, coefficients $\delta_1, \delta_2, \delta_3$ in specification (5), respectively, capture the effects of only videos, videos with coordinating product promotions, and videos with focal product promotions on coordinating product sales.

Table 4: Moderating effect of promotions on the product video effects

Dependent Variable (Sales in numbers)	Coefficient Estimates (Robust cluster corrected Std. Errors)	
	Focal product analysis	Coordinating product analysis
Product video variable	10.89** (5.06)	11.61** (5.05)
Coordinating product promotions		
Catalogue		103.37** (51.43)
Website home page		63.99* (37.21)
Category front page		49.83** (24.05)
Price markdown		89.82*** (9.72)
Email promotion		72.50*** (28.14)
Product video x price markdown		-5.66 (17.11)
Focal product promotions		
Catalogue	103.45** (48.80)	-9.64 (13.25)
Website home page	62.86*** (15.69)	13.72 (19.90)
Category front page	12.08 (21.28)	-9.60 (8.06)
Price markdown	68.02*** (8.35)	-1.34 (5.38)
Email promotion	69.70* (43.59)	-3.98 (16.67)
Product video x home page		-2.55 (30.01)
Product video x category front page	70.18** (35.84)	31.75 (24.18)
Product video x price markdown	60.40** (27.79)	-19.64 (20.15)
No. of product-weeks (No. of products)	6828 (297)	4708 (196)
R Sq	0.56	0.71

***, **, * = statistically significant at α = 0.01, α = 0.05, and α = 0.10 levels (two-sided test), respectively.
The standard errors are cluster-corrected at the product level.

To identify the coefficients of interaction terms in specifications (4) and (5), we require a sufficient number of observations in our data when product videos are applied with other promotions. For the 6,828 product-weeks of observations in our focal product analysis, videos were used along with price markdowns for 57 product-weeks, with category front page promotions for 22 product-weeks, and with other promotions for less than 10 product-weeks. For the 4,708 product-weeks of observations in the coordinating product analysis, videos were used with coordinating products' price markdowns for 66 product-weeks, with focal products' home page promotions for 52 product-weeks, with focal products' category front page promotions for 129 product-weeks, with focal products' price markdowns for 67 product-weeks, and with all remaining focal and coordinating product promotions for less than 10 product-weeks. Therefore, in specifications (4) and (5), we include the interaction terms for only those promotions that were applied for at least more than 20 product-weeks with video.[22] The estimated coefficients are reported in Table 4.

The coefficients in Table 4 reveal a higher return of video with promotions on focal product sales but statistically similar returns on coordinating product sales. Specifically, comparisons of coefficients of interaction terms and product videos indicate that introducing a focal product video with its price markdown or with its promotions on the category front page results in, respectively, seven or eight times higher returns over the returns from introducing only video.

4.5 Cost-Benefit Analysis of Product Video

Thus far, we have highlighted the benefits of introducing product videos in terms of increased focal and coordinating product sales. We now discuss the costs incurred in creating such videos and hosting them on the retailer's website. The retailer created 66 videos by employing several models for $2,000 and a photographer for $1,200 (8 hours per day for 3 days at $50 per hour). These videos were then edited by an in-house graphic designer for $500 (25 hours at $20 per hour). To host these videos on the website, the firm used an additional 300 gigabytes of bandwidth for $1,800 (300 gigabytes per month for six months of spring collection sales at the rate of $1 per gigabytes). Thus, the total expense to the retailer to create, edit and host 66 videos in the spring collection sale was $5,500. If we account for the time taken out of their regular working hours by the retailer's other office employees to oversee the video creation, the total cost incurred by the retailer is less than $7,000.

The videos for 66 focal products (having an average price of $19.90) were switched on for 774 product weeks. With estimated average additional sales of 16.7 per week, this translates into an additional $19.9 x 16.7 x 774 =$257,223 in focal product sales revenue. Similarly, 62 coordinating products (having an average price of $12.47) had the videos of their focal products switched on for 1,209 product-weeks. With estimated average additional sales of 12.34 per week, this translates into an additional $12.47 x

[22] We find qualitatively similar results by including the interaction terms between videos and those promotions that were applied for less than 20 product-weeks with videos.

12.34 x 1209 = $186,041 in coordinating product sales revenue. Therefore, the introduction of videos leads to an additional revenue of $443,264. If we assume a 10% profit margin, this translates into $44,000 in profit at an additional cost of less than $7,000 to introduce these videos – a profit of more than six times the cost to the retailer.[23]

4.6 Robustness Checks

Our estimated positive treatment effect of product videos may partially come from customers substituting their demand for the control products with the treated products. For example, upon the introduction of a product video for a dress, consumers may shift their choice from dresses without videos to the dress for which video was introduced. If all gains in sales of treated products come at the expense of loss in sales of control products, the net value of videos for the retailer would be close to zero. We examined this possibility in Appendix E and found no evidence of a decrease in sales of control products during the period when videos for treated products are switched on, indicating that the estimated increase in sales of treated products is not at the expense of a loss in sales of control products.

We also conducted our focal and coordinating product analyses on data from only pre-video and video switch-off periods, with a placebo treatment assigned to the treated products in the video switch-off period. We found insignificant placebo treatment estimates of 19.07 (standard error = 15.80) and -15.80 (standard error = 26.46) for the focal and coordinating product analyses, respectively. These insignificant estimates indicate that the sales of treated and control products are statistically similar in the periods without treatment, i.e., pre-video and video switch-off periods. This result not only supports the validity of our control products but also shows a lack of evidence for the persistence of the treatment effect of videos after they are switched off.

