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To Differentiate Or Not To Differentiate? The Role of Product Characteristics in the Sharing Economy

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TO DIFFERENTIATE OR NOT TO DIFFERENTIATE? THE ROLE OF PRODUCT CHARACTERISTICS IN THE SHARING ECONOMY

Research Paper

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Abstract

An important ambiguity in the sharing economy literature concerns the role of product variety. Do physical product characteristics provide scope for differentiation in a sharing economy context, and if so, under which circumstances? Resolving this ambiguity is important as it can have large operational and strategic implications for sharing economy businesses. We use discrete choice modeling on a unique carsharing dataset and behavioral online experiments to study how users select between product options of varying quality and brand in a shared consumption context. We find that, in general, there is a trend towards utilitarian access-based consumption in which product characteristics and product brand matter less. However, we observe that hedonistic use cases tend to shift preferences significantly toward more premium products. Our results highlight the need for a more nuanced consideration of product differentiation in sharing economy research.

Keywords: mobility-as-a-service, service systems, sharing economy, product differentiation

1 Introduction

In a recent interview with The Economist[1], Herbert Diess, CEO of Volkswagen (VW), was asked about the role of his company in a future where vehicles are increasingly shared and mobility is consumed as a service. The interviewer's hypothesis was that users would increasingly become indifferent to the quality and type of vehicle that provided the transportation service, leaving little room for product brands such as VW to differentiate against competitors. In contrast, Diess argued that users would pay in order not to be moved around in what he referred to as ”grey boxes”, i.e., undifferentiated and “boring” vehicles. While the CEO of a leading automotive manufacturer would be expected to hold that view, the conflicting viewpoints from this interview point to a wider tension pertaining to the role of physical products and their brands as a source of differentiation in the sharing economy, where these assets are temporarily accessed and shared among customers. This question yet remains unresolved in the current literature.

On the one hand, a substantial body of extant work postulates that in purely experiential and access-based consumption scenarios, product attributes become less relevant (Bardhi and Eckhardt, 2012, 2017;

[1] https://www.economist.com/podcasts/2021/02/18/when-will-the-electric-car-rule-the-road

Sundararajan, 2016). For instance, Bardhi and Eckhardt (2012), in their study of Zipcar, find that platform-mediated access-based consumption "is primarily guided by self-serving and utilitarian motivation" and functions "similar to commodity exchange but without the ownership transfer" (p. 895). Their work suggests that differentiation at the product-level (through brand or quality) may be of little use for sharing platform operators. Instead, differentiation in the sharing economy setting can mainly be derived through business model innovation (Eckhardt et al., 2019), not product innovation and differentiation. On the contrary, other authors (e.g., Costello and Reczek, 2020; Mocker and Fonstad, 2017; Morewedge et al., 2020; Zhou et al., 2021) argue, that consumers remain conscious of the characteristics (quality and brand) of the products they purchase access to. Specifically, Morewedge et al. (2020) recommend that sharing economy platform operators can differentiate by diversifying their product portfolio in an effort to more accurately tailor it to specific use cases and user preferences. In order to resolve this apparent ambiguity, we set out to answer the following research question: Do physical product characteristics (e.g., quality and brand) provide scope for differentiation in a sharing economy context, and if so, under which circumstances?

Carsharing is a key instantiation of the sharing economy (Eckhardt et al., 2019; Morewedge et al., 2020). We leverage trip-level data from ShareNow, the world's largest carsharing platform operator in this study. Contrary to other sharing platforms, ShareNow offers a differentiated portfolio of physical products both in terms of different vehicle quality segments (premium, medium, low), and brands (Smart, Mini, BMW, and Mercedes), which provides an ideal environment for testing hypotheses related to both product-quality and -brand differentiation effects in the sharing economy. We use discrete choice modeling to understand whether and if so under which circumstances users prefer one vehicle segment or brand over the other. Specifically for the latter, we only consider rental transactions of vehicles from the same quality segment to reduce potential confounding effects. To validate our findings, we additionally conduct behavioral online experiments.

The remainder of our work is structured as follows: We first discuss the core literature relevant to this study. We proceed with a description of the empirical context and our modeling approach. We then present our results. We end with a discussion of the implications of our findings for academia and practice and explore several avenues for future work.

2 Literature

The sharing economy, as a socio-technical phenomenon, has sparked substantial research interest across different management disciplines in recent years, including Information Systems (e.g., Constantiou, Marton, and Tuunainen, 2017; Mocker and Fonstad, 2017), Service Science (Beverungen et al., 2019), Marketing (e.g., Bardhi and Eckhardt, 2017; Belk, 2010; Eckhardt et al., 2019; Morewedge et al., 2020) and Operations Management (e.g., Benjaafar and Hu, 2020).

Sharing economy business models are typically based on digital platforms (Constantinides, Henfridsson, and Parker, 2018) via which users purchase on-demand access to a product. Generally, no transfer of ownership occurs. As such, the sharing economy constitutes an IS-enabled socio-technical phenomenon (Sarker et al., 2019), whose impact on human behaviour is of particular interest to IS scholars and has been the subject of a substantial amount of prior work (e.g., Babar and Burtch, 2020; Burtch, Carnahan, and Greenwood, 2018; Chan and Ghose, 2014; Sundararajan, 2016).

We focus here on a core unresolved ambiguity in the sharing economy literature, namely the role (and relative importance) of product-level characteristics. In most sharing economy contexts physical product characteristics are composed of product quality (e.g., size, comfort level of a shared vehicle) and product brand (e.g., brand of a shared vehicle). Two conflicting viewpoints regarding the importance of these physical product attributes exist: The first (1) argues that product-level characteristics become less relevant in an access-based consumption scenario as encountered in the sharing economy. The second (2) postulates that product-level characteristics remain important for consumer choice even when being consumed in an access-based manner and, thus, offer scope for differentiation in the sharing economy. We briefly summarize the core arguments per each school of thought in the following.

