

# Economic Value of Visual Product Characteristics

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Demand models typically use structured data for estimating the value of product characteristics. However, for several product categories such as automobiles, consumers emphasize that visual characteristics of the product are significant demand drivers. Since visual characteristics are typically in high-dimensional unstructured data (e.g., product images), this poses a challenge to incorporate them in demand models. We introduce a method that enables estimation of demand using visual characteristics, by building on the BLP demand model with recent advances in disentangled representation learning. Our method also overcomes the challenge of not having supervised signals, which are required for good disentanglement, by using the demand model as supervisory signal. We discover independent and human interpretable visual characteristics directly from product image data, while simultaneously estimating equilibrium demand in a competitive automobile market in the UK. We conduct a counterfactual analysis using a recent dramatic change in the visual design language of BMW cars, and show our predicted results align with actual changes in BMW market share. To our best knowledge, this work is the first to link visual product characteristics with demand—in other words, to quantify the economic value of design.

*Key words:* visual analytics, deep learning, demand models

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Exterior look/design is the top reason shoppers avoid a particular vehicle (30%), followed by cost (17%).

—*JD Power Avoider Study 2015*

## 1. Introduction

Products have long been represented as bundles of characteristics (Lancaster 1966), with both functional and form characteristics serving as value drivers (Rosen 1974). Visual characteristics comprising product form are often a primary factor in a product’s market success (Jindal et al. 2016, Veryzer Jr 1993). Visual characteristics are designed by firms for everything from communicating intended product differentiation and segmentation (Bloch 1995, Homburg et al. 2015), signaling brand equity (Aaker 1997), and of course, to making appealing products that consumers choose (Creusen and Schoormans 2005, Norman 2013).

Despite their importance, however, visual characteristics have received relatively little attention compared to structured product characteristics (e.g., size or brand) in widely-adopted quantitative models of consumer demand. This has arguably been due to two

related challenges. First, quantitatively representing the way a product looks is inherently challenging, as even low-fidelity product form representations (e.g., wireframes or silhouettes) may require hundreds of highly interdependent variables (e.g., Bezier curve control points); this challenge scales to the millions of variables when using product images.<sup>1</sup> This high dimensionality poses significant estimation challenges for conventional demand models that typically operate with 10's of structured product characteristics. Second, even with a tractable representation of high-dimensional product form representations, there are a lack of methods that aim to causally infer the effect of visual product characteristics on an economic primitive such as consumer demand.

Our research aims to estimate the economic value of visual product characteristics. We aim towards overcoming the two aforementioned challenges by integrating two methodologies that have typically been distinct in the fields of quantitative (econometric) models and machine learning. Specifically, we propose an overall model that integrates two component models, an econometric demand model and a “disentanglement”-based deep learning model. At a high level, the disentanglement-based deep learning model identifies visual characteristics from images of products, while the demand model identifies how those visual characteristics (alongside other more conventional structured product characteristics) affect a demand system comprised of a competitive market of firms and heterogeneous consumers. This leads to the following substantive and methodological research questions.

From a substantive perspective, we seek to understand whether any of the multiple identified visual characteristics impact consumer choices and market outcomes, and if so, to what degree. It is also useful to understand how consumers trade off between structured and visual characteristics. Second, we aim to examine whether and when products “close” in the space of structured characteristics are also close in the space of visual characteristics. Third, we aim to understand how substitution occurs with products close in structured characteristics compared to the space of visual characteristics.

From a methodological perspective, we seek to understand whether demand models can improve the deep learning component of our integrated model. Namely, we ask whether a demand model describing consumer choices can be used as a supervisory signal in the absence of “ground truth” to enable better discovery of such visual characteristics. Similarly, in the opposite direction, we seek to understand whether the deep learning component of this integrated model can improve the properties of the demand model; namely,

<sup>1</sup> For example, even a 1000 pixel  $\times$  1000 pixel black and image is 1 million variables, each having a value of 0 or 1.

whether preference parameters obtained by incorporating visual characteristics differ from a baseline that includes only structured characteristics.

For the demand model component of our overall model, we build upon the well-regarded and standard demand model of [Berry et al. \(1995\)](#) (BLP) to allow consumers to have preferences over visual product characteristics. BLP has been popular across a spectrum of applications in marketing and economics for a number of reasons; among them are that the approach can be used with market-level data on products and outcomes, it accommodates unobservable product characteristics, allows for observable and unobservable consumer heterogeneity, and importantly accounts for endogeneity of prices (which can depend on the unobservable product characteristics).

For the deep learning component of our overall model, we need a model that can identify visual characteristics from product image data. This task is challenging due to the aforementioned high dimensionality of images. However, to integrate visual characteristics with the demand model, it is necessary to obtain a lower-dimensional representation. One may first consider obtaining these lower-dimensional factors using classical linear approaches like PCA, or similarly, classical nonlinear approaches like autoencoders ([Bengio et al. 2013](#)). However, the resulting factors typically have no semantic meaning to humans (i.e., they are not interpretable). Alternatively, we could have prespecified the relevant visual characteristic, as in [Zhang et al. \(2021\)](#) or [Liu et al. \(2020\)](#). However, we might not be able to interpret what aspects of the images directly correspond to any given characteristic, limiting practical application by managers. Moreover, such an approach would not be able to generate products with different visual characteristics, limiting our ability to ask research questions with counterfactuals.

We instead leverage recent developments in an area of deep learning called “disentangled representation learning,” which aims at identifying the “true” set of visual characteristics from high-dimensional images in a manner that is semantically interpretable to humans. Our deep learning model is built on variational autoencoders (VAE) ([Kingma and Welling 2014](#)), and thus comprised of an “encoder” and “decoder.” The “encoder” takes an image of a product as input, which undergoes a sequence of highly non-linear transformations to output a lower-dimensional latent code corresponding to the visual characteristics. The “decoder” then takes that latent code as input and outputs a reconstruction of the original

image. This process thus represents the content of a high-dimensional image using a low-dimensional latent code. To promote disentanglement of the learned visual characteristics, we extend the VAE using additional losses to enforce learned visual characteristics to be uniquely represented, statistically independent, and minimally lossy relative to the original product image data. While the machine learning literature has shown this approach does not guarantee our goal of identifying the “true” semantically interpretable visual characteristics in a purely *unsupervised* manner (i.e., using only product image) (Locatello et al. 2019), one of our contributions is to use the demand model as a *supervised* signal for the deep learning component of our model.

Finally, our integrated demand-and-disentangled-representation-learning model has two distinct specifications, which we term “open loop” and “closed loop.” In the open loop specification, the (vector of) visual characteristics obtained are included as additional product characteristics in the utility specification and the demand model is estimated once. In contrast, in the closed loop specification, we jointly use the demand model as a supervisory signal in order to obtain a disentangled representation of visual characteristics. The demand model provides useful supervision, since it allows consumers to respond to visual characteristics (in addition to structured characteristics), and incorporate them in their choice process, which in turn must match market outcomes. Thus, improving the loss of the demand model could potentially benefit the visual disentanglement as well.

We next test our integrated model using an empirical application. Specifically, we evaluate the impact of visual characteristics on consumer preferences and aggregate demand for the automobile market in the UK. We focus on the automobile market because these represent important and substantial purchases for consumers, and it is a product where visual characteristics are likely to have an impact.<sup>2</sup> As discussed earlier, automobile buyers report that visual design is one of the most important criterion in purchase.<sup>3</sup> The data used here spans the period 2008-2017 and includes a total of 49 brands and 400 models, ranging in price from £6,413 (Perodua Kelisa) to £166,652 (Bentley Bentayga). We separately obtain structured data on prices, product characteristics and market outcomes, and unstructured image data corresponding to the “front view” of those automobile models.

<sup>2</sup> According to Leader Bank (<https://www.leaderloancenter.com/the-2nd-most-expensive-thing/>), an automobile is typically the most expensive consumer product other than a house

<sup>3</sup> According to JD Power 2015 US Avoider Study (<https://www.jdpower.com/business/press-releases/2015-us-avoider-study>), exterior design is the top reason shoppers avoid a particular vehicle).

We estimate both the open loop and closed loop variants of the model, and do so with and without incorporating visual characteristics into consumer preferences.

Our proposed approach obtains 3 visual characteristics that are human interpretable from the image in both the open and closed loop specifications of our model. These characteristics can be interpreted as body shape, boxiness (presence of angular versus curved features), and grille size. We find that the price elasticities are more negative in the presence of visual characteristics in the model, compared to the baseline BLP estimates.

We lastly use our model to simulate a counterfactual corresponding how changing the visual form of a product(s) impacts economic valuation and ultimately demand for the firm’s products. While most changes in automobile visual characteristics are relatively mild “facelifts” and “refreshes”, dramatic variations do occasionally come up in which a firm chooses to make dramatic changes. A recent example is BMW’s change in “design language” in Model Year 2020, in which BMWs changed their iconic and distinctive “kidney bean” front grille, a mainstay amongst BMWs continual product line of coupes, sedans, and CUV/SUVs. We conduct a counterfactual where BMW introduces such a visual design change earlier, and then evaluate market outcomes after this introduction. This counterfactual enables us to quantify the value of design, and also to identify how the substitution patterns change when the new design is introduced, and compare that to the case where the prior design was continued.

The rest of this paper is structured as follows: Section 2 discusses related literature, Section 3 introduces the proposed integrated economics-and-machine learning model, Section 4 details the empirical application of the approach, Section 5 simulates a counterfactual in visual design, and Section 6 concludes this work with a discussion and opportunities for future work.

