Production and Operations Management

Impact of Inventory Levels and Product Variety on Consumers' Perceptions of Brands

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Abstract: Past research in operations management and marketing on inventory levels and product variety has predominantly focused on their effects on brand performance indicators, such as sales and market share, while overlooking the influence on consumers' perceptions of brands. Brand perceptions, encompassing reputation, quality, credibility, and emotional associations, go beyond typical revenue metrics and offer foresight into a brand's future performance. Hence, understanding the effects of inventory and product variety on brand perceptions is crucial, and that constitutes the main contribution of this paper. Through a consumer-facing automobile search platform, we collect data on new cars' inventories of more than 20,000 dealerships in the United States from August 2020 to March 2021. We measure brand perceptions using 273,991 responses by *in-market consumers* collected by YouGov. To address endogeneity concerns, we model the effects of inventory and variety on perceived brand strength using three different empirical approaches: 1) high-dimensional fixed effects, 2) instrumental variables, and 3) causal forest. Across all analyses, we find that inventory has a positive effect on perceived brand strength but the main effect of product variety is not significant. Our second contribution is related to the fact that past research on inventory and variety does not, for the most part, investigate systematic heterogeneity due to brand- or consumer-specific factors that impact the effectiveness of inventory or variety; to help fill this gap in the literature, we investigate the role of two important and theoretically motivated moderators: consumer income and luxury status of the brand. We find that consumers' income levels and brands' luxury status negatively (positively) moderate the effects of product inventory (variety) on perceived brand strength. Our results have managerial implications for effective assortment planning under scarcity, determining the right range of product offerings for luxury versus non-luxury brands, optimizing the customer's online browsing experience, and targeting advertisements based on brand and consumer characteristics.

Key words: Brand Strength, Brand Equity, Inventory, Product Variety, Retailing

1 Introduction

Inventory and product variety management have crucial implications for retailers and consumers. A considerable amount of capital (roughly \$1.1 trillion) is tied up in inventory in the United States (US); this is equivalent to approximately 7% of US GDP (Belyh 2022). It is estimated that US-based retailers carry approximately \$1.43 in inventory for each \$1 they make in sales. Yet, effective management of inventory has always been a challenge due to the complicated nature of this problem as well as the uncertainties in supply and demand. This challenge was greatly intensified during the COVID-19 pandemic, with the value of out-of-stock items in 2020 estimated to exceed $1 trillion (Goodman and Chokshi 2021). Such supply chain shortages and disruptions could have considerable negative implications for brand performance and have been reported to cause significant harm to reputation (54%), logistics (54%), and finances (62%) in some cases (Belyh 2022).

Extensive work in the marketing and operations management literature investigates the impact of inventory levels and product variety (e.g., Bayus and Putsis 1999, Cachon et al. 2019, Wang and Vakratsas 2021), primarily examining brands' financial performance metrics such as market share or sales, without empirically studying the impact on consumers' perceptions of brands. Brand perceptions encompass a diverse range of intangible attributes, including brand reputation, quality, credibility, and emotional associations, extending beyond conventional revenue-based metrics such as sales or market share (Keller 1993). It is also important to recognize that the impact of a firm's actions on brand sales may not translate into equivalent effects on brand perceptions. For instance, a brand offering substantial discounts may witness a surge in sales, yet this does not guarantee an enhancement of brand equity or serve as a reliable predictor of future brand success. Thus, sales figures shed light on a brand's immediate performance but do not necessarily capture its long-term potential. Moreover, consumer perceptions "can be used as advance warning signals that allow enough time for managerial action before market performance itself is affected" (Srinivasan et al. 2010, p. 672). In light of these considerations, past research underscores the importance of consumers' brand perceptions (often referred to as consumer mindset metrics or consumer-based brand equity) as an effective measure of a *brand's overall health* (Aaker and Joachimsthaler 2012, Keller et al. 2011). Consequently, it is up to the managers to assess and continuously monitor consumers' perceptions of their brands and discern the influence of managerial actions on brand perceptions. To this end, the main contribution of this paper is to study the impact of inventory levels and product variety on consumers' perceptions of brands—to the best of our knowledge, we are the first in the literature to do so.

From a managerial perspective, understanding which brands and consumers are most impacted by shifts in inventory and product variety is crucial for optimizing product assortments, allocating resources during challenging times based on brand characteristics, and developing targeted (online) ads (Villanova et al. 2021). Yet, for the most part, past research on the effects of inventory and variety has not investigated systematic heterogeneity due to brand- or consumer-specific factors that impact the effectiveness of inventory or variety. To identify relevant brand- and consumer-level moderators for examination, we rely on theoretical mechanisms highlighted in prior research. The literature suggests that inventory levels and product variety can influence consumer perceptions by providing functional/utilitarian *and* emotional/psychological benefits (e.g., Berger et al. 2007, Cachon et al. 2019). Based on Maslow's (1943) seminal hierarchy of needs framework, we argue that consumers are more likely to focus on emotional/psychological benefits if their "basic" needs are satisfied, a condition more likely to hold for consumers with higher incomes (Du and Kamakura 2008) and for luxury brands, which offer social signaling benefits. We therefore contribute to the literature by examining the moderating roles of consumer income and luxury status of a brand on the effects of inventory level and product variety on brand perceptions.

To address our research questions, we focus on the automobile industry and study the impact of inventory levels and product variety on *perceived brand strength*. Using a leading consumer-facing automobile search platform, we collect data on the new car inventory of 20,372 car dealerships in the US over 8 months from August 2020 through March 2021. We measure perceived brand strength using data from YouGov, a leading UK-based market research firm. More specifically, we use the composite "brand health index" measure, which has been utilized in past research (e.g., Luo et al. 2013, Stäbler and Fischer 2020). We model a survey respondent's brand health index for a brand as a function of the rolling average inventory/variety of that brand in all the dealerships operating in the respondent's Designated Marketing Area (DMA) of residence over the 30 days leading up to their survey submission as well as other control variables, different sets of fixed effects, and Gaussian copulas.

We note that historically, visiting dealerships was the primary mechanism by which consumers learned about a brand's inventory and variety. Other sources included word-of-mouth, advertising campaigns, and observing new cars on the streets. However, consumers can now easily learn about a brand's inventory/variety through dealership websites. Nevertheless, in order to physically or virtually visit a dealership (and subsequently realize the inventory/variety), consumers must first be *in the market* for a car. Therefore, we focus our analysis on a subset of YouGov respondents who indicate that they are in the market for a car.

Given that the data were collected during the COVID-19 pandemic, the time period of our data was marked by supply chain disruptions (e.g., semiconductor chip shortage, COVID-19 waves, and factory shutdowns) that exogenously impacted different brands in a comparable manner irrespective of popularity (Blanco 2021). This partially helps alleviate concerns about the endogeneity of product inventory and variety, given that the primary drivers of the observed inventory and variety were supply-side factors.[1] To address the remaining endogeneity concerns, we complement our base model by conducting several extensions that utilize (a) high-dimensional fixed effects, (b) different sets of instrumental variables, and (c) a machine learning (ML) method for causal inference (i.e., causal forest).

Across all models, we find that inventory has a positive effect on perceived brand strength: when the inventory levels of a particular brand increase, consumers' average perception of that brand's strength increases. The main effect of product variety on brand strength is not significant. Moreover, we find that inventory has a weaker (stronger) effect on consumers' perceptions of luxury (non-luxury) automobile brands, which could stem from the perceived loss of exclusivity for luxury brands when they are abundantly

[1] We thank the SE for underscoring this characteristic of our empirical context.

available. Similarly, our results show that inventory has a weaker (stronger) effect on high- (low-) income consumers. Therefore, high-income consumers think more highly of a brand if it does not have a large inventory and the products are thus not easily available to other consumers in their market. In line with Maslow's hierarchy of needs framework, we also find that the household income and the car's luxury status positively and significantly moderate the effect of product variety on consumers' brand perceptions.

Our results have several managerial implications. We suggest that brand managers tailor the product variety offerings based on the brand. Luxury brands could benefit from offering a broad range of product options, whereas simplifying the product offerings can be more advantageous for non-luxury utilitarian brands. This is especially important for manufacturers like Volkswagen, who produce and sell both non-luxury and luxury brands. Meanwhile, dealerships can modify the organization of vehicles in their lots to enhance or reduce variety perceptions based on brand luxury status or the average income in the local area. The findings are also relevant for inventory management and assortment planning under supply constraints. Our results highlight the importance of prioritizing products that have the most positive impact on consumers' perception of the brand when retailers face supply shortages.

Moreover, managers can explore the option of website redesign to optimize the online browsing experience in terms of how inventory is presented based on factors such as the brand luxury status and average income in the area. Targeted online advertising could be another lever to utilize. We recommend that brands create distinct ads targeting low- and high-income consumers to highlight different aspects of the assortment. While product inventory can be emphasized for low-income consumers, it is preferable to showcase variety when targeting high-income consumers.

The remainder of the paper is organized as follows. Section 2 provides a review of the relevant literature and our theory. Section 3 describes the details of our data sets. Section 4 discusses our models and results. We present the robustness checks in Section 5, and concluding remarks in Section 6. The details of our data and results are relegated to the Electronic Companion.

2 Literature Review and Theory

2.1 Overview of Relevant Research Streams

Our work relates to two main streams of research. The first is the literature on consumer brand perception, specifically the influence that managerial activities have on brand perceptions. Marketing scholars have established the importance of examining consumer perceptions of brands (see e.g., Keller and Lehmann 2006, Mintz et al. 2021). To capture consumers' overall brand perceptions, marketing academics have for several decades focused on "brand equity," commonly defined as the value of a branded product compared with the same product without the brand name (Keller 1993). One approach to operationalizing such value is through consumer mindset metrics such as awareness, attachment, attitude, and perceptions toward the brand (Datta et al. 2017, Stäbler and Fischer 2020), which is the approach we adopt in this research. Consumer mindset metrics are considered to provide a holistic view of brand health and serve as early indicators for future brand performance (Srinivasan et al. 2010). Given this, it is important for managers to know what levers they can use to influence brand perceptions. For example, past research has examined the effects of marketing mix instruments (Srinivasan et al. 2010), social media activities (Colicev et al. 2018), and corporate social responsibility (Luo and Bhattacharya 2006) on consumers' perceptions of brands. We contribute to this literature by examining the effects of inventory levels and product variety on brand perceptions.

Another stream of research comprises extensive work in the marketing and operations management literature that examines the impact of inventory levels and product variety on financial metrics such as sales (e.g., Cachon et al. 2019, Wang and Vakratsas 2021), but to the best of our knowledge, past research has not investigated the impact of such factors on brand perception. In addition, reported results in the literature on the impact of inventory levels and product variety on brand performance are inconclusive, as some studies find these effects to be positive and others find them to be negative. Our results, therefore, shed further light on this debate. In the next section, we review this stream of research in more detail.

2.2 Research on the Effects of Inventory and Product Variety on Brand Performance

The literature on product inventory and variety spans multiple disciplines and topics, encompassing research on the drivers of inventory and variety (e.g., Shankar 2006), their supply chain implications (e.g., Kim 2008), and effects on consumer-market brand outcomes (e.g., Cachon et al. 2019). In this section, we focus on the latter, as it is most relevant to our research. Moreover, while acknowledging the significant theoretical contributions to this field (Dong et al. 2007, Mishra and Raghunathan 2004), to ensure a manageable scope, we mainly focus on empirical work.

Past research is inconclusive regarding the effect of inventory levels on brand performance, typically measured in terms of sales, market share, or consumer choice. One strand of research suggests that higher inventory levels improve performance. For instance, Ton and Raman (2010) show that increased inventory boosts store sales, while Park et al. (2020) find that inventory shortages negatively impact sales of durable goods. Conversely, past research also identifies a negative impact of inventory levels. Cachon et al. (2019) investigate the addition of vehicles to GM dealerships and show that after accounting for resulting changes in product variety and considering how vehicles are added to the dealerships in practice, increased inventory results in decreased sales. Cui et al. (2019) find that reduced product availability on Amazon leads to an increase in cart add-ins, serving as an indicator of potential sales. Relatedly, previous theoretical research elucidates the reasons and conditions under which inventory levels have varying effects on brand performance (Stock and Balachander 2005, Tereyağoğlu and Veeraraghavan 2012).

As with inventory levels, some research shows that more variety can improve brand performance and other studies show the opposite. Bayus and Putsis (1999) examine the impact of product proliferation on firm market outcomes in the PC industry and find that product line length positively affects market share. Similarly, Draganska and Jain (2005), who develop a game-theoretic model as well as an empirical study on yogurt, report positive effects of variety on market share and consumer choice. Cachon et al. (2019) arrive at a similar conclusion in the automobile context. Other studies present a more nuanced view of the effects of product variety, indicating mixed outcomes. Ton and Raman (2010) finds that while more variety increases store sales, it indirectly dampens sales via its impact on phantom products. Wang and Vakratsas (2021) find that product line width (depth) positively (negatively) affects consumer choice. Extensive research also documents the choice overload phenomenon, showing how variety can negatively affect consumer choice (see Chernev et al. 2015 for a review).

Table 1 summarizes the existing literature, and outlines how our work differs from and adds to previous studies. In summary, prior research highlights the importance of inventory and product variety for brand performance, but it mainly focuses on financial metrics, or consumer behavior toward brands (e.g., choice). Our primary contribution lies in examining how inventory and product variety influence consumer perceptions of brands. Moreover, previous research has not systematically investigated brand- and consumer-level variations in the effects of inventory and product variety.[2] Understanding how different types of brands and consumer segments react to inventory and variety is essential for managerial decisions such as targeting, assortment planning, and customization. Our second contribution, therefore, lies in exploring systematic sources of heterogeneity in the effects of inventory and variety. We do this by using consumer income and brand luxury status as theoretically-grounded moderators in our analysis.

