The Existence and Persistence of the Pay-per-use Bias in Car Sharing Services

Katharina Dowling (LMU Munich)
Puneet Manchanda (University of Michigan)
Martin Spann (LMU Munich)

Discussion Paper No. 193

October 23, 2019

Collaborative Research Center Transregio 190 | www.rationality-and-competition.de
Ludwig-Maximilians-Universität München | Humboldt-Universität zu Berlin
Spokesperson: Prof. Dr. Klaus M. Schmidt, University of Munich, 80539 Munich, Germany
+49 (89) 2180 3405 | info@rationality-and-competition.de

The Existence and Persistence of the Pay-per-use Bias in Car Sharing Services

Katharina Dowling Puneet Manchanda Martin Spann[1]

October, 2019

Abstract

A key benefit of using car sharing services (relative to car ownership) is that they are more cost effective. Car sharing firms offer a menu of pricing plans to make this happen. The two most common plans are flat-rate and pay-per-use pricing. However, little is known about how consumers choose among these pricing plans. In this study, we analyze consumers' choices between pay-per-use and flat-rate pricing using data from a car sharing provider in a large European city. We show that over 40% of customers make nonoptimal pricing plan choices (i.e., they do not choose the cost minimizing plan). In contrast to previous research, we find a prevalent and time-persistent pay-per-use bias; i.e., we find little evidence that consumers "learn". We propose three potential explanations for the existence and persistence of this bias. First, we suggest that customers underestimate their usage. Second, we propose that customers have a preference for flexibility, leading them to pay more. Finally, we show that the physical context, such as weather, increases the likelihood of a pay-per-use bias. We suggest that the pay-per-use bias may be the prevalent tariff choice bias in the Sharing Economy.

Keywords: Sharing Economy, Car Sharing, Pricing, Pay-per-use Bias, Flat-rate Bias.

---

[1] Katharina Dowling is a doctoral student at Ludwig Maximilian University, Munich; Puneet Manchanda is the Isadore and Leon Winkelman Professor of Marketing at the Ross School of Business, University of Michigan; and Martin Spann is Professor of Electronic Commerce and Digital Markets at Ludwig Maximilian University, Munich. The authors gratefully acknowledge the support of the anonymous company who provided the data and feedback from participants of the 2018 ISMS Marketing Science Conference in Philadelphia. Financial support by Deutsche Forschungsgemeinschaft through CRC TRR 190 (project number 280092119) is gratefully acknowledged. The authors may be contacted via email at dowling@bwl.lmu.de, pmanchan@umich.edu and spann@bwl.lmu.de.

1 Introduction

The so-called "Sharing Economy" that offers consumers flexible access over the ownership of goods is characterized by substantial and increasing economic importance – for example, Uber (ride sharing) and Airbnb (hospitality) are valued at $72bn (Price, 2018) and $31bn, respectively (Heathman, 2017). While ride sharing services have been active for quite a while now, car sharing services are expected to yield double-digit growth in the US until 2024 (Gerrard, 2017). Ride and car sharing services can be largely beneficial to society via traffic reduction, decreased demand for parking (Conner-Simons, 2017; Kiron, 2013) and/or decreased transportation costs for consumers. This decreased transportation cost is achieved through two types of pricing plans – flat-rate and pay-per-use pricing. Previous research in other contexts has demonstrated that consumers are not particularly good at making optimal pricing decisions under these plans. Therefore, and due to the novelty of ride sharing services, it is likely that consumers make "errors" when choosing a tariff related to their consumption, leading to tariff choice bias(es).

Current research indicates that the emergence of the Sharing Economy fundamentally changes consumers' consumption patterns (Zervas, Proserpio, & Byers, 2017). Although sharing and owning can be seen as substitutes, consumers' motives for using a sharing service often differ from those of owning (Lamberton & Rose, 2012). Specific characteristics of sharing services like flexibility and convenience might yield bias patterns that differ from the well-documented and prevalent flat-rate bias (e.g., DellaVigna & Malmendier, 2006; Lambrecht & Skiera, 2006). For example, a preference for flexibility might induce consumers to choose the pay-per-use option too often so they do not have to commit to the less flexible flat-rate option, leading to a pay-per-use bias (Krämer & Wiewiorra, 2012). Thus, it is unclear, if such biases exist, which tariff choice bias(es) might occur in the sharing context.