We further tested the robustness of our empirical results by using different subsets of our total data and control variables. Specifically, we found that our results are robust to: (1) dropping data on

[23] To protect its identity, the exact profit margin of the retailer are not disclosed. The assumed profit margin of 10% is representative of the fashion apparel industry.

products that were stocked-out in the middle of our study period, (2) dropping data for the last four weeks of the study period when prices were marked down for a large number of accessories[24], (3) only using a subset of control variables, and (4) using the log of weekly number of sales as dependent variables.

5.0 Conclusions

Ecommerce websites are increasingly using online videos to jointly advertise related products, but there is little guidance on how such product displays influence product demand. We conducted a randomized experiment on the live website of a mid-sized US fashion retailer to empirically answer this question. Specifically, we found that introducing a video on the focal product's page resulted in a 14.5 percent increase in focal product sales and a 28.3 percent increase in associated coordinating product sales. We further found that a substantial portion of this increase in coordinating product sales was due to the additional correlation in sales of the two products during the video switch-on period. These empirical findings are consistent with the literature on virtual product experience that suggests that the joint display of products in videos allows customers to learn about the products' complementarity. We further found a substantially higher effect of product videos on focal product sales when they are used with other focal product promotions, such as price markdowns and preferential display on category front pages. Additionally, we conducted a cost-benefit analysis of product videos in our field setup and found that the benefits of videos are six times the cost of introducing them. We highlight the economic value of introducing product videos on the website of a fashion apparel and accessories retailer.

Our study has direct managerial implications for multiproduct E-retailers who use videos to jointly advertise complementary products on their websites. First, our study provides the actual costs and benefits of introducing product videos in a real-life setting and thus helps managers evaluate their relative efficacy against other available methods of advertising products. Second, our study provides estimates on relative benefits to the sales of principal products and accessories due to their joint display in online

[24] We lost a large portion of the treatment switch-off period data and were thus unable to analyze treatment switch-on and switch-off period data.

videos. These insights can help managers decide how to group products in online videos to optimize their overall sales revenue. Third, our results indicate that videos help customers learn about the complementarity between principal products and accessories, which creates additional spillovers in product demand. This insight can be used to boost the sales of slow-moving accessories by jointly displaying them with popular principal products in online videos. Fourth, our results inform managers that combining product videos with other promotions can increase the sales of displayed products. Managers can use this insight to combine different elements of the marketing mix with videos to maximize their effect on product sales.

The present research is not without limitations. First, the aggregate sales data limits the analysis in several ways. There is an outside possibility that our results of increased aggregate focal and coordinating product sales may stem from different sets of customers buying these products. A more nuanced analysis of effects of joint display on demands of interrelated products on consumer-level data is required to gain further insight. Second, due to data limitations, we could only examine the moderating effect of a few promotions on product video effect. Future research on this topic can provide guidance to managers on the relative gains of combining different elements of the marketing mix with product videos. Most websites pre-decide the products that they will display jointly in videos. The benefits of online videos can be further leveraged by allowing consumers to match a focal product with various accessories and then watch a video of their selection of products. Estimating the impact of offering such control to customers to personalize their product bundle on product sales is another promising area of future research. Moreover, the retailer can use such collected data on consumer preferences for different focal product – accessory combinations to drive the products' overall sales. Another related research path would be to examine how the estimated correlation in the demands of jointly displayed products can inform inventory decisions.

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Online Appendix for "The Demand Effects of Joint Product Advertising in Online Videos"

Appendix A: Validating Integrity of Randomization

If videos are randomly assigned, we expect that: (1) the allocation of video in the full sample is proportionately transmitted to the subcategories of products (tops, dresses, bottoms, and auxiliary products) and (2) the mean characteristics of the treated and untreated products are statistically similar.

Table A1: Proportional transmission of treatment in product subcategories

Analysis	No. of treated products	Product subcategory	Percentage of treated products	95% CI for percentage treated products
Focal product analysis [297 Principal Products]	Yes -58 (19.5%)	Top (194)	40/194 (20.6%)	[13.9% - 25.1%]
		Bottom (15)	2/15 (13.3%)	[(-0.5%) - 39.6%]
	No - 239	Dress (88)	16/88 (18.2%)	[11.2% - 27.8%]
Coordinating product analysis [196 Products]	Yes - 62 (31.6%)	Top (43)	12/43 (27.9%)	[17.73% - 45.53%]
		Bottom (13)	6/13 (46.2%)	[6.35% - 56.91%]
	No - 134	Dress (20)	4/20 (20%)	[11.25% - 52.01%]
		Aux. Prod. (120)	40/120 (33.3%)	[23.31% - 39.95%]

If *p* denotes the proportion of video treated products in the full sample and *n* denotes the sample size of a subcategory, then the 95 percent CI for percentage of treated products in a subcategory = p +/- 1.96 x SQRT [p x (1-p)/n].[25] For example, for tops with n=194 and p=0.195, the 95% CI is [13.9% - 25.1%]. Table A1 reports the computed 95 percent CI for all product subcategories in the focal and coordinating product analyses, which shows that the observed percentage of treated products for each subcategory falls within its corresponding 95 percent CI indicating proportional transmission of video treatment from the full sample to different subcategories of products

Table A2: Proportional transmission of treatment for products with/without coordinating products

	No. of products having coordinating products	No. of treated products	Percentage of products with/without coordinating products	95% CI for percentage of products with /without coordinating products
297 Principal Products	Yes - 264/297 (88.9%)	Yes - 58/297	54/58 (93.1%)	[80.8% - 96.9%]
	No - 33/297	No - 239/297	210/239 (87.9%)	[84.8% - 92.9%]

[25] For using normal approximation of the error term of binomial distribution, we checked that n p>5 and n (1-p)>5 in each case.