2.3 Mechanisms for the Impact of Product Inventory and Variety on Brand Perceptions

To explain how inventory and product variety can influence consumers' perceptions of brands, we turn to signaling theory, which originally emerged from Spence's seminal work in the labor market context (Spence 1973); it was subsequently expanded by Nelson to encompass activities of firms and brands such as advertising (Nelson 1974). The fundamental premise of signaling theory is that both individuals and firms can utilize observable attributes (signals) to convey information about their quality, competence, or intentions and that these signals impact perceptions of the signaling entity. Extensive empirical research over the years demonstrated that various firm and brand activities indeed can shape consumers' perceptions. It is now established that factors such as advertising (Kirmani and Wright 1989), price promotions (Rajavi et al. 2019), product return policy (Abdulla et al. 2022), and product warranties (Boulding and Kirmani 1993) meaningfully influence consumers' perceptions of brands. We posit that product inventory and variety have the potential to shape consumers' brand perceptions by operating as signals conveying information about the brand's quality, credibility, and capabilities.

[2] A notable exception is Wang and Vakratsas (2021), which examines the moderating effect of consumers' choice diversification propensity. However, demographic variables that are readily applicable for managerial actions (e.g., targeting) remain unexplored.

Table 1 Summary of Select Empirical Studies of the Consumer-Market Effects of Inventory and Product Variety

Study	Examines Inventory?	Examine Variety?	Examines Mindset Metrics?	Brand-level Moderators	Consumer-level Moderators	Outcome Measures	Key Findings
Bayus and Putsis (1999)	No	Yes	No	No	No	Market Share	Line length positively affects market share. The estimated product line effect does not exhibit decreasing return to scale.
Draganska and Jain (2005)	No	Yes	No	No	No	Choice	Line length affects consumers' utility, but its effect is subject to diminishing returns.
Balachander et al. (2009)	Yes	No	No	No	No	Market Share	Relative introductory scarcity is associated with higher consumer preference.
Ton and Raman (2010)	Yes	Yes	No	No	No	Sales	More inventory and variety increase store sales but indirectly dampen sales via their impact on phantom products.
Cachon et al. (2019)	Yes	Yes	No	No	No	Sales	More dealer inventory lowers sales but adding variety improves sales.
Cui et al. (2019)	Yes	Yes	No	No[∓]	No	Future Sales	A decrease in product availability causally attracts more sales in the future.
Park et al. (2020)	Yes	No	No	No	No	Sales	Displaying messages about inventory shortages lowers sales of durable goods.
Wang and Vakratsas (2021)	No	Yes	No	No	Choice Diversification Propensity	Choice	Product line width (depth) positively (negatively) affects consumers' choice. The negative effect of line depth is stronger for households with higher choice diversification propensity.
Van Ewijk et al. (2022)	No	Yes	No[†]	No	No	Choice, Quality Beliefs	Adding new SKUs may lift the brand's perceived quality level, but it also makes consumers more uncertain about the quality of the brand.
This Paper	Yes	Yes	Yes	Luxury status of the brand	Income	Perceived Brand Strength (PBS)	Inventory positively impacts PBS. Effect of variety is not significant. Consumers' income and the luxury status of the brand negatively (positively) moderate the effects of product inventory (variety) on PBS.

[†] Van Ewijk et al. (2022) quantify consumers' beliefs about brand quality in a Bayesian fashion based on consumption patterns. Although perceived quality is a crucial aspect of mindset metrics, it offers an incomplete view without considering other facets of consumers' attitudes and perceptions toward brands.

[∓] Cui et al. (2019) examined time-varying product-level moderators (e.g., number of product reviews). Our focus is on inherent brand characteristics.

To examine the effect of a brand's inventory level, we draw upon insights from prior research. Inventory levels might be indicative of a product's *popularity*. A high inventory level might suggest that a brand is less popular. Whereas, limited inventory could indicate high demand for the brand (Balachander et al. 2009, Stock and Balachander 2005) and its *exclusiveness*, thereby boosting its *value* for consumers (Hamilton et al. 2019, Tereyağoğlu and Veeraraghavan 2012). Conversely, high inventory levels can positively affect consumer perceptions of a brand's *quality* and *reliability*: "a consumer might infer from a large inventory that the item is of good quality (why else would the dealer stock so many), making the item more appealing—a high-quality item is associated with useful features and durability" (Cachon et al. 2019, p. 1470). Additionally, ample inventory levels can reflect the manufacturer's supply chain *competence* or *resilience* to maintain high levels of supply (Yang et al. 2021). Such reliability can reassure consumers that the brand can consistently meet their needs, fostering a sense of *trust* in the brand's ability to deliver.

Next, we consider different mechanisms by which product variety can influence consumers' brand perceptions. Past research indicates that variety lends *uniqueness* and *identity-signaling* benefits to consumers (Berger and Heath 2007, Chan et al. 2012), thereby increasing the *value* of the brand for them. Additionally, brands offering a wide variety might be seen as having more category *expertise* or *competency* (Berger et al. 2007). Conversely, some studies highlight the drawbacks of excessive variety (the "choice overload" phenomenon). A large assortment with too many options can lead to confusion and frustration (Chernev 2003, Iyengar and Lepper 2000), thereby reducing consumer *satisfaction* and diminishing the perceived *value* of the brand. Moreover, too much variety could dilute a brand's identity, making it harder for consumers to associate the brand with a specific value proposition or product quality. Relatedly, it has been shown that more variety makes consumers more uncertain about the *quality* of the brand (Van Ewijk et al. 2022). Because of the opposing mechanisms discussed in the literature, we refrain from proposing formal hypotheses regarding the effects of inventory and variety on perceptions of brands. We next explain the circumstances that moderate these effects.

2.4 Moderators of the Effects of Inventory and Product Variety on Consumer Perceptions

Our review of literature on the effects of inventory and product variety suggests that they not only influence consumer perceptions by providing functional/utilitarian benefits, but they also offer psychological, social, and emotional benefits to consumers (through, for example, the exclusivity effect or social-class/identity signaling—see e.g., Berger et al. 2007, Hamilton et al. 2019, Tereyağoğlu and Veeraraghavan 2012). In general, some of these psycho-social benefits relate to consumers' *need for uniqueness*, said to manifest in seeking rare and scarce products or in a preference for products that consumers believe have been tailored to their specific tastes (Song and Sela 2023). Maslow's seminal hierarchy of needs framework (Maslow 1943) implies that consumers are more likely to focus on such higher-order emotional and psychological needs if their lower-level physiological and financial needs are satisfied. This propensity is particularly pronounced among consumers with higher incomes, who are more likely to have their basic needs satisfied, and can afford to seek products that fulfill higher-order needs. Moreover, luxury brands, by their nature, cater to consumers' demand for exclusivity and uniqueness. Thus, the effects of inventory level and product variety on brand perception are likely to vary as a function of consumer income and brand luxury status. Next, we review the literature on these moderating factors.

2.4.1 The Moderating Role of Consumer Income

A large body of research suggests that consumers' preferences and consumption patterns vary as a function of their income. Among other things, scholars have shown that higher income leads to less price sensitivity (Bijmolt et al. 2005), a stronger preference for branded products vis-à-vis private labels (Dubé et al. 2018), forward-looking behavior such as stockpiling (Pan et al. 2020), increased variety-seeking (Yoon and Kim 2018), and increased conspicuous consumption (Bricker et al. 2021).

Past research further shows that high-income consumers focus more on status-signaling and consuming "positional" goods—products that convey relative standing within society (Bricker et al. 2021, Kamakura and Du 2012). As Nobel laureates George Stigler and Gary Becker mention, an increase in someone's income "would increase his demand for social distinction" (Stigler and Becker 1977, p.88). After satisfying basic needs, people often seek to fulfill higher needs like signaling their economic status, in line with Maslow's hierarchy of needs. Thus, high-income consumers are more likely to engage in identity-signaling and prioritizing social distinction features. A high level of inventory is unlikely to be in line with high-income consumers' priorities since they will assume that many others in their area can obtain a similar product; the product will thus lack any exclusivity benefit. The effect of inventory on brand perception is therefore likely to be weaker for high-income consumers than for low-income consumers. As for product variety, income can have the opposite moderating effect: when a brand offers a higher variety of products, consumers are more likely to find a product that is not possessed by many other consumers in that market. This suggests that more variety will give high-income consumers a better chance to achieve the social distinction and exclusivity effects they seek. We therefore propose the following hypotheses:

Hypothesis 1a *Consumer income negatively moderates the effect of inventory on brand perceptions. That is, the effect of inventory on brand perceptions is more positive for low-income consumers than for high-income consumers.*

Hypothesis 1b *Consumer income positively moderates the effect of product variety on brand perceptions. That is, the effect of product variety on brand perceptions is more positive for high-income consumers than for low-income consumers.*

2.4.2 The Moderating Role of Brand Status

Previous studies have shown that the brand status, especially its luxury status, affects consumer behavior. Research suggests that, quality considerations aside, consumers usually purchase luxury brands to reflect their individual or social goals (Wilcox et al. 2009). Luxury products provide social-signaling benefits to consumers (Hamilton et al. 2019), and because of their higher perceived value, consumers are more willing to pay higher prices for them (Reyes-Menendez et al. 2022). The perceived value of luxury products and brands stems not only from financial exclusivity but also from a social perception that integrates uniqueness and social value (Wilcox et al. 2009). Moreover, consumers of luxury products value the experiential aspects of a product more than non-luxury buyers do (Pozharliev et al. 2015). Hence brand luxury status is likely to negatively moderate the effect of inventory on brand perceptions. High levels of inventory for a luxury product in the market should lower consumers' perceptions of that luxury brand, as luxury buyers are likely to believe that many other consumers in their market could obtain the same product. Higher product variety for a luxury brand, on the other hand, should improve consumers' brand perceptions because it provides more opportunities to obtain a product that is distinct, through which the consumer can gain a sense of uniqueness and social value. We thus expect that the luxury status will positively moderate the effect of product variety on brand perceptions. We propose the following hypotheses:

Hypothesis 2a *A brand's luxury status negatively moderates the effect of inventory on brand perceptions. That is, the effect of inventory on brand perceptions is more positive for non-luxury brands than for luxury brands.*

Hypothesis 2b *A brand's luxury status positively moderates the effect of product variety on brand perceptions. That is, the effect of product variety on brand perceptions is more positive for luxury brands than for non-luxury brands.*

3 Data

3.1 Research Setting

Our dataset pertains to the automobile market. In 2021, 14 million automobiles were sold in the United States, and the industry generated $1.5 trillion in revenue from vehicles and parts sales (Carlier 2022). Automobiles are highly complex durable goods that constitute one of the largest household expenses. Consumers undertake extensive research in a competitive market to find the specific car they need. Thus, the implications of inventory shortage and lack of variety for automakers and dealers can be far-reaching.

3.2 Inventory Data

To build our sample, we gathered data on the new car inventory mix of dealerships from a leading consumer-facing automobile search platform. Auto dealers use this platform to post their inventory listings online and connect with customers. We monitor the industry's dynamics by tracking dealers' online activity. We capture

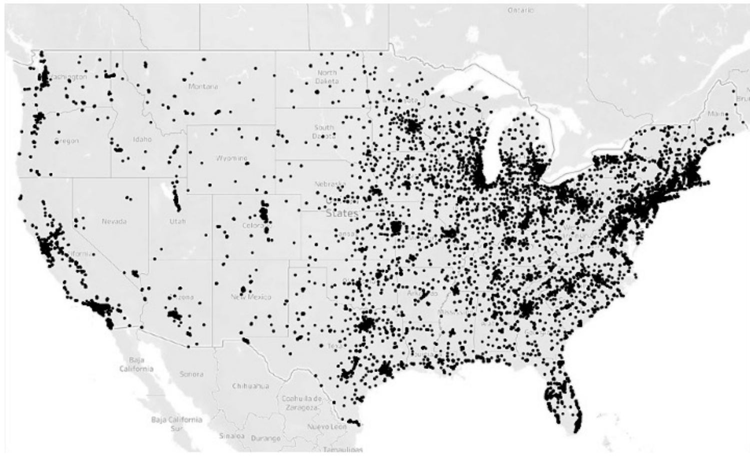

Figure 1 Map of Dealerships Covered in Our Data (Denoted by Dots).

new car information across 20,372 dealerships in the United States over 8 months (August 2020 through March 2021), as illustrated in Figure 1. For each dealer, we collect detailed inventory information containing each car's brand, make, model, and price, as well as the dealer's name, address, and other identifying information. On a typical day, we observe 584,774 unique new cars, with a mean price of $41,318; they cover 34 brands, 927 make-models, and 2,210 unique make-model-years.

Once inventory at each dealer is identified, we geolocate the dealers. The original data includes only partial addresses, with the street address but no zip code. Addresses are unstandardized, with possible typos, and formatting can vary across dealers and time. To correct these issues, we geocoded the partial addresses using the Google Maps API, which is robust to typos and missing parts (Pan and Wu 2020). This process yielded the standardized address, zip code, and latitude and longitude of each dealer.

3.3 Consumer Perception Data

We measure consumers' perceptions of brands using data from YouGov, a leading market research firm headquartered in the UK. YouGov operates an online panel of millions of consumers in 50+ countries, including the US, where YouGov maintains a panel of two million respondents. YouGov collects surveys on different topics (e.g., politics, celebrities, economy), and its *BrandIndex* tracks consumers' perceptions of thousands of brands across many sectors. Marketing researchers use YouGov's BrandIndex to examine the impact of firm and brand actions (Colicev et al. 2018, Du et al. 2019, Stäbler and Fischer 2020).

Demographic data help to ensure that YouGov's panel is representative of the US population. Panelists complete a maximum of one survey per month, thereby earning points that can later be redeemed for cash and gift cards. In each survey, panelists respond to a range of questions about brands in a particular sector. Questions are designed to capture multiple aspects of consumers' perceptions of and (self-reported) behaviors toward different brands. On most items, consumers determine whether they are positive, negative, or neutral about a brand. For example, for the *perceived quality* item, they identify brands that are of good

(+1) or bad (-1) quality. If a brand is not marked as good or bad, the respondent is assumed to be neutral (0) about its quality. Responses to an item can thus receive three possible values.[3] As we later note in Section 3.4, we use data on six YouGov items to measure consumers' perceptions of brands.