Therefore, the goal of this paper is to analyze consumers' pricing decisions and biases in a sharing context and to compare and contrast our results to previous research on tariff choice biases. Given that the Sharing Economy is growing rapidly and there is relatively little research on the behavior of consumers, firms, and platforms, our findings are likely to be timely and relevant for consumers, firms, and policy makers.[2] From an academic point of view, our paper focuses on the demand-side behavior of buyers with respect to pricing and consumption, a hitherto unexplored aspect of the Sharing Economy in academic research. Thus, this study can be seen as contributing at the intersection of two streams of the literature – consumer behavior vis-à-vis the Sharing Economy and tariff choice biases in service contracts.

Most studies on consumer behavior in the Sharing Economy focus on the reasons for participation, e.g., lowered overall cost due to on-demand access rather than ownership (Benoit, Baker, Bolton, Gruber, & Kandampully, 2017; Lamberton & Rose, 2012; Lawson, Gleim, Perren, & Hwang, 2016). This work also documents the role of nonprice-based factors leading to participation, e.g., flexibility, the ability to access goods that are desirable but out of (ownership) reach, the degree of substitutability and perceived product scarcity risk. With regard to price, most studies that focus on a sharing context focus on firm pricing behavior and its consequences. Zervas et al. (2017), for example, analyze the impact of Airbnb's relatively cheap prices on the traditional hotel industry and show that Airbnb's entry into the market significantly decreased the revenues of traditional hotels. Farajallah, Hammond, and Pénard (2019) study price setting by drivers on the ride sharing platform BlaBlaCar. Other papers focus on Uber and its surge pricing mechanism, which it uses to clear markets in the short-term (e.g., Hall, Kendrick, & Nosko, 2015).

[2] We hereby address one of the research gaps identified by Kannan and Li (2017), namely consumer behavior with regard to price in the context of a new form of platform.

In terms of tariff research, studies analyzing the drivers of tariff choice (e.g., DellaVigna & Malmendier, 2006; Uhrich, Schumann, & Wangenheim, 2013) and studies investigating consumer behavior given a certain tariff choice (e.g., Iyengar, Jedidi, Essegaier, & Danaher, 2011; Leider & Şahin, 2014) can be differentiated. Several studies focusing on tariff choice show that consumers do not always pick the tariff that minimizes their billing rate (DellaVigna & Malmendier, 2006; Lambrecht & Skiera, 2006; Train, McFadden, & Ben-Akiva, 1987). Interestingly, most studies primarily observe a flat-rate bias, i.e., consumers choosing a flat rate, although they would save money under a pay-per-use tariff (DellaVigna & Malmendier, 2006; Lambrecht & Skiera, 2006). Two explanations for this bias have been proposed. First, consumers are inherently subject to biases, leading them to commit errors. For example, DellaVigna and Malmendier (2006) propose that overconfidence about future self-control is a main driver of the substantial flat-rate bias they observe (in the context of gym memberships). Second, consumers have a preference for a respective tariff and thereby deliberately choose the more expensive tariff. For example, Lambrecht and Skiera (2006) show that tariff preferences can also cause a flat-rate bias because the payment is decoupled from consumption in flat-rate pricing.

Using car sharing data from a firm offering these services in a large European city, we find that consumers overwhelmingly choose pay-per-use pricing and that 41% of these consumers exhibit a pay-per-use bias. More interestingly, this bias persists over time, even for heavy users. These findings are novel in that they are in direct contrast to previous findings on biases.[3] We provide evidence for three possible explanations that are consistent with the existence and persistence of this bias: (1) demand underestimation, (2) preference

[3] Miravete (2002) documents a pay-per-use bias using data from a tariff *experiment* conducted by South Central Bell. In contrast to our setting, the consumers in Miravete's study *learn* after making an initial error in tariff choice and switch tariffs to minimize their monthly telephone bills.

for flexibility, and (3) the role of the physical context.[4] Finally, we conduct robustness checks, discuss the boundary conditions of our analysis and results, and propose policy implications of our findings.

