MODELING CONSIDERATION GIVES STRATEGIC DESIGN INSIGHT FOR ADDRESSING DIESEL AND BRAND PERCEPTION

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ABSTRACT

This paper explores consumer consideration and design response in the wake of a product scandal, namely the Volkswagen "clean diesel" scandal. It offers the novel contribution of designing for consideration, rather than final choice, with a linked market consideration and engineering model. The paper demonstrates how consideration modeling can be used to identify design strategy that capture lost consideration. A simulation study investigates three response design strategies: a design refresh by competitors; repricing by VW; and a new design by VW. The model used to investigate these scenarios includes data from a nation-wide survey conducted by Autolist that collected self-reported ratings of both VW and diesel consideration before and after the scandal. It also includes an engineering model that translates engineering variables (such as engine bore) into vehicle design attributes (such as fuel economy and rollover score). The case study finds that a design refresh by a competitor or a new vehicle design by VW can capture more consideration sets than VW repricing strategy alone, suggesting the importance of coordinating both design and economic strategies. The approach demonstrates the usefulness of design-for-consideration as a strategic before/after scenario analysis tool in the wake of an event that triggers shifts consumers' considerations.

1 INTRODUCTION

The first successful mass-produced advance technology vehicles, which use powertrain systems to reduce fuel consumption as defined by the U.S. Department of Energy [1], entered the United States automotive market as hybrid-electric vehicles (HEVs) in 1999. Since then, ATVs have struggled to gain market share, despite governmental incentives such as offering sales tax waivers, tax credits, and access to high-occupancy vehicle lanes [2]. HEVs comprise only 2.75% of the vehicles sold in the United States (US) during 2014 [3].

Researchers postulate that the structure of consumer automobile purchase decisions present a barrier-to-entry for ATVs. Consumers use cognitive rules to create a subset of all vehicles that are the vehicles they would consider purchasing—an approach modeled as consideration [4,5]. For a consumer to purchase a vehicle, they must first consider it. It is likely that entry into consideration sets is difficult for HEVs, with past research identifying that up to 50% of consumers would not consider a hybrid vehicle [6]. One reason for the lack of consideration is distrust in the novel powertrain technologies [7,8].

Advanced diesel vehicles, hereafter referred to as diesel vehicle, are another type of vehicle that have been promoted environmentally sustainable alternatives to gasoline powered vehicles. Green Car Journal selected VW’s 2009 Jetta TDI and 2010 Audi A3 TDI, diesel vehicles, as The Green Car of the Year in 2009 and 2010, respectively [9]. Diesel vehicles currently make up 2.6% of the consumer automobile market, up from 0.6% in 2010 [10,11]. However, this increase in purchase of diesels may be on the precipice of a decline.

Diesel vehicles produced by Volkswagen (VW) and Audi were recently exposed by a research group at West Virginia University [12] as violating the Clean Air Act through the use of a defeat device. In September, 2015, the Environmental Protection Agency (EPA) notified VW of the violations [13]. Barrett et al. have estimated that the noxious emissions from these vehicles could result in 59 early deaths in the United
States, costing approximately $450 million in social damages [14].

The discovery of the defeat device has effected perceptions of both VW and diesel engines. Exposure of VW’s defeat device impacts entities outside of VW as a German automaker. There are significant implications to the United States economy and global automobile market. According to a recent IBIS World report, VW has a 10.4% global market share in passenger vehicles and has experienced over 100% growth in developing countries during 2011 [15].

VW’s violation of regulations will significantly impact vehicle consumers. Previous VW diesel consumers need to address deception by their vehicle manufacturer, and vehicle consumers currently in the market will have an altered perception of corporations and advanced technologies [16]. Further, consumers that value high fuel economy will have a smaller set of available technologies [13].

VW’s violations will also impact other corporate entities. Privately-owned Volkswagen dealerships will need to accommodate space for unsellable diesel powered vehicles, or a large number of repairs, and alter business strategies to counter negative brand publicity [17]. At least one of the globally-distributed Volkswagen manufacturing facilities, which hire local workers, has already eliminated shifts and froze hiring [18]. Other vehicle manufacturers which employ similar technologies will also be at risk of decreased sales due to perceived association with the VW diesel violations [19]. Government regulatory and testing agencies, such as the EPA, are reviewing practices and eliminating opportunities for similar emissions violations by adding costly on-road testing procedures [20].

While the effects of the scandal may decrease over time, there is a lasting effect. In an analysis of the 2009 Toyota recalls, NADA found a maximum 22% decrease in the average price of used Toyota vehicles relative to competition during the incident, and that the competitive position remained 10% lower than before the recall two years after the recall began [21].

2 DESIGN IN THE WAKE OF A CONSIDERATION-SHIFTING EVENT

The VW scandal presents a unique opportunity for design researchers. A national scandal has produced a sudden and large change in preference for a product, as discussed below. While researchers can artificially induce changes in preference under survey contexts, for example, exposing to participants to negative information and measuring how preferences change, natural exposure offers a more realistic investigation of implications.

A number of survey companies have captured this natural shift in preference for VW and diesel. For this paper, Autolist, a San Francisco-based company that specializes in data-driven searches of vehicle buying and selling information, offered the authors free access to their survey data on the scandal. This data is used in the model in this paper. The survey was conducted between December, 2015 and March, 2016. 2,494 vehicle owners from locations across the United States responded. The survey asked respondents to self-report questions on consideration likelihood before and after the VW scandal. Note that, as all data was collected after the scandal, the before self-report answers have less accuracy than the after self-report answers. Overall, the Autolist survey found that 41% of individuals polled who previously strongly considered a diesel vehicle would be less likely to consider one [16] and 64% less likely to consider a VW. These survey results have been reflected in sales data as VW sales have decreased by 15.3% in the United States since the EPA’s announcement [22].

In this research, we focus on the vehicle design implications of these consideration shifts, asking two questions:

(1) How can US HEVs respond to the consideration lost by VW?

(2) Which is the better approach for VW to regain consideration: repricing all vehicles or designing a new VW HEV?

This paper explores the answer of these questions by investigating three scenarios. In the first scenario, six existing hybrid vehicles of US-based manufacturers refresh their designs to attract the consideration lost by VW. The second scenario optimizes the pricing strategies for the existing VW vehicles to maximize VW vehicle consideration, ensuring that if a consumer does not consider a VW, it is for a reason other than its pricing. The third scenario optimizes the design of a new VW HEV to maximize VW consideration. Note that these questions are explored through the use of a static model, as we are not interested in how preference is changing (as a dynamic model might articulate) but rather a comparison of "before" and "after" scenarios, which can be captured using static analysis. To coordinate consumer consideration and engineering performances in the design scenarios, we model both consumer consideration and design feasibility as provided in Frischknecht[23], as discussed in Section 4.