Traditionally, sharing economy platforms have focused mainly on business model and platform innovation as a source for competitive advantage (Constantiou, Marton, and Tuunainen, 2017; Eckhardt et al., 2019). For example, ridehailing platforms such as Uber and Lyft operate with similar (and overlapping) vehicle fleets as do electric scooter platforms that source scooters from the same suppliers. Indeed, a substantial body of sharing economy literature (e.g., Bardhi and Eckhardt, 2012, 2017; Belk, 2010) suggests, that in a scenario where consumption is experiential and access-based, competitive advantage is mainly grounded in the service dimension. In a carsharing scenario, this means that users select a shared car based on instrumental utility mostly (Bardhi and Eckhardt, 2012). Following this line of thought, sharing economy platforms can differentiate in terms of service level (e.g., availability, ease of use, etc.) (Bardhi and Eckhardt, 2017), rather than physical product quality. We would, thus, postulate that in a purely experiential and access-based consumption scenario like carsharing, product attributes become less relevant and differentiated vehicle portfolios would appear to make little sense. Whether this is actually true remains the subject of some debate. For example, Eckhardt et al. (2019) argue that the origin of consumer value in an “ephemeral, access-based, and dematerialized” (p.17) consumption scenario is poorly understood. While they hypothesize that traditional consumer value drivers (such as physical product characteristics or identity value) are likely less relevant in such cases, they agree that the extant research remains silent on these hypotheses.

A somewhat contrary body of literature suggests that product characteristics can matter and that people can develop a sense of ownership for tangible and intangible products that they do not legally own (Morewedge et al., 2020). With legal ownership not being a prerequisite for an individual to develop a sense of connection to a physical or intangible object, consumers can develop an attachment to platforms, brands, and products offered in a sharing economy scenario (Paundra et al., 2017; Pierce and Jussila, 2010). Morewedge et al. (2020) argue, that in a sharing economy context, tailoring the product portfolio and assortment (such as offering dedicated vehicles for different transportation use cases) can be a good strategy to achieve differentiation in the sharing economy. Indeed, selected survey-based studies from carsharing seem to indicate that consumers are conscious of the characteristics of the product they purchase access to (Paundra et al., 2017) as well as their brand, an observation that is also supported by a large pedigree of research on brand equity (Keller, 1993a,b; Mocker and Fonstad, 2017). As a related example, Audi AG, when exploring how to differentiate in the sharing economy, opted for product-level differentiation by offering only top-of-the-range vehicles for sharing (Mocker and Fonstad, 2017).

To this date, the above described tension and ambiguity remain unresolved, or as Mocker and Fonstad (2017) put it “the question [remains], what is the definition of premium in a more digitized world? Is it time? Is it features [...]? Is it convenience?” (p. 283). Our study aims to make important contributions toward understanding the role of product differentiation in the sharing economy, thus responding to calls for a concentrated research effort in this direction (Eckhardt et al., 2019).

3 Empirical Setting: ShareNow

We leverage a unique observational dataset from ShareNow, a leading car-based on-demand rental network operator focusing primarily on major European cities. With carsharing being a widely studied and generally accepted instantiation of the sharing economy (e.g., Bardhi and Eckhardt, 2012; Mocker and Fonstad, 2017; Morewedge et al., 2020; Sundararajan, 2013), ShareNow constitutes an excellent case to empirically explore this study’s research question. With more than three million registered customers and a fleet size of more than 12.000 vehicles, the company is one of the largest carsharing operators in the world.[2]

[2] https://brandhub.share-now.com/web/6570a0eb69e15b2f/factsheets/

ShareNow originated from a merger of the formerly competing rental networks Car2Go and DriveNow, which were part of Daimler AG and BMW AG, respectively. The merger was completed on January 15^{th}, 2020, and resulted in the creation of ShareNow, a single combined digital platform accessible via the ShareNow mobile app. ShareNow's vehicle fleet is comprised of previously Car2Go- (mainly Mercedes and Smart) and DriveNow-operated (BMW and Mini) vehicle fleets. The vehicle portfolio thus consists of multiple vehicle quality segments (as identified by three different price levels) and multiple brands. Table 1 summarizes the vehicle portfolio of ShareNow in Berlin, our region of study.

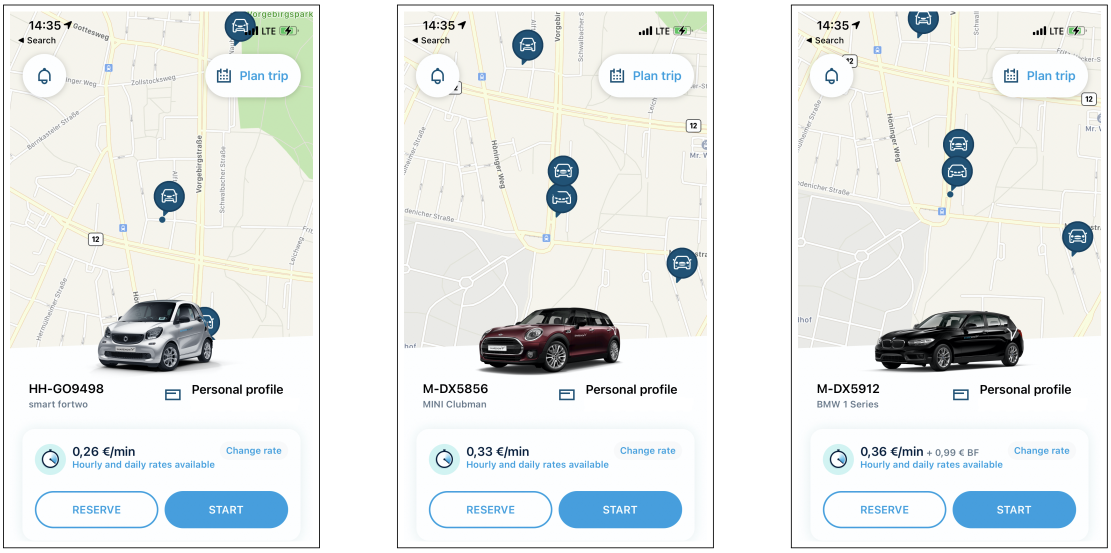
Vehicle Name	**Brand**	**Price** [EUR/min]	**Size of Fleet** [# vehicles]	**Avg. utilization** [# trips/vehicle/week]
Premium Quality Segment				
1-Series	BMW	0.36	149	13.34
2-Series Active Tourer	BMW	0.36	76	13.47
i3	BMW	0.36	102	9.26
X1	BMW	0.36	39	13.37
A-Class	Mercedes-Benz	0.36	122	17.83
GLA	Mercedes-Benz	0.36	101	18.34
Medium Quality Segment				
Mini 3-Door	Mini	0.33	182	16.92
Mini 5-Door	Mini	0.33	195	16.77
Mini convertible	Mini	0.33	183	16.02
Mini clubman	Mini	0.33	61	15.56
Mini countryman	Mini	0.33	17	16.16
Lowest Quality Segment				
Smart fortwo	Smart	0.26	882	42.88