2 Research Setting and Data

2.1 Contextual Background

We analyze panel data from a car sharing provider located in a large western European city. The car sharing provider operates a so-called "free-floating" business model; i.e., cars can be picked up and dropped off anywhere in a defined section of the city (this section comprises a large part of the overall area of the city). In terms of the competitive landscape, no other free-floating car sharing provider operates in the city in our observation period. Additional station-based car sharing providers similar to Zipcar exist. Station-based car sharing cars have to be picked up and dropped off at fixed parking spaces, and they are typically booked for longer trips. Beyond car sharing, the city has a well-developed network of public transportation. Moreover, multiple taxi and ride sharing providers like Uber operate in the city.

The government offers car sharing customers an advantage in terms of parking. In addition to public parking spaces, cars can be parked in residential parking areas that are usually reserved for residents. Beyond parking, we are not aware of any other incentives that the government or employers might offer to promote the usage of car sharing. However, even if employers offered incentives, these would apply to only a very small fraction of the sample, since customers declared only 2.7% of trips in our sample as business trips[5].

---

[4] It is outside the scope of this paper to determine the most likely explanation– we leave that for future research.

[5] Based on a total sample of 81,482 individual trips.

2.2 Description of the Dataset

The dataset contains trip-level data, including the starting and ending location of the trips and detailed information on the pricing plan choices. Cars are typically booked via a dedicated mobile app that provides customers with information on the location and distance to available cars and their characteristics (e.g., make and model). The data also include customer-level information, such as home address, age, and registration date. The data span 10 months in two distinct sample periods - February 2016 to July 2016 and November 2016 to February 2017. We use additional third-party data on aspects such as the weather, access to public transportation, and traffic patterns to augment the car sharing data.

2.3 Pricing Plan Options

The menu of pricing plans comprises two main choices. Customers can choose either a pay-per-use option, with a per-minute usage price, or one of two flat-rate options. The first flat-rate option is the purchase of an allowance of a certain number of minutes (at a price that is lower than the pay-per-use price) valid for 30 days (labeled "30-day package"). Once the allowance of minutes is used up, customers pay the pay-per-use price for additional minutes.[6] The minimum allowance of minutes is 60 minutes in the first sample period and 125 minutes in the second sample period, as shown in Table 1. The second flat-rate option is to buy an "hourly package" for one hour or multiple hours (that need to be used in a single block). With regard to the per-minute price, customers also have the option to book discounted cars (i.e., cars that have not been moved for a while) at a per-minute price that is lower than that for other cars. In addition, car-based price differentiation is introduced in our second sample period, i.e., different per-minute prices were charged for different car makes and models. The customers make pricing plan choices every time they

[6] In a strict sense, the "30-day-package" is a three-part tariff rather than a pure flat-rate offering unlimited driving minutes.

take a trip. Choices can be made via the dedicated app or via the menu on the display inside the car. For each trip, the customers must decide between the pay-per-use pricing option and one of the flat-rate options. However, if they book the 30-day package, it is valid for 30 days, and the customer will only have to make another plan choice once the 30 days have passed.

Period	**Price per minute**	**30-day packages**	
		Length	**Total price (price per min)**
Feb 16 - May 16	$0.52	60 min	$28 ($0.47)
		100 min	$46 ($0.46)
		200 min	$88 ($0.44)
		400 min	$172 ($0.43)
Nov 16 - Feb 17	$0.44 to $0.52*	125 min	$43 ($0.34)
		250 min	$83 ($0.33)
		400 min	$129 ($0.32)

Table 1 Overview of Price-per-minute and 30-day Packages

Note. Prices were converted to USD ($) using the mean conversion rate of the observation period.
*Different prices for different car models.

Prior to choosing a pricing plan and making a first trip, the customers must register for the service, including the payment of a registration fee of $13. To create awareness and to increase the sign-up numbers, the provider provided regular promotions that allowed customers to join the service for free. The provider additionally advertised the service via the following channels or media: TV, online, out-of-home campaigns in subway stations, flyers, an e-newsletter, and public relations. The provider did not promote a specific pricing plan but focused on increasing awareness of the service as a whole.