Compared with the existing methodology in engineering design, the paper contributes the following:

(1) The simulation in this paper expands current non-compensatory modeling methodology by incorporating empirically-built technical engineering models which ensure realism of the optimal design.

(2) The simulation scenarios analyze the impact of the changes in consumer sentiments to vehicle design strategies in new perspectives distinct from the traditional compensatory consumer modeling.

The paper proceeds as follows: Section 3 reviews background information on consideration models and market-based vehicle design; Section 4 presents the simulation methods of consideration modeling and engineering modeling; Section 5 formulates the strategic optimization problems in three scenarios. Section 6 demonstrates the use of consideration sets to analyze the impact of consideration shifts to diesel competitors; Section 7 presents the optimization results; Sections 8 provides discussions and conclusions.
3 BACKGROUND

3.1 Non-Compensatory Decision Models

Consumers’ consideration sets can be represented by a set of screening rules. These rules are termed non-compensatory, meaning that even if a product does very well in one area, say price, it cannot compensate for not satisfying requirements in another area, say, miles per gallon (mpg). A conjunctive rule is an example of a non-compensatory rule in which a product is only considered if the consumer finds all attributes of the product at an acceptable level. For example, consider a consumer whose consideration set, $C$, strictly only includes vehicles, $v$, that achieve more than 30 mpg out of a market of $V$ vehicles (depicted in Eq.(1)). A Kia Optima (which achieves an EPA combined fuel economy rating of 24 mpg), will never enter that consumer’s consideration set despite its others attributes, such as relatively low price.

$$C = \{v \in \{1, \ldots, V\}|v_{mpg} > 30\}$$

Due to the nature of the defeat device, consumers may have a strong emotional reaction to either VW branded vehicles or diesel technologies. These reactions are well-represented by a non-compensatory decision structure, in which, for example, a low price cannot compensate for a diesel engine. This study uses non-compensatory rules built from 874 real consumer preferences gathered before the disclosure of the defeat device, with additional alterations to match consumer surveys of VW and diesel perception after the disclosure, as explained in Section 4.2.

Non-compensatory consideration formally refers to modeling the decision-making behavior of quickly screening alternatives based on simple heuristics to form a consideration set [24]. In contrast to compensatory models of decision processes, which assume that a good score in one attribute can compensate for a poor score in another attribute, non-compensatory models do not allow such trade-offs. Non-compensatory rules have a rich research history. In 1956, Simon proposed that people seek out solutions that meet some minimal level of acceptance [25], suggesting an aspirational rule. Einhorn [26] built on earlier work by Coombs [27] to demonstrate that conjunctive and disjunctive rules well represent decision processes. Payne demonstrated that consumers commonly use non-compensatory decision processes when there are many discrete options [28]. Bettman and Park found that consumers use non-compensatory rules when they are familiar with the available options and attributes [29]. A vehicle purchase decision satisfies both of these conditions.

Recent marketing research has demonstrated that non-compensatory decision processes are important components of a consumer’s decision to purchase a product [4]. In a study of consumer preference for GPS units, Hauser et al. [30] found that consumers use a variety of non-compensatory screening rules, with 12% screening particularly on brand. Yee et al. conducted a survey of consumers’ smart phone preferences and found non-compensatory behavior associated with price as well as functional attributes (such as whether or not the phone flips or has a keyboard) [31].

Several researchers have used non-compensatory models to represent vehicle purchase decisions. Morrow et al. use a non-compensatory two-stage consideration-then-choose consumer model in a vehicle optimization simulation [32].

Motivated by the apparent lack of consideration of Chevrolet, even though its vehicles had competitive features, Dyzabura and Hauser created a machine learning algorithm to identify consumer consideration heuristics in the vehicle market based on a consumer survey [4]. Long and Morrow [33] found that non-compensatory models outperform compensatory models when consumers’ vehicle decisions have non-compensatory elements, and that satisfactorily modeling non-compensatory behavior in a compensatory framework requires unreasonably large amounts of data.

Researchers have explored a number of different types of non-compensatory screening rules, including: conjunctive, subset conjunctive, disjunctive and aspirational. In conjunctive screening, an individual will only consider a product if all of a product’s attributes have acceptable levels. For example, a conjunctive rule may be “I want a VW with at least 35 mpg and a price less than $25,000”. This rule can be expressed mathematically as follows:

$$\text{Consider } v_j \text{ if, and only if } r \cdot v_j \geq K \quad (2)$$

Where: $v_j$ is an aspect-coded binary vector representing an arbitrary vehicle, $j$, $r$ is a parallel aspect-coded binary vector representing an individual, and $K$ is some minimum required number of acceptable attributes for the product to be considered. In a conjunctive rule, the vehicle, $v$, will be considered if $K$ is equal to the number of product attributes. In the VW example provided immediately prior, the individual has three required attribute levels, thus $K$ equals three. A demonstration of a conjunctive rule is shown in Figure 1.

Figure 1. Example of conjunctive rule

Subset conjunctive screening is similar to conjunctive, but requires that $K$ be some number less than the total number of attributes be acceptable. The individual from the conjunctive example has three acceptable attribute levels: vehicle must be a VW, must achieve at least 35 mpg, and must cost less than $25,000. A subset rule would represent a consumer that would any vehicle with at least two of the previously mentioned rules.
met. This situation would be classified as a subset conjunctive rule with $K$ equals two.

Disjunctive rules are an example of a subset conjunctive rule in which a product is accepted if at least one attribute is acceptable ($K=1$). “I either want a Volkswagen OR a vehicle that has better than 35 mpg fuel economy OR a vehicle that costs less than $25,000.”

Aspirational screening rules are inspired by the concept of satisficing, and can be combined with any of the rule structures above. An alternative is considered if it exceeds some minimum threshold. Jedidi et al.[34] and Gilbride and Allenby [35] used a specified product utility level to represent that threshold. Although this study uses conjunctive rules, an example of an aspirational rule is presented below:

$$\beta_i = (\beta_{\text{mpg}}, \beta_{\text{brand}}, \beta_{\text{price}})$$  \hspace{1cm} (3)

$$\alpha_{ij} = \beta_{\text{mpg}} \cdot v_{\text{mpg},j} + \beta_{\text{brand}} \cdot v_{\text{brand},j} + \beta_{\text{price}} \cdot v_{\text{price},j}$$  \hspace{1cm} (4)

Consider $v_j$ if an only if $\alpha_{ij} \geq \alpha_i$  \hspace{1cm} (5)

Where: $v_j$ is vehicle representing the brand, fuel economy, and price or an arbitrary vehicle; $\beta_i$ is a vector corresponding to an individual’s part-worths; $\alpha_{ij}$ is vehicle $j$’s utility to individual $i$, and $\alpha_i$ is the utility threshold.

