

An Empirical Investigation of Dueling Attention Effects of Visible Faces in Product Display Images

Nima Jalali¹

Purushottam Papatla²

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¹Assistant Professor of Marketing, Department of Marketing, Belk College of Business, University of North Carolina-Charlotte, 9201 University City Blvd., Charlotte NC 28223, Email: nima.jalali@uncc.edu

²Professor of Marketing, Sheldon B. Lubar School of Business Administration, University of Wisconsin-Milwaukee, Milwaukee, WI 53211, Tel: (414) 229-4439, papatla@uwm.edu

Abstract

Product display images are the online retailer's equivalent of visual merchandising by traditional retailers. Consistent with the function of visual merchandising, therefore, a displayed image should function as an advertisement and take shoppers through at least the first two stages of *attention* and *interest* of the AIDA model. Given the frequent inclusion of people in product display images, we investigate in this research whether a visible face in a display image will have dueling effects on attention, i.e., attract enough attention leading the shopper to take a closer look but, during the closer look, result in negative transfer of attention away from the product thus reducing product page visits. Specifically, we empirically investigate whether this is the pattern that occurs in practice. We rely on data from nearly 130 thousand product images displayed on storefronts by 110 retailers in six product categories for this investigation. We find that the pattern does hold for a majority of the retailers and product categories. We provide implications of this finding for how retailers should use images with visible faces in visual merchandising. Specifically, online retailers should use product display images that do include visible faces as product display images so as to increase the number of closer looks. When the shopper is taking a closer look, however, retailers should present a zoomed-in version of the image where the face becomes smaller or is even invisible but the product becomes the most prominent part of the image.

Keywords: Online Retailing, Visual Merchandising, Product Display Images, Dueling Attention

Introduction

Online retailers display products on webpages that show several products (Figure 1). A display page is the online equivalent of an offline retailer's visual merchandising display (Khakimdjanova and Park 2005). If an online retailer is interested in converting a shopper into a buyer, therefore, one or more of the displayed images should capture her attention enough to want to view them more closely (Bailey and Baker 2021, Basu et al 2022, Lindstrom et al 2016, Park et al 2005). Additionally, when viewed closely, they should stimulate her interest in learning more about the products they display and lead her to pages with detailed product descriptions – a necessary precursor to purchase intentions (Khakimdjanova and Park 2005).

Each image in the online retailer's visual merchandising display should therefore function as an advertisement that can take the shopper through the first two stages of *attention* and *interest* of the classic AIDA model of advertising (Bergquist and Taylor 2022, Fortenberry and McGoldrick 2020). Failure to take her through the attention stage would make the images ineffective in taking her through the stage of instilling interest in the product (Maughan et al 2007) as well. In this article, we investigate how the presence of a face in a displayed product image helps or hinders its ability to take a shopper through these two stages.

We focus on the face because retailers often include people in online product display images. For instance, Khakimdjanova and Park (2005) and Lindstrom et al (2016) report that nearly 60% of online clothing retailers display their products using images that show them in use by human models. Visible faces of the humans in the images, however, can attract more attention than any other areas of their bodies and, in fact, faces have been shown to attract more attention than any other visual stimuli (Palermo and Rhodes 2007). A visible face in a display may therefore succeed in attracting attention and leading shoppers to take a closer look at the image. During

the closer look, however, the face's ability to attract the most attention of all visual stimuli may result in a negative transfer of attention (Pieters and Wedel 2004, Poffenberger 1925, Wells et al 2000) away from the advertised product. This could in turn hinder the image's ability to stimulate shoppers' interest in going on to pages that describe the product's features in detail to learn more about it. Whether faces in online product display images do have this pattern of contradictory effects or not – a combination, which we label *dueling attention effects* - and whether the pattern is similar or varies across product categories should therefore be questions of significant importance to online retailers.

The primary contribution of our research is a large-scale empirical investigation of the presence and patterns of dueling attention effects across multiple retailers and categories. Specifically, our investigation is based on data from nearly 130 thousand product images displayed on storefronts by 110 retailers in six product categories: athletics, beauty products, fashion products, housewares, jewelry, and shoes. For each displayed image, we track the number of times it is able to (1) attract shopper's attention for a closer look and (2) lead them to visit the page that provides more detail on features of the product that it displays. Cumulatively, over an observation period of 568 days, we observe more than 63 million closer looks at these displayed images and more than 2 million visits to the pages of the products that they display.

For our empirical analysis, we treat the total number of times that shoppers take a closer look at a product display image and the number of times that they go on to a page with details on the features of the product displayed in the image as counts. The two counts are modeled as draws from a Poisson distribution whose mean varies with (1) the presence of a visible face in the image (2) the prominence of the face visible in the image (i.e., the proportion of image's area occupied by the face), (3) the presence or absence of smiles on the faces, (d) demographics of the

visible face (race and gender) (4) facial features (presence of glasses) and (5) of additional visual characteristics of the image in terms of the mix and characteristics of different colors it includes. Additionally, we account for unmeasured characteristics of the image (e.g., visibility of other features like hands, whether a visible face is looking at or away from the viewer (To and Patrick 2021), other visible objects, and setting of the image, i.e., indoor vs. outdoor), using random effects via a Gamma mixture of the Poisson model resulting in a Negative Binomial model. Given that visits to pages follow closer looks, we allow the two counts to be dependent and use a copula to account for this dependence.

Across retailers, we find that a significant positive relationship between a visible face in an image and closer look at the image holds for 46 out of the 110 retailers that we study, not significant for 60 retailers, and negative for 4 retailers. Category-wise results show that the positive relationship between a visible face and closer looks holds for four of the six categories that we study (athletics, beauty, fashion and housewares) while there is no significant relationship in the other two categories (jewelry and shoes).

The negative relationship between a visible face in a product display image and visits to the page of the product that it displays, after a closer look at the image, is significantly negative for 29 retailers, not significant for 78 retailers, and significantly positive for 3 retailers. Category-wise, as well, the negative relationship between visible faces in product display images and visits to the page of the product that they display is significantly negative for five of the six categories (beauty, fashion, housewares, jewelry, and shoes) but is not significant for the sixth category, athletics.

From a marketing perspective, our findings therefore provide empirical evidence for the dueling attention effects of visible faces in product display images. They are likely to influence

shoppers differently at different stages of their visit to the store. Specifically, they increase the likelihood that shoppers will take a closer look at it but also decrease the likelihood that shoppers will visit the page with more details of the displayed product. Online retailers therefore need to take this differential role of faces in product display images into account as they decide on which images to display on their storefronts.

Our research also contributes to the increasing body of research on the role of faces in advertising. This body has been growing in scope in terms of the number of contexts studied (Twitter and Instagram - Li and Xie 2020, Hartmann et al 2021, online banner ads - Sojjachulpant and Ball 2014), the number of categories investigated (Li and Xie 2020, Hartmann et al 2021), the number of ads studied (Li and Xie 202, Hartmann et al 2021), the number and type of audience responses investigated (Hartmann et al 2021)), scale (experimental - Xiao and Ding 2014 vs. large-scale empirical - Li and Xie 2020, Hartmann et al 2021) and detail (the number of specific features of faces such as the size of the chin and the presence of a smile whose effects are investigated (Xiao and Ding 2014, To and Patrick 2021)). Collectively, these studies demonstrate a “nontrivial” (Xiao and Ding 2014, p.338) effect of faces on a number of key audience response metrics including attitude towards the ad and advertised brand as well as purchase intentions. To our knowledge, however, there are no studies that investigate how the presence of faces visible in product display images affect³ shoppers’ interest in taking a closer look at them and in learning more about the products that they display.

We organize the rest of the article as follows. In the next section, we provide a brief overview of the literature on viewers’ response to faces in images first from disciplines other than marketing followed by findings on their role in advertising. Next, we provide a detailed

³ We use “affects” to refer to our empirical estimates of the role of faces in shopper responses to product displays on online retailer storefronts and not in an experimentally tested causal sense.

description of our data, the data generating process, and our model. We then present results of our empirical investigation as well as findings on how the effects vary across retailers and product categories. We conclude with a review of the managerial implications of our findings and suggestions for additional research.

Extant Literature on the Role of Faces in Viewer Response

Findings in other disciplines

Humans receive a variety of sensory stimuli such as auditory, olfactory, haptic, and visual in their everyday interactions with the environment. Accumulated evidence (Hecht and Reiner 2009, Klein 1977, Posner et al 1976, Quinlan 2000, Rock and Harris 1967, Rock and Victor 1964, Sinnett et al 2007) over the last four decades points to the dominance of visual stimuli over others in attracting attention – a finding that has been labeled the Colavita effect (Colavita 1974).

Within visual stimuli, human faces probably attract the most attention. The importance of the face within the universe of visual stimuli has been argued to be a result of the evolutionary needs of humans to increase the chances of survival (Engell et al 2007, Winston et al 2002) by understanding the emotions and intentions of people that they are interacting with. In fact, the need for relying on faces and facial expressions to acquire such “social intelligence” (Winston et al 2002, p.277) was so fundamental to survival that the human brain developed special neural circuitry and a dedicated region called amygdala (Adolphs et al 1998, Winston et al 2002) to rapidly assess facial expressions and arrive at social judgments.

The evolutionary need for a rapid assessment of faces and facial expressions has also led to the human behavior of automaticity (Ohman 2002) wherein the amygdala engages spontaneously when a face is encountered. The face and its expressions are then assessed to arrive at a variety of judgments of the person such as trustworthiness and competence, (Todorov

et al 2015), extroversion (Olivola and Todorov 2010), and likability (Todorov et al 2013).

Encountering a face can thus lead people to spontaneously dedicate their attention to the face as they assess the stimulus to arrive at one or more of a vast array of judgments. Despite the availability of the dedicated amygdala region to this task, the spontaneity and the diversity of judgments that need to be made have been shown to give even a single face the ability to capture the viewer's attention (Fox et al 2001, Mathews, Mackintosh and Fulcher 1997, Ro et al 2001, Theeuwes and Stigchel 2006) to the detriment of attention to other visual stimuli.

Given this ability of faces to capture attention, product display images that include a face could attract more attention from visitors than other images thus engendering the first clicks. The primacy of human faces in attracting visual attention, and their ability to do so even when there are several other visual stimuli, however, also means that a face in a product display image can distract visitors from the product when people take a closer look at the image. Further, the magnitude of this negative effect would increase with the prominence of the face in the image (in terms of its surface area in the picture). This could result in fewer visits to product pages from display images that are clicked for a closer look but have prominent faces.