## **2. Literature Review**

Our work is related to three broad streams of literature: First, it is related to the BLP class of demand models in economics. Second, it builds on “disentangled” representation learning in the machine learning literature to find human-interpretable patterns within unstructured data corresponding to the visual characteristics we seek. Third, it is related to the use of unstructured data in empirical modeling within marketing.

## 2.1. Demand Models

The random coefficient logit model described in [Berry et al. \(1995\)](#) has been extensively used for estimating demand for differentiated products in economics as well as marketing. It addresses the potential endogeneity of price by using an instrumental variable approach similar to [Berry \(1994\)](#). It does so by assuming that a consumer’s utility for a good depends not only on its observed product characteristic (available as data to econometrician) but also on unobserved product characteristics (observed by the market participants such as firms and consumers but not observed by the econometrician). The unobserved product characteristics are correlated with price. Besides addressing price endogeneity, this model showed that allowing flexible substitution patterns to reflect the heterogeneity in customer tastes for observed product characteristics is important when estimating demand elasticities. Finally, another key aspect of this model is the ability to work with aggregate data at market level in which a large number of differentiated products are available.

Several papers have extended the BLP class of demand models. [Nevo \(2000\)](#) allowed for interaction of observed heterogeneity with product characteristics in addition to only considering unobserved heterogeneity. It also showed how to include product fixed effects into the BLP class of models. [Petrin \(2002\)](#) and [Berry et al. \(2004\)](#) provide an approach to incorporate micro data along with market data to estimate BLP models. They show that not only does incorporating micro data directly allow us to obtain more richer substitution patterns but also reduce the number of instruments required to solve the problem. Finally, [Grieco et al. \(2021\)](#) allow the average unobserved quality to change across markets. This allows them to study the evolution of market power over time.

We add to this rich literature by allowing for consumer’s utility to also depend on visual characteristics of products. These visual characteristics are learned from product images by using deep learning methods. Thus, we make available additional structured data to the econometrician that was earlier present only in the form of unstructured data and hence were unobservable to the econometrician.

## 2.2. Disentangled Representation Learning

Representation learning broadly refers to using machine learning to re-represent data from its original observed representation into a different (typically lower-dimensional) representation with properties now better suited to a given task ([Bengio et al. 2013](#)). For example, the classical model of principle component analysis (PCA) may be viewed under this lens if

one wanted to re-represent data into lower-dimensional linear subspace spanned by vectors that best explain the original representations variance; or likewise, the classical model of an autoencoder, which aims at nonlinearly compressing data while minimizing information loss of the new representation. In this work, we aim to re-represent high-dimensional unstructured data (i.e., images of automobiles) into representations that are not just lower-dimensional or uncorrelated, but are also semantically interpretable to humans for use in demand models. Recent advances in an area of deep learning known as “disentangled” representation learning seeks exactly such interpretable representations.

Most recent advances in disentanglement representation learning methods are built using deep generative models that both re-represent the original observed data to a corresponding lower-dimensional representation, as well as enable the generation of new data. Within deep generative models, variational autoencoders (VAEs) (Kingma and Welling 2014) have been most widely adopted for disentangled representation learning. This is due to the VAE being autoencoder, and thus naturally suited for nonlinearly re-representing high-dimensional data, but also due to the VAE being a probabilistic extension of the classical autoencoder that adopts a variational Bayesian formulation of the autoencoder. In our case, this latter is useful as it enables us to model full posterior uncertainty over the visual characteristics for each corresponding product image in a principled manner, while simultaneously enabling us to enforce disentanglement via statistical independence over the learned visual characteristics in aggregate.

Several methods accordingly extend the VAE in this manner by reformulating and/or reweighing the two terms in the traditional VAE, namely, the reconstruction accuracy between and observed image and the reconstructed image from the encoding and decoding process, and the KL-divergence of the learned characteristics from a reference prior distribution. (Higgins et al. (2017) showed that trading off these two terms by upweighting the KL-divergence term promoted disentanglement. This was further extended by Burgess et al. (2017), Kim and Mnih (2018), and Chen et al. (2018), who decomposed this KL-divergence term into several sub-terms to give even more fine-grained control over the disentanglement process which we elaborate formally in Section 3.2.

One key challenge of any disentanglement method is that, with purely unsupervised methods, there is no theoretical guarantee for learning unique disentangled representations Locatello et al. (2019). In other words, we need some form of relevant supervision to

identify independent and semantically interpretable visual characteristics. To address this challenge, [Locatello et al. \(2020\)](#) showed that a small number of labelled examples with even potentially imprecise and incomplete labels is sufficient to perform model selection to learn disentangled representations. Further, [Sisodia et al. \(2022\)](#) showed that structured product characteristics can also serve as a supervisory signal. An advantage of using structured product characteristics is that this data is typically available in marketing datasets. This means that there is no need for additional labeling. In this paper, we address this theoretical challenge by using a demand model as a supervisory signal. Implicitly, we assume that demand is a function of visual characteristics as well as other known observed product characteristics.

### 2.3. Empirical Models with Unstructured Data

Unstructured data (text, images etc.) are rich in content and very high dimensional, which makes it challenging to tractably incorporate in marketing models. There are several approaches to incorporate visual characteristics to study their effect on demand. First, we can define a specific set of visual or textual attributes of interest. For example, in a study on AirBnB images, [Zhang et al. \(2021\)](#) examines specific interpretable properties of images like composition, color or aspect ratio that can be derived from the image. Similarly, [Zhang and Luo \(2018\)](#) defines the visual characteristics of images uploaded by customers to Yelp to study their effect on restaurant exit, and [Malik et al. \(2019\)](#) defines the visual characteristics of profile pictures from an online professional social network to study beauty premium in career progression. Overall, in this approach, the selected characteristics typically have to be human labeled. More, this approach relies on researcher judgment, which creates a challenge if they select an unimportant visual characteristics while omitting an important one.<sup>4</sup> A second approach is to use classical statistical methods like PCA or autoencoders ([Bengio et al. 2013](#)), which can reduce the dimensionality automatically, however the disadvantage is that the characteristics obtained are not interpretable. [Dew et al. \(2021\)](#) combines textual and image data to augment visual design of new brand logos using autoencoders. Other empirical work using visual characteristics in marketing includes the study of how brands visual identity can be listened in using online image ([Liu](#)

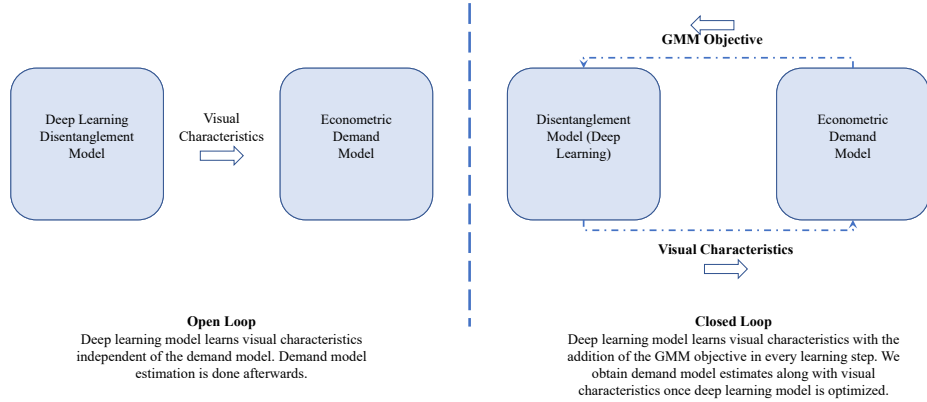
<sup>4</sup> For example, a researcher studying the effect of hair color on a worker's chance of getting promoted might conclude that hair color has explanatory power. However, hair color is correlated with race and the explanation behind the worker's promotion might possibly be due to race.



et al. 2020), identification of consumer needs for new products from textual review data (Timoshenko and Hauser 2019), and the use of images to augment how designers develop the aesthetics of products (Burnap et al. 2019). Liu et al. (2017) uses morphing techniques to find visual characteristics of automobiles instead of using deep learning methods.

Our disentanglement approach aims to achieve the advantages of both the above, automatically learning (discovering) and quantifying visual characteristics without human labeling, but also obtaining independent and semantically-interpretable visual characteristics. Our closed loop model also allows the deep learning and demand models to learn from each other, with a view to improving the outcomes of each model.

**Figure 1 An Integrated Model of Econometric Demand and Disentangled Representation Learning**



### 3. Methodology

We now propose a method for estimating the economic value of visual product characteristics. Our method may be at a high level conceptualized as a integrated model comprised of two component models, an econometric demand model and disentanglement-based machine learning model.

Figure 1 diagrams an overview of our integrated approach. At a high level, the disentanglement-based machine learning model identifies visual characteristics from images of products, while the demand model identifies how those visual characteristics (alongside other more conventional structured product characteristics) affect a demand system comprising a competitive market of firms and heterogeneous consumers. We next formalize the two components of our integrated model separately, followed by their integration using two

distinct model specifications. Section 3.1 describes the demand model, including its supply-side and demand-side assumptions, as well as parameter estimation. Section 3.2 describes the disentanglement-based deep learning model that identifies visual characteristics from product images. Section 3.3 describes the proposed integrated model, and specifically, the “open loop” and “closed loop” specifications of this model. We provide a table of notation in Table 1.