2.4 Sample

The data set comprises 81,482 individual trips. We exclude the months of June and July 2016, as 30-day packages were not offered in these two months, leaving 8 months of observation and 65,322 individual trips.[7] To make the pricing plan choices comparable across customers, we aggregate all trip-level information (e.g., duration and cost of trip) to the monthly level, as is typical in this strand of the literature (e.g., DellaVigna & Malmendier, 2006). Our final sample consists of 13,975 month-customer combinations, with 5,441 unique customers being active in this period in at least one month. Not all customers were active during the first month of our observation period.[8] Therefore, we carry out a cohort-based analysis.

2.5 Descriptive Statistics

Table 2 shows the descriptive statistics on trips and "errors", the booking of 30-day packages and discounted cars, and related third-party data. The first row "months with trips" refers to all month-customer combinations, in which customers took at least one trip within that month. Next, are the descriptive statistics of total trips and minutes per month for which no flat-rate packages were used. The dummy variables for the 30-day package and discounted cars count all months in which these were booked. "Months with errors" refers to all months in which customers made an error (i.e., they could have saved money by choosing a flat-rate package). The "error rate per customer" indicates in how many months with trips customers made an error (e.g., if they took trips in four months and made an error in two months, their error rate would be 50%).[9] More details on the supplementary data (weather, access to public transportation, and traffic) are discussed in part 4.2.

---

[7] The average number of trips per customer is stable across months. Thus, the usage patterns in June and July do not differ from the months included in the observation period. Appendix 1 shows the number of trips per month within the observation period.

[8] Appendix 2 shows the number of new customer registrations per month, and Appendix 3 displays the number of active customers per month within the observation period.

[9] Alternative error calculations are provided in section 5 as robustness checks.

	No of obs	Mean	SD	Min	Max
Months with trips (out of 8 possible)	13,975	2.52	1.77	1.00	8.00
Trips per month without package	13,975	4.23	5.91	0.00	72.00
Minutes per month without package	13,975	102.14	167.83	0.00	4943.00
30-day package (DV)	13,975	0.06	0.23	0.00	1.00
Discounted car (DV)	13,975	0.07	0.26	0.00	1.00
Months with errors (out of 8 possible)	3,461	3.04	1.96	1.00	8.00
Error rate per customer	5,441	0.18	0.31	0.00	1.00
Precipitation (mm)	13,975	0.90	0.45	0.17	1.60
Access to public transportation	10,314*	5.03	1.06	2.42	7.09
Traffic (mean)	9,729*	469.05	252.77	151.69	2522.87

Table 2 Descriptive Statistics

Notes. DV indicates a dummy variable.
* Fewer observations, as home address not available for all customers. For traffic, if distance btw. home location and air traffic counters > 2 km, set to missing.
Precipitation data from https://www.wunderground.com.

3 Pricing Plan Choices and Biases

3.1 Analysis of Pricing Plan Choices

We first analyze the pricing plan choices. At the trip level, the customers chose pay-per-use pricing for 90.43% of the trips and the flat-rate option for 9.57% of the trips. Of the 9.57% flat-rate choices, 5.57% were 30-day packages and 4% were hourly packages. Next, we examine whether tariff choice biases exist.

3.2 Existence of Tariff Choice Biases

Pay-per-use Bias

To identify a pay-per-use bias, we analyze the total monthly minutes used and the amount of the bills paid by the customers to assess whether a 30-day package could have reduced the customers' monthly bills. Thus, if a 30-day package would have reduced a customer's bill, we define the month as a month with an "error." Note that we focus on pay-per-use pricing; therefore, an "error" in the subsequent sections will refer to a pay-per-use bias. To express the regularity of errors in the pricing plan choices across customers, we form different error categories at the customer level. We differentiate between customers that accumulated enough minutes for a 30-day package to be paying off and those that did not accumulate enough minutes. Customers that did not accumulate enough minutes for a 30-day package to be paying off in any month with trips are in the category *cannot be wrong*. All other customers had enough minutes for a 30-day package to be paying off. We divide these customers into three groups depending on the regularity of their errors: *never wrong*: no error in any month with trips; *sometimes wrong*: error in some but not in all months with trips; and *always wrong*: error in every month with trips.