Research on Faces in Ads

In this subsection, we briefly review key extant research in the visual advertising literature that examines how the faces in ads affect both cognitive (attention, attitude towards the ad, attitude towards the advertised brand) and behavioral (clicks on the ads, purchase intentions for the advertised brands, and purchases of the advertised brands) responses.

In one of the early studies in this area, Xiao and Ding (2014) experimentally investigate how the features of faces included in ads can affect three two attitudinal responses (attitude towards the ad and attitude towards the advertised brand) and a behavioral response (purchase

intentions). Their experiment involves measures of the three responses by a pool of 989 participants that include college students and Amazon Mechanical Turk participants to 144 ads constructed for a 12×12 design (12 stimulus faces \times 12 product categories). Faces used in the study varied in six facial traits: baby facedness, masculinity, attractiveness, trustworthiness, aggressiveness and competence. Results from this study demonstrated that the differences in responses to the ads by a mere change in the face included in them can be substantial. For instance, switching the face in an ad from one of the stimulus faces to another resulted in “a more than 10% increase in attitude toward ad (from 8% to 25.8%), attitude toward brand (from 5.3% to 21.6%), and purchase intention (from 9.3% to 20.6%) (p.344).”

In a more recent study, Li and Xie (2020) empirically investigate three questions related to the role of images in user engagement with social media posts: (1) does the mere presence of a picture in a post affect engagement? (2) do the presence of a face and the emotions it expresses (happy vs. others) and other characteristics of the image (its colorfulness) influence user engagement? and (3) how does the fit between the text in the post and the image affect user engagement? Their study involving two large datasets from Twitter and one from Instagram related to airlines (Twitter and Instagram) and SUV's (Twitter) finds a substantial effect of the presence of a face and facial emotions in images included in the posts on sharing and liking responses. Specifically, the inclusion of a picture with a human face increases sharing by 80.4% and 291.4% respectively for airline and SUV tweets and 38.76% increase in liking for airline tweets (no significant change in liking for SUV tweets) compared to the case of pictures with no faces. Li and Xie (2020) also find significant effects of colors in the pictures on sharing and liking but the effects vary across the two categories as well as across Twitter and Instagram.

In yet another recent study, Hartmann et al (2021) report results from an investigation of consumer response to (a) posts by 185 brands on Instagram and Twitter (43,585 posts on Instagram and 214,536 posts on Twitter) and (b) click-through rates for 2,255 display ads. The goal of the study is to compare differences in responses to three conditions: (1) standalone product images included in the posts (2) consumer selfies in which a consumer's face appears along with the brand in the post and (3) brand selfies in which an invisible consumer holds the brand. Results from their study demonstrate a significant effect of the presence/absence of a face in the image. Specifically, compared to pack shots, consumer selfies receive more likes and comments while brand selfies receive more brand engagement, i.e., purchase intentions. Hartmann et al (2021) conclude that their results “suggest that a face being present diverts attention away from the brand even when the actual position and size of the product remains identical (p.1171).

Similar findings confirming a significant effect of the mere presence of a face in advertisements on consumer response to them are also reported in Adil et al (2018), Sojjachulapunt and Ball (2018) and To and Patrick (2021). To our knowledge, however, how visitor response to product displays on online retailer storefronts varies with whether they include a face or not is yet to be investigated either experimentally or empirically. Table 1 summarizes the research issues and findings in the literature reviewed in this sub-section and contrasts our research and contribution to online retailing.

Data

Our data is provided by an agency⁴ that helps online retailers create visual merchandising displays and monitor shopper response to each of the displayed images.

Aggregate Data on the Number of Closer Looks and Product Page Visits

The displays are designed so that clicking a displayed image enlarges it (these are the “closer looks” in our investigation) and clicking the enlarged image one more time opens the page of the product displayed in the image (“product page visits” in our investigation). The agency tracks the number of closer looks at each product display image and the number of times shoppers visit the page of the product that it displays. This is our primary dataset.

The retailers are heterogeneous in their revenues, product mixes, prices, and targeted consumers. The prices across the stores range from \$3 to \$3285. The targeted shoppers and hence the prices are therefore quite diverse across the retailers. In all, visual merchandising displays set up and tracked by the agency across these retailers included 130,063 product images of which we excluded about two thousand for two reasons. One, we excluded any images in which multiple faces were visible because of the operational difficulties in considering them in the investigation⁵. Two, because our empirical specifications (discussed shortly) include retailer fixed-effects and retailer-specific random errors, we did not include retailers that had too few observations. We therefore dropped retailers who displayed fewer than 100 images over the data collection period.

⁴ The agency uses a proprietary approach to search Instagram for images that show consumers using products from its client retailers. Visual merchandising displays designed and tracked with the agency’s software include only these images.

⁵ If the photo had multiple faces, our empirical analysis would have to consider several possible combinations of their effects on visitors’ attention. For instance, our investigation also accounts for the effect of a smile on a visible face. If, therefore, an image has multiple faces, we would need to account for how many of the faces had smiles. Additionally, we would have to allow for the effects of smiles on some faces on the attention drawn by faces without smiles.

This left us with 110 retailers who displayed the images. Cumulatively, these 130,063 images were enlarged 63,722,404 times leading to 2,003,255 visits to browse product pages.

The visual merchandising set up by the agency is organized as a matrix of rows with each row including several thumbnail images. Each matrix can be browsed by scrolling from left to right or from top to bottom. Scrolling beyond the left or right ends of the screen does not display any additional images but scrolling downwards beyond the bottom of the screen displays rows of images not yet displayed on the screen. A closer look at a displayed image by any visitor is included in the count of the total number of closer looks at that image. A visit to the page of the product displayed in an image following a closer look by any visitor becomes part of the count of the number of pages visited from the image. The two counts for each image are therefore aggregate totals across all shoppers that are exposed to the visual merchandising of the retailer displaying that image.

Ongoing Curation by the Agency

New images sourced by the agency for a retailer are added as new rows at the top of the matrix. Because of this ongoing addition of new images, visitors arriving at different times will see different visual merchandising setups. Thus, the likelihood of repeat visitors or repeat shoppers taking a closer look at the same images that they took a closer look at on previous visits is reduced. Counts of looks and pages are therefore unlikely to be dominated by actions of repeat visitors and shoppers.

The ongoing addition of new images also ensures that the look of the visual merchandising display of retailers also evolves over time. It is therefore unlikely that the images surrounding any image in the display remains the same for different visitors over time. For instance, if one of the displayed images is the only one that has a visible person and a face

among the images surrounding it at one point, the same image may be surrounded at another point by several other images that also include a visible person and a face. Thus, neither of the counts of looks or pages for any image are likely to be dominated due to the context of the other images that it is displayed in.

Based on conversations with the agency, and our own visits to the investigated retailers' sites before proceeding with this research, we also confirmed that visual merchandising for none of the investigated retailers systematically included more images with visible people than others. Additionally, the agency also informed us that none of their retailer clients was using specific heuristics to select the images that are displayed. For instance, there were no heuristics for any of the retailers that said that at least a specific proportion of the displayed images should include a visible person or face. Visitors are therefore unlikely to see more/less of, or click more/less often on, images with/without faces. The overall approach to setting up and updating the visual merchandising displays thus overrides the possibility that private unobserved retailer actions affect the number of looks that a displayed image gets and the number of times that shoppers visit the page of the product in that image following the look.

Measurement

As mentioned above, for each image i displayed by retailer k , the agency tracks the number of times the image received a closer look from visitors (NCL_{ik}) (we refer to the generic form of this variable as NCL from this point on) and the number of times this was followed by a visit to the page with more details of the displayed product (NPV_{ik}) (we refer to this variable as NPV from this point on). NCL_{ik} and NPV_{ik} are therefore our dependent variables.

The documented ability of visible faces in images to affect viewer response (Li and Xie 2020, Xiao and Ding 2014), raises the possibility that the effect could also depend on how

prominent a face is in the image. The prominence of a face, if one is visible in the image, is therefore also a key variable in our investigation. We operationalize *Prominence_{ik}* as the proportion of the image's area occupied by a face. Due to findings in the literature that the smile on a face in an image can affect the face's influence on viewer response (Wang et al 2017), we also measure the extent of a smile on a face (*Smile_{ik}*). Because of the size of our data, rather than relying on human assistance, we use computer vision to recognize the presence and size of faces and smiles in the displayed images. Details of the specific product that we use for this purpose, Face++, are included under *Overview of Face++* in the Appendix. *Smile_{ik}*'s values range between 0 and 1 with higher values representing a brighter (bigger) smile.

Controls

Findings in the advertising literature (Deshpande and Stayman 1994) indicate that the characteristics of people visible in ads (e.g., whether they are wearing eyeglasses), gender and race also affect consumer response. We therefore define variables *Asian_{ik}*, *African American_{ik}*, *Gender_Male_{ik}* and *Glasses_{ik}* (white, female and no glass are the bases) using Face++ to identify them in each image. Face++ also gives levels of its confidence in detecting people's characteristics correctly. We set the values of these variables to these confidence levels rather than indicators. We avoid using indicator variables because we will need to set them to a 1 only if the confidence level given by Face++ is more than a threshold, say, 90%. This would incorrectly result in assigning a zero to an indicator even when people are visible and do have discernable demographic characteristics although with a lower confidence of, say, below the threshold of 90%.

We also include several sets of additional controls in the investigation. The first is for the colors in an image. The effects of colors in marketing (Meyers-Levy and Peracchio 1995, Pieters

et al 2010, Wedel and Pieters 2014) and retailing (Belizzi and Hite 1992, Jalali and Papatla 2016) have been investigated extensively. Findings suggest that the quantities of red around a product increase interest in learning about it (Crowley 1993) and increases in blue in retail environments increase the likelihood of browsing and shopping (Belizzi and Hite 1992). Jalali and Papatla (2016) also find that increases in green in product display images are related to increased interest in the pictures. Additionally, higher chromatic intensity of hues can increase consumer response to images (Gorn et al 1997) as can brighter hues (Gorn et al 1997).

For each image in our sample, we got measures of the extent of RGB colors. Specifically, for each image, we have the average value of Red, Green, and Blue across all pixels in the photo and normalize the values to be between 0 and 1. Furthermore, the variations of chroma and brightness of hues can also affect how viewers respond to images (Pieters et al. 2010; Putrevu et al. 2004). We have two variables to capture these variations in each image: CVC_{ik} the coefficient of variation of chroma across all the pixels in the image and CVB_{ik} which is the coefficient of variation of brightness⁶ across all the pixels in the image.