Similarly, in Table A2, we found that the observed percentages of treated and control products having coordinating products are within the computed 95 percent CI, which shows the proportional transmission of treatment in products with and without coordinating products. Next, we found that the mean prices for the treated and control products are statistically similar for the sample of products in the focal and coordinating product analyses. Table A3 reports these results.

Table A3: Differences in prices of treated and control products

Analysis	Product type	Number	Mean	St. Dev.	Min	Max	*t-value* (Critical *t-value*)*
Focal product	Treated	58	20.39	4.74	7.9	34.9	-0.45 (12.70)
	Control	239	20.71	5.25	12.9	39.9	
Coordinating product	Treated	62	12.34	9.38	6	39.9	-0.02 (12.70)
	Control	134	12.37	7.84	6	29.9	

* The *t-values* are computed by Welch's t-test for unpaired groups with unequal sample sizes and variances. The critical *t-value* is read from the t-distribution table corresponding to degrees of freedom and two sided 95 % confidence interval.

Appendix B: Testing Ignorability of Treatment Assumption

The ignorability of treatment assumption requires that the treatment is not systematically assigned. Although random assignment of product videos in our case should satisfy this condition, nonetheless, we further check that the sales of treated and control products are statistically similar without videos. We consider three groups of treatment focal products: 1st treatment group →19 products for which videos were introduced between week 6-week 16; 2nd treatment group → 32 products for which videos were introduced between week 11-week 21; and 3rd treatment group →7 products for which videos were introduced between week 19-week 27. The control products in a week are those products that do not have their videos switched on in that week. For example, in week 10, all products in 1st treatment group are treatment products and all products that are left out of video assignment as well as the 2nd and 3rd treatment group products, as their videos are not switched on in this duration, are the control products. On similar lines, we consider three groups of treatment products in the coordinating product analysis. For example, 1st treatment group of coordinating products are the ones associated with the 1st treatment group of focal products. Table B1 reports the summary statistics for the three groups of treatment products in pre-video, video switch-on, and switch-off periods with their corresponding control products.

Table B1: Treatment group-wise summary statistics

Weekly sales in numbers	Focal Product				Coordinating Product			
	No. of product-weeks	Mean	Std. Dev.	*t-value* (critical *t-value*)*	No. of product-weeks	Mean	Std. Dev.	*t-value* (critical *t-value*)
Pre-video period (Wk 1- Wk 5)								
1st Treat Gr.	75	133.8	162.3	0.95	140	93.92	209.72	1.37
Control Gr.	704	115.64	103.28	(1.99)	681	69.23	76.93	(1.98)
Video Switch-on period (Wk 6- Wk 16)								
1st Treat Gr.	250	159.84	256.93	2.41	320	119.11	266.57	3.9
Control Gr.	2439	120.14	127.8	(1.97)	1564	60.24	97.83	(1.96)
Video Switch-off period (Wk 17- Wk 28)								
1st Treat Gr.	134	111.04	230.84	0.69	210	64.11	157.17	1.13
Control Gr.	2890	97.27	94.67	(1.97)	1393	51.68	66.79	(1.97)
Pre-video period (Wk 1- Wk 10)								
2nd Treat Gr.	243	119.9	119.93	-0.15	208	69.10	79.19	-0.89
Control Gr.	2177	121.16	127.16	(1.96)	1604	74.57	109.60	(1.96)
Video Switch-on period (Wk 11- Wk 21)								
2nd Treat Gr.	316	111.92	119.05	2.42	329	77.64	66.20	2.28
Control Gr.	2105	94.67	116.81	(1.96)	1158	66.90	101.35	(1.96)
Video Switch-off period (Wk 22- Wk 28)								
2nd Treat Gr.	200	100.36	101.47	1.43	125	41.27	38.03	-0.35
Control Gr.	1463	89.55	93.44	(1.97)	769	42.82	79.56	(1.96)
Pre-video period (Wk 1- Wk 18)								
3rd Treat Gr.	93	126.77	150.92	0.7	55	56.37	50.24	-2.2
Control Gr.	3767	115.7	123.7	(1.99)	2575	71.94	104.93	(1.99)
Video Switch-on period (Wk 19- Wk 27)								
3rd Treat Gr.	74	123.53	96.69	3.11	138	58.09	23.41	0.73
Control Gr.	2088	87.84	102.51	(1.99)	1146	55.68	88.59	(1.96)
Video Switch-off period (Wk 28)								
3rd Treat Gr.	7	69.14	50.01	0.52	3	36.33	9.29	-0.5
Control Gr.	233	59.21	47.28	(2.44)	132	39.74	47.57	(2.57)

* The *t-values* are computed by Welch's t-test for unpaired groups with unequal sample sizes and variances. The critical *t-value* is read from the t-distribution table corresponding to the degrees of freedom and two sided 95 % confidence interval.