It is important to acknowledge that the YouGov panel consists of individuals who may not have an immediate intention to purchase a car and hence may have limited exposure to auto dealerships and their websites, resulting in a lack of awareness regarding the inventory and variety levels offered by different brands. Therefore, their responses may not accurately reflect the impact of inventory and variety on brand perceptions. To mitigate this issue, our analysis focuses specifically on respondents who are actively in the market for a car. YouGov determines the "in-market status" of its panelists by asking them to rate how likely they are to purchase a car in the near future, with response options being: 1) not at all likely, 2) not very likely, 3) somewhat likely, 4) likely, and 5) very likely. We retain responses from panelists who chose one of the last two options (i.e., approximately one-fifth of the data).[4]

3.4 Data Aggregation, Variables, and Statistics

Past research in marketing mostly utilizes YouGov data that are aggregated across all panelists in a country (e.g., Colicev et al. 2018, Du et al. 2019). Our raw data, however, allow us to 1) measure inventory/variety more accurately, and 2) observe and utilize the respondents' self-reported demographic information, including income level. Namely, YouGov follows Nielsen Media Research in dividing the United States into 210 Designated Marketing Areas (DMAs). Thus, we observe the DMA where a panelist resides and use this information in our calculation of inventory and variety levels of different brands.[5]

To construct a holistic measure of consumers' perceptions of brands, we follow past research and YouGov's practice and measure perceived brand strength (*PBS*) by averaging each respondent's answers to six questions related to perceived value, perceived quality, satisfaction, impression, recommendation, and perceived reputation of brands (questions are listed in the E-Companion, EC.1). This measure, labeled *brand health index*, is YouGov's most managerially relevant and comprehensive index for capturing different aspects of a brand's well-being and has thus been used in prior research (e.g., Luo et al. 2013, Stäbler and Fischer 2020). *PBS* varies between -1 and 1, with a mean of 0.162 and a standard deviation of 0.409. Toyota and Honda have the highest average *PBS* scores across all respondents in the US in the time period of our data, whereas Fiat, Mini, and Mitsubishi have the lowest average brand strength scores.

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[3] For more information on YouGov's BrandIndex and its data collection methodology, see https://business.yougov.com/product/brandindex and Du et al. (2019).

[4] In the robustness section, we further restrict our sample to a) only those respondents who indicated that they are "very likely" to purchase a car, and b) the brands that the panelist indicates he/she is likely to consider for their next purchase. In both cases, our substantive findings remain unchanged.

[5] For privacy purposes, YouGov did not share the zip codes of the panelists with us.

Our focal independent variables are inventory level ($INVENTORY$) and variety ($VARIETY$). To compute inventory level, we track the number of cars available for sale at every dealership on any given day. To measure variety, we first compute the Herfindahl–Hirschman Index (HHI) of the unique automobile types available at each dealership on any given day (as detailed in EC.2). A unique automobile is defined as a unique make-model-year-trim combination. The HHI index is a common measure of variety in the literature, including studies of the automobile industry (Benkard et al. 2021, Pan et al. 2020). The index is minimized when the items in a list are fully homogeneously distributed across categories; it is maximized when one category accounts for all items (i.e., a full concentration). This metric allows us to discern how much variety exists in the set of cars carried by a dealership. The HHI is calculated by squaring the share of each item category in a list and summing the resulting values across categories. We reverse the sign of the HHI value to convert it from a measure of concentration to a measure of variety (as detailed in subsection EC.2.2).

After calculating inventory and variety of a brand at each dealership on a daily level, we take the average of the two variables across all dealerships belonging to a brand in a given DMA. Thus, average inventory and variety are calculated for all brand-DMA-day combinations. Based on these averages, we then construct our focal independent variables (i.e., $INVENTORY$ and $VARIETY$) corresponding to each YouGov response, as a function of the brand evaluated, the DMA where the respondent resides, and the day the respondent filled out the YouGov survey. Specifically, for each response for a brand on a particular date, we calculate the rolling average of that brand's inventory/variety across all its dealerships in the DMA where the panelist resides. This rolling average is computed over the 30 days that precede the survey submission date. Details and formulae for computing the independent variables are provided in EC.2.[6]

In order to identify brands' luxury status ($LUXURY$), we utilized the luxury car reports by the automotive research firm, *Good Car Bad Car* (2023), as detailed in Table EC.1. To control for the physical footprint of a brand in a market, we control for the number of dealers the brand operates in the region ($DEALERS$). We control for the average price of the automobiles for each brand ($PRICE$), as pricing might influence brand perceptions. Different brands might have different advertisement budgets in each region. In the YouGov dataset, we also observe the respondent's advertisement awareness for a particular brand ($ADAWARE$). To track the overall interest in a brand we control for the Google Trends search index of the brand name as the keyword in each DMA and month ($GTRENDS$).

In our YouGov data, we observe the annual household incomes of our panelists, which we use as our measure of respondent income ($INCOME$). Finally, we control for education ($EDUCATION$), gender ($GENDER$), and age (AGE) of the respondent. Table 2 presents the definitions of the variables used in our

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[6] Our assumption is that in the absence of precise information about the specific date(s) consumers physically/virtually visited dealerships, a 30-day rolling average serves as a reasonable proxy for their observations. This assumption could be problematic if daily changes in brand inventory/variety within a DMA exhibit significant fluctuations. In our data, such fluctuations are relatively minor over the course of days or even weeks, as evidenced by daily and weekly correlations exceeding 0.9 for both inventory and variety values. We thank the anonymous reviewer for bringing this to our attention.

Table 2 Variable Definitions

Variable	Definition
Brand Characteristics	
PBS	Perceived brand strength index
INVENTORY	Inventory level; average number of cars available for sale at dealerships
VARIETY	Inventory variety; average car variety (1-HHI) at the dealerships
LUXURY	Luxury status of the brand
DEALERS	Number of dealerships for a brand in a DMA
PRICE	Average automobile price at the dealerships (in 000 dollars)
ADAWARE	Advertising awareness of the respondent towards a brand
GTRENDS	Google Trends index of the brand
Consumer Characteristics	
INCOME	Annual family income of the respondents (in 00,000 dollars)
EDUCATION	Respondent education level (six categories, higher values indicate higher education)
GENDER	Respondent gender (1=male; 2=female)
AGE	Respondent age (1=below 18-34; 2=between 35 and 50; 3=above 50)

analysis. Table EC.2 provides the correlation matrix as well as the mean and standard deviation of variables. The correlations are generally small, indicating that multicollinearity is not a concern.

4 Empirical Analysis

We start our empirical analysis with a basic model, addressing endogeneity through control variables and Gaussian copula terms. Following discussion of this model's results, we alleviate endogeneity concerns through different sets of fixed effects that rule out other possible explanations. However, the use of extensive fixed effects raises the risk of overfitting. To address this challenge, we adopt two different styles of analysis. One approach utilizes the instrumental variables (IV) method that relies on the exogenous variation in inventory levels or product variety. Though this approach avoids overfitting concerns, it operates on the assumption that the theoretically-motivated IVs are valid, an assumption that cannot be empirically assessed. Alternatively, we utilize the causal forest method, a data-driven approach that retains only relevant covariates, fixed effects, and interactions. This method efficiently evades the need to include an extensive array of multi-way interactions that might lead to overfitting. Each approach comes with its own set of assumptions, advantages, and limitations. We recognize the challenges of obtaining causal estimates from observational data, and acknowledge that different techniques cannot fully substitute for the advantages of randomization (e.g., field experiments). However, we believe if the majority of results from various techniques qualitatively align, this can increase our confidence in the causal nature of the findings. We therefore conclude by synthesizing our findings across all models.

We present our base model, which will be used to examine the impacts of inventory level (*INVENTORY*) and product variety (*VARIETY*) on consumers' perceptions of brands (*PBS*) in Equation (1) below:

$$PBS_{ikbt} = \alpha + \beta_1 * ln(INVENTORY_{kbt} + 1) + \beta_2 * ln(VARIETY_{kbt} + 1) + \boldsymbol{\gamma} \cdot \boldsymbol{CONTROLS} + \boldsymbol{\kappa} \cdot \boldsymbol{COPULAS} + \theta_k + \delta_b + \lambda_m + \varepsilon_{ikbt} \quad (1)$$

where i represents respondents, k represents markets (DMA), b represents brands, t represents time (days), α is the overall intercept, β_1 and β_2 are coefficients of the main independent variables, γ is the vector of coefficients for the vector of control variables (*CONTROLS*), and κ is the vector of coefficients for the Gaussian copula variables (*COPULAS*). Other than the control variables included in the model, we account for different sources of variation in consumers' perceptions of brands by including three sets of fixed effects in our model. It could be argued that different brands are differentially perceived by consumers, irrespective of inventory or variety. We account for such cross-brand variations in brand perceptions by including brand fixed effects (δ_b). It could also be argued that common temporal shocks affect both variety and inventory, as well as brand perceptions. We account for time-specific variations by including month fixed effects (λ_m). Moreover, it is possible that different geographical areas are heterogeneously affected by supply chain shortages, and hence *PBS* varies as a function of the geographical location. To account for this possibility, we also include DMA fixed effects (θ_k).

In our empirical model, we use log-transformed *VARIETY* and *INVENTORY* for two reasons. 1) Enhancing the interpretability of coefficient estimates: *INVENTORY* and *VARIETY* are on different scales, which makes it difficult to directly compare the magnitude of their coefficients. After log-transformation, β_1 and β_2 respectively capture the effect of a one percent change in *INVENTORY* and *VARIETY* on *PBS* and are thus directly comparable. 2) Skewness: both *INVENTORY* and *VARIETY* are highly skewed (see EC.5). Log transformation helps reduce the impact of outliers on coefficient estimates.[7]

Several variables in our model are potentially endogenous. To address endogeneity concerns associated with *INVENTORY*, *VARIETY*, *PRICE*, *ADAWARE*, *GTRENDS*, and *DEALERS* we adopt Gaussian copulas. The Gaussian copula approach, recently applied in operations research (e.g., Deshpande and Pendem 2023), models and controls for the joint distribution of the endogenous variable and the error term using control functions (Park and Gupta 2012). This approach requires that the endogenous variables are not normally distributed. The Shapiro-Wilk test rejects the normality assumption for our six endogenous variables at a 0.01 level. We construct six Gaussian copulas and add them as control variables in the model.

We next present our full model specification, which will be used to examine the moderating impact of the brand luxury status (*LUXURY*) and respondents' income (*INCOME*) on the effects of inventory and variety on consumers' brand perceptions:

$$\begin{aligned} PBS_{ikbt} = {} & \alpha + \beta_1 * ln(INVENTORY_{kbt} + 1) + \beta_2 * ln(VARIETY_{kbt} + 1) \\ & + \beta_3 * ln(INVENTORY_{kbt} + 1) * INCOME_{ikt} + \beta_4 * ln(INVENTORY_{kbt} + 1) * LUXURY_b \\ & + \beta_5 * ln(VARIETY_{kbt} + 1) * INCOME_{ikt} + \beta_6 * ln(VARIETY_{kbt} + 1) * LUXURY_b \\ & + \boldsymbol{\gamma} \cdot \boldsymbol{CONTROLS} + \boldsymbol{\kappa} \cdot \boldsymbol{COPULAS} + \theta_k + \delta_b + \lambda_m + \varepsilon_{ikbt} \end{aligned} \tag{2}$$

where four interaction terms have been added to the model in Equation (1). Thus, β_3 and β_4 capture the moderating effects of *INCOME* and *LUXURY* on the effect of inventory on brand perception (respectively

[7] We do not log-transform *PBS* as it is not skewed and has negative values. All results hold with ln(*PBS*+2) as the dependent variable.

testing H1a and H2a). β_5 and β_6 represent the moderating effects of $INCOME$ and $LUXURY$ on the effect of product variety on consumers' perceptions of brands (testing H1b and H2b). Based on our proposed hypotheses in the theory section, we expect β_3 and β_4 to be negative, but β_5 and β_6 to be positive.

To estimate the model, we use STATA's REGHDFE, which allows for high-dimensional fixed effects. Since we have interaction terms in our final model, to enhance the interpretability of our estimates and reduce non-essential collinearity, we mean-center predictor variables. We estimate standard errors using multi-way cluster-adjusted standard errors (at the brand, DMA, and month levels).

4.1 Initial Results

Table 3 presents the initial results. We begin with the model described in Equation (1) (Model 1). We use these results to discuss the main effects of $INVENTORY$ and $VARIETY$. We then add interactions of $INVENTORY$ and $VARIETY$ with $INCOME$ (Model 2) and $LUXURY$ (Model 3). We arrive at the full model described in Equation (2) by including both sets of interactions with $INCOME$ and $LUXURY$ (Model 4). We use the results in Model 4 to discuss the moderating roles of $INCOME$ and $LUXURY$.

The results in Model 1 suggest that a brand's inventory level is positively and significantly related to consumers' perceptions of the brand (β_1=0.011, p<0.05). Therefore, it is implied that on average, the positive mechanisms associated with greater inventory levels (e.g., signaling brand capability and superiority) outweigh the negative mechanisms (e.g., lower perceptions of product uniqueness). We do not find significant evidence for the relationship between $VARIETY$ and *PBS* (β_2=-0.032, p>0.10). It thus appears that, on average, the positive (e.g., more choice and freedom for consumers) and negative (e.g., lower perceptions of quality) mechanisms discussed in the literature on variety cancel each other out.