Table 1. Overview of ShareNow's vehicle portfolio in Berlin.

This heterogeneous physical product portfolio (both in terms of quality characteristics and brand) which is accessible to all ShareNow customers via a single platform provides a unique opportunity to explore the impact of these factors on consumer choice. Figure 1 demonstrates the mobile app interface. The choice between different vehicle brands and segments is frictionless with users having perfect information of all relevant outside options in the vicinity.

4 Methodology

Our identification strategy draws on discrete choice modeling, particularly multinomial logistic regression methods, which are broadly used to examine the choice process in transportation studies and to isolate the influence of heterogeneous factors on the choice process (Train, 2003). As our dataset comprise observational rental records, we further demonstrate an approach to recover a quasi experimental setting to reduce selection bias, a procedure resembling traditional econometric matching (Iacus, King, and Porro, 2011; King and Nielsen, 2019; Rubin, 1996). We set up two different choice models, where the first attempts to shed light on whether the sharing economy leads to a commoditization (i.e., a lesser role of quality), and the second examines the product brands (given equivalent product quality). To substantiate the robustness of our findings from the aforementioned observational empirics, we additionally perform behavioral online experiments.



(a) Lowest Quality Segment *(b) Medium Quality Segment* *(c) Premium Quality Segment*

Figure 1. ShareNow mobile app screenshots illustrating the choice set.

4.1 Discrete Choice Modeling using Observational Data

4.1.1 Data & Preparation

Our empirical estimation approach relies on a unique carsharing dataset, which we retrieved in an automated fashion via the publicly accessible application programming interface (API) of ShareNow (and formerly DriveNow and Car2Go). We collected information of available vehicles in five-minute intervals over a period of slightly less than six months, from October 01^{st}, 2019 to March 20^{th}, 2020 for Berlin, Germany. This process for collecting non-personal data complies with applicable EU law. Note that this includes approx. 3 months of observations pre-merger and a similar amount post-merger, a fact which we exploit in later empirical analyses. The observation period is also limited to the pre-COVID period, thus avoiding any confounding effects related to behaviour shifts. For each vehicle, we observe the exact spatial location (latitude, longitude), vehicle type, vehicle model, rental price, and temporal information. Tracking vehicles appearing and re-appearing in our records allowed us to infer trips along with the origin, the destination and the duration of the respective rental trip. Our processed dataset consists of 1,983,246 car trips. In addition, we also compute the availability of nearby vehicles to capture important supply information. Apart from rental trip data, we collect publicly available weather data in hourly resolution from weather.com and point of interest (POI) data from OpenStreetMap (OSM). Furthermore, we utilized OSM to calculate the shortest routes between trip origins and trip destinations to obtain information on traveled distance.

Realizing that our rental dataset is observational in nature, we adopt techniques similar to matching (e.g., coarsened exact matching) to approximate a quasi-experimental setting (Iacus, King, and Porro, 2011; King and Nielsen, 2019; Rubin, 1996). Our motivation is to recover a true choice setting in which the full set of alternatives (e.g., all vehicle quality segments) was available to the user for each realized rental transaction. In order to do so, we overlay the service region with a hexagonal grid with a cell diameter of approximately 0.4km which falls into the range of acceptable walking distance (typically up to 500m) (Ampudia-Renuncio, Guirao, and Molina-Sanchez, 2018; Herrmann, Schulte, and Voß, 2014). For each rental record, we then count the number of nearby vehicles within the same hexagonal cell along with their vehicle class affiliation and their brand. We then remove those rental records where no relevant alternatives were available (i.e., where no true choice existed).

4.1.2 Dependent and Independent Variables

Current literature agrees that the choice of a vehicle depends on a number of different influences in addition to the alternatives (i.e., outside options) available (Cohen et al., 2016; Paundra et al., 2017). We, therefore, compile a set of independent variables that broadly reflect the purpose and external conditions of a trip. Firstly, we incorporate meteorological features such as $Temperature$ and $Precipitation$. Meteorological conditions have been shown to considerably influence user demand in a carsharing setting (Cohen et al., 2016; Hao et al., 2019). Second, traditional transportation literature has consistently demonstrated that trip factors such as trip length and trip duration are instrumental in mode choice decision processes (Ciari, Bock, and Balmer, 2014; Reck et al., 2021). We expect to uncover similar influences during the choice process and thus include both determinants $TripDistance$ (in meter) and $TripDuration$ (in minutes). For the former, we calculate shortest-path distances from the start and end positions available in our carsharing dataset using OpenStreetMaps (OSM) road network data. $TripDuration$ is calculated directly from our data as timestamps for trip start and end are measured. Third, we introduce one categorical determinant ($TimeBucket$) to capture nuances of the day of week and the time of day together, as successfully applied by Cohen et al. (2016). In other words, we stratify the temporal dimension into nine bins such as weekday morning, weekend evening, and bar hours. Fourth, we further include a temporal determinant that counts the number of weeks since the merger of DriveNow and Car2Go to ShareNow ($WeeksAfterMerger$). We expect that the established mobility habits of users of respective platforms (e.g. DriveNow and Car2Go) will change gradually (not immediately) in response to the merger. Finally, we seek to understand whether the destination of a trip – approximating the trip purpose – impacts the mode choice decision of users. Hence, we introduce a dichotomous spatial determinant $Hedonism$ that defines whether a trip ended in a region characterized by hedonistic facilities. Following Willing et al. (2017), we deliberately choose only the trip destination, since it can be freely chosen by users, whereas the starting location depends on the availability and proximity of vehicles. We calculate the specification of $Hedonsim$ as follows. We draw on publicly available POI data from OSM. At the coarsest level, OSM differentiates between 16 POI categories. However, we further consolidate these categories into two mutually exclusive POI categories, namely hedonistic and utilitarian as depicted in Table 2.