**Table 1 Table of Notation**

Demand Model		Disentanglement Model	
Symbol	Meaning	Symbol	Meaning
$j$	Products	$\mathbf{m}$	image
$t$	Markets	$\mathbf{v}$	visual characteristic
$i$	Consumers	$\rho(\mathbf{v})$	prior distribution
$f$	Firms	$\rho_\theta(\mathbf{m} \mathbf{v})$	Decoder neural net
$T$	Number of Markets	$q_\phi(\mathbf{v} \mathbf{m})$	Encoder neural net
$J_t$	Number of products in market $t$	$\theta$	Decoder’s parameters
$I_t$	Number of consumers in market $t$	$\phi$	Encoder’s parameters
$F_t$	Number of firms in market $t$	$c$	Ground-truth factor of variation
$\zeta$	Model Parameters	$\mathbf{v}_{\text{inf}}$	informative visual characteristic
$\zeta_1$	Linear demand-side parameters	$L(\theta, \phi; \mathbf{m}, \mathbf{v})$	Total Loss
$\zeta_2$	Non-linear common parameters	$\mathbf{E}_{q_\phi(\mathbf{v} \mathbf{m})}[\log \rho_\theta(\mathbf{m} \mathbf{v})]$	Reconstruction Loss
$\zeta_3$	Linear supply-side parameters	$I_q(\mathbf{v}, \mathbf{m})$	Mutual Information Loss
$p_{jt}$	Price	$KL \left[ q(\mathbf{v}) \parallel \prod_{j=1}^J q(v_j) \right]$	Total Correlation Loss
$c_{jt}$	Marginal Cost	$\sum_{j=1}^J KL[q(v_j) \parallel \rho(v_j)]$	Dimension KL Divergence Loss
$x_{jt}$	Observed product characteristic	$\lambda_1$	Weight on Total Correlation Loss
$v_{jt}$	Visual product characteristic	$\lambda_2$	Weight on GMM Objective
$U_{ujt}$	Indirect utility		
$\delta_{jt}$	Mean utility		
$\mu_{ijt}$	Heterogeneous utility		
$\epsilon_{ijt}$	Idiosyncratic taste shock		
$d_{ijt}$	Choice indicator		
$s_{ijt}$	Choice probability		
$s_{jt}$	Market share		
$\xi_{jt}$	Demand-side structural error		
$\omega_{jt}$	Supply-side structural error		
$Z^D$	Demand Instruments		
$Z^S$	Supply Instruments		
$W$	Weighting matrix		
$g$	Sample Moments		

### 3.1. Demand Model

We describe the BLP demand model (Berry et al. 1995) with the specification laid out in Berry et al. (1999).

**3.1.1. Consumers** In each market  $t = 1, \dots, T$ , there are  $J_t$  differentiated goods and  $I_t$  consumers. For each market, we observe average quantities, prices and product characteristics for all  $J_t$  products.

Consistent with the standard BLP model, the indirect utility of consumer  $i$  from purchasing product  $j$  in market  $t$  is a function of observed product characteristics  $\mathbf{x}_{jt}$ , unobserved product-market characteristics  $\xi_{jt}$ , price  $p_{jt}$ , consumer characteristics  $\nu_{it}$  and unknown parameters,  $\zeta$ . The total number of observed characteristics for the product is  $K$ . We use the specification written in Equation (1). Here, price  $p_{jt}$  is endogenous, since it could be based on the unobserved product-market characteristics  $\xi_{jt}$ , and hence correlated with it. The indirect utility is specified as:

$$U_{ijt} = \mathbf{x}_{jt}\overline{\beta_1} - \alpha p_{jt}/y_{it} + \xi_{jt} + \sum_{k_1} (\sigma_{\beta_1}^{k_1} x_{jt}^{k_1} \nu_{it}^{k_1}) + \epsilon_{ijt} \quad (1)$$

where  $\mathbf{x}_{jt}$  or observed product characteristics only includes structured product characteristics,  $p_{jt}$  is the price of product  $j$  in market  $t$ ,  $y_{it}$  is the income of the consumer  $i$  in market  $t$ ,  $\xi_{jt}$  is the unobserved product-market characteristic,  $\nu_{it}^{k_1}$  represents consumers  $i$ 's taste for characteristic  $k_1$  in market  $t$ , and finally,  $\epsilon_{ijt}$  denotes a mean-zero idiosyncratic taste shock. The unobserved product-market characteristics can reflect hard to quantify aspects of the product such as quality or style. The unobserved product characteristics can be decomposed into visual product characteristics  $\mathbf{v}_{jt}$  and rest of the unobserved product-market characteristics  $\tilde{\xi}_{jt}$ . This decomposition is written in Equation 2. In a demand model without visual characteristics, this would reduce to the typical BLP structural error  $\xi_{jt}$ . Note that, even after we account for visual characteristics, the remaining unobserved product-market characteristics  $\tilde{\xi}_{jt}$  may still contain some unobserved visual characteristic, as well as any other aspects of unobservable quality.

$$\xi_{jt} = \mathbf{v}_{jt}\overline{\beta_2} + \sum_{k_2} (\sigma_{\beta_2}^{k_2} v_{jt}^{k_2} \nu_{it}^{k_2}) + \tilde{\xi}_{jt} \quad (2)$$

Each consumer  $i$  in market  $t$  has unit demand. Consumers choose among  $J_t = \{0, 1, \dots, J_t\}$  discrete choices including the outside good, denoted by  $j = 0$ . The utility of

the outside good represents the choice of not purchasing any product in the market and is given by  $U_{i0t} = \epsilon_{i0t}$ . Consumers select the alternative (including outside good) with the highest utility:

$$d_{ijt} = \begin{cases} 1 & \text{if } U_{ijt} > U_{ikt} \text{ for all } k \neq j \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

Note that as in BLP, we can decompose the indirect utility in Equation (1) into a mean utility,  $\delta_{jt}$  in Equation (4) and a deviation from that mean,  $\mu_{ijt}$ , in Equation (5).

$$\delta_{jt}(\mathbf{x}_{jt}, p_{jt}, \xi_{jt}; \zeta_1) = \mathbf{x}_{jt} \overline{\beta_1} + \mathbf{v}_{jt} \overline{\beta_2} + \tilde{\xi}_{jt} \quad (4)$$

$$\mu_{ijt}(\mathbf{x}_{jt}, p_{jt}, \nu_{ijt}, y_i; \zeta_2) = -\alpha p_{jt}/y_{it} + \sum_{k_1} (\sigma_{\beta_1}^{k_1} x_{jt}^{k_1} \nu_{it}^{k_1}) + \sum_{k_2} (\sigma_{\beta_2}^{k_2} v_{jt}^{k_2} \nu_{it}^{k_2}) + \epsilon_{ijt} \quad (5)$$

where  $\mathbf{x}_{jt}$  or observed product characteristics only includes structured product characteristics,  $\mathbf{v}_{jt}$  is the visual product characteristics,  $p_{jt}$  is the price of product  $j$  in market  $t$ ,  $y_{it}$  is the income of the consumer  $i$  in market  $t$ ,  $\tilde{\xi}_{jt}$  is the unobserved product-market characteristic,  $\nu_{it}^{k_1}$  and  $\nu_{it}^{k_2}$  represents consumers  $i$ 's taste for structured product characteristics  $k_1$  and visual characteristics  $k_2$  in market  $t$ , and finally,  $\epsilon_{ijt}$  denotes a mean-zero idiosyncratic taste shock.

We denote  $\zeta = (\zeta_1, \zeta_2)$ , a vector of all the parameters in the model. The vector  $\zeta_1$  contain the linear parameters or the mean preference on  $\mathbf{x}_{jt}$ , i.e.  $\overline{\beta_1}$  and on  $\mathbf{v}_{jt}$ , i.e.  $\overline{\beta_2}$ . These preferences are common across all consumers. The vector  $\zeta_2$  contain the nonlinear parameters or the standard deviation from mean preference i.e.  $\sigma_{\beta_1}$  and  $\sigma_{\beta_2}$  as well as the term on the price  $\alpha$ . These nonlinear parameters introduce heterogeneity in preferences over structured product characteristics.

Using the standard assumption that  $\epsilon_{ijt}$  are i.i.d. with the Type I extreme value distribution, the probability  $s_{ijt}$  that consumer  $i$  chooses product  $j$  in market  $t$  is given by Equation (6) below.

$$s_{ijt} = \frac{\exp(\delta_{jt} + \mu_{ijt})}{\sum_{k \in J_t} \exp(\delta_{kt} + \mu_{ikt})} \quad (6)$$

Aggregate market shares  $s_{jt}$  are obtained by integrating over the choices made by heterogeneous consumers as represented in Equation (7).

$$s_{jt} = \int \frac{\exp(\delta_{jt} + \mu_{ijt})}{\sum_{k \in J_t} \exp(\delta_{kt} + \mu_{ikt})} dF_i \quad (7)$$

**3.1.2. Firms** We assume that automobile firms, indexed by  $f$  and part of a set  $F_t$ , play a static, full information, simultaneous move pricing game each period. Firms choose the price levels of all their models with the objective of maximizing overall profit. We specify a constant marginal cost  $c_{jt}$  for a product  $j$  in market  $t$ . The pricing first order condition for vehicle  $j$  is given by Equation (8).

$$s_{jt} + \sum_{j \in J_t} (p_{jt} - c_{jt}) \frac{\partial s_{jt}}{\partial p_{jt}} = 0 \quad (8)$$

We parameterize the marginal costs as written below in Equation (9).

$$c_{jt} = \mathbf{x}_{jt}\gamma_1 + \mathbf{w}_{jt}\gamma_2 + \omega_{jt} \quad (9)$$

where  $\mathbf{x}_{jt}$  are product characteristics,  $\mathbf{w}_{jt}$  are observable cost-shifters and  $\omega_{jt}$  are unobserved cost-shifters. We can estimate the marginal costs for each product when we solve the supply model jointly with the demand model. We do not explicitly include visual characteristics in the supply-side and so they are assumed to be part of the unobservables.