The results in Model 4 imply that the association between inventory and *PBS* is weaker (stronger) for high- (low-) income consumers (β_3=-0.006, p<0.01), supporting H1a. High-income consumers think more highly of a brand if it does not have a large inventory; i.e., when products are not easily available to other consumers. We also find that inventory has a weaker (stronger) relationship with consumers' perceptions of luxury (non-luxury) automobile brands (β_4=-0.011, p<0.05), supporting H2a. Along with functional benefits, luxury brands provide higher-order social-signaling and emotional benefits to consumers, including an enhanced sense of uniqueness. The uniqueness benefit does not align with high levels of inventory, because the consumer realizes that many others can obtain the same automobile. The sense of reduced uniqueness is less of an issue for non-luxury brands which are known for functional benefits.

INCOME and *LUXURY* both positively and significantly moderate the relation between variety and consumers' perceptions, supporting H1b and H2b. We find that consumers' income levels (*INCOME*) positively moderate their appreciation of the amount of variety offered by a brand (β_5=0.052, p<0.05). In other words, high-income consumers value product variety more than low-income consumers do. This finding further

Table 3 High-Dimensional Fixed Effects Regression Results

	Main Effect	Interaction Effects		Full Model
	(1)	(2)	(3)	(4)
INVENTORY	0.011^{**}	0.011^{**}	0.014^{***}	0.014^{***}
	(0.028)	(0.025)	(0.006)	(0.005)
INVENTORY × *INCOME*		-0.006^{***}		-0.006^{***}
		(0.003)		(0.003)
INVENTORY × *LUXURY*			-0.011^{**}	-0.011^{**}
			(0.011)	(0.010)
VARIETY	-0.032	-0.027	-0.052^{*}	-0.047
	(0.299)	(0.363)	(0.085)	(0.111)
VARIETY × *INCOME*		0.055^{**}		0.052^{**}
		(0.024)		(0.030)
VARIETY × *LUXURY*			0.168^{***}	0.162^{***}
			(0.001)	(0.001)
DEALERS	0.001	0.001	-0.001	-0.001
	(0.868)	(0.802)	(0.350)	(0.374)
PRICE	-0.001^{**}	-0.001^{**}	0.001	-0.001
	(0.038)	(0.037)	(0.947)	(0.992)
ADAWARE	0.106^{***}	0.105^{***}	0.105^{***}	0.105^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
GTRENDS	0.001	0.001	0.001	0.001
	(0.246)	(0.267)	(0.232)	(0.250)
INCOME	-0.013^{**}	-0.012^{***}	-0.013^{**}	-0.012^{***}
	(0.014)	(0.004)	(0.014)	(0.004)
EDUCATION	-0.004	-0.004	-0.004	-0.004
	(0.339)	(0.337)	(0.339)	(0.336)
GENDER	0.036^{***}	0.036^{***}	0.036^{***}	0.036^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
AGE	0.013^{***}	0.013^{***}	0.013^{***}	0.013^{***}
	(0.005)	(0.006)	(0.005)	(0.006)
Constant	0.161^{***}	0.161^{***}	0.157^{***}	0.158^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Brand FEs	YES	YES	YES	YES
Time FEs	YES	YES	YES	YES
DMA FEs	YES	YES	YES	YES
Copulas	YES	YES	YES	YES
LL	-130,593	-130,460	-130,433	-130,304
Observations	273,991	273,991	273,991	273,991

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

illustrates the greater importance of higher-order emotional and social-status benefits for wealthier consumers, who appreciate products that give them a sense of uniqueness, which is more likely to be achieved when they have a larger assortment of products to choose from. On the other hand, low-income consumers tend to focus on utilitarian attributes and are less worried about signaling their social status or satisfying their emotional needs. Product variety is thus less important in shaping their perceptions of brands.

Product variety has a more positive association with *PBS* for luxury brands (β_6=0.162, p<0.01). Luxury brands thus benefit from offering a varied range of products, a finding that is consistent with the argument that luxury buyers seek products that enhance their sense of uniqueness. Non-luxury brands are better off, at least when it comes to managing consumers' perceptions, focusing on fewer products and keeping it simple for their customers, who are more likely to value utilitarian attributes over hedonic ones.

Overall, results support the important role of emotional mechanisms associated with inventory and variety, and these mechanisms are especially pertinent to high-income consumers and luxury brands. We also present marginal effects of *INVENTORY* and HHI at different levels of *INCOME* and *LUXURY* in EC.6. Note that the coefficient estimates for interaction terms in Models 2 and 3 are similar to those reported in our final model in column 4, which alleviates concerns regarding multicollinearity.

The coefficient estimates from Equations (1) and (2) may be biased if the error term is correlated with the variables of interest. This is possible if there are unobserved variables not accounted for by our model. Even after including brand, month, and DMA fixed effects, our model does not account for other (unobserved) sources of variation that are related to both inventory/variety and *PBS*. For example, it is plausible that a brand uses different inventory/variety management techniques in areas where it is popular. In the following sections, we build on our initial model and use three general approaches to alleviate such endogeneity concerns: 1) including richer sets of interactive fixed effects, 2) utilizing different sets of instrumental variables, and 3) an ML-based approach for causal inference (i.e., causal forest).

4.2 Adding High-Dimensional Fixed Effects

Following recent practice in the economics and management literature (e.g., Bertrand et al. 2020, Hong and Shao 2021), we account for different sources of variation by including richer sets of fixed effects. Specifically, we include different combinations of the three main sets of fixed effects we incorporated in our main analysis (i.e., brand, month, and DMA fixed effects). The results reported in Table 4 still include all the control variables mentioned in Equation (2), but for brevity, we do not report their coefficient estimates.

In our main analyses, we accounted for general temporal shocks by including month fixed effects. Time-specific shocks could, however, vary across geographical locations. For example, bad weather or a greater number of COVID-19 infections might have differentially affected manufacturing plants (and dealerships) at different locations, and hence inventory and variety of products offered in that location at a specific time. To account for such possibilities, we add DMA*month fixed effects to our model. Results are reported in Model 1 of Table 4. We find support for the main effect of *INVENTORY* as well as the moderating roles of *LUXURY* and *INCOME* on the effects of inventory and variety on *PBS*.

In our main analyses, we accounted for heterogeneity in consumer perceptions of different brands by including brand fixed effects. Such differences in consumer perceptions of brands could vary across time, as a result of factors other than *INVENTORY* or *VARIETY*. For example, brands introduce their new models at different times, and this new product introduction is supported by advertising campaigns. To account for cross-time changes in consumer perceptions of different brands, we add brand*month fixed effects to our model. The reported results in column (2) of Table 4 replicate the findings from our initial model.

Moreover, consumers' perceptions of different brands vary across geographical locations. For example, consumers in Mississippi might have, on average, very different preferences for non-US brands compared to people in New York. At the same time, Toyota is likely to adopt a different inventory management strategy across these two markets. Failure to account for such differences could lead to biased estimates. We therefore add brand*DMA fixed effects to our model. This addition results in the inclusion of approximately 4,500 fixed effects. All our initial findings are replicated (see column (3) of Table 4).

Finally, we take a conservative approach and add brand*DMA*month fixed effects to our model (approximately 39,000 fixed effects). Adding a large number of fixed effects results in a great loss of statistical power, reducing significance levels. The results in Model 4 of Table 4 should thus be regarded as conservative estimates. Even after the addition of so many fixed effects that take into account differences across brands that vary by geography and time, our estimates are in line with our main findings.

Table 4 HDFE Regression Results with Alternative FEs

	(1)	(2)	(3)	(4)
INVENTORY	0.014^{***}	0.014^{***}	0.024^{***}	0.031^{***}
	(0.006)	(0.006)	(0.001)	(<0.001)
INVENTORY $\times$ *INCOME*	-0.007^{***}	-0.006^{***}	-0.006^{***}	-0.006^{***}
	(0.004)	(0.003)	(0.002)	(0.005)
INVENTORY $\times$ *LUXURY*	-0.010^{**}	-0.011^{**}	-0.023^{***}	-0.020^{***}
	(0.013)	(0.014)	(0.005)	(0.008)
VARIETY	-0.037	-0.051	-0.074^{**}	-0.044
	(0.196)	(0.101)	(0.020)	(0.404)
VARIETY $\times$ *INCOME*	0.051^{**}	0.052^{**}	0.048^{*}	0.051^{*}
	(0.032)	(0.029)	(0.057)	(0.061)
VARIETY $\times$ *LUXURY*	0.161^{***}	0.171^{***}	0.126^{***}	0.138^{*}
	(<0.001)	(0.001)	(0.009)	(0.081)
Control Variables	YES	YES	YES	YES
Brand, Month & DMA FEs	YES	YES	YES	YES
DMA*Month FEs	YES			
Brand*Month FEs		YES		
Brand*DMA FEs			YES	
Brand*DMA*Month FEs				YES
Copulas	YES	YES	YES	YES
LL	-126,811	-130,214	-127,762	-113,266
Observations	273,991	273,991	273,991	273,991

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Our previous models, with their extensive sets of fixed effects, help mitigate endogeneity. Yet, our key variables might still correlate with the error term. Despite the inclusion of 39,000 brand*DMA*month fixed effects, one might argue that brands strategically adjust online ad spending across weeks or days within a month. Such variations could impact consumers' perceptions. Tackling this issue with a fixed effect approach would necessitate adding brand*DMA*week or brand*DMA*day fixed effects. This is practically challenging, if not impossible, and will lead to overfitting problems. To address these concerns, we employ two approaches: 1) leveraging exogenous variation in the endogenous variables, via instrumental variables informed by theoretical and conceptual reasoning, and 2) retaining and controlling for relevant covariates, fixed effects, and their interactions in a data-driven manner. We discuss these two approaches next.

4.3 Instrumental Variable Regression

A widely adopted method to address endogeneity concerns involves the application of instrumental variables (IV). An appropriate IV should a) be strongly correlated with the potentially endogenous regressor (i.e., the relevance criterion), and b) not directly influence the dependent variable in the model, except through its correlation with the endogenous variable (i.e., the exclusion restriction criterion). Following past research (e.g., Hausman 1996, Nevo 2001), we utilize the multimarket nature of our dataset to operationalize *Hausman-style* IVs. Specifically, we construct the following sets of IVs:[8]

- IV1: Average inventory/variety for the same brand across non-neighboring DMAs in the region (i.e., Northeast, Midwest, South, West).
- IV2: Average inventory/variety for the same brand across all non-neighboring DMAs.
- IV3: Average inventory/variety of all other brands across non-neighboring DMAs in the region.
- IV4: Average inventory/variety of all other brands across all non-neighboring DMAs.

The IVs are likely to be sufficiently correlated with their corresponding endogenous variables because common shocks such as supply chain complications are likely to impact all firms operating in different geographical locations. A truck driver shortage, work restrictions due to COVID-19, or chip shortage, for example, could cause disruptions in production and distribution for all automakers. Across all analyses that we present in Table 5, the first-stage F-statistics are considerably greater than the accepted threshold of 10 (the average joint F-statistic of the IVs is 84.25).

The exclusion restriction assumption for IV1 and IV2 is that since market-specific valuations are independent across markets (Ghose et al. 2012, Nevo 2001), it is unlikely that a brand's inventory and variety levels in other DMAs influence consumers' perceptions of the brand in the focal DMA. The results are largely in line with our main findings and our hypotheses find support.

Table 5 High-Dimensional Fixed Effects Instrumental Variable Regression

	(1) IV1	(2) IV2	(3) IV3	(4) IV4
INVENTORY	0.008	0.034^{***}	0.030	0.058^{**}
	(0.864)	(0.006)	(0.481)	(0.031)
INVENTORY × *INCOME*	-0.015^{***}	-0.015^{***}	-0.008^{**}	0.001
	(<0.001)	(<0.001)	(0.040)	(0.871)
INVENTORY × *LUXURY*	-0.089^{**}	-0.048^{*}	-0.053^{**}	-0.053^{***}
	(0.033)	(0.072)	(0.013)	(0.005)
VARIETY	-0.150	0.112^{**}	0.104	0.018
	(0.367)	(0.015)	(0.263)	(0.789)
VARIETY × *INCOME*	0.105^{**}	0.131^{***}	0.100^{***}	0.329^{***}
	(0.035)	(<0.001)	(<0.001)	(<0.001)
VARIETY × *LUXURY*	-0.072	0.334^{***}	0.285^{***}	0.372^{***}
	(0.745)	(<0.001)	(0.002)	(<0.001)
Control Variables	YES	YES	YES	YES
Brand, Month & DMA FEs	YES	YES	YES	YES
First-Stage F-Statistic	33.214	176.562	37.395	91.041
LL	-101,789	-98,944	-90,486	-58,994
Observations	273,991	273,991	273,991	273,991

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[8] We exclude Gaussian copulas for *INVENTORY* and *VARIETY* from these IV analyses.

IV1 and IV2 are valid instruments under the assumption that for a particular brand, unobservables that are potentially correlated with *INVENTORY* and *VARIETY* are not correlated across markets. However, this assumption can be violated. Consider a strategic variable like the extent of rebates offered, which is missing from our model. This variable could potentially impact *PBS* and might be correlated with *INVENTORY* and *VARIETY* (e.g., a brand with higher inventory levels might choose to offer more rebates). If a brand decides to modify the amount of rebates offered across all markets, rebates tend to be highly correlated across these markets. Therefore, incorporating the variation in *INVENTORY* and *VARIETY* from other markets can still result in second-stage variables that are potentially correlated with the error term.

To alleviate this, we construct IVs using the variation in the average inventory and variety levels of *competing brands* across other markets (i.e., IV3 and IV4). They satisfy the relevance condition because supply chain issues during COVID-19 similarly affected all brands across all markets. These IVs are likely exogenous with respect to *PBS* of the focal brand because they utilize variation that is sufficiently distant from that of the focal brand-DMA and are unlikely to be related to unobservables that change the *PBS* of the focal brand. The results in Table 5 are mainly in line with our initial findings.