In Table B1, we also report the *t-value* and the critical *t-value* for the difference in means of treatment and control products in each period. A *t-value* higher than critical *t-value* for a pair of treatment and control products indicates statistically different mean weekly sales for the two. For both focal and coordinating products, we mostly find statistically similar mean weekly sales for the treatment and control products in pre-video and video switch-off periods indicating the similarity of the two groups in absence of video treatment. But we find a significantly higher sales for the treatment products during their video switch-on period as compared to the control products.

We examined the differential trends in weekly sales for the three groups of treatment products during the period when their videos are switched-on from the average seasonality for control products with the following specification

$$Sales_{it} = \alpha_i + \alpha_t + Treat1 \times \alpha_t + Treat2 \times \alpha_t + Treat3 \times \alpha_t + \boldsymbol{\beta} \times \boldsymbol{X_{it}} + \varepsilon_{it}, \qquad \text{------ (B1)}$$

where, *Treat1*, *Treat2*, and *Treat3* are, respectively, the indicator variables for the 1st, 2nd, and 3rd treatment groups. All other terms have the same meaning as in our specification (1). The 28 weekly coefficients for $Treat1 \times \alpha_t$, $Treat2 \times \alpha_t$, and $Treat3 \times \alpha_t$ capture the deviations of weekly sales of the 1st, 2nd, and 3rd treatment group products from the average seasonality in weekly sales (captured by week fixed effect α_t), respectively.

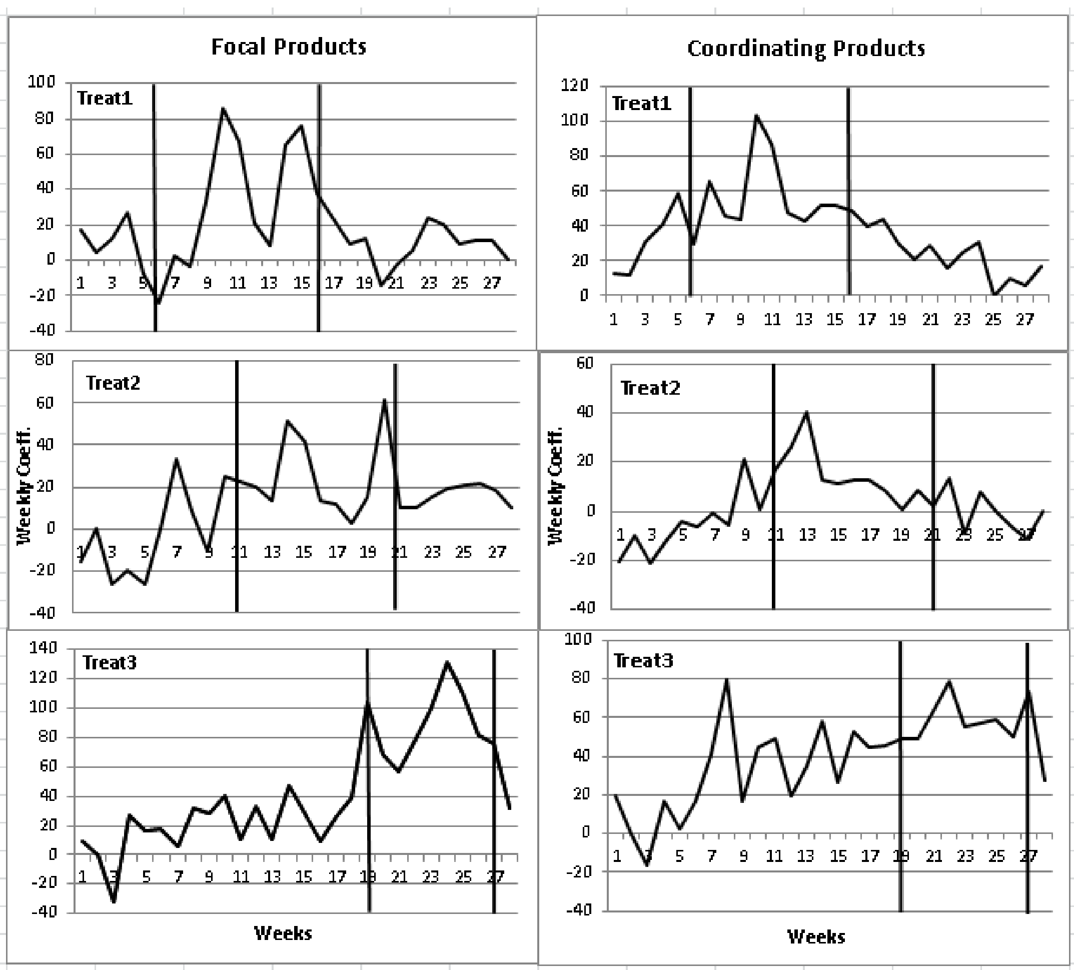

Figure B: Weekly sales trends for different groups of treatment products

We plot the weekly coefficients for the three treatment groups for focal products in the left pane of Figure B. Similarly, we estimated the weekly coefficients for the three treatment groups for coordinating products and plot them in the right pane of Figure B. In Figure B, we use two vertical lines to demarcate the period when the focal products' videos were switched on. For all treatment groups for both focal and coordinating products, we find a higher average weekly coefficient values in the video treatment period as compared to the period without treatment. We also find that the values of weekly coefficients decrease after the videos are switched off for all treatment groups.