The result of these rules is a small set of products, in this case vehicles, for further consideration by each consumer. In the larger consider-than-choose model [36], the next step is modeled as a comparison of the vehicles in this small set in a compensatory fashion, where a high score in one attribute can compensate for a low score in another. These attributes may or may not be the same attributes that were modeled as forming the consideration rules. This second phase of consider-then-choose, making the final choice for purchase, is not addressed in this paper. The goal of this research is to examine how consideration sets are modeled in different scenarios of brand and powertrain preferences and to design a vehicle for inclusion in the maximum number of consideration sets.

### 3.2 Vehicle Engineering Models in Market-based Design

For automobile manufacturers, the idealistic nature of consumer consideration must be paired with the realities of decision making, as a design should be feasible in satisfying relationships between design variables and engineering performance and at the same time profitable. Software packages, such as AVL Cruise, use complex models to represent vehicle powertrains and predict performance. To take advantage of these packages applicability to optimal vehicle design, but avoid high computational cost, researchers, such as Frischknecht[23], have created proxy models to decrease optimization computation time, yet retain the model’s insights. These proxy models are expanded upon and then implemented in the vehicle design optimization routines conducted in this study, as detailed in Section 5.

A number of researchers have used vehicle engineering models in the design of an optimal vehicle under market demand conditions. Michalek et. al. [37] used engineering models (including fuel economy and acceleration time) to observe alterations to an optimally designed vehicle in a variety of regulatory policies. Frischknecht and Papalambros [38] explore environmentally-friendly vehicle designs by investigating tradeoffs between firm objectives (i.e. profit) and negative public externalities (i.e. greenhouse gas emissions).

He and Chen [39] use design variables to derive “consumer-desired” HEV attributes in a compensatory market model. Their research suggests that optimal product designs change depending on the situation in which the HEV is used. Karabasoglu and Michalek [40] further investigate vehicle use heterogeneity with a plug-in HEV powertrain model and found that designs that are specifically targeted towards particular user groups can have much lower environmental impact. Kim et al. [41] use the design of a vehicle suspension, paired with purchase data from real consumers, to demonstrate an algorithm that explores disconnected design spaces, a problem frequently encountered in optimal vehicle design when populations exhibit non-compensatory disjunctions of conjunctive rules.

Vehicle headroom (with dimensions defined by Society of Automotive Engineers (SAE)) was found to affect human perception of vehicle safety in an optimal experimental design study by Hoyle et al. [42]. Ferguson et al. [43] use early-stage vehicle geometry design evaluation to demonstrate a method of applying a genetic algorithm with fewer system evaluations in a two-step evaluation method. Wang et al. [44] demonstrate an agent based method in which agents (manufacturers) compete and learn to produce better products by optimizing product design as well as price.

All of these works above that designed for purchase did so under the assumption of consumers having compensatory preferences, and not non-compensatory consideration, as is used in this paper. This is an important distinction, as [32] notes in a simple vehicle-design test case that ignoring consideration can lead to vehicle designs that are sub-optimal and do not maximize profit. Note that it was not studied whether or not any of the works mentioned above suffered from this problem.

### 4 SIMULATION FORMULATION

This section gives details of the simulation and analysis method using the engineering model and the consideration model.
4.1 Vehicle Market Representation

The 2014 WardsAuto database [45] provides the descriptive information for the available vehicles within our model. The market includes \( V \) vehicles. Vehicles are included if they are either new introductions as of 2014 or had 2013 sales greater than 10,000 units, as reported in AutoNews [46]. The 184 vehicles \( (V=184) \) that pass the threshold represent 18 manufacturers. Each vehicle is coded using eight attributes inspired by Dzyabura and Hauser [4]. Table 1 presents these attributes and their associated discretized levels. Alterations to the attributes used by Dzyabura and Hauser include: removal of brands that were defunct in 2013, the addition of a quality rating of 2, and the addition of diesel as a powertrain option. Rollover star scores were collected from the National Highway Transportation and Safety Administration (NHTSA), and the quality scores were collected from J.D. Power [47]. The EPA’s fuel economy website provided the city fuel economy ratings [48].

Each vehicle is represented as a binary vector of length 53, corresponding to the 53 different attribute levels. The total vehicle market is represented as \( \mathbf{v}_a \), where \( a \) is the index of a particular vehicle. Within that vehicle’s vector, a 1 represents that the vehicle has that particular attribute level, and a 0 represents that the vehicle does not. To illustrate, a vehicle, \( a \in \{1, \ldots, A\} \), that was only represented using number of cylinders and rollover score, the binary vector, \( \mathbf{v}_a \) would be:

\[
\mathbf{v}_a = \{4 \text{ cylinders}, 6 \text{ cylinders}, 8 \text{ cylinders}, 3 \text{ stars}, 4 \text{ stars}, 5 \text{ stars}\},
\]

(6)

If the Volkswagen Jetta (a four cylinder vehicle that scored four stars on the federal rollover test) was represented in this form, \( \mathbf{v}_j \), it would be embodied as the following vector:

\[
\mathbf{v}_j = \{1, 0, 0, 0, 1, 0\}
\]

(7)

4.2 Consideration Rules and Shifts in Consideration

The consumer population consists of 874 individuals that use conjunctive rules drawn from the vehicle survey of Dzyabura and Hauser [4]. The conjunctive rules screen on 8 attributes, in total 53 attribute levels as described in Table 1. The rule of an individual \( i \) is coded as a binary vector of length 53 \( r_i \), with 1 indicating the corresponding attribute level acceptable and 0 indicating unacceptable. The individual will consider a vehicle \( \mathbf{v}_j \) if and only if

\[
\mathbf{v}_j \cdot r_i' = 8
\]

(8)

That is, all eight attributes must be acceptable to be considered. The rest of this paper refers to this population as the “base population” to represent that the Dzyabura and Hauser...
consideration sets were modeled well before the VW scandal occurred. Within the base population, screening rules on VW brand and diesel powertrain come from the Autolist survey, which is summarized in Table 2. For continuity between before/after scandal consideration model, it was necessary to use VW consideration from the Autolist survey. Also, as [4] did not ask about diesel powertrain consideration, was necessary to extract this from the Autolist survey, as described below. Limitations of this combined approach are discussed in Section 8.

Table 2 summarizes the consideration of VW brand and diesel powertrain as the percentage of population who use one of the four screening rules \((r_{VW}, r_{diesel}) \in \{(0,0), (0,1), (1,0), (1,1)\}\), with 1 representing considered and 0 representing not. Table 3 summarizes the transition probability of the individual transit from one of the four screening rules to the other. For example, the probability in row “(0,1)” and column “(0,0)” indicates that the chance that an individual who considers VW but not diesel in the base population transitions to reject both is 0.71. The transition probabilities are based on the statistics of the Autolist survey in which respondents stated their consideration of VW and diesel vehicles before and after the scandal. The original Autolist survey used a rating scale of 1 to 5 where 5 = “definitely consider”. In this simulation, we take the rating of “5” to mean considered. This leads to a prediction of 21% of individuals rejecting VW, which is close to the 14% reported in the Dzyabura & Hauser’s survey [4]. Taking any more than the "5" rating to mean consider (such as "4") would have only widened the gap between these percentages.