**3.1.3. Instruments** In this demand model, we assume that a consumer's utility depends up on the observed product characteristics as well as unobserved (to the researcher) product characteristics. Firms observe these unobserved product characteristics and set then set prices, which implies that price is endogenous and necessitates the use of instruments. There are multiple options for instruments. First, we could use *exogenous cost shifters*. These are valid if we assume that firms respond to cost shifts by changing prices, and not by changing product characteristics. Second, we could use *observed product characteristics* other than price. This would be valid if we make a timing assumption that firms first set observed product characteristics, then observing the “unobserved” product characteristics (structural error), and then set prices. This assumption would be supported by the observation that firms change prices frequently, whereas product characteristics are altered less frequently. Third, we could use Hausman instruments, a common example of which includes prices in other markets, if we have multiple markets that have the same product. Finally, we could use observed product characteristics of other products. One example of these instruments is referred to as *BLP instruments* in which we take sums of characteristics of other products made by the same firm and sums of characteristics of all other firms. We present them in Equation (10). Another example instead uses differences

in characteristics. They are referred to as *differentiation IVs* (Gandhi and Houde 2019). To construct *differentiation IVs*, we define the difference in characteristic space between product  $j$  and product  $k$  (in market  $t$ ) as  $d_{jkt} = d_{kt} - d_{jt}$  for each characteristic in  $x_{jt}$ . Using the differences in characteristic space, we construct local and quadratic forms of *differentiation IVs*. Both these set of *differentiation IVs* assume that rival as well as non-rival products close to the focal product in the characteristics space affect the firm's pricing decision more than products far away. We present these instruments in Equation (11) and Equation (12). Conlon and Gortmaker (2020) found that *differentiation IVs* perform better than *BLP instruments* in simulation exercises. This result is not surprising because of the somewhat localized nature of competition in the product characteristic space. Moreover, differentiation IVs also reduces the problem of weak instruments that might be present in *BLP instruments*. Note that the instruments used in Sudhir (2001), who calculated average of characteristics only within the same segment and not the entire market, so as to reflect localized nature of competition is similar in spirit to differentiation IVs. In our main analysis, we use the *BLP instruments*.

$$Z_{BLP} = \{1, x_{jt}, w_{jt}, \sum_{j \in J_t} 1, \sum_{j \notin J_t} 1, \sum_{j \in J_t} x_{jt}, \sum_{j \notin J_t} x_{jt}\} \quad (10)$$

$$Z_{local} = \{1, x_{jt}, w_{jt}, \sum_{j \in J_t} 1(|d_{jkt}| < \sigma_l(d)), \sum_{j \notin J_t} 1(|d_{jkt}| < \sigma_l(d))\} \quad (11)$$

where  $\sigma_l(d)$  denotes the standard deviation of the distance in the characteristic space.

$$Z_{quadratic} = \{1, x_{jt}, w_{jt}, \sum_{j \in J_t} d_{jkt}^2, \sum_{j \notin J_t} d_{jkt}^2\} \quad (12)$$

With the addition of demand instruments  $Z_{jt}^D$ , we construct demand-side moment conditions of the form  $E[\tilde{\xi}_{jt} Z_{jt}^D] = 0$ . Similarly, we also construct supply-side moment conditions of the form  $E[\omega_{jt} Z_{jt}^S] = 0$  using supply instruments  $Z_{jt}^S$ .

**3.1.4. GMM Estimator** We construct a GMM estimator using both supply-side and demand-side moment conditions.

$$g(\theta) = \begin{bmatrix} \frac{1}{N} \sum_{jt} E[\tilde{\xi}_{jt} Z_{jt}^D] \\ \frac{1}{N} \sum_{jt} E[\omega_{jt} Z_{jt}^S] \end{bmatrix} \quad (13)$$

We construct a nonlinear GMM estimator for  $\zeta$  with some weighting matrix  $W$  in Equation (14). We solve this problem twice. First, we obtain a consistent estimate of  $W$  and then an efficient GMM estimator.

$$\min_{\theta} g(\zeta)'Wg(\zeta) \quad (14)$$

### 3.2. Disentangled Representation Learning

We now present a method to discover independent and human interpretable visual characteristics from product images. We refer readers to Sisodia et al. (2022) for more details. We have a dataset  $\mathbf{m}$  of images. We assume that they are generated from a distribution parameterized by visual characteristics  $\mathbf{v}$ . The generative model is a combination of the prior  $\rho(\mathbf{v})$  set to an isotropic unit Gaussian  $\mathcal{N}(0, 1)$  and a decoder neural net  $\rho_{\theta}(\mathbf{m}|\mathbf{v})$ . The true posterior is intractable as in variational Bayesian inference (Blei et al. 2017) and so it is approximated as  $\log q_{\phi}(\mathbf{v}|\mathbf{m}) = \log \mathcal{N}(\mathbf{v}; \boldsymbol{\mu}_d, \boldsymbol{\sigma}_d^2 \mathbf{I})$  where  $\boldsymbol{\mu}_d$  and  $\boldsymbol{\sigma}_d$  are the mean and the s.d. of the approximate posterior. The loss for the original VAE is written in Equation (15). We refer readers to Kingma and Welling (2014) for its detailed derivation.

$$\underbrace{L(\theta, \phi; \mathbf{m}, \mathbf{v})}_{\text{VAE Loss}} = \underbrace{\mathbf{E}_{q_{\phi}(\mathbf{v}|\mathbf{m})} [\log \rho_{\theta}(\mathbf{m}|\mathbf{v})]}_{\text{Reconstruction Loss}} + \underbrace{KL[q_{\phi}(\mathbf{v}|\mathbf{m})||\rho(\mathbf{v})]}_{\text{Regularizer Term}} \quad (15)$$

In Equation (16), we decompose the regularizer term in Equation (15) into three terms (Chen et al. 2018, Hoffman and Johnson 2016, Kim and Mnih 2018). We follow the  $\beta$ -TCVAE method (Chen et al. 2018) by imposing a heavier penalty on the total correlation loss term. We provide an intuition behind each of the loss terms below.

$$\begin{aligned} \underbrace{L(\theta, \phi; \mathbf{m}, \mathbf{v})}_{\text{Open Loop Loss}} &= \underbrace{\mathbf{E}_{q_{\phi}(\mathbf{v}|\mathbf{m})} [\log \rho_{\theta}(\mathbf{m}|\mathbf{v})]}_{\text{Reconstruction Loss}} + \underbrace{I_q(\mathbf{v}, \mathbf{m})}_{\text{Mutual Information Loss}} \\ &+ \lambda_1 \underbrace{KL \left[ q(\mathbf{v}) \parallel \prod_{j=1}^J q(v_j) \right]}_{\text{Total Correlation Loss}} + \underbrace{\sum_{j=1}^J KL[q(v_j)||\rho(v_j)]}_{\text{Dimension-Wise KL Divergence Loss}} \end{aligned} \quad (16)$$

*Reconstruction Loss:* Penalizing this term encourages the input data  $\mathbf{m}$  to be as similar to the reconstructed output  $\hat{\mathbf{m}}(\mathbf{v})$  as possible. This means that we want the discovered

visual characteristics to have the necessary information so that the reconstructed output is as close as possible to the input image.

*Mutual Information Loss:* Penalizing this term means encouraging the visual characteristics  $\mathbf{v}$  store as little information about the product image  $\mathbf{m}$  as possible from an information-theoretic point of view (Achille and Soatto 2018). Although it seems counter intuitive that penalizing this term would encourage disentangled representation, but it allows the visual characteristics to not store any nuisance information.

*Total Correlation Loss:* Penalizing this term encourages the discovered visual characteristics  $\mathbf{v}$  to be statistically independent (Watanabe 1960). A zero loss on this term means that KL divergence is zero and the discovered visual characteristics are statistically independent. A  $\lambda_1 > 1$  penalty on this term means that we are trading off reconstruction accuracy for more statistically independent disentangled representations.

*Dimension-Wise KL Loss:* Penalizing this term encourages the distribution of each visual characteristic of every datum to be close the prior distribution. The prior is typically assumed to be Gaussian. This term promotes a continuous latent space, which allows generation from a smooth and compact region of latent space.

### 3.3. Integrated Model of Visual Characteristics Discovery and Demand

In this section, we describe our proposed integrated model of econometric demand and disentangled representation learning, referred to integrated model hereafter. Our integrated model furthermore has two different model specifications, which we call **open loop** and **closed loop**.

In both open and closed loop model specifications, we assume that a consumer’s utility depends upon observed product characteristics (including structured and visual product characteristics), unobserved product characteristics, price as well as an idiosyncratic taste. The primary difference between the open loop and closed loop model specification is whether the demand model and disentangle representation learning model is separable or not. We later test the two specifications of of integrated model against a baseline approach. The baseline approach (Model B) is the same as the one described in Berry et al. (1995), and does not incorporate visual characteristics.

In the first model specification, **open loop**, we first automatically discover the visual characteristics using disentangled representation learning without specifying the number or nature of those characteristics. The discovered characteristics are obtained for each



product, and then included as visual product characteristics in the demand model. These visual characteristics are thus similar to structured product characteristics and can be treated as data during the estimation of the demand model. We can obtain estimates of consumer preferences for these visual characteristics similar to how preferences over structured characteristics are ordinarily obtained.