4.4 Causal Forest

The efficacy of the IV method is contingent on the validity of the IVs, particularly the exclusion restriction assumption, which cannot be tested empirically. Wooldridge (2009) suggests that one alternative approach to mitigate endogeneity concerns is to incorporate an extensive set of control variables (or fixed effects), aiming to diminish the potential correlation between variables of interest and the error term. As mentioned in section 4.2, adding different sets of fixed effects and their interactions can lead to overfitting. An effective solution is to employ machine learning techniques, which prioritize and retain only specific combinations of control variables deemed relevant by empirical metrics, bypassing the need to account for every potential interaction between variables and fixed effect.

Machine learning techniques (traditionally employed for prediction purposes) have been adapted by economists for causal inference. A popular approach is causal forest (Wager and Athey 2018), recently used by business scholars (Miao et al. 2023, Unal and Park 2023, Zhang and Luo 2023). Causal forest is a nonparametric estimation method that can be deployed to estimate average treatment effects (ATEs) and examine heterogeneous treatment effects as a function of other variables. Moreover, it can leverage observational data for the estimation of average partial effect when the variable of interest is continuous (Athey and Wager 2021, Zhang and Luo 2023). We use causal forest to estimate the causal effects of *INVENTORY* and *VARIETY*, and heterogeneity in their ATEs as a function of *LUXURY* and *INCOME*.

Causal forests build on the concept of nearest neighbor methods (Wager and Athey 2018). While classical approaches rely on distance/similarity metrics on predetermined variables to identify nearest neighbors, causal forests employ a criterion based on maximizing differences in treatment effects for covariate splits during training. These methods utilize a collection of causal trees to determine the nearest neighbors. After building a collection of trees, the causal forest algorithm records the frequency with which the test example and each training example share the same leaf in the trees built during training. This information is used to assign similarity weights to each neighboring training example which can be thought of as the probability of receiving the same treatment value. These similarity weights take into account the treatment level (Unal and Park 2023) and outcomes, and they are used to make predictions for the test observation. The predictions from multiple trees are then averaged to obtain the final estimated treatment effect. In contrast to basic regression, which models relationships using linear combinations of variables and potentially limited interactions specified by the researcher, the causal forest approach allows for non-parametric control of confounding factors (e.g., high-dimensional interactions) when estimating treatment effects. [9]

Using the GRF package in R, we run two separate models to estimate the effects of *INVENTORY* and *VARIETY*. In each model, we control for all the variables included in our base model in Equation (1), including approximately 250 dummy variables corresponding to different brands, DMAs, and months. In our first causal forest, we consider *INVENTORY* as the treatment variable, while retaining all other variables, including *VARIETY*, as control variables. Likewise, in our second causal forest, we consider *VARIETY* as the treatment variable, with all other variables serving as control variables.[10]

$$PBS_n = f(ln(INVENTORY_n + 1), X_n^1) + \eta_n \tag{3}$$

$$PBS_n = f(ln(VARIETY_n + 1), X_n^2) + \zeta_n \tag{4}$$

where X_n^1 and X_n^2 include all fixed effects and variables in Equation (1) (excluding copula terms). The difference between X_n^1 and X_n^2 is that X_n^1 also controls for *VARIETY* but X_n^2 has *INVENTORY* instead. For expositional ease, we use the subscript n to denote each distinct observation in our data. For each of the two causal forest models, we grow 2,000 trees. The resulting conditional ATE for *INVENTORY* is positive and significant ($\hat{\tau}$=0.0134, p<0.001), suggesting that more inventory leads to higher perceptions of brands. The conditional ATE of *VARIETY* is not significant ($\hat{\tau}$=-0.0032, p>0.10).

An important advantage of the causal forest approach is that it provides individual treatment effect estimates, allowing for explanation of treatment effects using other variables. This flexibility makes it a valuable tool for studying heterogeneous treatment effects. Therefore, we separately regress the estimated treatment effects for *INVENTORY* and *VARIETY* on *INCOME* and *LUXURY*:

$$\tau_n^{INV} = \gamma_0 + \gamma_1 * INCOME_n + \gamma_2 * LUXURY_n + u_n \tag{5}$$

[9] It is important to note that the effectiveness of the causal forest approach hinges on the comprehensiveness of control variables and fixed effects in the model and thus, the presence of unobservable confounders may still introduce bias into the results.

[10] For a similar approach to analyzing effects of continuous variables using multiple causal forests, see Zhang and Luo (2023).

$$\tau_n^{VAR} = \lambda_0 + \lambda_1 * INCOME_n + \lambda_2 * LUXURY_n + v_n \quad (6)$$

Both *INCOME* (γ_1=-0.0066, p<0.001) and *LUXURY* (γ_2=-0.0228, p<0.001) negatively moderate the impact of *INVENTORY* on *PBS*, indicating that higher income levels and car luxury status reduce *INVENTORY*'s effectiveness. Conversely, *INCOME* (λ_1=0.1233, p<0.001) and *LUXURY* (λ_2=0.1735, p<0.001) positively influence *VARIETY*'s effect on *PBS*, showing that these factors enhance *VARIETY*'s impact.[11] Overall, the findings from the causal forest analysis are qualitatively similar to our main findings.

5 Robustness Checks and Additional Analyses

Selection of Survey Responses. Each YouGov respondent evaluates nearly 20 brands in a survey submission. It is unlikely that an in-market respondent has accurate knowledge about *INVENTORY* and *VARIETY* of all those brands, as potential buyers focus on a subset of car brands. For example, a luxury buyer might physically/virtually visit dealerships of BMW, Audi, and Mercedes but most likely not Kia and Mitsubishi. Without the opportunity to make more precise observations by visiting dealerships, consumers rely on less precise sources of information regarding the inventory and variety of brands. This includes advertisements, word of mouth, and observations of new cars on the streets, among other sources.

YouGov's survey also asks a question in which each respondent has to specify whether they will consider a particular brand for their next purchase. On average, an in-market respondent indicated that they consider 2.5 brands for their purchase, and the consideration set varies greatly across survey respondents. In this analysis, we rerun our base model but only for the particular brands in the consideration set of each survey respondent.[12] Results are reported in Table EC.3. Despite the considerable drop in sample size (n=31,310) and thus the statistical power, we still find support for our findings.

Moreover, in our main analyses we specifically focused on *in-market* consumers, who are more inclined to visit dealerships. To ensure this, we selectively retained YouGov observations from respondents "likely" or "very likely" to purchase a car in the near future. In an additional analysis, we narrow down our sample to include only those respondents who chose "very likely." Results replicate our main findings (see EC.4).

Subsets Most Impacted by Supply Chain Disruptions. A notable aspect of our empirical setting is that the supply-side semiconductor chip shortage—caused by worldwide factory lock-downs and several waves of COVID-19, as well as water shortage, factory explosions, and geopolitical tensions in Taiwan (Fushion Worldwide 2021)—played a major role in determining brands' inventory and variety levels. This factor helps lessen concerns about the endogeneity of inventory and variety since their variations were strongly

[11] We conducted further heterogeneity analyses by including all covariates (rather than only *INCOME* and *LUXURY*) in the regression of the conditional ATEs. The findings regarding the moderating effects of *INCOME* and *LUXURY* remained robust.

[12] For instance, consumer *a* has chosen BMW and Mercedes Benz as their consideration brands, while consumer *b* has opted for Ford and GMC. In this analysis, we maintain only the *PBS* responses from consumer *a* with respect to BMW and Mercedes Benz, and from consumer *b* regarding Ford and GMC.

driven by supply-side issues. However, some brands were less affected by the chip shortage (Blanco 2021), and they likely had the flexibility to strategically adjust their inventory and variety. Conversely, brands more severely affected by the shortage had limited control over their inventory and variety, making these variables more exogenously influenced by supply-side constraints. As a robustness check, we focus only on brands that were more affected by the chip shortage, as reported by *Car and Driver* (Blanco 2021). Despite the loss of more than 40% of our brands and data points, our main findings are replicated in Model 1, Table EC.5.

Furthermore, we specifically focused on the period after December 2020 in which the impact of the chip shortage was more acutely felt in the US economy. According to data from the *Bureau of Labor Statistics* (2023) and *Micro Macro* (2023) semiconductor lead times and prices began their run-up in December 2020, continuing through 2021, indicating that the chip production shortfalls grew in magnitude. As reported in Table EC.5, we replicated our analysis focusing only on this period, once using all brands (Model 2) and then using only the brands most impacted by chip shortage (Model 3).

Other Robustness Checks. We also conduct other robustness checks that we describe in detail in the E-Companion. These pertain to: *(a)* excluding large DMAs (EC.7.3), *(b)* excluding outliers (EC.7.4), and *(c)* sample representativeness (EC.7.5). The analyses largely confirm our results.

Synthesizing Findings from Different Analyses Across different sections, we present results from 29 model specifications, including 26 full models (i.e., with all focal variables and interactions). While applying econometric and machine-learning techniques to observational data is not a perfect substitute for randomization, obtaining similar results from models with different underlying assumptions increases confidence in the causal nature of the results. Here we synthesize the 26 sets of results. Table 6 shows how many times a focal effect was positive and significant, negative and significant, and non-significant (i.e., p>0.10).

Table 6 Synthesizing Findings Across Different Analyses

	Positive & Significant	Negative & Significant	Non-significant (p>0.10)
$INVENTORY$	24/26	0/26	2/26
$INVENTORY \times INCOME$	0/26	25/26	1/26
$INVENTORY \times LUXURY$	0/26	25/26	1/26
$VARIETY$	1/26	8/26	17/26
$VARIETY \times INCOME$	26/26	0/26	0/26
$VARIETY \times LUXURY$	25/26	1/26	1/26

Based on our synthesis of results, we contend that the following findings exhibit robustness and extend beyond mere correlations: a) product inventory positively influences brand perceptions, b) consumer income and luxury status of a product negatively moderate the impact of inventory on brand perceptions, c) product variety, on average, does not influence consumer perceptions of brands, and d) consumer income and product luxury status positively moderate the impact of variety on brand perceptions.

6 Discussion

Our research contributes to the literature on the impact of inventory levels and product variety on brands' performance. The literature concentrates on how inventory and variety affect a brand's marketplace performance (Cachon et al. 2019, Wang and Vakratsas 2021), with relatively little focus on how these factors impact consumers' perceptions of brands. Sales figures provide insights into a brand's immediate performance but may not fully represent the brand's long-term potential or overall health (Keller et al. 2011, Srinivasan et al. 2010). Our research adds to previous studies by highlighting how inventory and product variety affect consumer perceptions of brands. We find that, on average, inventory levels enhance consumers' perceptions of brands, whereas product variety does not significantly influence such perceptions.

Extant studies of inventory levels' and product variety' effects on brand performance tend to overlook whether these effects vary systematically based on brand and consumer characteristics. Understanding brand- and consumer-level sources of heterogeneity in the effectiveness of managerial levers like inventory and variety is advantageous for achieving various managerial objectives, such as effective assortment planning, targeting, etc. Our second contribution is to examine brand- and consumer-level moderators of the effects of inventory and variety. Specifically, drawing on Maslow's hierarchy of needs, we focus on moderating roles of consumer income and luxury status of brands. Overall, we find support for the notion that when status- and identity-signaling are more important—for high-income consumers and luxury buyers—product variety (inventory) becomes more (less) important as it offers more (less) exclusivity benefits.

6.1 Managerial Implications

Table 7 summarizes the managerial implications of our findings. We document a significant link between inventory policies, as operational levers, and consumer perception of brands, which could have long-lasting effects. This finding implies that when making inventory decisions, managers might consider the impact of inventory policies on consumer mindset and brand perceptions, not just financial performance metrics such as costs, profits, or sales. Our findings also emphasize a crucial distinction between inventory quantity and variety. Elevating the inventory level yields a positive impact on consumer perceptions across the board, whereas expanding the variety does not have the same effect. This finding underscores the importance of considering the positive influence of inventory levels on brand perception, and how this may impact subsequent assortment decisions. This suggests that while leaner inventory reduces operational costs, the potential detrimental effects on brand reputation should also be factored into decision-making.

The findings have significant relevance for navigating inventory shortages. In times of supply shortages, managers at automobile manufacturers and dealerships are compelled to make strategic choices regarding the types of vehicles they produce or stock. While conventionally, the focus has been on prioritizing high-margin products, as demonstrated during the pandemic (Wayland 2022), our results introduce an alternative

Table 7 Summary of Findings and Managerial Implications

Finding	Managerial Implications
Increased inventory improves brand perceptions	**M†:** Diversify suppliers and plan for backups to prevent shortages. **M, D:** Present more inventory cues in all advertising formats.
Inventory's effect weakens with increase in consumer income	**M:** Prioritize maintaining inventory in low-income area dealerships. **M, D:** Highlight inventory in targeted ads for low-income consumers.
Inventory's effect is weaker for luxury brands compared to non-luxury brands	**M:** Prioritize maintaining inventory of non-luxury brands over that of luxury brands. **M, D:** Place more emphasis on inventory in ads for non-luxury brands.
Variety's effect strengthens with increase in consumer income	**M:** Prioritize maintaining variety in dealerships in wealthier areas. **D:** Optimize dealership assortment organization for greater (smaller) perceived variety in high-income (low-income) regions. **D:** Present website assortment horizontally (vertically) for greater (smaller) perceived variety in high-income (low-income) regions. **M, D:** Highlight variety in targeted ads for high-income consumers.
Variety's effect is stronger for luxury brands compared to non-luxury brands	**M:** Luxury brands should offer a broader range of product options, and non-luxury brands should simplify product offerings. **D:** Optimize dealership assortment organization for greater (smaller) perceived variety for luxury (non-luxury) brands. **D:** Present website assortment horizontally (vertically) for greater (smaller) perceived variety for luxury (non-luxury) brands.

† M = Manufacturers; D = Dealerships

and complementary perspective: emphasizing products with the most favorable influence on consumer perceptions of the brand. These vehicles may not always have the highest of margins, but satisfying customer needs during times of scarcity can cultivate a positive long-lasting impact on the company and its brand.