Table B2: Estimates with differential sales trends for the treated and control products

Dependent Variable (Weekly sales in numbers)	Coefficient Estimates (Robust Cluster Corrected Std. Errors)			
	Focal products analysis		Coordinating product analysis	
Product video	14.01^{**} (6.42)	11.04^{**} (5.01)	10.44^{**} (5.21)	7.45^{**} (3.70)
Treat 1. Linear time trends	1.52 (1.07)	3.56 (4.39)	-1.54 (1.09)	2.21 (2.55)
Treat 2. Linear time trends	1.13 (0.72)	2.30 (4.65)	0.25 (0.46)	2.75 (2.54)
Treat 3. Linear time trends	2.82^{*} (1.66)	16.59 (12.02)	1.31^{*} (0.78)	5.49^{**} (2.45)
Treat 1. Square time trends		-0.07 (0.15)		-0.13 (0.11)
Treat 2. Square time trends		-0.04 (0.14)		-0.08 (0.08)
Treat 3. Square time trends		-0.39 (0.34)		-0.13 (0.09)
No. of product-weeks (No. of products)	6828 (297)	6828 (297)	4708 (196)	4708 (196)

***, **, * = statistically significant at α = 0.01, α = 0.05, and α = 0.10 levels (two-sided test), respectively. The standard errors cluster corrected at the product level.

Next, we checked that the estimated treatment effect in our difference-in-difference specification is not due to pre-existing differential sales trends in the treatment and control products with the following specifications (B2) for the focal product analysis.

$$Sales_{it} = \alpha_i + \alpha_t + \delta_1 \, Vidwk_{it} + \delta_2 \, Treat1 \times t + \delta_3 \, Treat2 \times t + \delta_4 \, Treat3 \times t + \delta_5 \, Treat1 \times t^2 + \delta_6 \, Treat2 \times t^2 + \delta_7 \, Treat3 \times t^2 + \boldsymbol{\beta} \, \boldsymbol{X_{it}} + \varepsilon_{it}, \qquad \text{----- (B2)}$$

where, t= 1,2,3, …. 28 and α_t denote weeks the time fixed-effects, respectively. In this specification, coefficients δ_2, δ_3, and δ_4 account for the differential linear time trends and δ_5, δ_6, and δ_7 capture the differential quadratic time trends for the three groups of treated products, respectively. Thus coefficient δ_1 in this specification estimates the net gain in sales of the treated products due to the introduction of videos after controlling for the differential time trends in sales for the treated and control products. We ran similar specification for the coordinating product analysis and report the coefficient estimates for the two analyses in Table B2. We found qualitatively similar treatment effect coefficients indicating the robustness of our results.

Appendix C: Effect of Stocked-out Products

If the random assignment of videos in the full sample is proportionately transmitted to the products that are stocked out and products that are not stocked out, it indicates that the probability of stock out is not systematically different for the treated and control products. Therefore, we performed a similar integrity check on randomization as in Appendix A, and found that the observed proportions of stocked-out treated and control products fall within their computed 95 percent CI indicating equal probability of stock out for the treated and control products.

Table C1: Stock-out probabilities

Analysis	No. of stocked-out products	No. of treated products	Percentage of stocked-out products	95 percent CI for percentage of stocked-out products
Focal products analysis	Yes 53/297 (17.9%)	Yes 58/297	11/58 (18.9%)	[7.9% - 27.7%]
	No 244/297	No 239/297	42/239 (17.6%)	[13.0% - 22.7%]
Coordinating products analysis	Yes 25/196 (12.8%)	Yes 62/196	5/62 (8.1%)	[4.4% - 21.1%]
	No 171/196	No 134/196	20/134 (14.9%)	[7.1% - 18.4%]

We further conducted focal product analysis for only those products that were not stocked-out, and found qualitatively similar treatment effect estimates as shown in Table C2. This further reassures us that our results are not due to systematic differences in attrition rates of treated and control products.

Table C2: Estimates for only stocked-out products

Dependent Variable (Weekly sales in numbers)	Coefficient Estimates (Robust Cluster Corrected Std. Errors)	
	Focal products analysis for full sample of products	Focal product analysis for products that are not stocked-out
Product video	16.70** (8.02)	12.27** (6.05)
Catalogue	103.80** (48.95)	106.44** (51.08)
Website home page	61.08*** (15.53)	55.19*** (17.06)
Category front page	29.44 (20.90)	18.51 (20.31)
Price markdown	76.62*** (8.75)	83.43*** (11.03)
Email promotion	68.91* (41.75)	70.06 (45.59)
No. of product-weeks (No. of products)	6828 (297)	5944 (244)
R Square	0.56	0.48

***, **, * = statistically significant at $\alpha = 0.01$, $\alpha = 0.05$, and $\alpha = 0.10$ levels (two-sided test), respectively.
The standard errors are cluster corrected at the product level.