The open loop class of demand model relies on an unsupervised method for finding disentangled representations. Although the unsupervised method for finding disentangled representations has been found to work in practice, [Locatello et al. \(2019\)](#) proved out that there was no theoretical guarantee to learn disentangled representations without supervision. When the visual characteristics are known ex-ante, then we refer those characteristics as ground truth. When ground truth for visual characteristics is available, then the deep learning literature suggests using the learned visual characteristics to predict the known labels of ground truth [Locatello et al. \(2020\)](#).

In the second specification, called **closed loop**, we allow for the disentanglement representation learning to use the demand model as a supervisory signal. Although supervisory signals used in the ML literature always rely on knowing ground truth about the visual characteristics, such an approach would not be suitable here since the purpose of our framework is to specifically discover these visual characteristics. Our idea of using the demand model to supervise the disentanglement model addresses this theoretical challenge by supervising the VAE-based method to learn disentangled representations on the demand model discussed in the Section [3.1](#).

The rationale for supervising on a demand model is that it captures how consumers respond to changes in both structured and visual product characteristic space. This endogenous response of consumers making choices and ensuring that those choices are consistent with observed market outcomes provides us with additional variation that the disentanglement model can learn from. Supervising on a demand model means that the demand model's loss (or objective) function is included in the disentanglement model's objective function. The modified loss equation is specified in Equation [\(17\)](#). Whereas in both open and closed loop specifications, the visual characteristics are incorporated similarly into the demand model, in the open loop the visual characteristics discovered at the completion of the disentanglement model do not change during the estimation process. However, in the closed loop, as the demand model is estimated, the parameters (and objective function)

of the learned demand model impact the estimation and results of the disentanglement model, and therefore the discovered visual characteristics are continually updated to be consistent with the demand model. In short, the discovered visual characteristics and the estimates from the demand model will be different depending on whether we use open loop or closed loop.

We detail the implementation details of how the demand model is incorporated within the deep learning model in Table 1.

$$\begin{aligned}
 \underbrace{L(\theta, \phi; \mathbf{m}, \mathbf{v})}_{\text{Closed Loop Loss}} &= \underbrace{\mathbf{E}_{q_\phi(\mathbf{v}|\mathbf{m})} [\log p_\theta(\mathbf{m}|\mathbf{v})]}_{\text{Reconstruction Loss}} + \underbrace{I_q(\mathbf{v}, \mathbf{m})}_{\text{Mutual Information Loss}} \\
 &+ \lambda_1 \underbrace{KL \left[ q(\mathbf{v}) \parallel \prod_{j=1}^J q(v_j) \right]}_{\text{Total Correlation Loss}} + \underbrace{\sum_{j=1}^J KL [q(v_j) \parallel p(v_j)]}_{\text{Dimension-Wise KL Divergence Loss}} + \lambda_2 \underbrace{GMM(\mathbf{v})}_{\text{Demand Model Objective}}
 \end{aligned} \tag{17}$$

---

**Algorithm 1** Closed Loop Estimation Algorithm

---

Initialize visual characteristics

Estimate demand model and store  $(\bar{\beta})$

**do**

▷ Training Epochs Start

**do**

▷ Steps within Epoch

Learn  $v_{jt}$  for images in a batch

Compute  $\tilde{\xi}_{jt}$  using the  $v_{jt}$  and  $\bar{\beta}$

Compute  $E[\tilde{\xi}_{jt} Z_{jt}]$  and add it to the overall loss term

**while** end of epoch

▷ Epoch Ends

Obtain visual characteristics of entire data

Update mean coefficients  $(\bar{\beta})$

Input  $\bar{\beta}$  in subsequent epoch

**while**  $epochs \leq 200$

▷ Training Ends

---

**3.3.1. Hyperparameter Selection using UDR Metric** Both open and closed loop models require us to make modeling choices in the form of hyperparameters, which impact the estimation process but are not parameters estimated with the model (e.g., number

of training epochs). In both model specifications, we have a number of hyperparameters, which are detailed in Table 2.

In the open loop model, we have a hyperparameter  $\lambda_1$ , which is the weight on the total correlation loss within the disentanglement loss (Chen et al. 2018). In the closed loop model, in addition to  $\lambda_1$ , we have a hyperparameter  $\lambda_2$ , which represents the weight of the demand loss when incorporated into the loss of the disentanglement model. For instance, a higher value of  $\lambda_2$  will weigh or prioritize the demand loss more relative to disentanglement loss terms like mutual information or reconstruction loss, which could reduce the quality of disentanglement. See Section 3.2 for more details.

Hyperparameter selection additionally requires we define a metric for model selection. We use the Unsupervised Disentanglement Ranking (UDR) (Duan et al. 2020) metric for hyperparameter selection. This metric measures the robustness of disentangled representations to variance at different starting points. It relies on the assumption that for a particular dataset, a disentangling VAE will converge on the same disentangled representation (up to *permutation*, *sign inverse*, and *subsetting*).<sup>5</sup> We select the hyperparameters  $\lambda_1$  and  $\lambda_2$  corresponding to the highest UDR. Moreover, this metric does not require access to the ground truth data generative process unlike other metrics such as  $\beta$ -VAE metric (Higgins et al. 2017), the FactorVAE metric (Kim and Mnih 2018), Mutual Information Gap (MIG) (Chen et al. 2018) and DCI Disentanglement scores (Eastwood and Williams 2018). We describe the steps to calculate UDR below in Table 3.

**3.3.2. Neural Net Architecture** Figure 2 shows the detailed neural net architecture. Our architecture is a modified version of the one used in Burgess et al. (2017). We modify the architecture to use images of  $128 \times 128$  pixels as well as to incorporate a demand model. We use Convolutional Neural Net (CNNs) to construct the encoder neural net because we are working with images. We stack a sequence of CNN layers in the encoder neural net so that we learn high-level concepts for images. We then use 2 fully-connected

5

1. Permutation: The same ground truth factor may be encoded by a model with two different seed values at a different index position.
2. Sign inverse: A model with two different seed values may learn to encode the values of the generative factor in the opposite order to each other.
3. Subsetting: A model from one seed value may learn a subset of the factors that the a model with a different seed value has learned. This is because different seed values may encourage a different number of latents to be switched off in the two models.

**Table 2 Hyperparameter Selection (Open and Closed Loop)**

Step	Description
1	Fix all the hyperparameters except $\lambda_1$ (and $\lambda_2$ in case of closed loop)
2	Fix <sup>‡<sub>1</sub></sup> batch size=64, number of visual characteristics=20, learning rate=0.0005, and the number of epochs=200
3	Sweep over $\lambda_1 = [1, 5, 10, 20, 30, 40, 50]$ (and $\lambda_2 = [0, 5, 10, 20, 30, 40, 50]$ in case of closed loop)
4	Obtain disentangled representations for every combination of $\lambda_1$ (and $\lambda_2$ in case of closed loop)
5	Calculate Unsupervised Disentanglement Ranking (UDR) <sup>‡<sub>2</sub></sup> <a href="#">Duan et al. (2020)</a>
6	Select $\lambda_1$ (and $\lambda_2$ in case of closed loop) for disentanglement model with the highest UDR.
7	Obtain the learned visual characteristics $\mathbf{v}$ for both open loop and closed loop

<sup>‡<sub>1</sub></sup> Intuition for Hyperparameters:

1. Batch Size: On the one hand, if a very low value for batch size is used, then the model takes longer to converge. On the other hand, if a very high value for batch size is used, then the model loses its generalizability beyond the training set.
2. Number of Visual Characteristics: On the one hand, if a very low number of visual characteristics is specified, then the model would force multiple factors of variation to be coded into a single visual characteristic. On the other hand, if a very high number of visual characteristics is specified, then the model would encourage a single factor of variation would be split into multiple visual characteristics.
3. Learning Rate: On the one hand, if a very low learning rate is used, then the model can get stuck on a local minima. On the other hand, if a very high learning rate is used, then the model may overshoot the minima.
4. Number of Epochs: On the one hand, training for a very low number of epochs may lead the model not to converge. On the other hand, training for a very high number of epochs may lead to overfitting the training data.