As shown in Table 3, 32.97% of the customers are *sometimes wrong* and 7.65% are *always wrong;* i.e., they made an error in at least one of their months with trips. The remaining 59% of the customers did not have enough minutes (*cannot be wrong*) or did not ever make an error (*never wrong*). Thus, the majority of the customers actually made rationally optimal choices by picking the pay-per-use option. However, looking at the corresponding months with trips shown in Table 3, the customers that exhibit a pay-per-use bias (in at least one of the months with trips) account for 61% (55.23% + 5.81%) of all months with trips. In sum, 41% of the customers with a pay-per-use bias (*sometimes wrong* or *always wrong*) account for more months with trips than the customers without this bias.

Error category	**Customer level**		**Months with trips**	
	Frequency	Percent	Frequency	Percent
Cannot be wrong	2,642	48.56	4,713	33.72
Never wrong	589	10.83	732	5.24
Sometimes wrong	1,794	32.97	7,718	55.23
Always wrong	416	7.65	812	5.81
Number of observations	5,441		13,975	

Table 3 Error Categories at the Customer Level

Note: Shaded area = pay-per-use bias.

Next, we focus on months with trips as the unit of analysis (rather than the customer level). We have the following error categories: *no error possible*: not enough minutes for a 30-day package to be paying off in that month; *no error*: no error in that month; and *error*: error in that month.[10] Table 4 shows that customers made an error in approximately 25% (24.77%) of months with trips. We compare these months with errors to approximately 16% (15.84%) of the months with *no error* to identify the characteristics and drivers of the pay-per-use bias, which results in a sample of 5,675 months with trips.

Error category	**Monthly level**	
	Frequency	Percent
No error possible	8,300	59.39
No error	2,214	15.84
Error	3,461	24.77
Number of observations	13,975	

Table 4 Error Categories at the Monthly Level

Flat-rate Bias

A flat-rate bias is also present but to a much smaller degree. We defined a month as having a flat-rate bias if the sum of the monthly minutes stayed below the breakeven number of minutes between the two options (54 min. for period 1 and 98 min. for period 2). Using this definition, the customers exhibited a flat-rate bias in 15% of the 5.77% of month-customer combinations with 30-day packages, i.e., only in 0.87% of all month-customer combinations (N = 13,975).[11] At the customer level, only 103 customers (1.89%) had a flat-rate bias compared to 2,210 customers that exhibited a pay-per-use bias (41% - *sometimes wrong* or *always wrong*).

Given the low usage of the flat-rate tariff and the almost negligible presence of the flat-rate bias, we focus on the dominant tariff, pay-per-use, in our subsequent analysis. It is also important to note that, interestingly, we did not find both the flat-rate bias and pay-per-use

[10] Unlike before, we do not have an error category “sometimes error” here since at the monthly level, we can only account for whether an error occurred in the respective month. The “sometimes error” category only applies to the individual level, at which individuals can have errors in certain months but not in other months.

[11] At the trip-level, 5.57% of the trips involved the use of 30-day packages (as noted in Section 3.1).

bias *within* the same customer. Thus, our analysis does not confound the type of bias within customers.

4 Analysis of Pay-Per-Use Bias

4.1 Economic Importance and Persistence of the Pay-Per-Use Bias

Having demonstrated the existence and prevalence of the pay-per-use bias, we now analyze the average error size, its persistence, and differences between customer groups.

The size of errors relative to bill payments shows the economic importance of the pay-per-use bias. At the monthly level, customers with errors lose on average $9.65, which accounts for 23% of the average monthly bill payment. The maximum monthly missed savings is $649.95.[12] Over all months with trips, customers with errors lose on average $24.67, which accounts for 12% of total bill payments. Here, the maximum loss is $3928.10. Thus, the loss, i.e., missed savings from choosing a nonoptimal pricing plan, can be quite substantial, especially for customers with high trip frequency over a long time period.