Hedonistic	**Number of POI**	**Utilitarian**	**Number of POI**
accomodation	557	animals	105
service	1866	education	1873
sustenance	6914	facilities	14625
arts and culture	753	healthcare	1578
historic	1017	public places	498
leisure and entertainment	6337	shops	9016
tourism	1693	financial	791
natural	310	transport	17772

Table 2. Frequency of hedonistic and utilitarian POIs.

Next, we use kernel density estimation to compute two spatial distributions for both hedonistic and utilitarian POIs (Parzen, 1962). The benefit of using a continuous distribution to model POI densities lies in its ability to more accurately capture adjacent influences. In terms of kernel specification, we opt for an Epanechnikov Kernel (Marron and Nolan, 1988) and a bandwidth of 1000m to account for the linear decreasing influence of adjacent POIs. Then, we evaluate each rental record's destination using both KDEs. To allow comparison between hedonistic and utilitarian densities, we standardize the respective sample probabilities by adjusting for their mean and dividing by their standard deviation. Finally, we set $Hedonism$ to one if the standardized hedonistic density exceeds the standardized utilitarian density.

We now turn our attention to the categorical dependent variables representing the choice alternatives. In the carsharing platform we consider (i.e., ShareNow), a user can typically select between different shared cars with varying product characteristics such as quality and brand (see Table 1). Based on the rental price per minute, the vehicles can be divided into roughly three vehicle classes, namely low quality (0.26 EUR/min), medium quality (0.33 EUR/min) and premium quality vehicles (0.36 EUR/min). While the low quality segment consists of only Smarts, the other categories contain more luxurious vehicles such as Mini (medium quality), Mercedes-Benz, and BMW (premium quality). Accordingly, we introduce a dependent variable *VehicleClass* to capture the choice of individuals in terms of product quality characteristics. Additionally, due to the merger of DriveNow and Car2Go to ShareNow, we are able to compare brand effects. As a result of the merger, ShareNow offers both premium brands to their customers allowing us to examine the influence and role of brands in the sharing economy. Furthermore, the available premium vehicles (e.g., Mercedes-Benz A-Klasse vs. BMW 1) can be considered as equivalent competing products leading to an excellent opportunity to isolate ceteris paribus effects. In particular, the product quality differences between the competing premium cars of Mercedes-Benz and BMW are marginal, meaning that any difference in consumer choice must be a result of the product brand. Hence, we include the second dependent variable *Brand*.

4.1.3 Estimation Approach

Our overall objective is to obtain detailed insights into the vehicle choice process of individuals in on-demand vehicle sharing networks. A prominent method to explain decision processes between discrete alternatives is multinomial logistic regression, a generalization of logistic regression with more than two discrete outcomes (Train, 2003). Multinomial logistic regression models are typically defined as follows

$$P_{i1} = \frac{1}{1+\sum_{j=1}^{J} e^{V_{ij}}} = \frac{1}{1+\sum_{j=1}^{J} e^{\beta_j \cdot x_i}}, \qquad k = 1, \tag{1}$$

$$P_{ik} = \frac{e^{V_{ik}}}{1+\sum_{j=1}^{J} e^{V_{ij}}} = \frac{e^{\beta_k \cdot x_i}}{1+\sum_{j=1}^{J} e^{\beta_j \cdot x_i}}, \qquad k = 2,3,\ldots,J, \tag{2}$$

where i refers to the ith observation, k refers to the vehicle alternative, V_{ik} is the representative utility an individual i gets from choosing alternative j. Note that $k = 1$ is set as the reference outcome, which means that all model estimates must be regarded relative to the reference.

As for the purpose of this research study, we define the representative utility as follows

$$V_{ij} = \beta_{j0} + \beta_{j1} \cdot H_i + \beta_{j2} \cdot M_i + \beta_{j3} \cdot T_i + \beta_{j4} \cdot C_i, \tag{3}$$

where H refers to the destinations characterized by hedonistic facilities (i.e., *Hedonism*), M refers to meteorological factors (i.e., *Temperature*, *Precipitation*), T refers to trip-related factors (i.e., *TripDistance*, *TripDuration*), and C captures temporal factors (*TimeBucket*, *WeeksAfterMerger*).

We consider two categorical output variables. To explore whether the sharing economy leads to commoditization effects, we use *VehicleClass* as the output variable. This choice allows us to explore whether users predominantly prefer only the cheaper vehicle alternative. To test the relevance of product brand, given the choice between multiple vehicles of equivalent quality, we set the output variable to *Brand*.

4.2 Behavioral Online Experiments

Next, we present the design of our behavioral online experiments which we perform to corroborate the results from the previous observational study. We focus here on the impact of hedonistic use cases on the choice of premium-quality vehicles (i.e., *VehicleClass*), as the core result from the discrete choice modeling exercise above. In the future, we plan to supplement these analyses with further experiments on the role of product and platform brands.