<sup>‡<sub>2</sub></sup> See Section 3.3 for details related to UDR

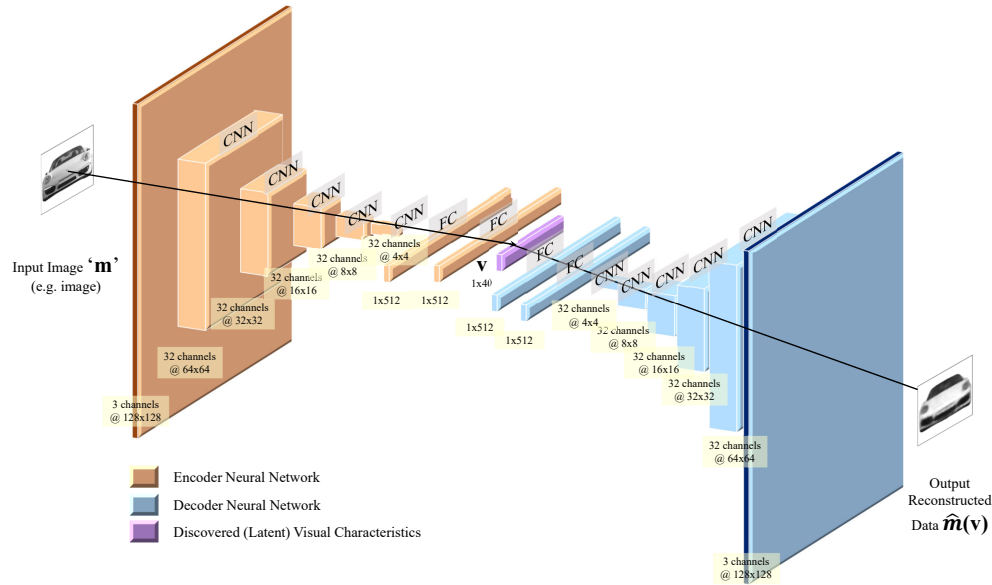
(FC) layers to first flatten the output of the sequence of CNN layers and then reduce the number of dimensions in order to learn a maximum of 20 visual characteristics. The decoder neural net is simply the transpose of the encoder neural net, and is designed to reconstruct the image from the 20-dimensional latent visual characteristics. Finally, we feed the discovered visual characteristics in conjunction with structured product characteristics to estimate demand. We add the GMM objective from the demand model to the loss of the neural network. This ensures that the learned visual characteristics not only help in

**Table 3** UDR Algorithm

Step	Description
1	For each trained model $\tau(\lambda)$ , perform $\kappa = 10$ pairwise comparisons
2	Pairwise comparisons: models trained with the same $\lambda$ but with different seed values
2	Calculate the $UDR_{\tau_{s_1}\tau_{s_2}}$ , where $\tau_{s_1}$ and $\tau_{s_2}$ index the model $\tau$ learned with two different seed values
3	Calculate $UDR_{\tau_{s_1}\tau_{s_2}}$ score as similarity matrix $R_{\tau_{s_1}\tau_{s_2}}$ where each entry is the Spearman correlation between the responses of individual latent units of the two models.
4	Calculate absolute value of the similarity matrix as $ R_{\tau_{s_1}\tau_{s_2}} $
5	Compute the score $UDR_{\tau_{s_1}\tau_{s_2}}$ for each pair of models <sup>‡</sup>
6	Compute the final score $UDR_{\tau}$ for model $\tau$ by taking the median of $UDR_{\tau_{s_1}\tau_{s_2}}$

$$^{\ddagger} UDR_{\tau_{s_1}\tau_{s_2}} = \frac{1}{v_{\text{inf}_a} + v_{\text{inf}_b}} \left[ \sum_b \frac{r_a^2 I_{KL}(b)}{\sum_a R(a,b)} + \sum_a \frac{r_b^2 I_{KL}(a)}{\sum_b R(a,b)} \right]$$

where  $a$  and  $b$  index the latent units of models  $\tau_{seed_1}$  and  $\tau_{seed_2}$ , respectively,  $r_a = \max_a R(a,b)$  and  $r_b = \max_b R(a,b)$ .  $I_{KL}$  indicates an *informative* visual characteristics within a model and  $v_{\text{inf}}$  is the number of such characteristics:  $v_{\text{inf}_a} = \sum_a I_{KL}(a)$  and  $v_{\text{inf}_b} = \sum_b I_{KL}(b)$

**Figure 2** Schematic Illustration of Proposed Approach

disentanglement but also help in finding a lower GMM objective for the demand model. Note that, the demand model is not estimated using neural nets and so not included part of the neural net architecture.

## 4. Empirical Application: UK Automobile Market

### 4.1. Data

We compiled a data set covering 2008 through 2017 consisting of automobile characteristics, market shares and their images from the UK. Our primary source of data is manufacturer suggested retail prices (MSRP), and characteristics of all automobiles sold in the UK from 2008-2017 that we obtain from Parker's. We obtain information on sales (in 1000's) and images of the automobiles from DVM-CAR (Huang et al. 2021). Market research studies have shown that 70% of consumers identify and judge automobiles by the appearance of headlights and grille located on the face of the automobile.<sup>6</sup> So we only select the images of the front face of the automobiles and ignore other views. Since our sales data comes at the make-model level, we choose the entry-level trim's product characteristic as the product characteristic. This is similar to similar to other studies of the automobile market (Berry et al. (1995), Sudhir (2001), Petrin (2002), Berry et al. (2004)). We have product characteristics for number of seats, number of doors, weight, horsepower, length, width, miles per gallon, luggage capacity and dummy variables for whether the automobile has automatic transmission, front wheel or rear wheel or four wheel drivetrain. The price variable is the list price (in £1000's) for the entry-level model. Prices in all years are deflated to 2015 UK using the consumer price index.

We supplemented the Parker's information with additional information, including vehicle country of production and company ownership information. We also supplemented additional information from the Office of National Statistics, UK. We gathered the price of ultra low sulphur petrol per gallon and ultra low sulphur diesel per gallon as well as the number of households in the UK. Similar to Berry et al. (1995), we calculated miles per UK pound (MP£) as miles per gallon divided by the price per gallon. We measure the market size as the number of households in the UK. We use 'HP/Weight', 'MP£', 'Space' to construct the quadratic form of *differentiation IVs*.

In Table 4, we display summary statistics for the products at the make-model-year level. There are 2460 observations in our sample and a total of 400 distinct models. The variables include quantity (in units of 1000), price (in £000 units), the ratio of horsepower to weight (in HP per 10 lbs.), the number of ten mile increments one could drive for one £ of gasoline (MP£), tens of miles per gallon (MPG), and size (measured as length times width). We

<sup>6</sup> URL: <https://www.wsj.com/articles/SB114195150869994250>

provide sales-weighted means for each variable. We see that automobiles have improved in terms of both power and fuel efficiency over these ten years. Prices for automobiles has also gone up substantially from 2008 to 2017.

**Table 4 Descriptive Statistics**

Market	No. of Observations	Quantity	Price	HP/Wt	Space	MPG	MP£
2008	240	5.992	21.374	0.416	1.245	4.577	0.760
2009	247	6.159	21.089	0.411	1.229	4.838	0.905
2010	243	6.655	21.584	0.414	1.247	5.022	0.837
2011	231	6.876	21.784	0.421	1.261	5.183	0.782
2012	244	7.028	21.533	0.422	1.264	5.422	0.825
2013	241	8.075	21.351	0.423	1.268	5.573	0.878
2014	251	8.608	21.697	0.431	1.277	5.702	0.962
2015	251	9.148	22.754	0.443	1.290	5.787	1.126
2016	253	9.225	24.067	0.457	1.305	5.692	1.149
2017	259	8.262	24.847	0.465	1.318	5.498	1.052
All	2460	7.626	22.353	0.433	1.274	5.390	0.948

In Table 5, we provide a range of continuous demand characteristics along by providing the minimum, median and maximum values. The least expensive automobile in our sample is the Perodua Kelisa while the Mercedes-Benz CL is the most expensive. Similarly, Citroen Dispatch has the lowest ratio of horsepower to weight and Nissan GT-R has the highest ratio of horsepower to weight. Smart fortwo is the smallest automobile and Audi SQ7 is the largest automobile in terms of space. Finally, the Vauxhall VXR8 is the least fuel-efficient automobile while the Lexus CT is the most fuel-efficient automobile.

**Table 5 Range of Continuous Demand Characteristics**

Variable	0th Percentile	50th Percentile	100th Percentile
Price	6.485	24.001	164.706
	Perodua Kelisa	Volkswagen Golf	Bentley Bentayga
HP/Wt	0.0597	0.4697	1.3304
	Aixam Crossline	Chevrolet Trax	Audi RS7
Space	0.6619	1.3363	1.7898
	Aixam a751	Hyundai Kona	Mercedes-Benz V Class
MPG	16.00	47.50	99.43
	Hummer H2	Renault Laguna	Hyundai Ioniq
MP£	2.824	8.360	19.357
	Hummer H2	Audi A5	Hyundai Ioniq

In Figure 3, we display images of 25 automobiles present in our dataset. Note that, we converted color images to grayscale for our study (sales are also not available separately by color). For each image, we have its associated make, model, year, structured product characteristics and price.

**Figure 3** Sample of Automobile Images

## 4.2. Results

**4.2.1. Disentanglement** For model training, we initially set model hyperparameters including the number of epochs=200, batch size=64, number of latent space dimensions=20, learning rate=0.0005, and the threshold value on KL loss term=0.01. Table 2 in the methodology section explains the intuition behind these terms. We select the hyperparameters corresponding to the weight on the total correlation term  $\lambda_1$ , and the weight on the demand loss term  $\lambda_2$  by using the UDR metric described in the methodology section. Higher values of the UDR metric correspond to better disentanglement and discovery of independent visual characteristics. Table 6 details the UDR metrics for the top 5 (high UDR) and bottom 3 (low UDR) configurations. We find that the best model corresponds to a positive weight on the demand loss term. The best configuration was with the weight on the total correlation term or  $\lambda_1 = 30$  and the weight on the demand loss term or  $\lambda_2 = 40$ . This finding implies that supervising the disentanglement model on the demand model (closed loop) aids in finding visual characteristics, as measured by the UDR metric. The best disentanglement model with no supervision (open loop) corresponds to the weight on the total correlation term or  $\lambda_1 = 30$  and the weight on the demand loss term or  $\lambda_2 = 0$ .