Appendix D: Effect of Promotional Control Variables

The retailer may systematically promote products with video to derive maximum benefit, which would make the promotion related control variables endogenous in our specifications. We ran specifications (D1) to check whether the retailer offered statistically different promotions to the treated products during their video switch-on period

$$Prom_{it} = \alpha_i + \alpha_t + \beta\, Vidwk_{it} + \varepsilon_{it}, \qquad \text{------- (D1)}$$

where, $Prom_{it}$ denotes the number of promotions offered on product i in week t. We used the number of non-price and price promotions separately in specification (D1). The number of non-price promotions for product i in week t is the sum of indicator variables $Homepgwk_{it}$, $Catpgwk_{it}$, $Catwk_{it}$, and $Emailwk_{it}$ as described in specification (1). The number of price promotion is one if the product i gets a price markdown in week t, and 0 otherwise. All other variables have the same meaning as in specification (1). A positive and significant estimate of β would indicate a higher number of promotions for the treated products in the video switch-on period. We found insignificant estimates of β for both non-price promotions [-0.028 (Std. Err. 0.022) and 0.002 (Std. Err. 0.02)] and price promotions [0.029 (Std. Err. 0.026) and -0.007 (Std. Err. 0.01)] for the focal and coordinating products, respectively. Thus we fail to find evidence for statistically different promotions for the treated products during their video switch-on period.

To further show that our estimated treatment effect is not merely due to the endogenous promotion variables, we estimated the treatment effect on a sample of only those treated and control products that were not exposed to any promotions. But before that, we verify the random assignment of videos in the sample of products that received no promotions. The results in Table D1 show that the proportion of video allocation in the full sample of non-promoted products and in the various subcategories of products in this sample are statistically similar.

Table D1: Randomization check

Analysis	Video assignment	Product subcategory	Percentage of treated products	95% CI for percentage of treated products
Focal product analysis [152 Principal Products]	Yes -22 (14.5%)	Top (99)	13/99 (13.1%)	[7.5% - 21.4%]
		Bottom (10)	1/10 (10.0%)	[(-7.3%) - 36.3%]
	No - 130	Dress (43)	8/43 (18.6%)	[3.9% - 24.9%]
Coordinating product analysis [66 Products]	Yes - 21 (31.8%)	Top (21)	3/21 (14.3%)	[11.9% - 51.7%]
		Bottom (11)	5/11 (45.5%)	[4.3% - 59.3%]
	No - 45	Dress (8)	0/8 (0%)	[-0.4% - 64.1%]
		Aux. Prod. (26)	13/26 (50%)	[13.9% - 49.7%]

We then ran specifications (1) and (2) on the sample of products that received no promotions and report the coefficient estimates in Table D2. Table D2 shows qualitatively similar video coefficients (magnitude and statistical significance) for the sample of products that received no promotions and the full sample of products.

Table D2: Parameter estimates for products that received no promotion

Dependent Variable (Weekly sales in numbers)	Coefficient Estimates (Robust Cluster Corrected Std. Errors)			
	Focal product analysis		Coordinating product analysis	
	All products	Products without promotion	All products	Products without promotion
Product video	16.70^{**} (8.02)	18.54^{**} (8.34)	12.34^{**} (5.61)	13.12^{**} (6.47)
No. of Product-weeks (No. of products)	6828 (297)	3480 (152)	4708 (196)	1498 (66)

$^{***}, ^{**}, ^{*}$ = statistically significant at $\alpha = 0.01$, $\alpha = 0.05$, and $\alpha = 0.10$ levels (two-sided test), respectively.

Next, in Table D3, we compared the treatment effect estimates from specifications (1) and (2) with and without the promotional control variables. We find that in all cases, the point estimates of the treatment coefficient are similar (in magnitude as well as significance), which assures us that our treatment estimates are robust to the endogeneity of promotional control variables.

Table D3: Treatment effect of product videos with and without control variable

Dependent Variable (Weekly sales in numbers)		Product Video Coefficient Estimates (Robust Cluster Corrected Std. Errors)		
		(A)	(B)	(C)
Focal product analysis	With control variables	16.70^{**} (8.02)	23.55^{**} (9.81)	17.47 (10.11)
	Without control variables	16.82^{**} (8.39)	22.54^{**} (10.24)	18.82 (13.48)
Coordinating product analysis	With control variables	12.34^{**} (5.61)	10.41^{**} (4.92)	11.58^{*} (6.12)
	Without control variables	11.48^{**} (5.25)	9.54^{**} (4.46)	11.97^{*} (6.89)

$^{***, **, *}$ = statistically significant at $\alpha = 0.01$, $\alpha = 0.05$, and $\alpha = 0.10$ levels (two-sided test), respectively. Columns A, B, and C, respectively, display the coefficient estimates for the full dataset, pre-treatment and switch-on-period data, and treatment switch-on and switch-off-period data only. The standard errors are cluster corrected at the product level

Appendix E: Substitution Effect of Product Video

The customers may simply shift their demands of control products to the treated products after watching their videos. If this is the case, then introduction of product videos does not result in an overall increase in product demands and hence not beneficial for the retailer. We ran the following interrupted time series specification (E1) on 239 control products in our focal product analysis to check for this possibility

$$Sales_{it} = \alpha_i + \alpha_t + \delta_1\, t + \delta_2\, Wkvid_t + \delta_3\, t \times Wkvid_t + \boldsymbol{\beta}\, \boldsymbol{X_{it}} + \varepsilon_{it} \;, \qquad \text{-- (E1)}$$

where, $t = \{1, 2, 3, \ldots 28\}$ denotes the weeks; *Wkvid* is an indicator variable equal to one during week 6-week 21 when the majority of videos are introduced on the retailer's website, and zero otherwise; and the remaining terms have same meaning as in specification (1). In this specification, δ_1 captures the average sales trend over the entire period, δ_2 captures the change in level of sales during the video switch-on weeks, and δ_3 captures the incremental change in sales trend (slope) during the video switch-on weeks. We additionally control for the seasonality in product demands through time fixed-effects.[26]