Considering the moderating effect of luxury status, we suggest that managers tailor the variety of their brand's offerings based on its luxury status. Luxury brands could benefit from offering a broader range of options, whereas simplifying the product offerings can be more advantageous for non-luxury utilitarian brands. This recommendation is particularly relevant for manufacturers like Volkswagen, who produce both non-luxury and luxury brands, enabling them to allocate their resources accordingly. Further, considering the greater significance of inventory levels for non-luxury brands, it is crucial for manufacturers to allocate resources effectively during times of supply shortage. Ensuring that non-luxury brands maintain adequate inventory levels should be a priority in such circumstances.

Managers could also benefit from our findings on the moderating role of consumer income. One idea is to tailor product inventory and variety at dealerships based on income level of the county or zip code where the dealership is located. Dealerships in high-income areas are advised to prioritize product variety over inventory levels. However, achieving the optimal balance between inventory and variety can be difficult, especially during supply chain disruptions, when dealerships may have limited control over these elements.

Research in marketing shows that managers can influence product assortment perceptions by changing assortment structure (Kahn and Wansink 2004), which has been shown to influence consumers' perceptions. Kahn and Wansink (2004, pp. 520-521) note that "All things being equal, an increase in actual variety will increase perceived variety. For sets with a large number of options, however, a disorganized assortment can make it more difficult for consumers to recognize and appreciate the full extent of the variety. By contrast, for small sets, the organization of the assortment may make it relatively obvious that there are not many alternatives available, whereas disorganization can obscure this fact and increase the perception of variety. Thus, for small sets, disorganized assortments may appear to have more perceived variety, but the opposite might be true for assortments with a large mix of different options." Dealerships have the flexibility to modify the organization of available vehicles in their lots to either enhance or reduce perceptions of variety. By strategically arranging the vehicles dealerships can create an impression of greater or lesser variety based on brand luxury status or the average income in their geographical area. Managers can also explore the option of redesigning their websites to align with the desired perception of variety. This strategy involves optimizing the online browsing experience, especially in terms of how dealership inventory is presented to consumers based on factors such as car luxury status and average income in the area. For instance, Deng et al. (2016) demonstrate that a horizontal display of the assortment positively influences consumers' perceived assortment variety. By implementing these design considerations, managers can effectively shape consumers' perception of variety when interacting with the brand online.

Another implication of our findings is for targeted online advertising. Online ad platforms like Google and Facebook offer the ability to target ads based on demographic information, including income. We recommend that brands create distinct ads targeting low- and high-income consumers. When targeting low-income consumers, it is preferable to emphasize product inventory. Conversely, when targeting high-income consumers, the focus should be on showcasing product variety in the advertisements. Lastly, our findings have implications for the Just-In-Time (JIT) methodology. Given that maintaining an appropriate inventory level can enhance a brand's reputation, JIT systems should be optimized not only to reduce costs and waste but also to bolster brand strength by avoiding stockouts that could adversely affect consumer perceptions. This balance is particularly critical in competitive or luxury markets where brand image is paramount.

6.2 Limitations and Future Research

The context of our study (i.e., the automobile industry during the COVID-19 period) limits the generalizability of our findings. The automobile industry differs from most industries. On the one hand, since automobiles are high-involvement products, consumers are more likely to pay attention to the brand's activities making managerial actions more salient (Rajavi et al. 2019). On the other hand, compared to most product categories, inter-purchase frequency is lower in the automobile industry. This implies that at any time, a large group of consumers are not in the market and hence are less likely to pay attention to brand activities and characteristics. Future research should examine whether the effect of inventory on brand perception is weaker or stronger in other product categories (e.g., consumer packaged goods, electronics, hotels).

Focusing on the post-COVID-19 period, marked by supply-driven inventory shortages, allowed us to harness variations in inventory and product variety that were less susceptible to endogeneity concerns. Subsequent research should explore the influence of inventory and variety on brand perceptions during different timeframes. Hamilton and colleagues argue that "an important moderator of the effect of product scarcity on product evaluations is the inferences consumers make about *why* the product is scarce ... If a product is scarce due to excessive demand, consumers are likely to infer that product is more popular" (Hamilton et al. 2019, p. 537). Thus, we conjecture that the effect of inventory on brand perceptions is larger during normal times when consumers are more likely to infer that an inventory shortage is the result of product popularity, rather than supply shortages. Also, it could be argued that consumers are more likely to satisfy their basic needs and focus on higher-order needs during economic expansions (Kamakura and Du 2012). The exclusivity effect would thus be stronger in expansions, making variety more effective.

YouGov and many market research firms depend on self-reported survey data, a method known to be susceptible to bias (Podsakoff et al. 2003). Recently, some market research companies (e.g., Infegy Atlas, Brandwatch) began measuring consumer attitudes toward different brands by analyzing social media posts. We contend that utilizing brand-perception data derived from user-generated content could offer a more precise representation of consumer attitudes, making it a valuable resource for future studies. Also, our YouGov data were available only at the make level, necessitating aggregation of our inventory and variety measures at that level. We acknowledge that consumers with a particular interest in specific models may not consider the overall inventory and variety of all vehicles from a brand but instead focus on the inventory and variety of their desired model. In our empirical context, we implicitly assumed that the aggregated inventory and variety of a brand can serve as a reasonable proxy for the inventory and variety of its individual models and trims, a notion supported by the high correlations observed between the inventory and variety of various models and trims within a brand. However, more detailed data that specify the consumer's intended model or trim could provide valuable insights for future research.

Our study opens avenues for further exploration in multiple directions. While we concentrated on income as a moderating factor at the consumer level, delving into additional segmentation based on demographics, psychographics, or behavioral patterns may reveal nuanced perspectives on how various consumer groups respond to inventory levels and product variety. Moreover, our study focused on short-term effects. Longitudinal studies using longer time windows could help ascertain whether the identified effects persist, diminish, or evolve as market conditions change. Moreover, future research can delve into the underlying mechanisms that drive the observed effects. For example, our findings suggest that product variety does not affect brand perceptions. Future research can investigate whether this nonsignificant effect arises from counteracting mechanisms (such as *expertise* and *quality*, as discussed in Section 2.3) canceling out each other's effects, or whether no single mechanism significantly impacts brand perception.

Finally, it is worth reiterating the importance of randomization in establishing causal relationships. While employing various econometric and machine learning techniques helps address concerns related to causality, field experiments provide an opportunity to directly manipulate variables of interest and assess their causal impact. Thus, future research could examine our findings through field experiments and offer stronger evidence for causal conclusions made in our observational study.

References

Aaker, David A, Erich Joachimsthaler. 2012. *Brand leadership*. Simon and Schuster.

Abdulla, Huseyn, James D Abbey, Michael Ketzenberg. 2022. How consumers value retailer's return policy leniency levers: An empirical investigation. *Production and Operations Management*, 31 (4), 1719-1733.

Athey, Susan, Stefan Wager. 2021. Policy learning with observational data. *Econometrica*, 89 (1), 133-161.

Balachander, Subramanian, Yan Liu, Axel Stock. 2009. An empirical analysis of scarcity strategies in the automobile industry. *Management Science*, 55 (10), 1623-1637.

Bayus, Barry L, William P Putsis. 1999. Product proliferation: An empirical analysis of product line determinants and market outcomes. *Marketing Science*, 18 (2), 137-153.

Belyh, Anastasia. 2022. The ultimate list of inventory management statistics for 2022. *Founderjar*, URL `http://tinyurl.com/4m7h83pj`.

Benkard, C Lanier, Ali Yurukoglu, Anthony Lee Zhang. 2021. Concentration in product markets. Tech. rep., National Bureau of Economic Research.

Berger, Jonah, Michaela Draganska, Itamar Simonson. 2007. The influence of product variety on brand perception and choice. *Marketing Science*, 26 (4), 460-472.

Berger, Jonah, Chip Heath. 2007. Where consumers diverge from others: Identity signaling and product domains. *Journal of Consumer Research*, 34 (2), 121-134.

Bertrand, Marianne, Matilde Bombardini, Raymond Fisman, Francesco Trebbi. 2020. Tax-exempt lobbying: Corporate philanthropy as a tool for political influence. *American Economic Review*, 110 (7), 2065-2102.

Bijmolt, Tammo HA, Harald J Van Heerde, Rik GM Pieters. 2005. New empirical generalizations on the determinants of price elasticity. *Journal of Marketing Research*, 42 (2), 141-156.

Blanco, S. 2021. The models that are being affected by chip shortage, URL `http://tinyurl.com/sm4enssn`.

BLS. 2023. Import price index (naics): Semiconductor and other electronic component manufacturing, URL `http://tinyurl.com/2m9tup9m`.

Boulding, William, Amna Kirmani. 1993. A consumer-side experimental examination of signaling theory: Do consumers perceive warranties as signals of quality? *Journal of Consumer Research*, 20 (1), 111-123.

Bricker, Jesse, Jacob Krimmel, Rodney Ramcharan. 2021. Signaling status: The impact of relative income on household consumption and financial decisions. *Management Science*, 67 (4), 1993-2009.

Cachon, Gérard P, Santiago Gallino, Marcelo Olivares. 2019. Does adding inventory increase sales? evidence of a scarcity effect in US automobile dealerships. *Management Science*, 65 (4), 1469-1485.

Carlier, Mathilde. 2022. Automotive industry in the United States. URL `http://tinyurl.com/bdejfvfr`.

Chan, Cindy, Jonah Berger, Leaf Van Boven. 2012. Identifiable but not identical: Combining social identity and uniqueness motives in choice. *Journal of Consumer Research*, 39 (3), 561-573.

Chernev, Alexander. 2003. When more is less and less is more: The role of ideal point availability and assortment in consumer choice. *Journal of Consumer Research*, 30 (2), 170-183.

Chernev, Alexander, Ulf Böckenholt, Joseph Goodman. 2015. Choice overload: A conceptual review and meta-analysis. *Journal of Consumer Psychology*, 25 (2), 333-358.

Colicev, A, A Malshe, K Pauwels, P O'Connor. 2018. Improving consumer mindset metrics and shareholder value through social media: The different roles of owned and earned media. *Journal of Marketing*, 82 (1), 37-56.

Cui, Ruomeng, Dennis J Zhang, Achal Bassamboo. 2019. Learning from inventory availability information: Evidence from field experiments on Amazon. *Management Science*, 65 (3), 1216-1235.

Datta, Hannes, Kusum L Ailawadi, Harald J Van Heerde. 2017. How well does consumer-based brand equity align with sales-based brand equity and marketing-mix response? *Journal of Marketing*, 81 (3), 1-20.

Deng, X, B E Kahn, H R Unnava, H Lee. 2016. A "wide" variety: Effects of horizontal versus vertical display on assortment processing, perceived variety, and choice. *Journal of Marketing Research*, 53 (5), 682-698.

Deshpande, Vinayak, Pradeep K Pendem. 2023. Logistics performance, ratings, and its impact on customer purchasing behavior and sales in e-commerce platforms. *Manufacturing & Service Operations Management*, 25 (3), 827-845.

Dong, Yan, Venkatesh Shankar, Martin Dresner. 2007. Efficient replenishment in the distribution channel. *Journal of Retailing*, 83 (3), 253-278.

Draganska, Michaela, Dipak C Jain. 2005. Product-line length as a competitive tool. *Journal of Economics & Management Strategy*, 14 (1), 1-28.

Du, Rex Y, Mingyu Joo, Kenneth C Wilbur. 2019. Advertising and brand attitudes: Evidence from 575 brands over five years. *Quantitative Marketing and Economics*, 17 (3), 257-323.

Du, Rex Y, Wagner A Kamakura. 2008. Where did all that money go? understanding how consumers allocate their consumption budget. *Journal of Marketing*, 72 (6), 109-131.

Dubé, Jean-Pierre, Günter J Hitsch, Peter E Rossi. 2018. Income and wealth effects on private-label demand: Evidence from the great recession. *Marketing Science*, 37 (1), 22-53.

Ghose, Anindya, Panagiotis G Ipeirotis, Beibei Li. 2012. Designing ranking systems for hotels on travel search engines by mining user-generated and crowdsourced content. *Marketing Science*, 31 (3), 493-520.

Good Car Bad Car. 2023. Luxury car sales, URL `https://tinyurl.com/yehpkcrr`.

Goodman, P S, N Chokshi. 2021. How the world ran out of everything. *New York Times*, URL `http://tinyurl.com/y93p55hs`.

Hamilton, Rebecca, Debora Thompson, Sterling Bone, Lan Nguyen Chaplin, Vladas Griskevicius, Kelly Goldsmith, Ronald Hill, Deborah Roedder John, Chiraag Mittal, Thomas O'Guinn, et al. 2019. The effects of scarcity on consumer decision journeys. *Journal of the Academy of Marketing Science*, 47 532-550.

Hausman, Jerry A. 1996. Valuation of new goods under perfect and imperfect competition. *The economics of new goods*. University of Chicago Press, 207-248.

Hong, Yili, Benjamin BM Shao. 2021. On factors that moderate the effect of buyer-supplier experience on e-procurement platforms. *Production and Operations Management*, 30 (4), 1034-1051.

Iyengar, Sheena S, Mark R Lepper. 2000. When choice is demotivating: Can one desire too much of a good thing? *Journal of Personality and Social Psychology*, 79 (6), 995.

Kahn, Barbara E, Brian Wansink. 2004. The influence of assortment structure on perceived variety and consumption quantities. *Journal of Consumer Research*, 30 (4), 519-533.

Kamakura, Wagner A, Rex Y Du. 2012. How economic contractions and expansions affect expenditure patterns. *Journal of Consumer Research*, 39 (2), 229-247.

Keller, Kevin Lane. 1993. Conceptualizing, measuring, and managing customer-based brand equity. *Journal of Marketing*, 57 (1), 1-22.

Keller, Kevin Lane, Donald R Lehmann. 2006. Brands and branding: Research findings and future priorities. *Marketing Science*, 25 (6), 740-759.