**Table 6** Disentanglement Model Evaluation

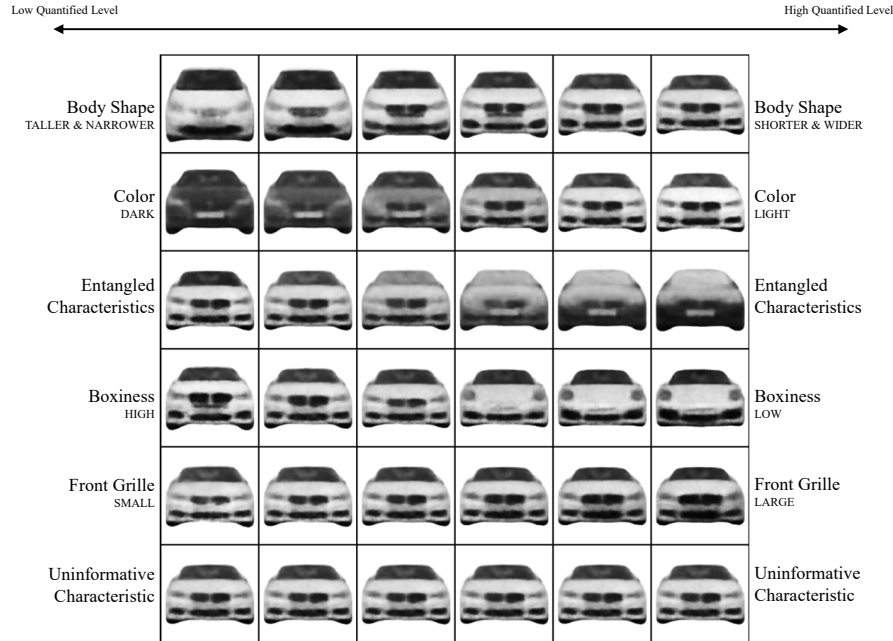
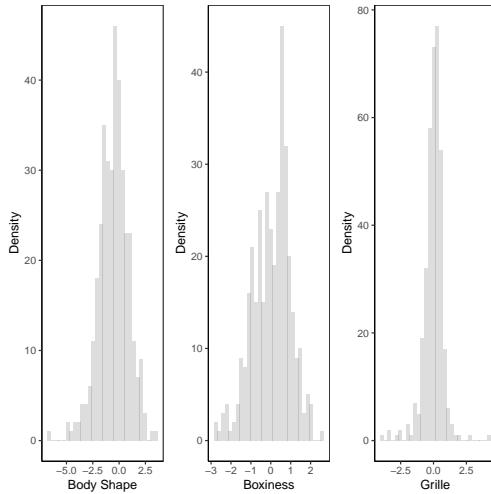
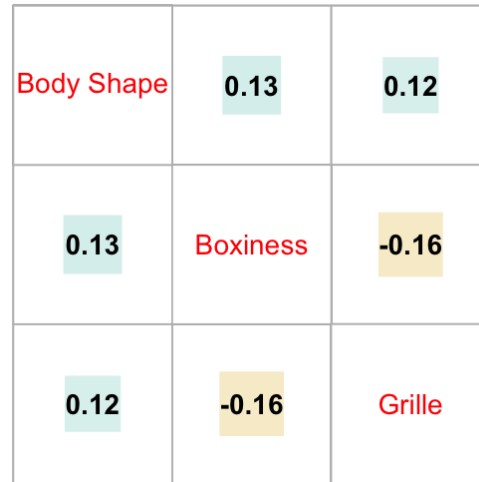
Weight on total correlation loss	Weight on demand loss	UDR (Best to Worst)	Model Type
<b>30</b>	<b>40</b>	<b>0.382</b>	<b>Closed Loop</b>
30	30	0.381	Closed Loop
30	10	0.378	Closed Loop
<b>30</b>	<b>0</b>	<b>0.377</b>	<b>Open Loop</b>
40	30	0.371	Closed Loop
...	...	...	...
1	0	0.042	Open Loop
1	50	0.041	Closed Loop
1	10	0.040	Closed Loop

We show the discovered visual characteristics in Figure 4. Each row in the image corresponds to a visual characteristics. In each row, we change the value of one visual characteristic while fixing the value of all the other characteristics. We find five visual characteristics of a automobile’s front view to be informative. Rest of the visual characteristics were uninformative i.e. changing the visual characteristic produces no change in the image. We interpret these visual characteristics as written below, subject to validation by human coders.

1. Body Shape: This characteristic can be interpreted as ratio of width to height. Automobiles with a low value on this visual characteristic have a low width to height ratio and vice-versa.
2. Color: Automobiles with a low value on this visual characteristic are darker and vice-versa. We ignore this characteristic in the demand model as automobiles come in multiple colors and sales data is only available at make-model level.
3. We ignore this characteristic as this is entangled with color
4. Boxiness: Automobiles scoring low on this characteristic have a box-like shape and vice-versa.
5. Grille: Automobiles scoring low on this characteristic have a smaller grille and vice-versa.

Figure 5a shows the density plot of the discovered visual characteristics. Figure 5b shows the visualization of the correlation between the three discovered visual characteristics.

**4.2.2. Demand Model** In this section, we compare a demand model only including structured product characteristics with a demand model including both structured product characteristics as well as visual product characteristics. Following [Berry et al. \(1995\)](#), we first present results using OLS Logit and IV Logit. We include the ratio of horsepower

**Figure 4** Discovered Visual Characteristics**Figure 5** Summary of Discovered Visual Characteristics**(a) Density Plot of Visual Characteristics****(b) Visualization of Correlation Matrix**

to weight (HP/Weight), miles per pound (MP£), and space as structured product characteristics. We also include three visual characteristics: body shape, boxiness and grille. As expected, Table 7 shows that adding differentiated IVs as instruments for price shows consumers are more price sensitive.

Next, we compare different specifications using the random coefficients demand model in Table 8. The first specification does not include visual characteristics. The second spec-

**Table 7 OLS Logit & IV Logit Model Results**

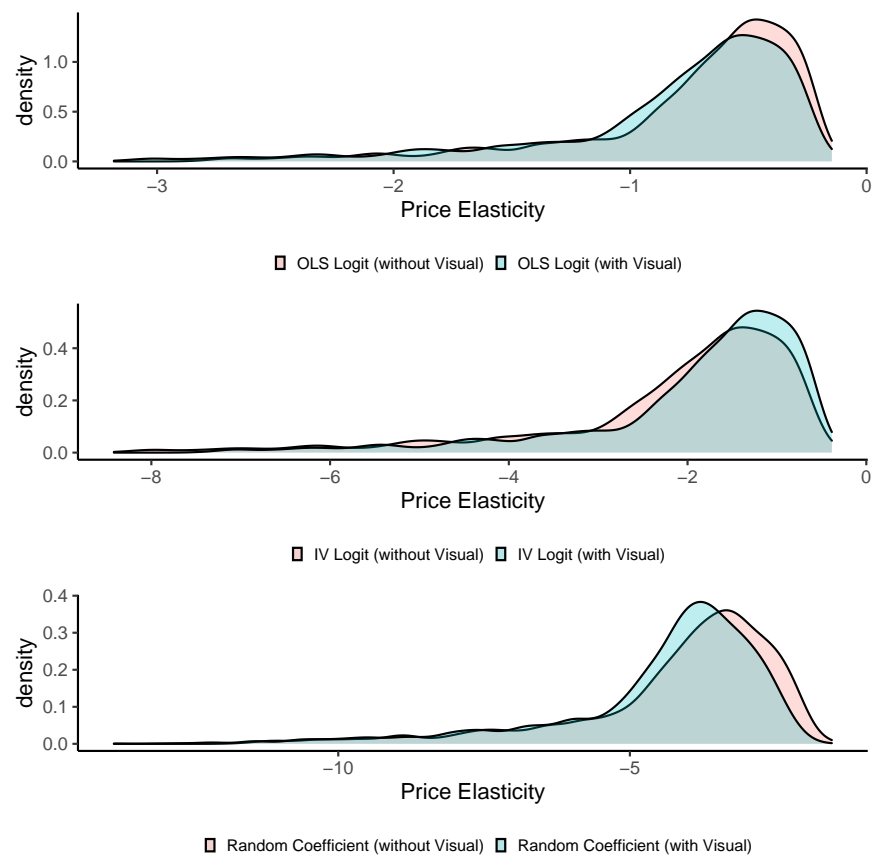
	OLS Logit Demand			IV Logit Demand		
	Baseline	Open Loop	Closed Loop	Baseline	Open Loop	Closed Loop
Constant	−12.46 (0.37)	−11.79 (0.40)	−11.73 (0.40)	−16.54 (0.96)	−15.35 (1.10)	−15.30 (1.13)
HP/Weight	0.88 (0.35)	0.30 (0.38)	0.29 (0.38)	8.29 (1.49)	7.33 (1.77)	7.23 (1.80)
MP£	3.90 (0.19)	3.82 (0.20)	3.81 (0.20)	2.62 (0.33)	2.68 (0.34)	2.71 (0.34)
Price	−0.02 (0.005)	−0.02 (0.005)	−0.02 (0.005)	−0.17 (0.03)	−0.16 (0.04)	−0.16 (0.04)
Space	0.97 (0.25)	0.83 (0.25)	0.81 (0.25)	5.35 (0.96)	4.84 (1.11)	4.74 (1.12)
$V_{bodyshape}$		0.16 (0.04)	0.15 (0.04)		0.29 (0.05)	0.28 (0.05)
$V_{boxiness}$		0.04 (0.05)	0.06 (0.05)		−0.24 (0.09)	−0.22 (0.09)
$V_{grille}$		0.17 (0.07)	0.21 (0.06)		0.31 (0.07)	0.32 (0.07)
Observations	2,460	2,460	2,460	2,460	2,460	2,460

ification includes visual characteristics when the demand model was not supervised on the disentanglement model (open loop). The third specification includes visual characteristics when the demand model was supervised on the disentanglement model (closed loop). Figure 6 plots the distribution of price elasticity for a specification only including structured product characteristics (baseline) and a specification including both structured product characteristics as well as visual product characteristics (closed loop).