The consideration shifts modeled in the simulation have not accounted for changes in preference over time. Modeling consideration dynamics require different survey tools and tracking methods, which are out of the scope of the Autolist survey instrument, and not necessary for the "snapshot" modeling approach taken here.

Table 2. The consideration of VW brand and diesel powertrain in the base population

<table>
<thead>
<tr>
<th>Screening rule ((r_{VW}, r_{diesel}))</th>
<th>(0,0)</th>
<th>(0,1)</th>
<th>(1,0)</th>
<th>(1,1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>% of the whole population</td>
<td>70.2%</td>
<td>8.5%</td>
<td>13.9%</td>
<td>7.4%</td>
</tr>
</tbody>
</table>

Table 3. The transition probabilities of VW brand and diesel powertrain screening rules

<table>
<thead>
<tr>
<th>Screening rule ((r_{VW}, r_{diesel}))</th>
<th>Altered population</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(0,0)</td>
</tr>
<tr>
<td>Base population</td>
<td>(0,0)</td>
</tr>
<tr>
<td></td>
<td>(0,1)</td>
</tr>
<tr>
<td></td>
<td>(1,0)</td>
</tr>
<tr>
<td></td>
<td>(1,1)</td>
</tr>
</tbody>
</table>

### 4.3 Engineering Model

In this paper, the design scenarios described in Section 5 focus on the new design or redesign of an HEV, thus a design feasibility model for an HEV is created. The simulation specifies engineering variables of a full hybrid vehicle, rather than vehicle attributes directly, to ensure the designed vehicles are realistic. Full hybrid vehicles have excellent emissions ratings; the full hybrid vehicles in this study’s marketplace attained either Bin 2 or Bin 3 classification in the EPA’s Tier 2 rating platform [49–51] and occupy an engineering variable space that encapsulates the engineering design space of this optimization. The diesel powered vehicles offered by Volkswagen attained a Bin 5 rating in Tier 2 [50]. The constraint that the designed hybrid vehicle must perform better than the diesel vehicles it is replacing will be inactive.

The engineering variables come from an engineering model based on the dissertation of Frischknecht [23] and other information described below. Frischknecht provides the basis of the fuel economy, roll over score, and vehicle cost models. Following Frischknecht, the performance of a full hybrid vehicle with a nickel-metal hydride battery is predicted by specifying eight engineering variables: the engine bore, \(x_{bore}\), bore-to-stroke ratio, \(x_{B/S}\), final drive ratio, \(x_{FD}\), vehicle length, \(x_L\), vehicle width, \(x_W\), vehicle height, \(x_H\), vehicle wheelbase, \(x_{WB}\), and peak battery power, \(x_{bP}\).

Figure 3 demonstrates how the eight attributes are linked to the proceeding engineering models. Brand, powertrain, quality, and cylinders (denoted with white boxes) are given assumed values. Class, price, fuel economy, and rollover score are determined using the engineering variables contained in the text box.

Frischknecht’s models include a city fuel economy model of hybrid vehicles that translated AVL Cruise simulations into explicit expressions. This equation for city fuel economy, \(z\), is proportional to the linear sum of the following terms:
\[ x_{WB}, x_{FD}, x_{H}, x_{BAT}, x_{L}, x_{R}, x_{H}^2, x_{L}^2, x_{WB}^2, x_{R}^2, x_{BAT}^2, x_{H}^2, x_{R}^2, x_{BAT}^2, x_{F}, x_{WD}, x_{B}, x_{FD}, x_{BAT}, x_{L}, x_{R}, x_{H}^2, x_{L}^2, x_{WB}^2, x_{R}^2, x_{BAT}^2. \]

The city fuel economy ratings are scaled by a multiplier of 1.254 to account for the improvement in technology since Frischknecht created the models in 2008. Imposing a 1.254 multiplier allowed the real fuel economy of all ten full HEV vehicles in the synthetic marketplace to remain within 7.5% of the model predicted fuel economy. Error! Reference source not found., previous page, demonstrates the mpg model results as applied to these vehicles.

Frischknecht also proposes a parametric method of determining the static stability factor, \( y \), (see Eq. (9)) based on mass distribution assumptions, with input from industry experts. The specifications of the third generation Toyota Prius informed parameter values (vehicle foot room, wheel diameter, etc.). The vehicle’s vertical center of gravity, \( n \), was determined by summing the weights of vehicle components and vertical height off the pavement and dividing by the total mass, as demonstrated in Eq. (10) (where \( t_x \) stands for vertical height of component \( x \), and \( m_x \) stands for mass of component \( x \)). Components considered include: engine \( (t_0, m_0) \), gas tank \( (t_1, m_1) \), passengers \( (t_2, m_2) \), front and rear axle \( (t_3, m_3) \), cargo \( (t_4, m_4) \), suspension \( (t_5, m_5) \), transmission \( (t_6, m_6) \), exhaust \( (t_7, m_7) \), bumpers \( (t_8, m_8) \), body \( (t_9, m_9) \), traction battery \( (t_{10}, m_{10}) \).

\[
y = \frac{wn}{2} \tag{9}
\]

\[
n = \frac{\sum_{x=0}^{10} (t_x m_x)}{\sum_{x=0}^{10} (m_x)} \tag{10}
\]

Frischknecht’s original model was designed for standard ignition vehicles and did not account for hybrid vehicle electric architecture. A traction battery weight term was added by assuming a battery weight, \( m_{10} \), of 29.26 kg (comparable to the Prius battery’s 28 1.045 kg modules) \([52]\). The battery is vertically located at the top of the wheel \( (t_{10} = 431 \text{ mm}) \).

The static stability factor is subsequently used to calculate the NHTSA rollover stars, \( s \):

\[
s = 5 - [160.94y^4 + 862.33y^3 + 1733.00y^2 - 1551.40y + 524.44] \tag{11}
\]

The GA in this paper applies Frischknecht’s empirical unit manufacturing cost model, which accounts for the increased cost of the hybrid architecture by including battery parameters (including peak power output), the controller, and inverter, cables, and brackets.

Cumulative vehicle cost is the sum of Frischknecht’s production cost and additional corporate overhead and distribution costs amounting to 45.5% of the vehicle manufacturing cost, in accordance with a study on alternative hybrid vehicle production costs by Vyas et al.\([53]\).