The second set of controls that we include is filters. Before posting images, users can change color composition of the images using Instagram filters. The data provided by the agency includes information on whether an image was modified by a user with a filter before it was posted and, if it was, which Instagram filter was used. Although more than twenty filters are available, not all are used by people. We therefore select the ten most used filters and combine the other filters into an ‘other’ category. For each of the ten selected filters, we set an indicator variable to 1 for the image in which it was used. For the filters that are not selected, if one of

⁶ Brightness represents how bright or dark a color is (Othman and Martinez 2008) and chroma is the depth of the color (Gorn et al 1997).

them is used, we set an indicator for the *other* filter to 1. Thus, we have 11 indicator variables, $Filt_{ik,N}$, $N = 1 \dots 11$, to represent filters.

Finally, the number of times a displayed image is in a gallery seen by visitors can affect the number of times it is clicked for closer looks and hence the number of times the product's page is then visited. The data provided to us by the agency however does not include data on this. We therefore include a variable, $Days_{ik}$, which is the number of days for which image i of brand k was displayed in a gallery, as a proxy for the number of times that it was seen by visitors. To summarize, our focal variables are: $Presence_{ik}$, $Prominence_{ik}$, $Smile_{ik}$. The control variables are: $Asian_{ik}$, $African American_{ik}$, $Gender_Male_{ik}$, $Glasses_{ik}$, R_{ik} , G_{ik} , B_{ik} , $Filt_{ik,N}$, CVC_{ik} , CVB_{ik} and $Days_{ik}$. Table AT1 in the Appendix gives a description and measurement approach for each variable and Table 2(a) presents descriptive summaries of all the variables.

Individual-level Data for Insights into the Data Generating Process

The dependent variables that we defined above – the number of closer looks NCL_{ik} at image, i , displayed by retailer k and the number of visits NPV_{ik} to the page of the displayed product - are aggregated counts across all visitors to the retailer's site. These variables, however, cannot provide insights into the data generating process at the individual level. Although this is not the focus of our research here, an investigation of the process even on a sample could provide insights into whether there is *prima facie* evidence for the whether visible faces in product display images may have dueling effects on attention. We therefore requested the agency to provide us at least a small sample of individual-level data for this purpose. Despite their product not being set up to track and collect data at the individual-level, the agency kindly agreed to

provide data on a small sample of randomly selected shoppers for a total of about 2000 views of product display images from a retailer of beauty products.

The agency set up the process to identify each shopper through a cookie. A total of 151 shoppers cumulatively viewed 105 product display images for a total of 1986 times. Of these total views, they took a closer look at an image 241 times. Section (b) of Table 2 provides descriptive summaries of these closer looks. The agency also tracked the time spent by each shopper looking at an image if the shopper chose to take a closer look at it. The time was measured as the interval between the time that the closer look appeared on the shopper's screen and the time that she either chose to (1) go to the page of the displayed product, (2) switch to an entirely different image, or (3) close the closer look. Of the 151 shoppers who took at least one closer look, we retained 64 who took a closer look at least at two different images⁷. These 64 shoppers took 502 closer looks at 102 product display images. We therefore have 502 measures of time spent by these shoppers with an image from the time they started taking a closer look at it before taking one of the three actions above. We relied on this sample to gain some empirical insights into the relationship between the visibility of a face in a product display image and (1) whether it gets a closer look and (2) the time spent looking at the closer look. Part (c) of Table 2 presents descriptive statistics of this sample.

Empirical Investigation

Overall Approach

We proceed through our empirical investigation in three steps. In step one, we use the two samples of individual-level data to gain insights into this role, i.e., if there is a relationship between the visibility of a face in a product display image and (1) whether it gets a closer look

⁷ We imposed this constraint to ensure that we had the minimum required number of observations on each shopper to estimate the random effects model that we will discuss shortly.

and (2) the time for which the closer look is on the screen. The collection of the samples was clearly not in a controlled experimental setting. Even if this analysis does reveal a significant positive relationship between a visible face in an image and whether it gets a closer look and the time for which the closer look stays on the screen, we cannot say if this is because of the ability of faces to capture attention.

In step two, we use the much larger aggregate data and seek model-free evidence of whether a visible face in product display images plays a role in the number of closer looks and number of product page visits. Nonetheless, a relationship would provide *prima facie* evidence, in addition to the individual level analysis, that a visible face in an image is associated with a larger number of closer looks, but a smaller number of visits to product pages. Finally, in step three, we investigate if any such evidence is also manifested using the much larger data on the number of closer looks and the number of product page visits from different product display images across the 110 retailers in our data.

Investigation at the Individual-level of the relationship between a closer look and a visible face

We framed the decision of a shopper to take a closer look at a product display image as a choice and estimated the following Logit of the choice on product display image i by individual j as follows:

$$P_{\text{CloserLook}_{ij}} = \frac{e^{(U_{ij})}}{1+e^{(U_{ij})}} \quad (1)$$

$$U_{ij} = \beta_0 + \alpha_j + \beta_1 \text{Presence}_i + \beta_2 \text{Prominence}_i + \beta_3 \text{Red}_i + \beta_4 \text{Green}_i + \beta_5 \text{Blue}_i + \beta_6 \text{Red}_i \times \text{Green}_i + \beta_7 \text{Red}_i \times \text{Blue}_i + \beta_8 \text{Blue}_i \times \text{Green}_i + \beta_9 \text{Blue}_i \times \text{Red}_i \times \text{Green}_i + \beta_{\text{CVC}} \text{CVC}_i + \beta_{\text{CVB}} \times \text{CVB}_i \quad (2)$$

β_0 is the intercept and α_j is the mean zero individual specific random effect, which captures baseline differences among individuals' propensity to take a closer look at the photos. Estimates of the parameters of the model (1) presented in Table 3(a), indicate that the probability of a closer look increases with the presence of a face and that prominence has no role (although the estimated parameter is negative).

Next, we estimated the Cox proportional hazards specification below to estimate the relationship between the time, t_{ij} that a product display image i continues to stay on a shopper j 's screen while she takes a closer look at it:

$$\gamma(t_{ij}) = \gamma_0(t)e^{(U_{ij})} \quad (3)$$

U_{ij} is specified as in (2) above⁸. Estimates of the parameters for this investigation are presented in Table 3(b). The parameter for the presence of a face is negative and significant indicating that the presence of a face increases the time that the closer look stays on the screen before the shopper takes the next action. The parameter for prominence is also negative although not significant.

Together, both of these investigations provide evidence that a face in a product display increases the likelihood that shoppers will take a closer look at it and continue to view at the closer look. Whether the increase in time spent viewing the image is however on the face or on the product in the image is not clear from this investigation.

⁸ The specification of U_{ij} in (3) does not include the intercept since the intercept is capture by $\gamma_0(t)$.

Model-Free Evidence of the Number of Closer Looks and Visits to Product Pages

We examine the much larger aggregate data for model-free evidence on whether the number of closer looks at displayed images and the number of visits to the pages of the displayed product from them do vary with whether they have a visible face or not. Table AT2 in the Appendix presents the mean number of closer looks and the mean visits to product pages from displayed images with/without a visible face by retailer. Any highlighted number in the columns for closer looks indicates that, based on a two-sample t-test it is significantly larger or smaller than the corresponding number for the same retailer for the two clicks. For instance, the mean number of closer looks at images with a face is significantly larger than for those without for retailer 1. Highlighted numbers under the columns for visits to product pages in each retailer's row indicate that the difference between that entry and the corresponding entry next to it is significant based on a two-sample t-test. Thus, for retailer 5, visits to the pages of the products in displayed images, following a closer look at the images, are significantly fewer when those images have visible faces than when they do not. Entries in Table 4 summarize this evidence across all the retailers in our dataset and indicate that a visible face in a product display image is likely to result more often than not in (a) more closer looks at the image and (b) fewer visits to the page of the displayed product consistent with the facial positive-negative combination.

Figures 2 and 3 present additional model-free evidence at the aggregate level for each retailer in the data. Specifically, Figure 2 demonstrates that, as the number of product display images with visible faces, as a percent of the total images displayed by a retailer increases, the average number of closer looks at the product display images may increase. Figure 3 shows an opposite pattern for visits to the pages of the products when the displayed images have a visible face.

Aggregate Analysis of the Number of Closer Looks and Visits to Product Pages

We treat number of closer looks of image i displayed by retailer k , NCL_{ik} , as a count and assume that it is Poisson distributed with a rate $\lambda_{NCL_{ik}}$ that varies with the characteristics of the image and a random effect $\varepsilon_{CL,ik}$ specific to the image:

$$NCL_{ik} \sim Pois(\lambda_{NCL_{ik}} \varepsilon_{CL,ik}) \quad (4)$$

$\varepsilon_{CL,ik}$ captures the role of unobserved differences between the images in the close look clicks.

Following Winkelmann (2008), we assume that $\varepsilon_{CL,ik} \sim Gamma(r_{CL}^k, r_{CL}^k)$ where r_{CL}^k is retailer-specific parameter and is to be estimated. One advantage of including the Gamma distributed random effect is that the resulting Poisson-Gamma mixture captures over-dispersion (and zero-inflation) of NCL_{ik} similar to a Negative Binomial model (Fader, Hardie and Lee 2005). We next specify $\lambda_{NCL_{ik}}$ of photo i displayed by retailer k as a function of the focal and control variables:

$$\begin{aligned} \log(\lambda_{NCL_{ik}}) = & \beta_{0k,CL} + \beta_{1k,CL}Presence_{ik} + \beta_{2,CL}Prominence_{ik} + \beta_{3,CL}Smile_{ik} + \\ & \beta_{4,CL}Asian_{ik} + \beta_{5,CL}African\ American_{ik} + \beta_{6,CL}Male_{ik} + \beta_{7,CL}Glasses_{ik} + \beta_{Red,CL}Red_{ik} + \\ & \beta_{Green,CL}Green_{ik} + \beta_{Blue,CL}Blue_{ik} + \beta_{Red,Green,CL}(Red_{ik} \times Green_{ik}) + \beta_{Red,Blue,CL}(Red_{ik} \times \\ & Blue_{ik}) + \beta_{Green,Blue,CL}(Green_{ik} \times Blue_{ik}) + \beta_{Red,Green,Blue,CL}(Red_{ik} \times Green_{ik} \times Blue_{ik}) + \\ & \sum_{N=1}^{11} \gamma_{N,CL}Filt_{ik,N} + \beta_{CVC,CL}CVC_{ik} + \beta_{CVB,CL}CVB_{ik} + \beta_{D,CL}\log(Days_{ik}) \end{aligned} \quad (5)$$

We include below a few notes about the specification:

1. The specification includes retailer fixed-effects $\beta_{0k,CL}$ to control for unobserved differences between the retailers. Because the retailers carry different products, $\beta_{0k,CL}$ also captures the role of product heterogeneity in closer look clicks.