**Table 8 Demand Model Estimates**

		Baseline	Open Loop	Closed Loop
		(1)	(2)	(3)
Means ( $\bar{\beta}'s$ )	Constant	-18.00 (0.73)	-17.00 (3.90)	-16.00 (4.00)
	HP/Weight	9.00 (1.80)	5.90 (2.10)	5.40 (2.20)
	MP£	3.90 (0.32)	2.50 (0.96)	2.50 (0.97)
	Space	11.00 (0.89)	8.20 (2.90)	7.80 (2.80)
	V <sub>bodyshape</sub>		1.90 (0.40)	2.00 (0.39)
	V <sub>boxiness</sub>		-0.37 (0.10)	-0.34 (0.10)
	V <sub>grille</sub>		0.28 (0.19)	0.41 (0.19)
Standard Deviation ( $\sigma'_{\beta}s$ )	Constant	0.00 (0.00)	5.00 (4.00)	4.90 (4.10)
	HP/Weight	3.70 (1.50)	0.00 (0.00)	0.00 (0.00)
	MP£	0.00 (0.00)	4.80 (1.80)	4.80 (1.70)
	Space	0.00 (0.00)	3.80 (1.50)	3.80 (1.40)
	V <sub>bodyshape</sub>		1.70 (0.37)	1.90 (0.40)
	V <sub>boxiness</sub>		0.00 (0.00)	0.00 (0.00)
	V <sub>grille</sub>		0.00 (0.00)	0.00 (0.00)
Term on Price	(-p/y)	-18.00 (1.40)	-16.00 (2.70)	-15.00 (2.80)
Supply-Side Terms	Constant	3.70 (0.05)	3.70 (0.05)	3.70 (0.05)
	ln(HP/Weight)	0.74 (0.03)	0.78 (0.04)	0.78 (0.04)
	ln(MPG)	-0.38 (0.04)	-0.31 (0.04)	-0.31 (0.04)
	ln(Space)	1.60 (0.05)	1.60 (0.06)	1.60 (0.06)
	Trend	0.01 (0.00)	0.01 (0.00)	0.01 (0.00)
Mean Own-Price Elasticity		-7.45	-8.80	-8.62
S.D. Own-Price Elasticity		0.34	0.30	0.30
Mean Markup		0.15	0.13	0.13
GMM Objective		290	220	210

Figure 6    Density Plot - Price Elasticities



**Figure 7 Evolution of BMW Kidney Bean Grille**

## 5. Counterfactual Analysis: BMW Kidney Bean Grille

Admitting he had “noticed” and “been hurt” by the criticism of the enormous grille – which has sparked countless memes on the internet and social media – BMW design chief Adrian van Hooydonk says he understands why both buyers and the design community had been shocked.

– *Car Sales Blog, June 26, 2019*

While visual characteristics are important across products (automobile models), most products would not have dramatic variation across time or markets. However, there are cases where firms choose to make dramatic changes in visual design. A recent example is BMW’s change in “design language” in 2018, which was very polarizing. Historically, BMWs have always had a grille known as the “kidney beans,” distinctively a visual cue for all BMW models (Bangle 2001). For model year 2018, this longstanding mainstay visual design was disrupted by dramatically elongating the grille, with many commentators having a negative opinion on the new lung-shaped grille imposed on much of the BMW product line.

We conduct a counterfactual analysis where BMW introduces such a visual design change earlier at the end of our data period (2017), and then evaluate market outcomes following this change. This counterfactual enables us to compare BMW’s market shares for the original and the new design. We also seek to examine how the results differ for models that include visual characteristics and those that do not.

We detail the steps to conduct the counterfactual analysis. First, we evaluate the case where no change happens in BMW’s “design language” which represents the true outcome we observe. We compute equilibrium prices and market shares for the entire market in 2017 using the demand estimates from the baseline model (without visual characteristics)

and closed loop model (with visual characteristics). We report the model predicted BMW’s market shares in 2017 in column (2) and column (3) of Table 9.

Next, we examine the case where BMW changes its “design language” in 2017. For the closed loop model (with visual characteristics), we change the levels of the visual characteristic  $v_{grille}$  and assume no change in unobserved product characteristic  $\tilde{\xi}_{jt}$  corresponding to BMW models. (Recall that  $\tilde{\xi}_{jt}$  captures unobservable product characteristics *excluding* the visual characteristics). The counterfactual visual design can be specified by changing the discovered visual characteristics, specifically the characteristic  $v_{grille}$  for a change in grille. We then recompute the equilibrium prices and market shares for the entire market in 2017 using the demand estimates from model (with visual characteristics). We report BMW’s counterfactual market shares in 2017 in column (5) of Table 9. Note that, with a baseline model, when the BMW changes its “design language”, there is a change in the unobserved product characteristic  $\xi_{jt}$  corresponding to BMW models, which implicitly also captures visual characteristics (and any other unobservables at the product market level). We assume that the unobserved product characteristic  $\xi_{jt}$  for BMW models come from a standard gaussian distribution. We find the mean and standard deviation of  $\xi_{jt}$  corresponding to BMW models. Next, for the counterfactual, for each make-model we take multiple draws from this distribution and report the predicted market shares in column (3) of Table 9. Finally, we report the ratio of BMW’s market shares with the counterfactual design change to BMW’s market shares with no design change for the baseline model and the closed loop model in column (6) and column (7) of Table 9. We note that our model predicts an increase in the market share of BMW models with this new design change. This finding is directionally and qualitatively consistent with the actual increase in sales for Model Year 2018 (by 26%) for the BMW X-Series, where the change is grille was most pronounced. Unsurprisingly, the baseline model does not point to any change in the market shares for BMW models.

## 6. Discussion & Conclusion

Visual product characteristics are important to quantify in a semantically-interpretable manner and incorporate into traditional demand models used in marketing and economics. However, this is a challenging task especially when the model is required to discover visual characteristics automatically. We propose a model that combines a disentanglement VAE-based deep learning model that discovers visual characteristics with a BLP demand model

**Table 9 Counterfactual Design Change for BMW automobiles**

Make-Model	Original Data (1)	Baseline (No Design Change) (2)	Predicted Share in 2017		Closed Loop (CF Design Change) (5)	Ratio of (3) to (2) (6)	Ratio of (5) to (4) (7)
			Baseline (CF Design Change) (3)	Closed Loop (No Design Change) (4)			
1 Series	0.0040	0.0046	0.0046	0.0032	0.0044	1.00	1.38
2 Series	0.0023	0.0026	0.0026	0.0018	0.0025	1.01	1.37
3 Series	0.0045	0.0052	0.0053	0.0036	0.0049	1.03	1.34
4 Series	0.0025	0.0028	0.0029	0.0020	0.0027	1.03	1.35
5 Series	0.0022	0.0025	0.0025	0.0018	0.0023	1.01	1.29
6 Series	0.0002	0.0002	0.0002	0.0002	0.0002	1.00	1.30
M2	0.0004	0.0004	0.0005	0.0003	0.0004	1.01	1.29
M3	0.0001	0.0002	0.0002	0.0001	0.0001	1.00	1.30
M4	0.0003	0.0003	0.0004	0.0002	0.0003	1.02	1.29
X1	0.0020	0.0022	0.0022	0.0016	0.0021	1.00	1.35
X3	0.0012	0.0013	0.0013	0.0009	0.0012	1.02	1.32
X4	0.0003	0.0003	0.0003	0.0003	0.0003	1.00	1.34
X5	0.0009	0.0010	0.0010	0.0008	0.0010	1.01	1.30
X6	0.0002	0.0002	0.0002	0.0002	0.0002	1.00	1.30

to evaluate the economic impact of visual characteristics. Methodologically we compare an open loop approach where the demand model just incorporates the visual characteristics similar to structured characteristics, to a closed loop approach where the results of the demand model can help train the disentanglement model to obtain better visual representations.

We obtain 3 distinct visual characteristics (body shape, grille and boxiness) obtained from the closed loop integrated model. We also find that after incorporating visual characteristics, our estimates of elasticity are more negative relative to the baseline without visual characteristics. We also conduct a counterfactual to examine the market impact of a visual design change by an auto manufacturer (BMW), and find that market shares in the counterfactual (in the new equilibrium) are higher for BMW, implying that the design change had a positive impact.

Our research has certain limitations. First, although we use a standard demand model like BLP, we do not have access to any individual consumer-level microdata. Thus, we are not able to evaluate an approach like [Berry et al. \(2004\)](#). Second, the product images we use in the model are currently limited to the front view of the automobile. It is likely that the side and rear view might matter as well to buyers, and could be potentially useful to study. Third, similar to most demand models, we assume exogeneity of product characteristics, which include visual characteristics as well.

The framework presented here can be readily extended along several aspects. First, our model can be applied across a broader class of demand models than considered in this paper. In marketing applications, consumer-level data is commonplace and it would be useful to extend our approach with such data. Second, it would be interesting to explore where consumers form ‘visual consideration sets’ in addition to consideration sets that are



usually based on structured characteristics [Mehta et al. \(2003\)](#). Finally, it would be helpful to study the impact of visual design across other product categories.

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