[26] Besides one week indicator variable dropped out of the total 28 weeks, three additional weeks' fixed-effect indicators in specifications (E1) are dropped due to multicollinearity → two between week 6 – week 21 due to multicollinearity with variable *Wkvid* and *Wkvid* × *t*, and one in the remaining weeks for multicollinearity with variable *t*.

Table E1: Evidence of no substitution effect of product video

Dependent Variable (Weekly sales in numbers)	Coefficient Estimates (Robust Cluster Corrected Std. Errors)			
	Focal product analysis		Coordinating product analysis	
Weeks with video (*Wkvid*)	73.82*** (11.78)	65.39*** (11.09)	86.99*** (9.41)	52.84*** (10.01)
Linear time trend (t)		-3.37*** (0.31)		-3.41*** (0.42)
$Wkvid \times t$		-1.77*** (0.51)		-2.27*** (0.51)
No. of product-weeks (No. of products)	5436 (239)	5436 (239)	3180 (134)	3180 (134)

***, **, * = statistically significant at α = 0.01, α = 0.05, and α = 0.10 levels (two-sided test), respectively. Standard errors are cluster corrected at the product level

In Table E1, we find a significant and positive value for δ_2, which indicates a higher level of sales of control products during the period when videos for the majority of treated products were switched on. A negative and significant estimate for δ_1 indicates that the control products have an average declining sales trend. A negative and significant estimate for δ_3 indicates a higher rate of sales decline during the video switch-on weeks. But we find that the higher gain in sales level due to δ_2 more than compensates for the loss due to a higher declining rate of sales during video switch-on period. We observe similar results in the coordinating product analysis. Thus, the estimated increase in sales of treated products are not at the expense of loss in sales of control products.

Appendix F: Computation of Omitted Variable Bias

Any time varying unobserved shock to the demand of one product can simultaneously affect the demand of its complementary product, thereby making the sum of sales of associated focal products endogenous in specification (3). This could lead to biased estimate of coefficient δ_2, and possibly biased estimates for other coefficients in specification (3). In the following, we derive the expression for omitted variable bias for coefficients of specification (3) and show that as long as videos are randomly assigned, the coefficient associated with video variables remains unbiased.

For simplicity, we use the following specification for specification (3)

$$S_c = \delta_1 V + \delta_2 S_f + \delta_3 V S_f + \varepsilon, \quad \text{------------------ (F1)}$$

where, S_c and S_f, respectively, denote the coordinating and focal products sales, and V denotes the video variable. Let's say an omitted variable Z in the error term of (F1) is correlated with S_f. So the full specification that would give unbiased coefficient estimates is

$$S_c = \delta_1 V + \delta_2 S_f + \delta_3 V S_f + \delta_z Z + \text{u} \qquad \text{-------------------- (F2)}$$

From the partialling out explanation of multiple regression, the biased coefficient of endogenous variable S_f in specification (F1) can be obtained as

$$\widehat{\delta_2} = \frac{Cov\,(S_c,\ \gamma)}{Var\,(\gamma)}, \qquad \text{------------------- (F3)}$$

where, γ is the OLS error from regressing S_f on V and VS_f. Substituting for S_c in (F3) from (F2), we get

$$\widehat{\delta_2} = \frac{Cov\,(\delta_1 V + \delta_2 S_f + \delta_3 V S_f + \delta_z Z + \text{u},\ \gamma)}{Var\,(\gamma)}$$

$$\widehat{\delta_2} = \delta_1 \frac{Cov\,(V,\ \gamma)}{Var\,(\gamma)} + \delta_2 \frac{Cov\,(S_f,\ \gamma)}{Var\,(\gamma)} + \delta_3 \frac{Cov\,(V S_f,\ \gamma)}{Var\,(\gamma)} + \delta_z \frac{Cov\,(\text{Z},\ \gamma)}{Var\,(\gamma)} + \frac{Cov\,(\text{u},\ \gamma)}{Var\,(\gamma)}$$

The OLS error γ (satisfying OLS assumptions) is uncorrelated with variables V and VS_f, i.e., Cov (V, γ) = Cov (VS_f, γ) = 0. Also it can be easily shown that Cov (S_f, γ) = Var (γ). The error u from full specification (F2) is uncorrelated to the endogenous variable S_f and thus uncorrelated to γ, i.e. Cov (u, γ) =0. Substituting these values, the above equation simplifies to

$$\widehat{\delta_2} = \delta_2 + \delta_z \frac{Cov\,(\text{Z},\ \gamma)}{Var\,(\gamma)} \qquad \text{------------------ (F4)}$$

Bias in δ_2 – The omitted variable Z is correlated to S_f and thus it is correlated with γ, error from regressing S_f on variables V and VS_f. Therefore, $Cov\,(\text{Z}, \gamma) \neq 0$ and hence $\widehat{\delta_2}$, coefficient of S_f estimated from specification (F1), will be biased i.e. different from its unbiased value δ_2.