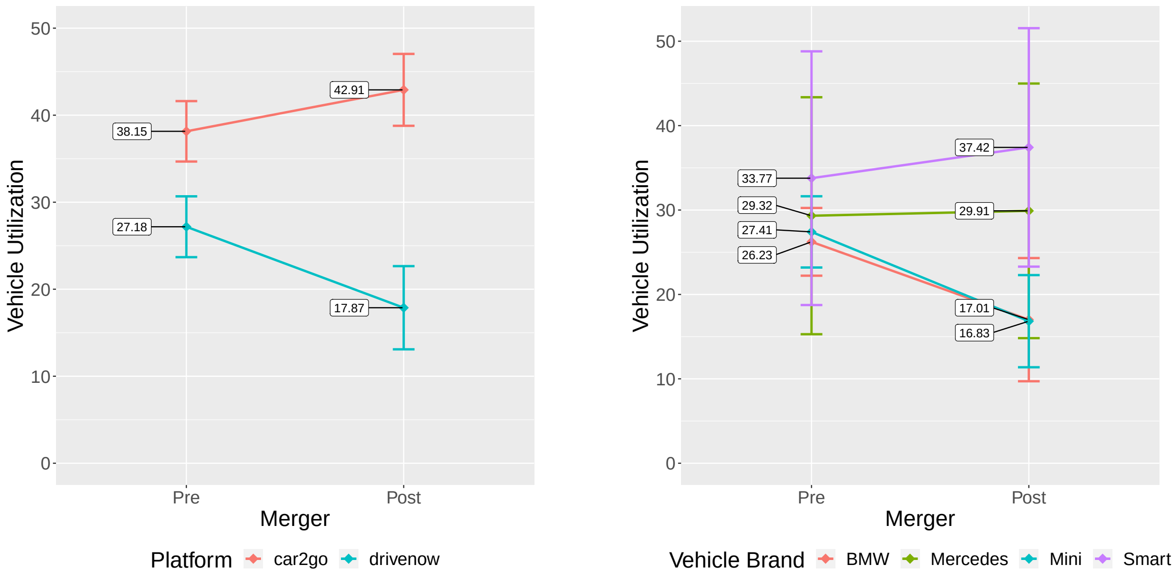
We perform online experiments with a one factor, two level within-subject design to examine the user preferences with regard to premium vs. low-quality, low-cost vehicles under either hedonistic or utilitarian conditions. First, participants are presented with a short introduction to carsharing and are then successively exposed to two different scenarios (each participant sees both scenarios). The first scenario is a hedonistic trip activity (i.e., "Image you are on your way to the movies."). The second scenario describes a trip of utilitarian nature (i.e., "Image you are on your way to work."). After each scenario introduction, we immediately present participants with a choice between two available shared vehicles: Model A and Model B. Model A is a low-quality, low-cost car with a standard interior, small engine, and a rental price of 0.26€/min. Model B is a premium car with a high-quality interior and a powerful engine at a rental costs of 0.33€/min. Both cars have the same amount of seats. Next, we measure the participants' preference for either of the two vehicle options under each of the presented scenarios (utilitarian and hedonistic). The preference is measured on a 7-point Likert scale (1 = *Definitely Model A*, 7 = *Definitely Model B*). We randomize the order of the two presented scenarios across participants. Lastly, we also include an attention check and a manipulation check. The attention check (i.e., "Please recall the second trip scenario presented. What was the destination of this trip?") confirms whether the participants can correctly reproduce the sequence of the scenarios presented. To test whether the manipulations are successful, we ask the participants to characterize the reason for their two trips (i.e., "Would you characterize the reason for your first (second) trip as primarily a functional activity or an entertaining activity?"). Again, answers are recorded using a 7-point Likert scale (1=*primarily functional*, 7 = *primarily entertaining*).

5 Results

The results from the choice modeling routine and the respective experimental validation studies allow us to draw conclusions on whether (1) product commoditization has taken place, or whether (2) products remain a potential source for differentiation. In the first case, our choice modeling results would indicate a structural preference for the low cost option always (i.e., significant intercept estimate skewed heavily toward the low cost commodity option). We also expect the parameter estimates for all other contextual factors to be close to zero (i.e., users always pick the low-cost option, independent of the situation). In the opposite case (product differentiation) we would expect strong preferences for one or the other product segment/brand for different situations. The results presented below can best be interpreted against these two extreme cases.

5.1 Impact of product quality on consumer choice in a sharing economy setting

Our first analysis exploits the fact that we have observational data from before and after the ShareNow merger. Prior to the merger, DriveNow, operated a more premium fleet, on average, comprising only medium (Mini-branded) and premium (BMW-branded) quality segment vehicles, while Car2Go's fleet relied heavily on the lower quality segment (Smart fortwo) with a smaller portion of premium vehicles (Mercedes-branded). Following the merger, former DriveNow customers enjoyed friction-less access to a new low quality tier product category (at a lower price), which was previously not available to them without the need for switching to another platform. Thus, if users are mostly interested in getting from A to B, and not so much in the vehicle that takes them there (commoditization effect), we would expect a migration of former DriveNow users to the low quality tier Smart vehicles. To check this, we run traditional ANCOVA analyses to explore the interaction effect of product quality with pre- and post-merger and its impact on vehicle utilization. We then dig deeper and review the vehicle brand-level interaction effects of the merger. The results are shown in Figure 2. Both analyses indicate that former DriveNow users appear to have migrated to the newly available low quality tier option (i.e., Smarts). Fleet utilization of previous Car2Go-operated vehicles (mainly Smarts) rises from 38.15 to 42.91 trips per vehicle per week, while previously DriveNow-operated vehicles experience a drop in utilization from 27.18 per-merger to 17.87 trips per vehicle per week post-merger. This is confirmed in part (b) of Figure 2, where we show that user migration took place mainly from former DriveNow brands to Smarts, leaving the premium Mercedes-branded vehicles largely unaffected.



(a) Platform-level fleet utilization. *(b) Brand-level fleet utilization.*

Figure 2. Pre- and Post-Merger Fleet Utilization per Platform and Vehicle Brand

Next, we turn to the results from the multinomial logistic regression model estimates to verify and add nuance to the previous ANCOVA findings. Here we focus on the consumer choice with respect to *VehicleClass*. We limit our analysis to the post-merger period (i.e., where a true choice between all vehicle models exist) and estimate a model as laid out in Equation 3. Note that the estimated coefficients of the respective utility functions corresponds to a change in log odds of the outcome category (e.g., premium quality vehicle) per unit increase in the value with respect to the reference category. The reference segment here is the low quality class.