The engineering models link vehicle class to four vehicle dimensions (length, wheelbase, height, width) by training a decision tree to the vehicles in this experiment’s market. WardsAuto’s database provided the vehicle classes. Dimensions were quantified according to SAE standards \([54]\) and sourced from the respective manufacturer’s website. Figure 4 presents the resulting decision tree, which had a misclassification rate of 10.7% among the hatchbacks, compact sedans, standard sedans, small SUVs, large SUVs, pickup trucks, and minivans. Sports cars were not included in this tree due to their characterization being reflective of engine performance, which was not included in this model. Crossovers were omitted due to the extremely small training size in the 2014 market explored in this study.

\[\text{Figure 5. Vehicle class classification tree}\]

5.1 Scenario I: US HEV Manufacturers Design to Capture VW’s Lost Consideration

Scenario I strategy of US HEVs: This scenario refreshes the design of six existing HEVs of three US brands – Chevrolet, Ford and Lincoln, while VW removes their diesels from the market. Suppose each of these refreshed HEVs retain their original body types but change prices and other design variables such as engine bore, bore-to-stroke ratio, final drive ratio, and battery peak power. The objective of these US HEVs is to attract the consideration sets lost by VW. Specifically, the optimization problem solved for each hybrid vehicle is:

\[
\text{maximize: } \sum_{i=1}^{n} \delta_{l,h}(r_i, p_h(x_h))
\]

\[
\cdot \min \left\{ 1, \sum_{j \in VW \text{vehicles}} \delta_{l,j}(r_i, p_j) \right\}
\]

\[
\cdot (1 - \min \left\{ 1, \sum_{j \in VW \text{vehicles}} \delta_{l,j}(r_i, p_j) \right\})
\]

\[w. r. t. x_h, p_h\]

s.t. \( c(x_h) \leq p_h\) \tag{13}

and

\[E_h \leq E_{Jetta TDI}, E_{Passat TDI}, E_{Golf TDI}, E_{Beetle TDI}\] \tag{14}
The Indicator function $\delta_{ij}(\cdot)$ takes value 1 if the conjunctive screening $\mathbf{v}_j \cdot \mathbf{r}_i' = 8$ is satisfied, and 0 otherwise, with $\mathbf{r}_i$ denoting the screening of without consideration changes (i.e. the base case) and $\mathbf{r}_i'$ denoting the rule with consideration changes (i.e. the altered case). Thus, the $\min\{,\}$ operator counts the individuals who consider at least one VW vehicle. The objective function counts the individuals who lost consideration during consideration changes and consider the refreshed hybrid. The design variables vector $\mathbf{x}_h = (x_{Bore},x_{BTS},x_{FD},x_{BatPow})$ represents, respectively, engine bore, bore-to-stroke ratio, final drive ratio, and peak battery power. The mapping from design variable to consumer observed attribute vector $\mathbf{v}(\mathbf{x}_h)$ is provided in Fig.3. Eqn.(13) constrains the manufacturing cost of the vehicle $\mathbf{c}(\cdot)$ to be lower than the price. Eqn.(14) enforces the refreshed design to have a superior emission rating than those of the VW Jetta TDI, Passat TDI, Golf TDI, and the Beetle TDI.

### 5.2 Scenario II: VW Repricing to Capture Consideration

In a compensatory framework, repricing may entice consumers to buy a VW. This strategy may not necessarily produce the desired results in a non-compensatory framework. The optimal pricing strategy is examined here for a situation where the prices of all non-diesel VW vehicles are set to maximize VW consideration set inclusion. In other words, the price of all VWs is set to a value considered by all consumers—the most optimistic case possible. Therefore, in this scenario, if a consumer does not consider a VW, it is because of an attribute other than price. To create this scenario, the following pricing optimization problem is solved:

$$\max \sum_{i=1}^{l} \min \left\{ 1, \sum_{j \in VW vehicles} \delta_{ij}(\mathbf{r}_i, \mathbf{v}_j(p_j | x_j')) \right\} \quad \text{w. r. t. } p_j \text{ for all } j \in VW vehicles \quad \text{s.t. } \mathbf{c}(x'_j) \leq p_j$$

(15)

Indicator function $\delta_{ij}(\cdot)$ takes value 1 if the conjunctive screening $\mathbf{v}_j \cdot \mathbf{r}_i' = 8$ is satisfied, and 0 otherwise. Variable $p_j$ is the price of each existing VW vehicle that does not violate the emission standards, and $x'_j$ is the fixed design features. The attributes observed in the consumer model are mapped from the price and fixed feature via $\mathbf{v}_j(p_j | x'_j)$. Same as Scenario I, the $\min\{,\}$ operator counts the individuals who consider at least one VW vehicle. The fixed design variables vector $x'_j = (x_{Bore},x_{BTS},x_{FD},x_{BatPow},x_{WB},x_{Wb},x_{Br},x_l)$ includes, respectively, engine bore, bore-to-stroke ratio, final drive ratio, peak battery power, vehicle wheelbase, width, height, length.

### 5.3 Scenario III: VW Designs to Recapture Lost Consideration

The scenario investigates the strategy of introducing a new VW HEV to maximize the number of consideration sets that contain at least one VW vehicle, assuming the removal from the market of all VW diesels, as expressed in Eq. (15)-(17).

$$\max \sum_{i=1}^{l} \min \left\{ 1, \sum_{j \in VW vehicles} \delta_{ij}(\mathbf{r}_i, \mathbf{v}_j(\mathbf{x}_h, p_h)) \right\} \quad \text{w. r. t. } \mathbf{x}_h, p_h \quad \text{s.t. } \mathbf{c}(\mathbf{x}_h) \leq p_h$$

(17)

$$E_h \leq E_{Jetta TDI}, E_{Passat TDI}, E_{Golf TDI}, E_{Beetle TDI}$$

(19)

Indicator function $\delta_{ij}(\cdot)$ takes value 1 if the conjunctive screening $\mathbf{v}_j \cdot \mathbf{r}_i' = 8$ is satisfied, and 0 otherwise. Same as Scenario I, the $\min\{,\}$ operator counts the individuals who consider at least one VW vehicle. The design variables vector $\mathbf{x}_h = (x_{Bore},x_{BTS},x_{FD},x_{BatPow},x_{WB},x_{Wb},x_{Br},x_l)$ includes, respectively, engine bore, bore-to-stroke ratio, final drive ratio, peak battery power, vehicle wheelbase, width, height, length and price.