2. The specification of $\beta_{1k,CL}$ allows for retailer-specific parameters for the role of a visible face in the number of closer looks at product display images. We assume a normal distribution for $\beta_{1k,CL}$, hence it is a random coefficient model.
3. The specification also includes $\log(Days_{ik})$ as a proxy for the total number of times a displayed image was seen regardless of whether shoppers saw it in a closer look or not. This controls for the possibility that differences in NCL_{ik} may also be due to differences in how long the images are displayed on the retail sites.
4. In addition to main effects, we also include interactions among the three main colors because of findings in the literature that colors in images also have interactive effects in that the extent of one color in the image can affect the role of a different color in how consumers respond to that image (Jalali and Papatla 2016, p. 380).

As mentioned, we rely on the number of days for which an image was displayed by a retailer, $Days_{ik}$, as a proxy for the number of shoppers who might have seen that image which could affect the number of times that it attracted a closer look. In the case of the number of visits to the page with more details of a displayed product, NPV_{ik} , however, we do not need a proxy. We have an exact count, NCL_{ik} , of the number of times that shoppers took a closer look at the image i displayed by retailer k and decided whether or not to visit the page with details of the displayed product. We therefore assume that each closer look of a displayed product image is an independent Bernoulli trial and the number of visits to the page with details of the displayed product is the number of successes from several such trials. This allows us to use the Poisson approximation of a Binomial to specify the distribution of the number of visits to the displayed product's page following a closer look at its image. Specifically, the approximation posits that a Binomial (n, p) converges to the Poisson distribution with a rate of np for large n of independent

events (Feller 1968, Johnson and Kotz 1969, Winkelmann 2013). Thus, NPV_{ik} , which is also a count, conditional on NCL_{ik} , is assumed to be Poisson distributed with a rate $\lambda_{NPV_{ik}}$, which is itself assumed to be the product of the number of closer looks NCL_{ik} and a probability $p_{PV_{ik}}$ of a click to visit the product's page. $p_{PV_{ik}}$ in turn is modeled as a Logit of the focal and control variables. Our model for the number of clicks to visit product pages is therefore:

$$NPV_{ik} | NCL_{ik} \sim Pois(\lambda_{NPV_{ik}} \varepsilon_{PV,ik}) \quad (6)$$

As in the case of the number of closer looks, we assume that $\varepsilon_{PV,ik} \sim Gamma(r_{PV}^k, r_{PV}^k)$ with r_{PV}^k to be estimated.

$$\lambda_{NPV_{ik}} = NCL_{ik} p_{PV_{ik}} \quad (7)$$

$$p_{PV_{ik}} = \frac{e^{(U_{PV,ik})}}{1+e^{(U_{PV,ik})}} \quad (8)$$

$$\begin{aligned} U_{PV,ik} = & \beta_{0k,PV} + \beta_{1k,PV}Presence_{ik} + \beta_{2,PV}Prominence_{ik} + \beta_{3,PV}Smile_{ik} + \beta_{4,PV}Asian_{ik} + \\ & \beta_{5,PV}African\ American_{ik} + \beta_{6,PV}Male_{ik} + \beta_{7,PV}Glasses_{ik} + \beta_{Red,PV}Red_{ik} + \\ & \beta_{Green,PV}Green_{ik} + \beta_{Blue,PV}Blue_{ik} + \beta_{Red,Green,PV}(Red_{ik} \times Green_{ik}) + \beta_{Red,Blue,PV}(Red_{ik} \times \\ & Blue_{ik}) + \beta_{Green,Blue,PV}(Green_{ik} \times Blue_{ik}) + \beta_{Red,Green,Blue,PV}(Red_{ik} \times Green_{ik} \times Blue_{ik}) + \\ & \sum_{N=1}^{11} \gamma_{N,PV}Filt_{ik,N} + \beta_{CVC,PV}CVC_{ik} + \beta_{CVB,PV}CVB_{ik} + \beta_{D,PV}log(Days_{ik}) \end{aligned} \quad (9)$$

The specification in (9) is similar to that for the closer look clicks. We retain $Days_{ik}$ to control for possible effects of the number of days an image is displayed for on the number of visits to the page with details of the displayed product. For instance, a shopper could have taken a closer look at a product's display image multiple times over multiple days and eventually decided to take one final closer look before visiting the page of the displayed product. In such cases, the display over longer periods would have resulted in more visits to the page of the displayed product.

The joint probability of a product display image receiving NCL_{ik} and NPV_{ik} closer looks and visits to the displayed product's page respectively is therefore the product of the marginal distribution of NCL_{ik} and the conditional distribution of NPV_{ik} conditioned on NCL_{ik} as below:

$$p(NCL_{ik}) \times p(NPV_{ik} | NCL_{ik}) = Pois(\lambda_{NCL_{ik}} \varepsilon_{CL,ik}) \times Pois(\lambda_{NPV_{ik}} \varepsilon_{PV,ik}) \quad (10)$$

$$\varepsilon_{EC,ik} \sim Gamma(r_{CL}^k, r_{CL}^k), \varepsilon_{BC,ik} \sim Gamma(r_{PV}^k, r_{PV}^k) \quad (11)$$

To allow for unobserved retailer-specific characteristics that could affect both the number of closer looks and the number of visits to the pages of the displayed products, we allow both errors to be correlated and use a Gaussian copula (Danaher and Smith 2011) to combine them into a copula density. We therefore estimate a joint specification (equation 10) assuming that the errors are correlated with marginal distributions as in (11). We also estimate three versions of the models in each of these three cases to empirically assess the ability of different types of variables to explain the number of closer looks at, and the number of product page visits from, product display images. Specifically, we estimate the following specifications:

- Only the presence and prominence of a visible face but no other variables included
- Including the presence and prominence of a visible face as well as the characteristics of the face, i.e., visible eyeglasses, gender and race (Asian, African American)
- Including variables related to color and the use of filters in the picture, i.e., the same specifications as in (5) and (9)

We rely on MCMC methods for inference using a $N(0,1000)$ prior on the parameters to run a single chain. Next, we compare the fits of all three estimated versions and discuss the inferred model parameters for the best version.

Results

Assessing the Model's Specification

Table 5 compares the Deviance Information Criterion (DIC) of the three estimated versions of the models⁹. Because of our MCMC approach to inference, although we estimated the joint model for closer looks *and* product page visits, we were able to obtain likelihoods and, hence, DIC's separately for closer looks, visits to product pages and the joint model. Entries in the table display the DIC in each of the three cases for two nested specifications of the joint model as well as the full specification. The first nested specification (N1) only includes variables for the presence and prominence of a face while the second one (N2) also includes facial features, i.e., whether the face includes eyeglasses, gender of the person, whether the person is Asian, and whether the person is African American.

Going down the column corresponding to closer looks, we see that the DIC for N2 is worse than that for N1 indicating that the addition of facial features in the specification does not provide enough additional explanation to compensate for the added variables. The DIC for the full specification on the other hand is substantially smaller than that for both N1 and N2. This pattern thus reconfirms the important role of colors in attracting shoppers to take a closer look at product display images (Jalali and Papatla 2016). It also confirms that the variables for colors, their intensity (chroma and brightness), and variations (coefficients of variation of chroma and brightness) in the model are ensuring that the effects of colors in closer looks are not seeping into the parameters for the presence and prominence of a face (if one is present) in the displayed image. The pattern in the column corresponding to product page visits, however, is quite

⁹ The joint model has an extra component from the copula density in the likelihood. We however only consider the likelihood arising from the Poisson densities of the models for closer looks and product page visits in computing the Deviance Information Criterion.

different from that for closer looks. There is a small improvement in model fit going from N1 to N2 and then the full specification.

The DIC's for the joint model, computed as the sum of the DIC's for the models for the number of closer looks and number of product page visits following closer looks of course reflect the same pattern as in the column for the number of closer looks. They also confirm that the full specification has the best fit to our data.

Discussion of the Estimated Parameters of the Full Specification

The MCMC approach to inference gives us the ability to obtain insights through model parameters inferred at three levels: (1) overall inferences across all the retailers and categories obtained as empirical means of the draws for the parameters, their empirical standard deviations, and confidence intervals (2) retailer-specific inferences of the model parameters obtained as empirical means of the draws for the parameters, their empirical standard deviations, and confidence intervals within each retailer and, hence, separately for each of the retailers in our data and (3) category-specific inferences of the model parameters obtained as empirical means of the draws for the parameters, their empirical standard deviations, and confidence intervals, within each category and across all the retailers who displayed images in that category. We next present and discuss the first level of inferred parameters (across all retailers and categories in our data) and follow with a presentation and discussion of the parameter for the presence of a visible face in product display images at the retailer and category levels.

Overall Inferences

The inferred values of all model parameters for the entire dataset are presented in Table 6. The contradictory effects of a visible face in product display images on the number of times shoppers take a closer look at them and the number of times they visit the page of the displayed

product, following a closer look, are striking. Specifically, the parameter for the presence of a visible face is positive and significant for closer looks but negative and significant for visits to the page of the displayed product. The pattern is therefore consistent with findings in the literature that (a) visible faces in ads attract attention to them and (b) visible faces in ads may also result in negative transfer of attention away from the products¹⁰.

Also striking is the negative role of the prominence of a visible face not only in the number of visits to pages of the displayed products but in the number of closer looks at the images as well. This pattern of a positive role of the presence, but a negative role of prominence, of a visible face in the number of closer looks is also consistent with the dueling attention effects of faces. Specifically, a visible face in a displayed image is likely to attract attention and stimulate a desire to take a closer look at it but, if the face is sufficiently prominent that shoppers can see it quite well without having to take a closer look at the entire image, they may indeed pass it by without taking a closer look.