Keller, Kevin Lane, MG Parameswaran, Isaac Jacob. 2011. *Strategic brand management: Building, measuring, and managing brand equity*. Pearson Education India.

Kim, Hag-Soo. 2008. Research note—revisiting "retailer-vs. vendor-managed inventory and brand competition". *Management Science*, 54 (3), 623-626.

Kirmani, Amna, Peter Wright. 1989. Money talks: Perceived advertising expense and expected product quality. *Journal of Consumer Research*, 16 (3), 344-353.

Luo, Xueming, Chitra Bhanu Bhattacharya. 2006. Corporate social responsibility, customer satisfaction, and market value. *Journal of Marketing*, 70 (4), 1-18.

Luo, Xueming, Sascha Raithel, Michael A Wiles. 2013. The impact of brand rating dispersion on firm value. *Journal of Marketing Research*, 50 (3), 399-415.

Maslow, Abraham H. 1943. A theory of human motivation. *Psychological Review*, 50 (4), 370-396.

Miao, Wei, Yiting Deng, Wei Wang, Yongdong Liu, Christopher S Tang. 2023. The effects of surge pricing on driver behavior in the ride-sharing market: Evidence from a quasi-experiment. *Journal of Operations Management*, 69 (5), 794-822.

MicroMacro. 2023. Global lead times for semiconductor deliveries, URL `http://tinyurl.com/2p9ztrhb`.

Mintz, Ofer, Timothy J Gilbride, Peter Lenk, Imran S Currim. 2021. The right metrics for marketing-mix decisions. *International Journal of Research in Marketing*, 38 (1), 32-49.

Mishra, Birendra K, Srinivasan Raghunathan. 2004. Retailer-vs. vendor-managed inventory and brand competition. *Management Science*, 50 (4), 445-457.

Nelson, Phillip. 1974. Advertising as information. *Journal of Political Economy*, 82 (4), 729-754.

Nevo, Aviv. 2001. Measuring market power in the ready-to-eat cereal industry. *Econometrica*, 69 (2), 307-342.

Pan, Xiaodan, Martin Dresner, Benny Mantin, Jun A Zhang. 2020. Pre-hurricane consumer stockpiling and post-hurricane product availability: Empirical evidence from natural experiments. *Production and Operations Management*, 29 (10), 2350-2380.

Pan, Yuchen, Desheng Wu. 2020. A novel recommendation model for online-to-offline service based on the customer network and service location. *Journal of Management Information Systems*, 37 (2), 563-593.

Park, Sungho, Sachin Gupta. 2012. Handling endogenous regressors by joint estimation using copulas. *Marketing Science*, 31 (4), 567-586.

Park, Sungho, Elliot Rabinovich, Christopher S Tang, Rui Yin. 2020. The impact of disclosing inventory-scarcity messages on sales in online retailing. *Journal of Operations Management*, 66 (5), 534-552.

Podsakoff, Philip M, Scott B MacKenzie, Jeong-Yeon Lee, Nathan P Podsakoff. 2003. Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of applied psychology*, 88 (5), 879.

Pozharliev, Rumen, Willem JMI Verbeke, Jan W Van Strien, Richard P Bagozzi. 2015. Merely being with you increases my attention to luxury products: Using EEG to understand consumers' emotional experience with luxury branded products. *Journal of Marketing Research*, 52 (4), 546-558.

Rajavi, Koushyar, Tarun Kushwaha, Jan-Benedict EM Steenkamp. 2019. In brands we trust? a multicategory, multi-country investigation of sensitivity of consumers' trust in brands to marketing-mix activities. *Journal of Con-*

sumer Research, 46 (4), 651-670.

Reyes-Menendez, Ana, Pedro Palos-Sanchez, Jose Saura, Carmen Santos. 2022. Revisiting the impact of perceived social value on consumer behavior toward luxury brands. *European Management Journal*, 40 (2), 224-233.

Shankar, Venkatesh. 2006. Proactive and reactive product line strategies: asymmetries between market leaders and followers. *Management Science*, 52 (2), 276-292.

Song, Camilla Eunyoung, Aner Sela. 2023. Phone and self: how smartphone use increases preference for uniqueness. *Journal of Marketing Research*, 60 (3), 473-488.

Spence, Michael. 1973. Job market signaling. *The Quarterly Journal of Economics*, 87 (3), 355-374.

Srinivasan, Shuba, Marc Vanhuele, Koen Pauwels. 2010. Mind-set metrics in market response models: An integrative approach. *Journal of Marketing Research*, 47 (4), 672-684.

Stäbler, Samuel, Marc Fischer. 2020. When does corporate social irresponsibility become news? Evidence from more than 1,000 brand transgressions across five countries. *Journal of Marketing*, 84 (3), 46-67.

Stigler, George J, Gary S Becker. 1977. De gustibus non est disputandum. *The American Economic Review*, 67 (2), 76-90.

Stock, Axel, Subramanian Balachander. 2005. The making of a "hot product": A signaling explanation of marketers' scarcity strategy. *Management Science*, 51 (8), 1181-1192.

Tereyağoğlu, Necati, Senthil Veeraraghavan. 2012. Selling to conspicuous consumers: Pricing, production, and sourcing decisions. *Management Science*, 58 (12), 2168-2189.

Ton, Zeynep, Ananth Raman. 2010. The effect of product variety and inventory levels on retail store sales: A longitudinal study. *Production and Operations Management*, 19 (5), 546-560.

Unal, Murat, Young-Hoon Park. 2023. Fewer clicks, more purchases. *Management Science*, 69 (12), 7317-7334.

Van Ewijk, Bernadette J, Els Gijsbrechts, Jan-Benedict EM Steenkamp. 2022. The dark side of innovation: How new skus affect brand choice in the presence of consumer uncertainty and learning. *International Journal of Research in Marketing*, 39 (4), 967-987.

Villanova, Daniel, Anand V Bodapati, Nancy M Puccinelli, Michael Tsiros, Ronald C Goodstein, Tarun Kushwaha, Rajneesh Suri, Henry Ho, Renee Brandon, Cheryl Hatfield. 2021. Retailer marketing communications in the digital age: getting the right message to the right shopper at the right time. *Journal of Retailing*, 97 (1), 116-132.

Wager, Stefan, Susan Athey. 2018. Estimation and inference of heterogeneous treatment effects using random forests. *Journal of the American Statistical Association*, 113 (523), 1228-1242.

Wang, Wei-Lin, Demetrios Vakratsas. 2021. The dual impact of product line length on consumer choice. *Production and Operations Management*, 30 (9), 3054-3072.

Wayland, Michael. 2022. Chip shortage has detroit automakers struggling to maintain truck production and meet orders. *CNBC*, URL `https://tinyurl.com/yn8nrmd9`.

Wilcox, Keith, Hyeong Min Kim, Sankar Sen. 2009. Why do consumers buy counterfeit luxury brands? *Journal of Marketing Research*, 46 (2), 247-259.

Wooldridge, J. M. 2009. *Introductory econometrics: a modern approach, 4th edition*. CENGAGE Learning, Canada.

Yang, Jie, Hongming Xie, Guangsheng Yu, Mingyu Liu. 2021. Antecedents and consequences of supply chain risk management capabilities: An investigation in the post-coronavirus crisis. *International Journal of Production Research*, 59 (5), 1573-1585.

Yoon, Sunyee, Hyeongmin Christian Kim. 2018. Feeling economically stuck: The effect of perceived economic mobility and socioeconomic status on variety seeking. *Journal of Consumer Research*, 44 (5), 1141-1156.

Zhang, Mengxia, Lan Luo. 2023. Can consumer-posted photos serve as a leading indicator of restaurant survival? Evidence from Yelp. *Management Science*, 69 (1), 25-50.

Electronic Companion to "Impact of Inventory Levels and Product Variety on Consumers' Perceptions of Brands"

EC.1 YouGov Items Used for *PBS*

In constructing our measure for *PBS* we use the following six YouGov items:

Impression: Overall, of which of the following car makers do you have a POSITIVE impression? Now which of the following car makers do you have an overall NEGATIVE impression?

Recommend: Which of the following car makers would you RECOMMEND to a friend or colleague? And, which of the following car makers would you tell a friend or colleague to AVOID?

Quality: Which of the following car makers do you think represents GOOD QUALITY? Now which of the following car makers represents POOR QUALITY?

Value: Which of the following car makers do you think represents GOOD VALUE FOR MONEY? By that we don't mean "cheap", but that the brands offer a customer a lot in return for the price paid. Now which of the following car makers do you think represents POOR VALUE FOR MONEY? By that, we don't mean "expensive", but that the brands do not offer a customer much in return for the price paid.

Reputation: Imagine that you were looking for a job (or advising a friend looking for a job). Which of the following companies would you be PROUD TO WORK FOR? Imagine you (or your friend) were applying for the same sort of role at the following companies that you currently have or would apply for. Now which of the following companies would you be EMBARRASSED TO WORK FOR?

Satisfaction: Of which of the following car makers would you say that you are a "SATISFIED CUSTOMER"? Of which of the following car makers would you say that you are a "DISSATISFIED CUSTOMER"?

EC.2 Computation of Independent Variables

EC.2.1 Inventory Measure

As discussed in the subsection 3.4, our measure of daily inventory tracks the number of automobiles available for sale at any given time. We first count the number of cars each dealer carries in inventory in each day, $INVENTORY^{D}_{dbt}$, where, d is the dealer index, b is the brand index, and t is the day index. The YouGov data that we use to measure perceived brand strength has information on DMA of the respondents. Thus, we aggregate our independent variables to the DMA-level and construct $INVENTORY^{D}_{kbt}$, where k is the DMA index. Finally, we compute the moving average of $INVENTORY^{D}$ over the last 30 days, as indicated in formula EC.2-1 below.

$$INVENTORY_{kb\tau} = -\sum_{t=\tau-29}^{\tau} INVENTORY^{D}_{kbt}/30 \tag{EC.2-1}$$

where, τ is index of the day for which the 30-day moving average is computed. When computing the aforementioned value, if there are fewer than 30 days of observed data (e.g., during the initial month of data collection or in case of missing values), we utilize the maximum number of available days instead of the standard 30-day period.

EC.2.2 Variety Measure

Our measure of variety is the opposite of the Herfindahl–Hirschman index of the items carried in dealer inventories. For each dealer-brand-day combination, we first compute the variety in each dealer's daily inventory as indicated in formula EC.2-2 below.

$$VARIETY^{D}_{dbt} = -\sum_{j} s^{2}_{jdbt} \tag{EC.2-2}$$

where, d is the dealer index, j is the inventory item index corresponding to each make-model-trim-year combination, b is the brand index, t is the day index, and s_j is the share of that item in the dealer's inventory based on its frequency.

Similar to the inventory measure, we aggregate our variety measure to the DMA level and obtain $VARIETY^{D}_{kbt}$. Finally, we compute the moving average of $VARIETY^{D}$ over the last 30 days, as indicated in formula EC.2-3 below.

$$VARIETY_{kb\tau} = -\sum_{t=\tau-29}^{\tau} VARIETY^{D}_{kbt}/(30) \tag{EC.2-3}$$

Similarly, whenever there are less than 30 days of data observed, we use the maximum number of available days.

EC.3 Brand List

Table EC.1, below, provides the list of brands that are covered in our sample. To classify cars, we used a series of reports on luxury cars by the automotive market research firm *Good Car Bad Car* (2023).

Table EC.1 Brand List

	Frequency	Percent
Luxury		
Brand		
Acura	6,765	2.48%
Alfa Romeo	4,685	1.71%
Audi	7,839	2.87%
BMW	8,110	2.97%
Cadillac	9,395	3.44%
Genesis	2,764	1.01%
Infiniti	6,456	2.36%
Jaguar	6,784	2.48%
Lexus	7,514	2.75%
Lincoln	8,918	3.26%
Mercedes	8,073	2.95%
Porsche	6,948	2.54%
Tesla	682	0.25%
Volvo	7,666	2.80%
Non-Luxury		
Brand		
Buick	10,012	3.66%
Chevrolet	10,279	3.76%
Chrysler	10,054	3.68%
Dodge	10,194	3.73%
Fiat	7,535	2.76%
Ford	10,174	3.72%
GMC	9,859	3.61%
Honda	9,599	3.51%
Hyundai	9,318	3.41%
Jeep	10,285	3.76%
Kia	9,361	3.43%
Land Rover	6,849	2.51%
Mazda	8,691	3.18%
Mini	4,029	1.47%
Mitsubishi	8,393	3.07%
Nissan	9,396	3.44%
Ram	8,764	3.21%
Subaru	8,791	3.22%
Toyota	9,894	3.62%
Volkswagen	9,233	3.38%

EC.4 Correlation Matrix

Table EC.2 Correlation Matrix and Descriptives

	1	2	3	4	5	6	7	8	9	10	11	Mean	Median	S.D.
PBS	1.00											0.14	0.00	0.39
INVENTORY	0.05	1.00										136.96	89.97	130.96
VARIETY	-0.04	-0.33	1.00									0.32	0.28	0.18
LUXURY	0.02	-0.18	0.04	1.00								0.41	0.00	0.49
DEALERS	-0.02	0.37	-0.18	-0.19	1.00							3.26	2.00	4.65
PRICE	0.01	-0.10	-0.24	0.52	0.08	1.00						40.48	36.41	19.24
ADAWARE	0.19	0.09	-0.05	-0.10	0.01	-0.05	1.00					-0.75	-1.00	0.66
GTRENDS	0.01	0.16	-0.23	-0.13	0.37	0.24	0.03	1.00				41.50	53.00	33.49
INCOME	-0.03	0.03	0.00	0.03	0.03	0.02	-0.01	-0.00	1.00			73.15	55.00	76.51
EDUCATION	-0.04	0.03	-0.01	0.03	0.03	0.02	-0.02	0.01	0.30	1.00		3.91	4.00	1.42
GENDER	0.03	-0.00	-0.00	-0.01	-0.00	-0.01	-0.09	-0.00	-0.13	-0.19	1.00	1.55	2.00	0.50
AGE	0.02	-0.02	0.01	-0.00	-0.02	-0.02	0.07	-0.01	-0.00	-0.07	-0.09	2.57	3.00	0.71

EC.5 Skewness in the Explanatory Variables

Figure EC.1 illustrates the histograms of *INVENTORY* and *VARIETY*. As shown, there is considerable skewness in both variables.