### 6 VALIDATION OF CONSIDERATION MODEL WITH REAL-WORLD DATA

Before discussing the results of the design optimizations, this section provides some partial validation to the model by comparing the model’s predicted considerations to actual industry data. By simulating the 874 consumer consideration sets, we investigate two potential impacts to the diesel competitors: (1) vehicles that share the same consideration sets with the VW diesels may gain more attention due to the removal of VW diesels from the market; and (2) the changed in consideration for VW and diesel powertrain in the model is event in real-world data. Table 5 illustrates the impacts to consideration set inclusion to three non-VW diesels in the existing market. Table 6 summarizes the observed lead volume (the request for vehicle details to dealers submitted by consumers) provided by Autolist, and the monthly sales provided by Autonews.com; the percentages calculate the fraction of lead volume (or sales) of a specific vehicle model in the total lead volume (or sales) of the 184 vehicles studied in this simulation.

For the BMW 328d, the number of consideration sets increases from four to five before/after because there is still a chance for individuals change from reject diesel to consider diesel (See transition probabilities in Table 3). Also, two out of its five consideration sets in the "after" case include the removed VW diesels. Thus, the BMW 328d would benefit from both the change of diesel consideration and the removal of VW diesel. The increment of lead volume and the sales in the real-world data are consistent with this prediction from the model.
For the BMW 535d, the decrease of the consideration of diesel powertrain causes the consideration set participation of the 535d to decrease from six to five. However, the removal of the VW diesels from two of its five consideration sets may counteract the decrease of consideration sets. Both the lead volume and sales data show a decrease.

The Chevrolet Cruze loses five consideration sets due to the change of diesel consideration. This loss may be counteracted by the removal of VW diesels from six of its consideration sets. Moreover, there are also non-diesel VW vehicles that are taken away from three of its consideration sets due to the change of VW brand consideration. In the real-world data, the lead volume remains at the same level and the sales shows an increase of 0.15% share, although such increase is still smaller compared to the increment of the same period of the previous year.

Comparing the statistics of the consideration model (Table 5) with the real-world lead volume and sales data (Table 6), the model has potential to provide clues in explaining the real world changes. Specifically, in the case of the BMW 328d, the simulation predicts consideration will be larger after the scandal and the real world sales data and lead volume validate this trend. Yet, the comparison also exposes the challenge of perfectly matching the model predictions with the lead volume and sales. Particularly, the model is unclear about whether or not the BMW 535d or Chevrolet Cruze TDI will benefit from the scandal. One possibility is that the consequence of the lost consideration sets cannot be counteracted by gaining more attention in the remaining consideration sets. As consideration sets do not model the final purchase choice, the connection between real world sales and the model may not be direct.

### Table 4. The Consideration set statistics of three non-VW diesel vehicles

<table>
<thead>
<tr>
<th>Vehicle Model</th>
<th>Consideration Set Inclusion</th>
<th>Consideration Sets Shared With Removed VW diesel(s)</th>
<th>Consideration Sets Shared With Vehicles that Lost Considerations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Base Case</td>
<td>Altered Case</td>
<td>Altered Case</td>
</tr>
<tr>
<td>BMW 328d</td>
<td>4</td>
<td>5</td>
<td>2</td>
</tr>
<tr>
<td>BMW 535d</td>
<td>6</td>
<td>5</td>
<td>2</td>
</tr>
<tr>
<td>Chevrolet Cruze TDI</td>
<td>18</td>
<td>13</td>
<td>6</td>
</tr>
</tbody>
</table>

### Table 5. Lead volume and sales change from September to October, 2015

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>BMW 3 series</td>
<td>+0.27%</td>
<td>+0.15%</td>
<td>+0.05%</td>
</tr>
<tr>
<td>BMW 5 series</td>
<td>-0.17%</td>
<td>-0.13%</td>
<td>+0.35%</td>
</tr>
<tr>
<td>Chevrolet Cruze</td>
<td>0%</td>
<td>+0.15%</td>
<td>+0.55%</td>
</tr>
</tbody>
</table>

### 7 DESIGN OPTIMIZATION RESULTS

Using the problem formulations in Section 5, a genetic algorithm (GA) was used to search for the optimal vehicle. GAs use biological concepts such as natural selection to produce optimal designs over successive generations. Their ability to handle discontinuities allow them to handle non-compensatory heuristics well [32]. The genetic algorithm designs a vehicle by specifying nine alleles that correspond to the eight engineering variables presented in Frischknecht’s work and vehicle price, as shown in Fig. 2. Each allele has 15 levels (excluding price) which are represented in Table 6. Additionally, the vehicle price is constrained to be greater than the sum of the manufacturing [23] and overhead costs [53].

The algorithm applies 40 generations of a GA population, each with 50 potential designs. In each generation, the GA applies two-parent selection and one point crossover with a 65% replacement rate. The parameters were specified after a systematic evaluation demonstrated that the genetic algorithm would consistently design similar vehicles for a specific population from a variety of initial allele sets. The number of generations required was determined by locating the number of generations at which solutions’ objective function value plateaued.

### Table 6. Genetic algorithm allele representation

<table>
<thead>
<tr>
<th>Allele</th>
<th>Min. Value</th>
<th>Max. Value</th>
<th>Num. of Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Engine Bore</td>
<td>87.5 mm</td>
<td>92 mm</td>
<td>15</td>
</tr>
<tr>
<td>Bore-to-Stroke Ratio</td>
<td>0.9</td>
<td>1.18</td>
<td>15</td>
</tr>
<tr>
<td>Final Drive Ratio</td>
<td>3.25</td>
<td>5</td>
<td>15</td>
</tr>
<tr>
<td>Battery Peak Power</td>
<td>30 kw</td>
<td>65 kw</td>
<td>15</td>
</tr>
<tr>
<td>Wheel Base</td>
<td>2200 mm</td>
<td>3200 mm</td>
<td>15</td>
</tr>
<tr>
<td>Width</td>
<td>1650 mm</td>
<td>2000 mm</td>
<td>15</td>
</tr>
<tr>
<td>Height</td>
<td>1400 mm</td>
<td>1800 mm</td>
<td>15</td>
</tr>
<tr>
<td>Length</td>
<td>4300 mm</td>
<td>5100 mm</td>
<td>15</td>
</tr>
<tr>
<td>Price</td>
<td>$12,000</td>
<td>$45,000</td>
<td>7</td>
</tr>
</tbody>
</table>

We ran the GA 100 times with different initial populations. The GA optimization uses the GAlib C++ library created by Wall [55]. Computation was executed on a Macbook Pro with a 2.4 GHz processor and 8 GB of RAM.

#### 7.1 Results from Scenario I: US HEV Manufacturers Design to Capture VW’s Lost Consideration

As described in Section 5.1, we created an optimization scenario to investigate which US-manufactured HEVs could be refreshed to capture VW’s lost consideration. Table 8 compares the current design and the refreshed solutions of six HEVs. For each HEV, the row labeled “current” is the vehicle design and pricing in the existing market "before”; the “mean”, “min” and “max” rows are respectively the mean, minimum and maximum values across the optimal solutions for the "after" the scandal market, observed in 10 simulation runs. Except for the Chevrolet Impala LT Eco, the optimal strategies suggest the automakers can pick up the consideration sets by lowering the current prices. The results suggest slightly sacrificing the mpg levels and battery power to accommodate the lowered prices with lower costs. Interestingly, for Chevrolet Impala LT Eco,
the result points to both higher battery power and higher mpg, in addition to the lower price. The simulation identifies Ford Fusion SE Energi Hybrid as the most strategically-positioned to refresh its design and capture the consideration VW lost, because the optimal refreshed solution is very similar to its current design.