Most of the other characteristics of a face including the presence of a smile do not have any significant positive or negative roles in the number of closer looks or visits to product pages. In terms of the significant roles, the number of closer looks has a negative relationship with the presence of a male or African American face in displayed product images. The number of visits to product pages, on the other hand, has a significant positive relationship with a visible Asian face.

Turning to the role of the colors in the images, one interesting pattern is that red and blue have significant positive parameters for the number of closer looks as well as the number of

¹⁰ We note that we are only taking a position that the pattern is consistent with the findings in the literature regarding the role of a visible face in advertisements on attention to the ad and to the product in the ad. Our research as noted is an empirical investigation. This is therefore an empirical finding and we do not claim or test that the pattern is due to the effects of a visible face on attention.

visits to product pages while green has no significant role in either of the shopper actions.

Interestingly, however, parameters for the interaction of green with both red and blue are positive in increasing the number of closer looks. This suggests that, while green by itself may not be helpful in increasing the number of closer looks or product page visits, it can strengthen the roles of red and blue in stimulating closer looks by shoppers. Interactions of red with blue either by itself or in combination with green (the three-way interaction of red, green and blue) also have significant negative parameters that increasing levels of either red or blue when both are present in the image are associated with fewer closer looks. The interaction of red and blue, however, has a significant positive parameter indicating that higher presence of both colors is associated with an increase in the number of visits to product pages after closer looks. Similar to the role of the presence of a face, which is associated with an increase in the number of closer looks but a reduction of the number of product page visits, therefore, the interaction of red and blue has dueling effects on these actions of shoppers.

Another striking pattern is that filters in images have a negative role in the number of closer looks *and* the number of visits to product pages. Thus, clearly, online retailers should not use images that have been filtered to display their products. Variations in the chroma or brightness of colors in the images also have significant, but dueling, roles in the number of closer looks and the number of visits to product pages. Specifically, increasing variations in the brightness of colors in display images is associated with an increase in the number of closer looks at them. In contrast, increases in the variations of both chroma and brightness have a negative role in the number of visits to product pages. Finally, the number of days for which an image is displayed has a significant positive role in the number of closer looks it gets but the effect is similar although much smaller in the number of visits to product pages.

Retailer-specific Inferences

As mentioned previously, because of our MCMC approach to inference, we are able to compute the empirical mean and standard deviation of the parameter for the role of the presence of a face in product display images in the number of closer looks at, and the number of visits to product pages from, the displayed images. Figure 4 presents a box plot of the parameter for each of the 110 retailers in our data. In all, we find that the parameter is positive and significant for 46 retailers, not significant for 60, and significantly negative for the remaining four. Overall, therefore, these individual retailer level results indicate that there is either a positive relationship, or no relationship, between the presence of a visible face in product display images and the number of closer looks they get for the vast majority of retailers in the data.

A similar box plot of the parameter for the role of the presence of a face in product display images in the number of visits to the pages of the product displayed in those images is presented in Figure 5. The parameter is significantly negative for 29 retailers, not significant for 78, and significantly positive for 3. Thus, these retailer-level results show that a visible face in product display images either reduces the number of visits to pages of the displayed products or has no effect for most of the retailers. Together, therefore, these retailer-level summaries of the parameter also provide evidence of the dueling attention effects of faces in product display images.

Category-specific Inferences

Similar to the retailer-level summaries presented above, we next present category-level summaries of the parameter for the role of a visible face in product display images in the number of closer looks and the number of visits to product pages. Figure 6(a) displays these summaries for the number of closer looks. We find that this number has a positive relationship with the

presence of a face in the displayed images for athletics, beauty, fashion and housewares but does not have a significant relationship in the case of jewelry and shoes. Thus, we find at the category-level as well that the presence of a face in product display images is helpful for the number of closer looks in a majority of the studied product categories.

Figure 6(b) has a category-wise summary of the parameter for the presence of a face in product display images for the number of visits to product pages. It shows that the parameter is significantly negative for five of the six categories - beauty, fashion, housewares, jewelry, and shoes – but not significant for athletics. The pattern of dueling attention effects of visible faces in product display images that we reported previously across all categories and retailers is therefore repeated at the category level as well.

Managerial Implications, Limitations and Future Research Directions

Managerial Implications

Our findings suggest that the presence of faces in product display images can have substantial effects on the closer looks and visits to product pages. We first demonstrate the implications of these effects with a simple calculation of the elasticity of close looks and clicks to visit product page relative to the presence and prominence of a face in the display images. Following this, we discuss implications of our findings.

An analysis of the elasticity of both clicks to varying levels of the presence and prominence of a visible face in our data based on our results (Table 6) indicates the following. Based on our results (Table 6), a visible face can approximately result in an average increase of 17.1% in closer look clicks, but an average reduction of 20.5% in visits to product pages. We also need to account for the effect of face prominence on both clicks. We therefore consider the average prominence of the face, which is 0.06 in our data, and its respective parameters on both

clicks, which are -0.214 and -0.440 respectively. Considering the total number of clicks to visit product pages and close look clicks in our data, which as mentioned earlier were close to about 2 million, and 63 million respectively, a rough average estimate would suggest that about 3% of closer look clicks lead to clicks to visit product pages. Suppose an image without a face had an initial total of 1000 closer looks and hence 30 visits to product pages. Holding all other types of content in the image constant, replacing a part of this image with one that includes a visible face increases the number of closer looks to 1158 ($0.171 - 0.214 * 0.06 = 0.158$) or an increase of 15.8%. The presence of a face however means that the number of clicks to visits product pages would be 26 (23% reduction in 3% of 1158 where $0.23 = 1 - 0.205 - 0.440 * 0.06$) thus resulting in a net reduction of about 13% in the number of visits to product pages.

An obvious implication of this example computation is that visible faces in product display images can increase the number of closer looks but will also decrease the number of visits to product pages. Retailers therefore need to implement visual merchandising strategies that take advantage of the increase in the number of closer looks but also avoid the reduction in product page visits. One approach for this would be to use product display images that do include visible faces as product display images so as to increase the number of closer looks. When the shopper is taking a closer look, however, retailers should present a zoomed-in version of the image where the face becomes smaller or is even invisible but the product becomes the most prominent part of the image.

Limitations and Future Research Directions

Our research has some limitations that could be addressed in the future. First, given our focus on the effects of a face in a product display images on closer looks at the images and product page visits from them, we limit our data to images with a single face or no face.

Additional research on how multiple faces in product display images affect the number of closer looks and visits to browse the product pages is therefore an important avenue for future research. Specifically, it would be helpful to investigate whether the presence of multiple faces in an image which reduces the prominence of any specific face can mitigate the negative effects of the presence of a single face in the image.

A second limitation of our research is that we do not account for the role of the number and type of objects and their organization in the image on product page visits. Pieters et al's (2010) findings suggest that these aspects of an image, which they label as *design complexity*, can increase consumers' attention to and improve attitude towards ads. Investigations of whether design complexity could also attract visual attention in a way that draws attention away from a face, smiles or people in the image thus reducing their negative effects on visits to browse product pages would therefore be an interesting additional avenue for future research.

Finally, it is likely that the presence of a face, smile or people is less negative for products or services where they can act as an additional source of information rather than resulting in negative transfer of attention. An understanding of such differences across categories is therefore an additional promising direction for future research.

References

- Adil, S., Lacoste-Badie, S., & Droulers, O. (2018). Face presence and gaze direction in print advertisements: how they influence consumer responses—an eye-tracking study. *Journal of Advertising Research*, 58(4), 443-455.
- Adolphs, Ralph, Daniel, T., and Antonio R. D (1998), “The Human Amygdala in Social Judgment,” *Nature*, 393 (June), 470–74.
- Bailey, S., & Baker, J. (2021). *Visual merchandising for fashion*. Bloomsbury Publishing.
- Basu, R., Paul, J., & Singh, K. (2022). Visual merchandising and store atmospherics: An integrated review and future research directions. *Journal of Business Research*, 151, 397-408.
- Bellizzi, J. A., & Hite, R. E. (1992). Environmental color, consumer feelings, and purchase likelihood. *Psychology & marketing*, 9(5), 347-363.
- Bergkvist, L., & Taylor, C. R. (2022). Reviving and improving brand awareness as a construct in advertising research. *Journal of Advertising*, 51(3), 294-307.
- Colavita, F. B. (1974), “Human sensory dominance,” *Perception & Psychophysics*, 16(2), 409-412.
- Danaher, P. J., & Smith, M. S. (2011), “Modeling multivariate distributions using copulas: Applications in marketing,” *Marketing Science*, 30(1), 4-21.
- Deshpandé, R., & Stayman, D. M. (1994), “A tale of two cities: Distinctiveness theory and advertising effectiveness” *Journal of Marketing Research*, 31(1), 57-64.
- Engell, Andrew D., James V. Haxby, and Alexander Todorov (2007), “Implicit Trustworthiness Decisions: Automatic Coding of Face Properties in Human Amygdala,” *Journal of Cognitive Neuroscience*, 19(9), 1508–19.
- Feller, W. (1968), “An introduction to probability theory and its applications: Volume 1”.
- Fortenberry, J. L., & McGoldrick, P. J. (2020). Do billboard advertisements drive customer retention?: Expanding the “AIDA” model to “AIDAR”. *Journal of Advertising Research*, 60(2), 135-147.
- Fox, E., Russo, R., Bowles, R. J., and Dutton, K. (2001), “Do Threatening Stimuli Draw or Hold Visual Attention in Sub-Clinical Anxiety?” *Journal of Experimental Psychology: General*, 130, 681 -700.
- Gorn, G. J., Chattopadhyay, A., Yi, T., and Dahl, D. W. (1997), “Effects of Color as an Executional Cue in Advertising: They’re in the Shade,” *Management Science*, 43(10), 1387–1400.
- Hartmann, J., Heitmann, M., Schamp, C., & Netzer, O. (2021). The power of brand selfies. *Journal of Marketing Research*, 58(6), 1159-1177.
- Hecht, D., and Reiner, M. (2009), “Sensory Dominance in Combinations of Audio, Visual and Haptic Stimuli,” *Experimental Brain Research*, 193(2), 307-314.
- Jalali, Nima Y., and Purushottam Papatla (2016“), "The Palette That Stands Out: Color Compositions Of Online Curated Visual UGC That Attracts Higher Consumer Interaction," *Quantitative Marketing and Economics* 14(4), 353-384.
- Johnson, N.L. and Kotz, S. (1969) *The Discrete Distributions in Statistics*, John Wiley and Sons.