	Low (Ref) vs. Medium				Low (Ref) vs. Premium			
	Beta	Exp(Beta)	Std. Error.	P-Value	Beta	Exp(Beta)	Std. Error.	P-Value
Intercept	-2.06	0.13	0.05	0.00	-2.15	0.12	0.05	0.00
Hedonism	0.10	1.11	0.03	0.00	0.16	1.17	0.03	0.00
Temperature	0.04	1.04	0.00	0.00	0.03	1.03	0.00	0.00
Precipitation	0.17	1.19	0.03	0.00	0.22	1.24	0.03	0.00
TripDistance (km)	-0.02	0.98	0.00	0.00	-0.02	0.98	0.00	0.00
TripDuration (10min)	0.03	1.03	0.00	0.00	0.04	1.04	0.00	0.00
TimeBucket								
BarHours	0.35	1.42	0.05	0.00	0.23	1.26	0.05	0.00
EveningRush	0.21	1.23	0.04	0.00	0.12	1.13	0.05	0.01
MorningRush	-0.06	0.94	0.05	0.21	-0.20	0.82	0.05	0.00
WeekdayEvening	0.16	1.17	0.05	0.00	0.14	1.15	0.05	0.00
WeekdayNighttime	0.15	1.16	0.06	0.02	0.31	1.36	0.06	0.00
WeekendDaytime	0.24	1.28	0.04	0.00	0.29	1.33	0.04	0.00
WeekendEvening	0.27	1.31	0.06	0.00	0.10	1.11	0.07	0.14
WeekendNighttime	0.24	1.27	0.12	0.05	0.50	1.64	0.11	0.00

Table 3. Estimated Coefficients of Multinomial Logistic Regression between Low (Ref.), Medium, and Premium quality vehicles.

We find a strong commoditization effect in on-demand vehicle sharing systems. If available, the cheapest options is generally preferred over medium and premium quality vehicle options as indicated by the alternative specific *Intercepts* with significant odd ratios of 0.13 and 0.12, respectively. This means, if individuals have the choice between vehicles of different quality, they – generally – opt for the cheapest alternative. However, we find that this effect is attenuated by different heterogeneous influences. Most notably, our results indicate that individuals significantly prefer medium (1.11) and premium quality (1.17) vehicles over low quality vehicles if their trip ends in a region characterized by hedonistic facilities (*Hedonism*). Weather also has an interesting effect on the vehicle choice process. With an odd ratio of 1.04 (medium) and 1.03 (premium), we observe that the higher the *Temperature*, the higher the preference of individuals for higher quality vehicles. Interestingly, we also find a strong preference for higher vehicle segments, 1.19 (medium) and 1.24 (premium), in rainy conditions (*Precipitation*). Trip-related characteristics exhibit a slight influence on the vehicle choice process. Low Quality vehicles are preferred for shorter distances (*TripDistance*) and shorter rentals (*TripDuration*). Lastly, we review the impact of temporal factors on the choice decision process. Note that the reference value for the categorical variable *TimeBucket* corresponds to weekday daytime which means that all estimated coefficients must be considered relative to the reference. Our results clearly show that low quality vehicles are preferred during morning rush hours (i.e., for commutes). Conversely, we see that during the remaining time buckets, the preference strongly tends towards the higher quality segments. In particular, at times with hedonistic nature such as *BarHours* and *WeekendEvening* with significant odd ratios of 1.42 and 1.31 for medium quality vehicles and 1.26 and 1.11 for premium quality vehicles.

Our findings are strongly supported by the behavioral online experiment we conducted. Using Amazon M-Turk, we recruited 334 participants, 186 of whom passed the attention check. A third of the participants were women (124 men, 62 women, 0 third-gender) and the average age of participants was 36.6 years (std=8.99). Our manipulation checks unveil that the participants correctly perceived the hedonistic (mean=5.77, std=1.33) and utilitarian (mean=4.27, std=2.26) scenario manipulations and that this difference is significant (p<0.001). To identify differences in users' vehicle choice preferences for hedonistic and utilitarian trips, we employ a repeated measures ANCOVA identification strategy which allows us to control for treatment ordering effects. As reported in Figure 3, we find a statistically significant difference in users' vehicle choice preferences between hedonistic (mean=4.83, std=2.14) and utilitarian (mean=4.48, std=2.23) conditions, F(1, 184) = 5.43, p = 0.021, $\eta_p^2 = 0.03$. Thus, we also experimentally demonstrate and further validate that hedonistic influences induce users to rent higher quality vehicles.

Taken together, these results paint a nuanced view. We find that users only seem to be indifferent about vehicle quality for specific (utilitarian) use cases. Users will generally opt for low cost and low quality vehicle options if their intention is to get from A to B quickly (such as during rush hours and/or when traveling to the office (i.e., a non-hedonistic destination)). Thus, our findings suggest that the sharing economy is fundamentally leading to a commoditization and not the response of users to a new available segment of vehicles. This is particularly evident given that pre-merger utilization levels of the cheapest vehicles are higher than those of premium vehicles for both DriveNow and Car2Go. In particular, the case of Car2Go underpins this argument as Car2Go's product portfolio offered vehicles from all three quality segments. On the other hand, users explicitly opt for higher quality segments if the travel purpose is of a more hedonistic nature.

5.2 Impact of product brand on consumer choice in a sharing economy setting

In order to investigate product brand effects, we turn our attention to the vehicle choice process with respect to decision variable *ProductBrand*. Again, we limit our study period to the post-merger period, where a true choice between the different vehicle options (i.e., different carmaker brands in ShareNow app available) existed. We also limit the analysis to the premium quality segment only, where a choice between brands (Mercedes and BMW) exists. Our results are reported in Table 4.