The Ford Fusion series attracted 48.6% of the VW lost considerations on average, followed by Ford C-Max series with 44.3%, and the Chevrolet Impala LT Eco with 37.4%. The mean values are shown in Figure 6, where the error bars represent the minimum and maximum observations over 10 simulation runs. The refreshed MKZ hybrid of Lincoln has significantly lower potential to capture the considerations—it is only able to capture 2.3% on average. The Ford Fusion SE Energi is in the best position to pick up the lost consideration of VW among these six American HEVs, given it is most capable for attracting considerations without significantly changing its current pricing and design strategy.

![Figure 6. Refreshed American HEVs capture consideration sets lost by VW.](image)

### 7.2 Scenarios II and III: Should VW Reprice or Design a New Vehicle?

As explained in Section 5, here we investigate if VW should design a new HEV to recapture consideration or reprice all existing non-diesel vehicles.

Both strategies, repricing and introducing a new design, increase consideration. On average, introducing a new HEV gained more consideration sets than re-pricing. Figure 7 presents the mean results of the consideration sets inclusion under different strategies. The error bars represent maximum and minimum observed over 10 simulation runs. The optimal vehicle to increase consideration sets is a small SUV with a fuel economy of above 35 mpg, a roll over score of 3, and a price of $22,000. Table 9 presents the levels of optimal vehicles’ engineering variables found over the simulation runs.

### Table 7. Optimal refreshing strategy of Six American HEVs

<table>
<thead>
<tr>
<th>HEV</th>
<th>$X_{bore}$ (mm)</th>
<th>$X_{BS}$ (mm)</th>
<th>$X_{FD}$ (mm)</th>
<th>$X_{batPow}$ (kw)</th>
<th>mpg</th>
<th>Price (SK)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chevrolet Impala LT Eco</td>
<td>current 88.0</td>
<td>0.90</td>
<td>2.77</td>
<td>15</td>
<td>25</td>
<td>32</td>
</tr>
<tr>
<td></td>
<td>mean 87.8</td>
<td>1.15</td>
<td>4.03</td>
<td>32</td>
<td>40</td>
<td>27</td>
</tr>
<tr>
<td></td>
<td>min 87.5</td>
<td>1.14</td>
<td>3.65</td>
<td>30</td>
<td>39</td>
<td>27</td>
</tr>
<tr>
<td></td>
<td>max 88.5</td>
<td>1.16</td>
<td>4.75</td>
<td>38</td>
<td>40</td>
<td>27</td>
</tr>
<tr>
<td>Ford C-Max SEL</td>
<td>current 87.5</td>
<td>1.05</td>
<td>2.57</td>
<td>35</td>
<td>42</td>
<td>27</td>
</tr>
<tr>
<td></td>
<td>mean 90.8</td>
<td>0.93</td>
<td>4.14</td>
<td>30</td>
<td>37</td>
<td>25</td>
</tr>
<tr>
<td></td>
<td>min 89.8</td>
<td>0.90</td>
<td>3.25</td>
<td>30</td>
<td>37</td>
<td>22</td>
</tr>
<tr>
<td></td>
<td>max 91.8</td>
<td>0.96</td>
<td>4.88</td>
<td>30</td>
<td>38</td>
<td>27</td>
</tr>
<tr>
<td>Ford C-Max Energi SEL</td>
<td>current 87.5</td>
<td>1.05</td>
<td>2.57</td>
<td>35</td>
<td>44</td>
<td>27</td>
</tr>
<tr>
<td></td>
<td>mean 91.3</td>
<td>0.95</td>
<td>4.20</td>
<td>30</td>
<td>37</td>
<td>26</td>
</tr>
<tr>
<td></td>
<td>min 89.8</td>
<td>0.90</td>
<td>3.50</td>
<td>30</td>
<td>37</td>
<td>22</td>
</tr>
<tr>
<td></td>
<td>max 91.8</td>
<td>0.96</td>
<td>4.88</td>
<td>30</td>
<td>38</td>
<td>27</td>
</tr>
<tr>
<td>Ford Fusion S hybrid</td>
<td>current 87.5</td>
<td>1.05</td>
<td>2.57</td>
<td>35</td>
<td>44</td>
<td>27</td>
</tr>
<tr>
<td></td>
<td>mean 87.9</td>
<td>1.15</td>
<td>3.89</td>
<td>32</td>
<td>41</td>
<td>27</td>
</tr>
<tr>
<td></td>
<td>min 87.5</td>
<td>1.12</td>
<td>3.38</td>
<td>30</td>
<td>40</td>
<td>27</td>
</tr>
<tr>
<td></td>
<td>max 89.0</td>
<td>1.16</td>
<td>4.75</td>
<td>35</td>
<td>42</td>
<td>27</td>
</tr>
<tr>
<td>Ford Fusion SE Energi</td>
<td>current 87.5</td>
<td>1.05</td>
<td>2.91</td>
<td>35</td>
<td>41</td>
<td>35</td>
</tr>
<tr>
<td></td>
<td>mean 88.0</td>
<td>1.14</td>
<td>4.26</td>
<td>34</td>
<td>41</td>
<td>27</td>
</tr>
<tr>
<td></td>
<td>min 87.5</td>
<td>1.08</td>
<td>3.25</td>
<td>30</td>
<td>40</td>
<td>27</td>
</tr>
<tr>
<td></td>
<td>max 89.5</td>
<td>1.16</td>
<td>4.88</td>
<td>40</td>
<td>42</td>
<td>27</td>
</tr>
<tr>
<td>Lincoln MKZ Hybrid</td>
<td>current 87.5</td>
<td>1.05</td>
<td>2.56</td>
<td>35</td>
<td>45</td>
<td>37</td>
</tr>
<tr>
<td></td>
<td>mean 88.1</td>
<td>1.13</td>
<td>3.84</td>
<td>33</td>
<td>40</td>
<td>35</td>
</tr>
<tr>
<td></td>
<td>min 87.5</td>
<td>1.10</td>
<td>3.25</td>
<td>30</td>
<td>39</td>
<td>27</td>
</tr>
<tr>
<td></td>
<td>max 89.5</td>
<td>1.16</td>
<td>4.88</td>
<td>38</td>
<td>41</td>
<td>45</td>
</tr>
</tbody>
</table>