- Khakimdjanova, L., & Park, J. (2005). Online visual merchandising practice of apparel e-merchants. *Journal of Retailing and Consumer Services*, 12(5), 307-318.
- Klein, R. M. (1977), "Attention and Visual Dominance: A Chronometric Analysis," *Journal of Experimental Psychology: Human Perception and Performance*, 3, 365-378.
- Li, Y., & Xie, Y. (2020). Is a picture worth a thousand words? An empirical study of image content and social media engagement. *Journal of Marketing Research*, 57(1), 1-19.
- Lindström, A., Berg, H., Nordfält, J., Roggeveen, A. L., & Grewal, D. (2016). Does the presence of a mannequin head change shopping behavior?. *Journal of Business Research*, 69(2), 517-524.
- Mathews, A., Mackintosh, B., & Fulcher, E. P. (1997). Cognitive biases in anxiety and attention to threat. *Trends in cognitive sciences*, 1(9), 340-345.
- Maughan, L., Gutnikov, S., & Stevens, R. (2007). Like more, look more. Look more, like more: The evidence from eye-tracking. *Journal of Brand management*, 14(4), 335-342.
- Meyers-Levy, J., & Peracchio, L. A. (1995), "Understanding the Effects of Color: How the Correspondence Between Available And Required Resources Affects Attitudes," *Journal of Consumer Research*, 22(2), 121-138.
- Ohman, A. (2002), "Automaticity and the Amygdala: Nonconscious Responses to Emotional Faces," *Current Directions in Psychological Science*, 11(2), 62-66.
- Olivola, C. Y., and Todorov, A. (2010), "Fooled By First Impressions? Reexamining the Diagnostic Value of Appearance-Based Inferences," *Journal of Experimental Social Psychology*, 46(2), 315-324.
- Park, J., Lennon, S. J., & Stoel, L. (2005). On-line product presentation: Effects on mood, perceived risk, and purchase intention. *Psychology & Marketing*, 22(9), 695-719.
- Palermo, R., & Rhodes, G. (2007). Are you always on my mind? A review of how face perception and attention interact. *Neuropsychologia*, 45(1), 75-92.
- Pieters, R., & Wedel, M. (2004). Attention capture and transfer in advertising: Brand, pictorial, and text-size effects. *Journal of marketing*, 68(2), 36-50.
- Pieters, R., Wedel, M., and Batra, R. (2010), "The Stopping Power of Advertising: Measures and Effects of Visual Complexity," *Journal of Marketing*, 74(5), 48-60.
- Poffenberger, A. T. (1925). *Psychology in advertising*. AW Shaw Company.
- Posner, M. I., Nissen, M. J., and Klein, R. M. (1976), "Visual Dominance: An Information Processing Account of Its Origins and Significance," *Psychological Review*, 83, 157-171.
- Putrevu, S., Tan, J., & Lord, K. R. (2004), "Consumer responses to complex advertisements: the moderating role of need for cognition, knowledge, and gender," *Journal of Current Issues & Research in Advertising*, 26(1), 9-24.
- Quinlan, P. [T.] (2000), "The "Late" Locus of Visual Dominance," *Abstracts of the Psychonomic Society*, 5, 64.
- Ro, T., Russell, C., and Lavie, N. (2001), "Changing Faces: A Detection Advantage in the Flicker Paradigm," *Psychological Science*, 12(1), 94-99.
- Rock, I., and Harris, C. S. (1967, May 17), "Vision and Touch," *Scientific American*, 216, 96-104.

- Rock, I., and Victor, J. (1964), "Vision and Touch: An Experimentally Created Conflict between the Two Senses," *Science*, 143, 594-596.
- Sajjacholapunt, P., & Ball, L. J. (2014). The influence of banner advertisements on attention and memory: human faces with averted gaze can enhance advertising effectiveness. *Frontiers in psychology*, 166.
- Sinnett, S., Spence, C., and Soto-Faraco, S. (2007), "Visual Dominance and Attention: The Colavita Effect Revisited." *Perception and Psychophysics*, 69(5), 673-686.
- Theeuwes, J., and Van der Stigchel, S. (2006), "Faces Capture Attention: Evidence from Inhibition of Return," *Visual Cognition*, 13(6), 657-665.
- To, R. N., & Patrick, V. M. (2021). How the eyes connect to the heart: The influence of eye gaze direction on advertising effectiveness. *Journal of Consumer Research*, 48(1), 123-146.
- Todorov, A., Dotsch, R., Porter, J. M., Oosterhof, N. N., and Falvello, V. B. (2013), "Validation of Data-Driven Computational Models of Social Perception of Faces," *Emotion*, 13(4), 724.
- Todorov, A., Olivola, C. Y., Dotsch, R., and Mende-Siedlecki, P. (2015), "Social Attributions from Faces: Determinants, Consequences, Accuracy, and Functional Significance," *Annual Review of Psychology*, 66, 519-545.
- Wang, Ze, Huifang Mao, Yexin Jessica Li, and Fan Liu (2014), "Smile Big or Not? Effects of Smile Intensity on Perceptions of Warmth and Competence," *Journal of Consumer Research*, 787-805.
- Wedel, M., and Pieters, R. (2014), "The buffer effect: the role of color when advertising exposures are brief and blurred," *Marketing Science*, 34(1), 134-143.
- William, John Burnett, and Sandra Moriarty (2000), *Advertising Principles & Practice*, 5th ed. Upper Saddle River, NJ: Prentice Hall.
- Winkelmann, Rainer (2013), *Econometric Analysis of Count Data*, Springer Science and Business Media.
- Winston, Joel S., Bryan A. Strange, John O'Doherty, and Raymond J. Dolan (2002), "Automatic and Intentional Brain Responses during Evaluation of Trustworthiness of Faces," *Nature Neuroscience*, 5(3), 277-83.
- Xiao, L., & Ding, M. (2014). Just the faces: Exploring the effects of facial features in print advertising. *Marketing Science*, 33(3), 338-352.

Table 1: Summary of Related Literature

| Article | Focus | Research Context | Key finding related to visible faces in imagery | Implications for visible faces in product images displayed by online retailers |
|--------------------------------|---|--|--|--|
| Xiao and Ding (2014) | "Do faces affect how a viewer reacts to an advertisement on the metrics that advertisers care about?" (p.338) | Print Advertising | Differences in responses to the ads by a mere change in the face included in them can be substantial | No |
| Adil et al (2018) | "Examines the impact of face presence and model gaze direction in print advertisements." (p.443) | Print Advertising | "Face presence increases attention paid to advertisement elements, including product and brand. The product receives even more attention when the model's gaze direction is toward the product, versus toward the viewer." (p.443) | No |
| Sojjachulapunt and Ball (2018) | "Investigated the efficacy of faces located in banner advertisements to enhance the attentional processing and memorability of banner contents." (p.1) | Online banner Advertising | "Faces with averted gaze increased attention to the banner overall, as well as to the advertising text and product." (p.1) | No |
| Li and Xie (2020) | "Are social media posts with pictures more popular than those without?" (p.1) The role of faces is also investigated. | Social Media Posts | Finds a substantial effect of the presence of a face and facial emotions in images included in the posts on sharing and liking responses. | No |
| Hartman et al (2021) | "Classifies social media brand imagery and studies user response." (p.1159) | Social Media Posts | "Face being present diverts attention away from the brand even when the actual position and size of the product remains identical." (p.1171) | No |
| To and Patrick (2021) | "Does where the ad model's eyes look matter?" (p.123) | Print Advertising | "Averted gaze (direct gaze) enhances narrative transportation (spokesperson credibility) to boost the effectiveness of emotional (informative) ads." (p.123) | No |
| This research | Investigate whether a visible face in a display image will have dueling effects on attention, i.e., attract enough attention leading the shopper to take a closer look but, during the closer look, result in negative transfer of attention away from the product thus reducing product page visits. | Product display images in online retailing | Investigation using data from nearly 130 thousand product images displayed on storefronts by 110 retailers in six product shows that the pattern indicated by the dueling effects of a visible face on attention does hold for a majority of the retailers and product categories. | Yes |

Table 2: Descriptive Summaries of Variables

| (a) Total Number of Image 130,063 | | | | | | | |
|---|------------------|------------------|------------------|-------------|------------------|------------------|-------|
| | Min | 1st Qu | Median | Mean | 3rd Q | Max | |
| Clicks | | | | | | | |
| NCL | 31 | 89 | 208 | 489.9 | 514 | 33392 | |
| NPV | 0 | 0 | 3 | 15.4 | 10 | 6626 | |
| Face Characteristics (for 11788 images with a face) | | | | | | | |
| Prominence | 0.005 | 0.007 | 0.017 | 0.066 | 0.082 | 0.760 | |
| Smile | 0.001 | 0.118 | 0.415 | 0.463 | 0.822 | 0.999 | |
| Demographics (when a face is present) | | | | | | | |
| | Frequency | | Frequency | | Frequency | Frequency | |
| Asian | 2091 | African American | 483 | Gender Male | 2156 | Glass | 2269 |
| Filters | | | | | | | |
| | Frequency | | Frequency | | Frequency | Frequency | |
| Amaro | 6100 | lo-fi | 3702 | Rise | 3331 | x-pro ii | 3978 |
| Hefe | 1636 | Mayfair | 4234 | Sierra | 1809 | Other | 24816 |
| Hudson | 2282 | Nashville | 1601 | Valencia | 8064 | No filters | 68510 |
| Colors (Continuous) | | | | | | | |
| | Min | Q1 | Median | Mean | Q3 | Max | |
| Red | 0 | 0.199 | 0.500 | 0.464 | 0.754 | 0.981 | |
| Green | 0 | 0.164 | 0.375 | 0.412 | 0.691 | 0.981 | |
| Blue | 0 | 0.168 | 0.363 | 0.389 | 0.641 | 0.981 | |
| Visual Complexity and Duration of Display | | | | | | | |
| CVC | 0 | 5.500 | 12.070 | 12.630 | 18.420 | 103.50 | |
| CVB | 0 | 3.778 | 9.222 | 9.699 | 14.254 | 74.286 | |
| Days | 1 | 32 | 60 | 83.26 | 112 | 568 | |
| (b) Individual Level Data – First Sample – Closer Look Clicks | | | | | | | |
| | Min | 1st Qu | Median | Mean | 3rd Q | Max | |
| Number of photos seen by each visitor | 2 | 5 | 6 | 13.2 | 12 | 115 | |
| Prominence (for 35 photos with a face) | 0.010 | 0.077 | 0.121 | 0.177 | 0.181 | 1 | |
| Red | 0.215 | 0.534 | 0.591 | 0.611 | 0.689 | 0.897 | |
| Green | 0.172 | 0.468 | 0.524 | 0.554 | 0.622 | 0.884 | |
| Blue | 0.162 | 0.447 | 0.511 | 0.528 | 0.605 | 0.879 | |
| CVC | 0.240 | 0.764 | 0.970 | 1.056 | 1.202 | 2.768 | |
| CVB | 0.126 | 0.396 | 0.497 | 0.499 | 0.596 | 1.157 | |
| (c) Individual Level Data – Second Sample – Duration of Photo View | | | | | | | |
| | Min | 1st Qu | Median | Mean | 3rd Q | Max | |
| Duration of photo view (seconds) | 0.0 | 1.6 | 3.3 | 5.8 | 6.6 | 52.6 | |
| Number of photos seen by each visitor | 2 | 2 | 5.5 | 7.8 | 10 | 67 | |
| Prominence (for 35 photos with a face) | 0.019 | 0.091 | 0.171 | 0.191 | 0.190 | 1 | |
| Red | 0.265 | 0.534 | 0.591 | 0.599 | 0.676 | 0.897 | |
| Green | 0.172 | 0.457 | 0.513 | 0.536 | 0.607 | 0.884 | |
| Blue | 0.162 | 0.422 | 0.504 | 0.504 | 0.574 | 0.879 | |
| CVC | 0.240 | 0.756 | 0.903 | 0.978 | 1.091 | 2.768 | |
| CVB | 0.126 | 0.408 | 0.486 | 0.510 | 0.602 | 1.039 | |