Given that users had the choice between either a premium vehicle from Mercedes or BMW, in other words, comparable vehicles from each brand were available, our results unveil that they prefer vehicles

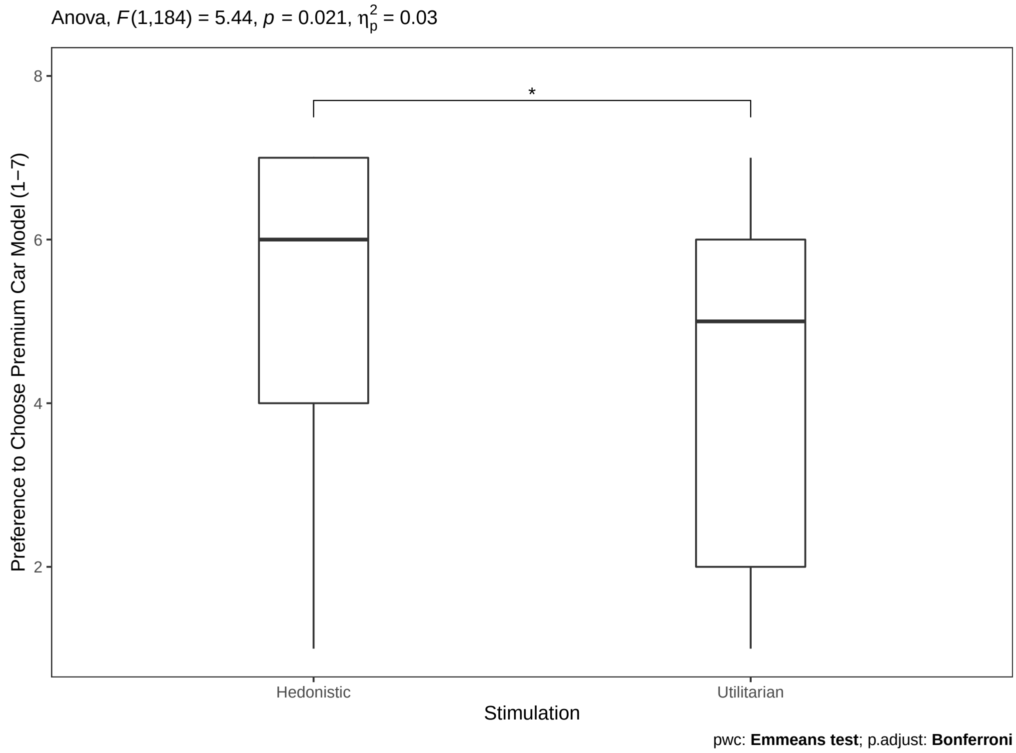


Figure 3. Resulting difference of users' intention to select a premium vehicle under hedonistic and utilitarian conditions.

from Mercedes-Benz with a significant odd ratio of 0.6 ($Intercept$). However, we further find that this preference towards Mercedes-Benz diminishes over time as indicated by $WeeksAfterMerger$ with an odd ratio of 1.03 per week after the merger. We attribute these results to the fact that Car2Go has historically had a larger market share with more customers habituated to Mercedes-Benz cars, and that through the merger, naturally a larger proportion are previous Car2Go customers who were used to the typical Car2Go brands such as Mercedes-Benz. Our results, thus, suggest, that the preference for Mercedes over BMW within the same product segment seems to diminish. To test this assumption we re-estimate our model for just the last 4 post-merger weeks in our records. The results are displayed in Table 5 and show that the individuals' preferences towards Mercedes-Benz have remarkably decreased (and become insignificant) lending strong support to the above interpretation.

This reasoning is further underpinned by the fact that almost all heterogeneous factors – except for $WeekdayNighttime$ – fail to explain the choice process. This means that we cannot find any significant evidence that the heterogeneous factors considered, moderate the choice decision between Mercedes and BMW cars. Thus, this finding hints at the fact that individuals do not prefer a certain car brand for particular purposes in vehicle sharing platforms, provided the vehicles share the same general product characteristics and quality. Our results indicate that users tend to be indifferent about the vehicle brand given that vehicles of choice are of similar quality and price.

6 Discussion and Future Work

In this study, we investigate the role of physical product characteristics in a liquid consumption setting as encountered in the sharing economy (Bardhi and Eckhardt, 2017). Taking the case of carsharing (ShareNow) we aim to resolve the tension between two conflicting theories on consumption in the sharing economy: The first (e.g., Bardhi and Eckhardt, 2017) argues that the role of product characteristics

	Mercedes-Benz (Ref) vs. BMW			
	Beta	Exp(Beta)	Std. Error.	P-Value
Intercept	-0.51	0.60	0.11	0.00
Hedonism	-0.02	0.98	0.05	0.59
Temperature	0.00	1.00	0.01	0.83
Precipitation	0.05	1.05	0.06	0.37
TripDistance (km)	-0.00	1.00	0.01	0.90
TripDuration (10min)	0.00	1.00	0.00	0.01
TimeBucket				
BarHours	-0.09	0.92	0.09	0.35
EveningRush	-0.05	0.95	0.07	0.50
MorningRush	0.06	1.06	0.09	0.48
WeekdayEvening	0.01	1.01	0.08	0.87
WeekdayNighttime	-0.39	0.68	0.11	0.00
WeekendDaytime	0.06	1.07	0.07	0.38
WeekendEvening	-0.14	0.87	0.12	0.25
WeekendNighttime	0.31	1.36	0.22	0.16
WeeksAfterMerger	0.03	1.03	0.01	0.00

Table 4. *Estimated Coefficients of Multinomial Logistic Regression between premium vehicle brand of Mercedes-Benz (Ref.) and BMW.*