### Table 8. Optimal vehicle variable levels and characteristics

<table>
<thead>
<tr>
<th>HEV</th>
<th>$X_{bore}$ (mm)</th>
<th>$X_{BS}$ (mm)</th>
<th>$X_{FD}$ (mm)</th>
<th>$X_{batPow}$ (kw)</th>
<th>$X_{WB}$ (mm)</th>
<th>$X_{H}$ (mm)</th>
<th>$X_{L}$ (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean</td>
<td>89.78</td>
<td>1.13</td>
<td>4.06</td>
<td>34.25</td>
<td>2790</td>
<td>1653</td>
<td>1590</td>
</tr>
<tr>
<td>min</td>
<td>87.50</td>
<td>1.06</td>
<td>3.25</td>
<td>30.00</td>
<td>2400</td>
<td>1650</td>
<td>1575</td>
</tr>
<tr>
<td>max</td>
<td>91.75</td>
<td>1.16</td>
<td>4.88</td>
<td>45.00</td>
<td>3100</td>
<td>1675</td>
<td>1625</td>
</tr>
</tbody>
</table>
8 CONCLUSION

This study joins a conjunctive consideration survey-based model, self-report consideration data on before and after a product scandal event, real world market data and an engineering feasibility model to investigate design strategies. It first provided partial, trend-level-only, validation of the consideration model using industry sales data. Then, with three simulation scenarios, the study suggests (1) that US automakers may capture VW’s lost consideration by refreshing an existing HEV and (2) that VW will benefit more from designing a new HEV rather than repricing all existing vehicles.

Modeling consideration provides new insight for strategic design and pricing decisions. Rather than assuming universal impacts to the vehicle market, as in the traditional compensatory modeling mind-set, modeling consideration sets identifies targeted opportunities for gaining competitive advantage.

HEVs of US brands such as Ford and Chevrolet are in a good position to gain the consideration lost by VW. These manufacturers have distinct advantages when they refresh the existing hybrid vehicles: (1) they are not directly affected by the scandal; (2) they are already acceptable brands in larger fraction of the consumer population; and (3) refreshing an existing HEV saves overhead costs of designing from scratch, thus a lower price point may be economically viable.

Repricing is a strategy derived from the concept of compensatory preference in which consumers are assumed to trade-off between price and the brand/powertrain perception. However in the view of consideration modeling, the power of re-pricing is limited. By maximizing consideration set inclusion, the simulation points out another strategic option, introducing a new VW HEV. In the simulation runs, designing a new VW HEV gained more consideration sets than repricing every VW to be considered by every consumer, which is the most optimistic (and also likely unprofitable) repricing scenario possible. This finding demonstrates that a company should carefully weigh the advantages of economic strategy, such as pricing, with design strategy, such as introducing a new product.

There are several limiting assumptions to this study. This study assumes that consumers only evaluate vehicles on eight attributes (see Fig. 3) at prescribed, discretized levels, which can be determined by nine variables (see Table 6). The evaluated design attributes are largely functional; quantifying consumer consideration of vehicle style elements is out of the scope of this paper, but will influence consideration.

Additionally, this study combines data from a variety of sources with different levels of internal accuracy. If the results of this study were to be taken forward by a manufacturer, a much more robust approach would be to include uncertainty in the model that captures these discrepancies. Further, the surveys on consumer perceptions and preferences come from different snapshots of time. As much as possible, it is a much better approach to capture all of this information in one survey, but this is beyond the budget and scope of this project.

The study has not considered time effects, such as how consideration changes overtime or game theoretic competitive design decisions. Instead it uses a before/after scandal scenario analysis approach. Including time effects requires new survey methods to track and observe the dynamics of the consideration rules; and a dynamic model of competitors’ design and pricing decisions. While there may be more to be learned from a model with time effects, it is debatable whether or not the associated increases in computational time and uncertainties/errors within the model parameters would be balanced by additional insights. As this study suggests that consideration modeling provides unique insights when designing for large shifts in consumer preference, further research is warranted.

ACKNOWLEDGMENTS

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NOMENCLATURE

\[ a_{ij} \] Vehicle \( j \)'s utility to individual \( i \)
\[ a_t \] The threshold utility
\[ \beta_i \] The vector of individual \( i \)'s partworths
\[ c \] Optimal vehicle’s cost
\[ \mathcal{C} \] An individual’s vehicle consideration set
\[ x_{BatPow} \] Peak battery power
\( x_{\text{Bore}} \) Engine bore
\( x_{\text{BTS}} \) Bore-to-stroke ratio
\( x_{\text{FD}} \) Final drive ratio
\( x_{\text{H}} \) Vehicle height
\( x_{\text{L}} \) Vehicle length
\( x_{\text{W}} \) Vehicle width
\( x_{\text{WB}} \) Vehicle wheelbase
\( E_j \) EPA emissions rating of vehicle \( j \)
\( \delta_{i,j} \) Indicator function describing whether vehicle \( j \)
is acceptable to individual \( i \)
\( l \) Number of individuals in synthetic population
\( K \) The minimum number of acceptable attributes
to be considered
\( m_0 \) Engine mass
\( m_1 \) Gas tank mass
\( m_2 \) Passenger mass
\( m_3 \) Front and rear axle mass
\( m_4 \) Cargo mass
\( m_5 \) Suspension mass
\( m_6 \) Transmission mass
\( m_7 \) Exhaust mass
\( m_8 \) Bumper mass
\( m_9 \) Body mass
\( m_{10} \) Battery mass
\( r^j \) The synthetic population’s rule vectors
\( r_i \) Individual \( i \)'s decision rule vector
\( r_{\text{VW}} \) Conjunctive rule on VW brand
\( r_{\text{Diesel}} \) Conjunctive rule on diesel powertrain
\( m \) Optimal vehicle’s price
\( n \) Vertical center of gravity of vehicle
\( p \) Price of the optimal hybrid vehicle
\( o \) Binary vector indicating if an individual considered a Volkswagen
\( q_{i,j} \) Binary variable indicating if individual \( b \)
considered the Volkswagen vehicle \( a \)
\( t_0 \) Engine vertical height
\( t_1 \) Gas tank vertical height
\( t_2 \) Passenger vertical height
\( t_3 \) Front and rear axle vertical height
\( t_4 \) Cargo vertical height
\( t_5 \) Suspension vertical height
\( t_6 \) Transmission vertical height
\( t_7 \) Exhaust vertical height
\( t_8 \) Bumper vertical height
\( t_9 \) Body vertical height
\( t_{10} \) Battery vertical height
\( u \) A vector storing the number of VW vehicles
considered by each individual
\( v \) Number of vehicles in the 2014 market
\( v^j \) The vehicle marketplace’s vector
representations
\( v_i \) Vehicle \( i \)'s vector representation
\( y \) Vehicle static stability factor

REFERENCES