Table 3: Individual Level Analysis

| | (a) Click to View a Closer Look at the Product Display Image | | (b) Duration of Closer Look View of the Product Display Image | |
|--------------------|--|----------------|---|----------------|
| | Estimate | Standard Error | Estimate | Standard Error |
| Intercept | -2.167** | 0.147 | | |
| Presence | 0.405** | 0.203 | -0.340** | 0.712 |
| Prominence | -0.146 | 0.604 | -0.709 | 0.492 |
| Red | 0.168 | 0.342 | -0.250 | 0.779 |
| Green | 0.662 | 0.718 | 0.037 | 1.038 |
| Blue | -0.767 | 0.486 | 0.185 | 1.203 |
| Red × Green | -0.913 | 0.585 | -0.380 | 0.684 |
| Red × Blue | 0.291 | 0.777 | 0.682** | 1.978 |
| Green × Blue | 0.678** | 0.319 | -0.190 | 0.823 |
| Red × Green × Blue | 0.064 | 0.059 | -0.065*** | 0.937 |
| CVC | -0.169 | 0.138 | -0.008 | 0.992 |
| CVB | 0.327* | 0.189 | -0.886 | 0.412 |

*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.01

Table 4: Summary of Model-Free Evidence Regarding How Closer Looks and Visits to Pages of Displayed Products Are Related to Whether the Display Image Has a Visible Face

| | Closer Look at Displayed Product Image | Visits to the page of the displayed product after a closer look at the display image |
|--|--|--|
| Number of retailers with enough display images with a visible face and display images without a visible face for a paired t-test | 107 | 106 |
| Number of retailers with significant difference between shopper actions when display images have a face vs. when they do not ^a | 48 | 45 |
| Number of retailers with significantly more closer looks at the displayed product image when the image has a visible face | 36 | |
| Number of retailers with significantly fewer closer looks at the displayed product image when the image has a visible face | 12 | |
| Number of retailers with significantly fewer visits to the page of the displayed product when the display image has a visible face | | 41 |
| Number of retailers with significantly more visits to the page of the displayed product when the display image has a visible face | | 4 |

^a There were no significant differences between the images with faces and those without for the other retailers.

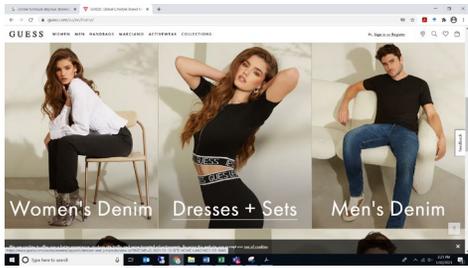
Table 5: Comparison of Variable Sets on Model Fit

| | Closer Looks | Product Page Visits | Both |
|--|---------------------|----------------------------|-------------|
| N1: Presence + Prominence | 589,528 | 536,138 | 1,125,666 |
| N2: Presence + Prominence + Face Features | 787,543 | 529,838 | 1,317,381 |
| Full: Presence + Prominence + Face Features + Colors + Filters + Visual Complexity | 125,050 | 527,489 | 652,539 |

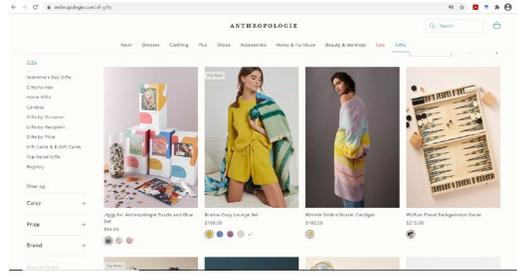
Table 6: Estimated Parameters of the Model in (10)

| Variable | Closer Look at Displayed Product Image | | | Visit to Page with Details of Displayed Product | | |
|-----------------------------|--|-----------------------|--------|---|-----------------------|--------|
| | Mean | 95% Credible Interval | | Mean | 95% Credible Interval | |
| | | 2.50% | 97.50% | | 2.50% | 97.50% |
| Focal Variables | | | | | | |
| Presence | 0.171* | 0.097 | 0.250 | -0.205* | -0.282 | -0.133 |
| Prominence | -0.214* | -0.307 | -0.151 | -0.440* | -0.645 | -0.187 |
| Face Characteristics | | | | | | |
| Smile | -0.020 | -0.051 | 0.008 | -0.010 | -0.076 | 0.055 |
| Gender – Male | -0.066* | -0.089 | -0.036 | -0.009 | -0.066 | 0.050 |
| Glass | -0.003 | -0.020 | 0.019 | 0.007 | -0.037 | 0.054 |
| Race – Asian | -0.006 | -0.033 | 0.018 | 0.047* | 0.004 | 0.095 |
| Race – African American | -0.094* | -0.135 | -0.047 | -0.091 | -0.190 | 0.018 |
| Colors | | | | | | |
| Red | 0.197* | 0.187 | 0.205 | 0.139* | 0.072 | 0.190 |
| Green | 0.000 | -0.009 | 0.015 | -0.042 | -0.087 | 0.008 |
| Blue | 0.131* | 0.116 | 0.153 | 0.047* | 0.014 | 0.095 |
| Red × Green | 0.057* | 0.014 | 0.079 | 0.002 | -0.093 | 0.101 |
| Red × Blue | -0.190* | -0.228 | -0.159 | 0.107* | 0.006 | 0.187 |
| Green × Blue | 0.780* | 0.717 | 0.842 | -0.052 | -0.154 | 0.052 |
| Red × Green × Blue | -0.987* | -1.053 | -0.895 | -0.040 | -0.154 | 0.085 |
| Filters | | | | | | |
| Filter – Amaro | -0.048* | -0.065 | -0.028 | -0.083* | -0.113 | -0.054 |
| Filter – Hefe | -0.097* | -0.120 | -0.076 | 0.014 | -0.043 | 0.072 |
| Filter – Hudson | -0.063* | -0.084 | -0.045 | -0.126* | -0.181 | -0.076 |
| Filter – Lofi | -0.084* | -0.101 | -0.062 | -0.008 | -0.047 | 0.035 |
| Filter – Mayfair | -0.081* | -0.098 | -0.063 | 0.004 | -0.027 | 0.039 |
| Filter – Nashville | -0.061* | -0.080 | -0.038 | -0.136* | -0.192 | -0.083 |
| Filter – Rise | -0.060* | -0.087 | -0.033 | -0.085* | -0.123 | -0.044 |
| Filter – Seirra | -0.036* | -0.059 | -0.010 | -0.136* | -0.189 | -0.081 |
| Filter – Valencia | -0.045* | -0.058 | -0.017 | -0.028* | -0.051 | -0.001 |
| Filter – X Pro | -0.086* | -0.105 | -0.069 | -0.040* | -0.079 | 0.001 |
| Filter – Other | -0.001* | -0.017 | 0.025 | -0.011* | -0.031 | 0.009 |
| Visual Complexity | | | | | | |
| CV – Chroma | 0.000 | -0.001 | 0.001 | -0.001* | -0.002 | -0.000 |
| CV – Brightness | 0.003* | 0.002 | 0.004 | -0.003* | -0.004 | -0.002 |
| Other Parameters | | | | | | |
| Log(Days) | 0.752* | 0.749 | 0.756 | 0.030* | 0.023 | 0.038 |
| Copula Correlation | | | | 0.105* | 0.098 | 0.111 |

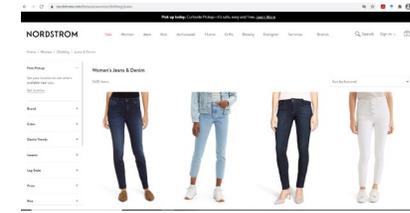
Figure 1: Online Retail Product Display Images