Bias in δ_1 – For estimating bias in δ_1, γ is the error from regressing V on variables S_f and VS_f. Due to random video assignment, the omitted variable Z is uncorrelated with V and thus it is uncorrelated with γ, i.e. Cov (Z, γ) =0. Therefore, $\widehat{\delta_1}$ – coefficient of V estimated from specification (F1) – will be equal to its unbiased value δ_1.

Bias in δ_3 – For estimating bias in δ_3, equation (F4) can be written as

$$\widehat{\delta_3} = \delta_3 + \delta_z \frac{Cov\,(Z\,,\ \gamma\,)}{Var\,(\gamma)},$$

where, $VS_f = \pi_1 V + \pi_2 S_f + \gamma$. Substituting the value of γ in the covariance term we get

$$\widehat{\delta_3} = \delta_3 + \delta_z \frac{Cov\,(Z,\ VS_f - \pi_1 V - \pi_2 S_f)}{Var\,(\gamma)}$$

$$\widehat{\delta_3} = \delta_3 + \frac{\delta_z}{Var\,(\gamma)}[Cov\,(Z, VS_f) - \pi_1\, Cov\,(Z, V) - \pi_2\, Cov\,(Z, S_f)] \quad \text{------------- (F5)}$$

Due to random video assignment, $Cov\,(V, Z) = Cov\,(V, S_f) = Cov\,(V, ZS_f) = 0$. Moreover, $Cov\,(V, ZS_f) = E(VZS_f) - E(V)\,E(ZS_f) = 0 \Rightarrow E(VZS_f) = E(V)\,E(ZS_f)$. Therefore, the first covariance term in brackets in (F5) can be simplified as

$$Cov\,(Z, VS_f) = E(ZVS_f) - E(Z)E(VS_f) = E(V)E(ZS_f) - E(Z)E(V)E(S_f) = E(V)Cov\,(Z, S_f)$$

The coefficient π_2 can be obtained by regressing VS_f on S_f, i.e.

$$\pi_2 = \frac{Cov\,(VS_f,\ S_f)}{Var\,(S_f)} = \frac{E(S_f{}^2 V) - E(VS_f)E(S_f)}{Var\,(S_f)} = \frac{E(V)[E(S_f{}^2) - E(S_f)E(S_f)]}{Var\,(S_f)} = E(V)$$

Therefore, the first and third term inside the brackets in equation (F5) cancels out and the second term is equal to zero making the coefficient $\widehat{\delta_3}$ – estimated from specification (F1) – equal to its unbiased value δ_3. The intuition behind this result is that since V is randomly assigned, the correlation between VS_f and Z comes entirely from the correlation between S_f and Z. Once the correlation between Z and S_f is absorbed by the main S_f term, the interaction term VS_f becomes exogenous in specification (F1).

Simultaneity issue – The systems of equations in specification (3) also suffers from simultaneity issue because the dependent variable in one equation is part of an independent variable in the second equation, and the dependent variable in the second is part of an independent variable in the first. For instance, suppose a pair of pants as a coordinating product has three associated focal products (a top, a sandal, and a scarf), but the top, in turn, appears as a coordinating product for three focal products (the same pair of pants, a purse, and an earring). Let $S_{c(pant)}$, $S_{c(top)}$, $S_{f(pant)}$,and $S_{f(top)}$, respectively, denote the sales of the coordinating product pair of pants, coordinating product top, associated focal products including the pair of pants, and associated focal products including the top. Then specification (F1) for sales of the coordinating products, pair of pants and top, can be written as

$$S_{c(pant)} = \delta_1 V + \delta_2 S_{f(top)} + \delta_3 V S_{f(top)} + \varepsilon_1 \qquad \text{-------------------- (F6)}$$

$$S_{c(top)} = \delta_1 V + \delta_2 S_{f(pant)} + \delta_3 V S_{f(pant)} + \varepsilon_2 \qquad \text{--------------------- (F7)}$$

Suppose $S_{f(top)} = a \times S_{c(top)}$ and $S_{f(pant)} = b \times S_{c(pant)}$, where a and b are constants. Solving for $S_{f(top)}$, it can be shown that $S_{f(top)}$ is a linear function of ε_1 and hence endogenous in equation (F6). Similarly, $S_{f(pant)}$ is a linear function of ε_2 and therefore endogenous in (F7). Thus, simultaneity can be viewed as endogeneity due to omitted variable in error term that is correlated with the associated focal products sales. Therefore, as per the above exposition on omitted variable bias, such endogeneity of sales of associated focal products (S_f) due to simultaneity will lead to bias in coefficient (δ_2) but it would not bias our coefficients of interest (δ_1 *and* δ_3) as long as the videos are assigned randomly.

Endogenous promotion variables – The above exposition on omitted variable bias suggests that estimating our specifications with endogenous promotional variables would lead to biased coefficients for the promotional variables but unbiased coefficients for the video variable and its interaction with the promotional variables. For this reason, we find qualitatively similar estimates for coefficients of video variables in specifications (1), (2), & (3) with and without inclusion of the endogenous promotional variables. Similarly, the estimated coefficients for video variable and its interaction with endogenous promotional variables in specifications (4) and (5) would be unbiased.