	Mercedes-Benz (Ref) vs. BMW			
	Beta	Exp(Beta)	Std. Error.	P-Value
Intercept	-0.18	0.83	0.13	0.16
Hedonism	-0.07	0.93	0.06	0.28
Temperature	0.00	1.00	0.01	0.95
Precipitation	-0.07	0.93	0.09	0.40
TripDistance (km)	-0.00	1.00	0.01	0.76
TripDuration (min)	0.01	1.01	0.00	0.04
TimeBucket				
BarHours	-0.04	0.96	0.14	0.76
EveningRush	0.07	1.08	0.10	0.46
MorningRush	0.13	1.14	0.12	0.28
WeekdayEvening	0.12	1.13	0.12	0.30
WeekdayNighttime	-0.21	0.81	0.15	0.16
WeekendDaytime	0.13	1.14	0.11	0.23
WeekendEvening	-0.11	0.90	0.17	0.53
WeekendNighttime	0.18	1.20	0.35	0.60

Table 5. *Estimated Coefficients of Multinomial Logistic Regression between vehicle brand of Mercedes – Benz (Ref.) and BMW using sub sample data from March 2020.*

diminishes in a sharing economy setting, while the other (e.g., Morewedge et al., 2020) makes the opposite case arguing that physical product characteristics can be an important source for differentiation in the sharing economy.

Our results show that there is a general trend towards experiential and access-based consumption (i.e., commoditization) in which product characteristics (esp. quality) matter less. For the most part, users tend to prefer low-cost low-quality product options whenever they are available. We attribute this to the fact that users exhibit low psychological ownership (Morewedge et al., 2020) to the physical product and instead seems more interested in accessing a vehicle mainly for the purpose of traveling from A to B (Bardhi and Eckhardt, 2012). This suggests a lower relevance of product characteristics in the sharing economy, echoing the literature on experiential consumption (Belk, 2010). However, our investigations also highlight important nuances. We unveil that for certain purposes vehicle product characteristics regain their relevance. We observe that hedonistic purposes shift individuals' vehicle preference significantly toward more premium vehicle segments. Interestingly, when investigating the role of product brands (within the same quality segment), we also find evidence that vehicle brands become less influential. For example, users seem to be indifferent whether to use a BMW 1-Series or a Mercedes A-Class, two vehicles of the same quality segment, for their travel. This is true both for utilitarian and hedonistic use cases. At this point, we would like to reiterate that our vehicle choice modeling based on the rental transaction dataset is akin to a quasi-experiment, yet it is not a controlled experiment; therefore, statements about effects should be taken with a grain of salt. To address this deficiency and substantiate our key findings, we successfully conducted controlled online experiments allowing us to infer grounded causal effects.

Our findings invite researchers and managers to think differently about differentiation in the sharing economy. First, the two conflicting theories of consumption of sharing economy services, which contrasts experiential and product-/brand-based perspectives, are incapable of fully explaining consumption. Instead, our results indicate that one or the other theory comes into effect depending on context. Indeed, we show that products should be differentiated based on identifiable use cases. Thus, managers should seek to understand customers' needs and segments in detail and tailor their physical product portfolio accordingly. For example, for the case of carsharing, we identified that individuals' vehicle choice preference for trips with hedonistic purposes shift towards more premium vehicle segments. These insights are instrumental for managers to decide on long-term strategic questions (e.g., vehicle portfolio based on users' preferences) and short-term operations management tasks (e.g., to balance the vehicle fleet in spatio-temporal resolution considering users' preferences). Further, we reveal that the influence of product-level brands of comparable products with similar affordances diminishes in the sharing economy. Brands typically help customers identify a product, differentiate it from other vendors (Dibb et al., 2005), and recognize affiliated added values such as quality or prestige aspects (Chernatony, 1997). The role and importance of physical product brands in the sharing economy must be re-evaluated accordingly. In particular, managers should try to differentiate their brand in a more nuanced manner, particularly in relation to the available alternatives, and importantly create awareness for this. Furthermore, we speculate that the platform brand takes on the role of the product brand, thus transferring the platform brand's characteristics and associated added values to the respective products (Morewedge et al., 2020).

Our research is subject to a number of possible weaknesses. Most importantly, our observational study draws on observational rental records without explicit user information. For example, the exact number of passengers occupying a rented vehicle is not available for us. We also do not observe user preferences (e.g., preferences for product variety) and demographic information such as income, gender, age, etc., which might influence consumer choice. However, in many cases, this exact information is not even available to the platform operator, as individuals cannot report the number of passengers during the rental process. Furthermore, the current research relates utilitarian motives solely to the mobility service of getting from one location to another. However, other determinants, such as vehicle safety, could also constitute a utilitarian motive and will be considered in future work. Also, brands allow customers to save search and information costs and thus might be regarded as a utilitarian motive. We, however, suspect that due the limited number of available brands on the considered sharing platform (i.e., ShareNow), this effect is negligible. Moreover, we use the coarsest characterization of POIs for our current study. A finer classification of POIs would facilitate a more accurate and robust partitioning of POIs into hedonistic and utilitarian destinations. The asymmetric price difference between the different vehicle segments is another confounding factor in our empirical vehicle choice analysis. Lastly, our data also stems from a period just after the ShareNow merger. Due to COVID-19, extending our study period was not feasible.

We have attempted to circumvent most of these weaknesses with initial laboratory-based experimental studies, which we aim to significantly expand in future work. As reported in this work, we have already successfully conducted the first online experimental study on the influence of trip purpose on vehicle quality preferences. These studies confirm findings from the previous observational study. Further experiments investigating the role of product brands, platform brands, and potential boundary conditions are currently ongoing. We believe this to be crucial to further support the above described findings. We have also resumed data collection of ShareNow rental transactions. Once the effects of COVID-19 on the transportation sector are diminishing as economies re-open we aim to test the robustness of our results on a newer dataset where any immediate merger-related effects can be assumed to have waned. We encourage other scholars to investigate similar research endeavors from different perspectives and in different domains such as property sharing (e.g., AirBnB). Specifically, future work should focus on enhancing the role of platform brands in the sharing economy. For example, to identify and quantify the determinants influencing individuals' preferences between competing platforms such as Lime and Tier offering largely the same product (i.e., electric kick scooters).

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