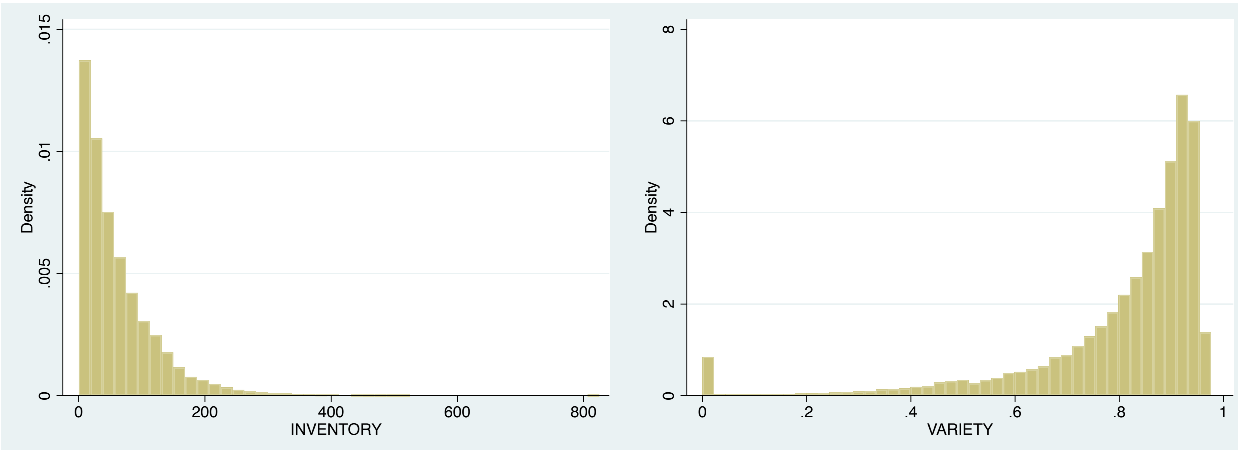

Figure EC.1 Histograms of *INVENTORY* and *VARIETY*

EC.6 Predictive Margins

Figure EC.2 illustrates the marginal effects of $ln(INVENTORY)$ and $ln(VARIETY)$ for luxury and non-luxury cars. Figure EC.3 illustrates the marginal effects of $ln(INVENTORY)$ and $ln(VARIETY)$ at low and high levels of *INCOME*.

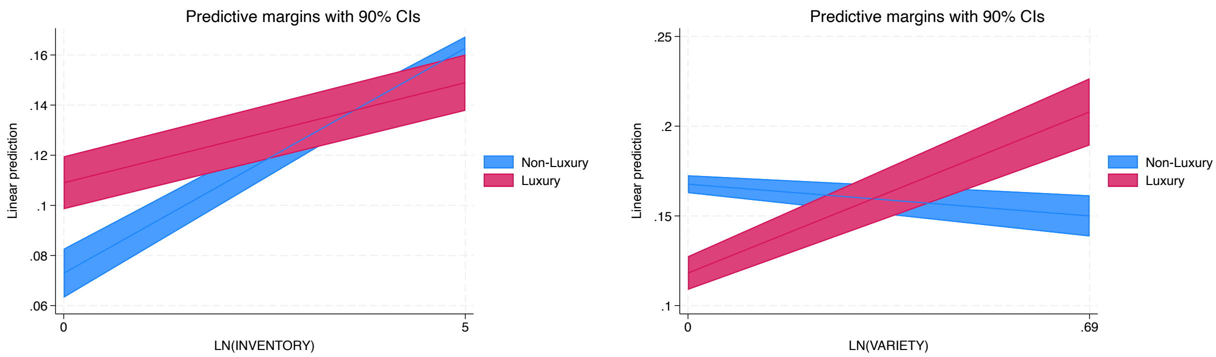

Figure EC.2 The marginal effects of log of inventory and variety for luxury and non-luxury cars.

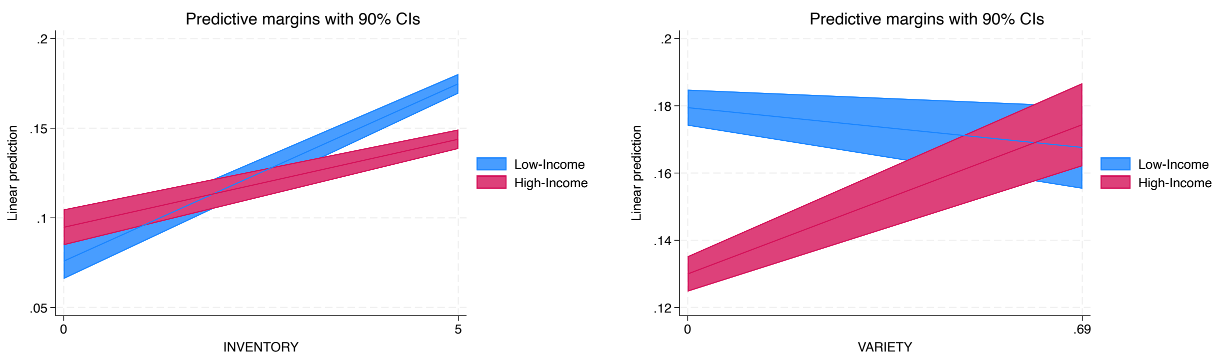

Figure EC.3 The marginal effects of log of inventory and variety at low and high levels of *INCOME*.

EC.7 Results from Different Robustness Checks

EC.7.1 Selection of Survey Responses

Table EC.3 Customers with Immediate Purchase Intention

	PBS
INVENTORY	0.012***
	(0.007)
INVENTORY × *INCOME*	-0.008*
	(0.082)
INVENTORY × *LUXURY*	-0.023***
	(0.005)
VARIETY	-0.299***
	(0.002)
VARIETY × *INCOME*	0.104***
	(0.002)
VARIETY × *LUXURY*	0.162**
	(0.021)
Control Variables	YES
Brand, Month & DMA FEs	YES
Copulas	YES
LL	-8,178
Observations	31,310

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table EC.4 Customers Very Likely to Buy a Car

	PBS
INVENTORY	0.012**
	(0.014)
INVENTORY × *INCOME*	-0.007***
	(0.002)
INVENTORY × *LUXURY*	-0.010**
	(0.044)
VARIETY	-0.071*
	(0.060)
VARIETY × *INCOME*	0.054**
	(0.036)
VARIETY × *LUXURY*	0.168***
	(<0.001)
Control Variables	YES
Brand, Month & DMA FEs	YES
Copulas	YES
LL	-83,036
Observations	273,991

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

EC.7.2 Subsets Most Impacted by Supply Chain Disruptions

Table EC.5 Segments Most Impacted by the Chip Shortage

	(1) Most Impacted Brands	(2) Most Impacted Periods	(3) Most Impacted Brands & Periods
INVENTORY	0.011**	0.013**	0.010*
	(0.023)	(0.041)	(0.077)
INVENTORY × *INCOME*	-0.008***	-0.005**	-0.007**
	(0.003)	(0.033)	(0.034)
INVENTORY × *LUXURY*	-0.009**	-0.010**	-0.007
	(0.037)	(0.047)	(0.119)
VARIETY	-0.075**	-0.067**	-0.102**
	(0.046)	(0.016)	(0.019)
VARIETY × *INCOME*	0.062**	0.075*	0.087**
	(0.022)	(0.076)	(0.040)
VARIETY × *LUXURY*	0.191***	0.161**	0.196**
	(<0.001)	(0.025)	(0.030)
Control Variables	YES	YES	YES
Brand, Month & DMA FEs	YES	YES	YES
Copulas	YES	YES	YES
LL	-80,787	-70,823	-43,860
Observations	162,867	148,447	88,358

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

EC.7.3 Excluding Large DMAs

DMAs vary with respect to geographical area they cover. The smallest DMAs are approximately 1,000 square miles (Victoria and Zanesville DMAs) and the largest ones are about 100,000 square miles (Denver and Albuquerque-Santa Fe DMAs). In larger DMAs, it is unlikely that respondents check the inventory of all dealerships in their DMA. For example, driving from Denver (which is roughly at the center of the Denver DMA) to the edges of this DMA takes four to six hours. It is unlikely that respondents, even virtually, check the websites of dealerships more than a few hours away from them. To ensure that our findings have not been driven by averaging *INVENTORY* and *VARIETY* at the DMA level (i.e., aggregation bias), we exclude the largest DMAs from our analysis. Table EC.6 reports our findings after excluding the DMAs that are among the top 1%, 5%, 10%, and 25% in terms of covered area. All our results are replicated.

Table EC.6 Dropping Top DMAs Percentiles By Size

	(1) C99	(2) C95	(3) C90	(4) C75
INVENTORY	0.014***	0.015***	0.015***	0.016***
	(0.005)	(0.005)	(0.003)	(0.005)
INVENTORY × *INCOME*	-0.007***	-0.007***	-0.007***	-0.007***
	(0.002)	(0.003)	(0.002)	(0.002)
INVENTORY × *LUXURY*	-0.011***	-0.011***	-0.012***	-0.013***
	(0.009)	(0.008)	(0.004)	(0.005)
VARIETY	-0.047	-0.049*	-0.046	-0.053
	(0.104)	(0.099)	(0.117)	(0.104)
VARIETY × *INCOME*	0.052**	0.054**	0.047*	0.043*
	(0.036)	(0.031)	(0.062)	(0.074)
VARIETY × *LUXURY*	0.161***	0.156***	0.147***	0.144***
	(<0.001)	(<0.001)	(0.001)	(0.002)
Control Variables	YES	YES	YES	YES
Brand, Month & DMA FEs	YES	YES	YES	YES
Copulas	YES	YES	YES	YES
LL	-127,875	-122,897	-116,621	-96,458
Observations	268,599	257,986	245,047	205,600

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

EC.7.4 Excluding Outliers in Focal Variables

To ensure that our results are not driven by outliers, we removed outliers in *INVENTORY*, *VARIETY*, *INCOME* (top and bottom 1%). As reported in Table EC.7, the results remained consistent.

Table EC.7 HDFE Regressions with Outlier Removal

	INVENTORY	*VARIETY*	*INCOME*
	(1)	(2)	(3)
INVENTORY	0.014***	0.012**	0.014***
	(0.005)	(0.013)	(0.005)
INVENTORY $\times$ *INCOME*	-0.006***	-0.007***	-0.006*
	(0.004)	(0.003)	(0.093)
INVENTORY $\times$ *LUXURY*	-0.010**	-0.009**	-0.011**
	(0.011)	(0.022)	(0.012)
VARIETY	-0.051*	-0.009	-0.045
	(0.069)	(0.755)	(0.131)
VARIETY $\times$ *INCOME*	0.053**	0.055**	0.061*
	(0.028)	(0.032)	(0.073)
VARIETY $\times$ *LUXURY*	0.167***	0.146***	0.164***
	(<0.001)	(<0.001)	(<0.001)
Control Variables	YES	YES	YES
Brand, Month & DMA FEs	YES	YES	YES
Copulas	YES	YES	YES
LL	-128,865	-127,458	-129,767
Observations	270,648	264,650	271,469

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

EC.7.5 Sample Representativeness

In our dataset, the average number of observations per DMA-month is 186. However, the number of observations differs among DMA-month pairings, with some DMA-months having less than 50 observations due to a limited number of respondents surveyed by YouGov in those areas. These smaller sample sizes raise concerns about the representativeness of the data and whether our findings can be generalized to the overall population. To alleviate such concerns, we re-ran our primary analysis, specifically retaining observations belonging to DMA-months with more than 50 observations (N=261,917), more than 100 observations (N=246,416), more than 250 observations (N=200,819), and more than 500 observations (N=144,008). In all four analyses, we successfully replicated our main findings, as the results in Table EC.8 demonstrate. Notably, we did not identify any discernible patterns after applying these data filters, as the coefficient estimates remained consistent. This suggests that our results are not dependent on representation of DMAs within the YouGov data and are robust to variations in the number of observations, thereby alleviating representativeness concerns.

Table EC.8 Dropping DMA-Months with Small Number of Observations

	(1) C50	(2) C100	(3) C250	(4) C500
INVENTORY	0.014^{***}	0.013^{**}	0.013^{**}	0.015^{*}
	(0.008)	(0.011)	(0.029)	(0.053)
INVENTORY $\times$ *INCOME*	-0.006^{***}	-0.007^{***}	-0.007^{***}	-0.007^{***}
	(0.005)	(0.004)	(0.002)	(0.004)
INVENTORY $\times$ *LUXURY*	-0.010^{***}	-0.011^{***}	-0.013^{**}	-0.016^{**}
	(0.010)	(0.006)	(0.019)	(0.048)
VARIETY	-0.043	-0.040	-0.011	0.030
	(0.160)	(0.184)	(0.767)	(0.591)
VARIETY $\times$ *INCOME*	0.057^{**}	0.059^{**}	0.062^{***}	0.080^{**}
	(0.022)	(0.013)	(0.008)	(0.020)
VARIETY $\times$ *LUXURY*	0.149^{***}	0.146^{***}	0.146^{***}	0.120^{**}
	(<0.001)	(0.001)	(0.004)	(0.013)
Control Variables	YES	YES	YES	YES
Brand, Month & DMA FEs	YES	YES	YES	YES
Copulas	YES	YES	YES	YES
LL	-123,778	-116,360	-93,825	-65,533
Observations	261,917	246,416	200,819	144,008

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$