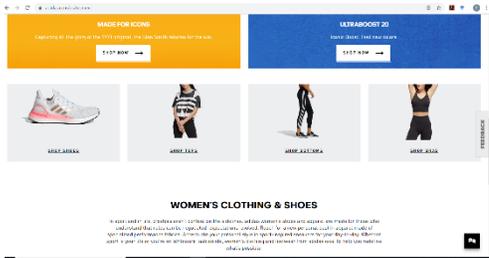
www.guess.com



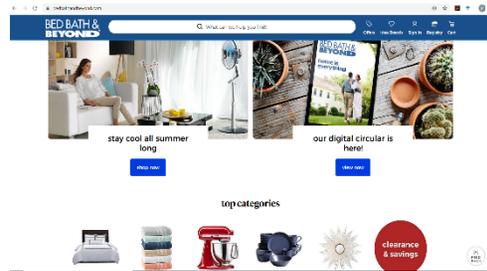
www.anthropologie.com



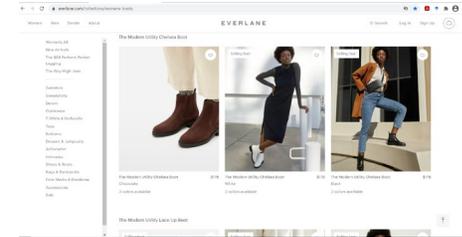
www.nordstrom.com



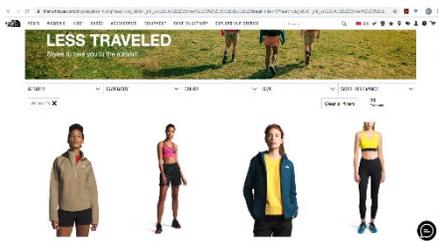
www.adidas.com



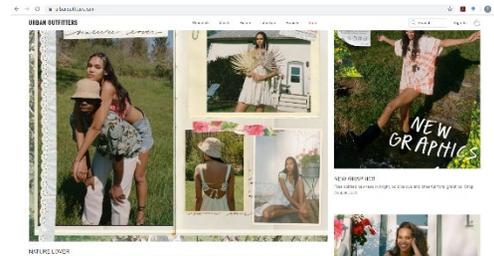
www.bedbathandbeyond.com



www.everlane.com



www.thenorthface.com



www.urbanoutfitters.com



www.target.com

Figure 2: Average Number of Closer Looks at the Product Display

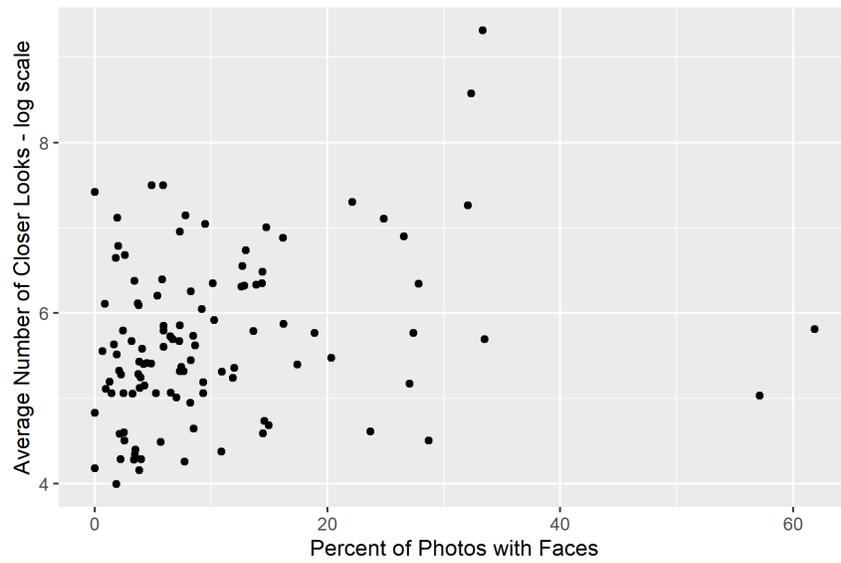


Figure 3: Average Rate of Visits to Product Page with Details of Displayed Product

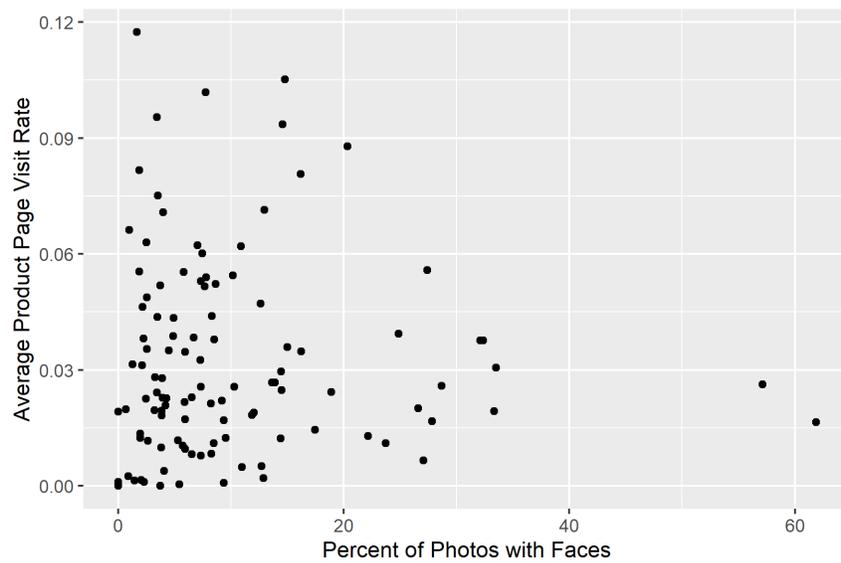


Figure 4: Effect of Visible Face on Click to Take a Closer Look across Retailers

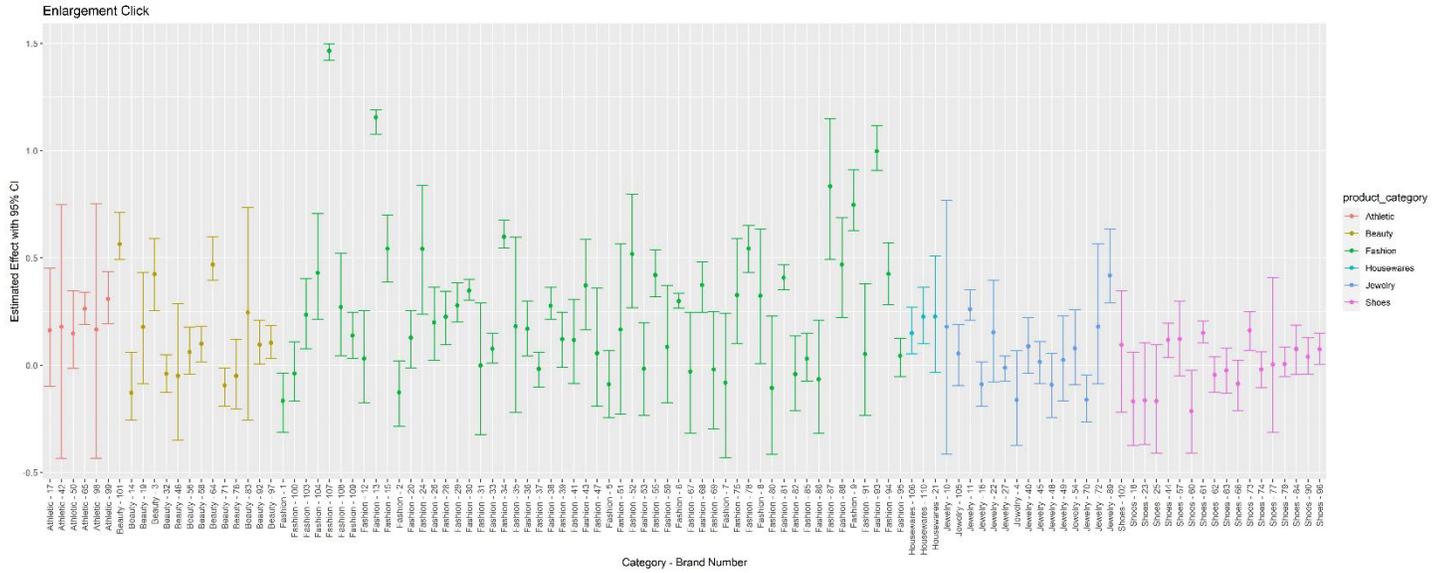


Figure 5: Effect of Visible Face on Click Rates to Visit Product Page across Retailers

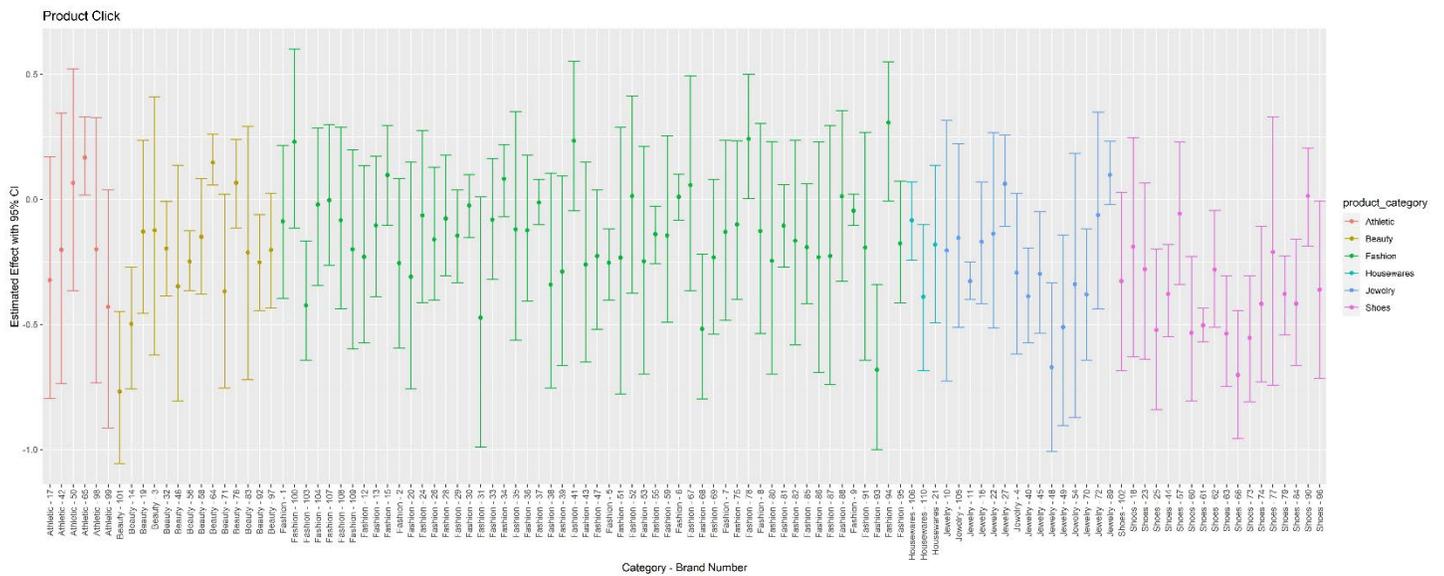


Figure 6: Effect of Visible Face across Categories