Next, we analyze the persistence of the pay-per-use bias and whether the consumers learn to correct this bias over time, as has been documented in other contexts (Iyengar, Ansari, & Gupta, 2007; Lambrecht & Skiera, 2006; Miravete, 2002). For this analysis, we focus on customer cohorts, i.e., customers active in all months starting February 2016 and customers active only in February 2017.[13] We illustrate our findings based on the cohort active in all eight months (comprising 1,199 customers and 5,230 corresponding months with trips).

[12] The amounts vary considerably between low- and high-frequency customers. High-frequency customers (customers with on average of more than 3.7 trips per month) lose $16.14 per month on average, whereas low-frequency customers lose $3.64 on average.

[13] We define a cohort as customers being active in certain months of our observation period. However, unlike the conventional definition of a cohort, for our definition, the customers within one cohort did not all join the service at the same time. A probit regression at the user level shows that the longer a customer is registered, the more likely s/he is to have a pay-per-use bias.

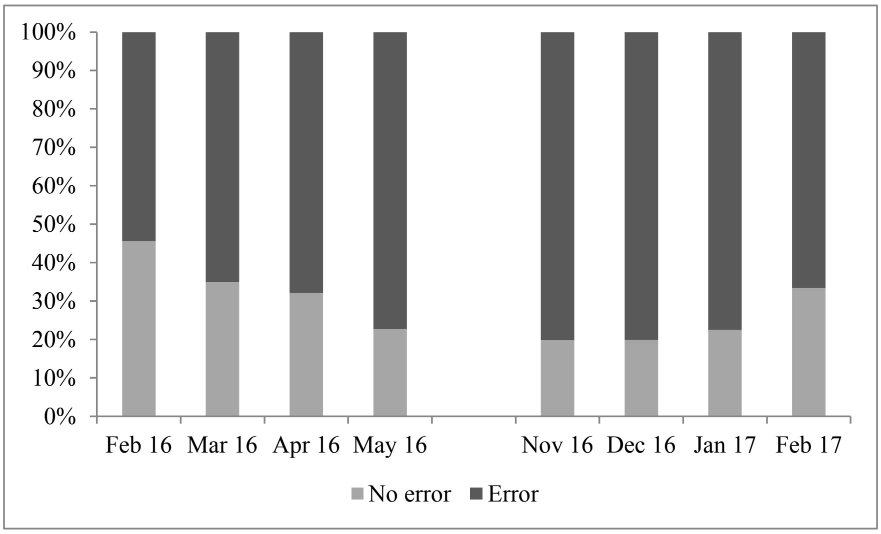

Figure 1 Development of Errors and No Errors

Figure 1 shows the development of the rates of *errors* and *no errors* within our sample period for this cohort.[14] As Figure 1 shows, the error rate slightly decreases in the second sample period, but overall, it is rather stable; i.e., the pay-per-use bias persists over time. This suggests that in our sample period, the customers do not seem to learn. One possibility is that this finding is driven by infrequent customers. Frequent customers have more opportunities to assess their usage rate and corresponding cost. Thus, they should be more likely to detect the suboptimal pricing plan choices that they made and correct for them over time. We therefore look at the high-frequency customers (N = 1,355 customers; 24.9%) – customers that take on average more than 3.7 trips per month[15] – and find a very similar pattern, as shown in Figure 2 below.[16]

[14] The absolute number of errors decreases in our second sample period from November 2016 to February 2017. This effect mainly originates from a structural change in the offering of 30-day packages between the two periods. In the first sample period, the smallest 30-day package offered comprised 60 prepaid minutes. In the second sample period, the smallest 30-day package offered comprised 125 prepaid minutes. With a mean of 102 minutes without the flat-rate package per month, fewer customers accumulated sufficient minutes for a package to pay off in the second sample period than in the first sample period.

[15] High-frequency customers are above the 75th percentile of mean trips/month/user (i.e., > 3.7 trips/month/user). Medium-frequency customers are above the 50th percentile to ≤ 75th percentile of mean trips/month/user (i.e., > 2 and ≤ 3.7 trips/month/user).

[16] The results are robust to other customer group formation criteria, e.g., the maximum number of trips per month, total trips per customer or a more granular division of customers.

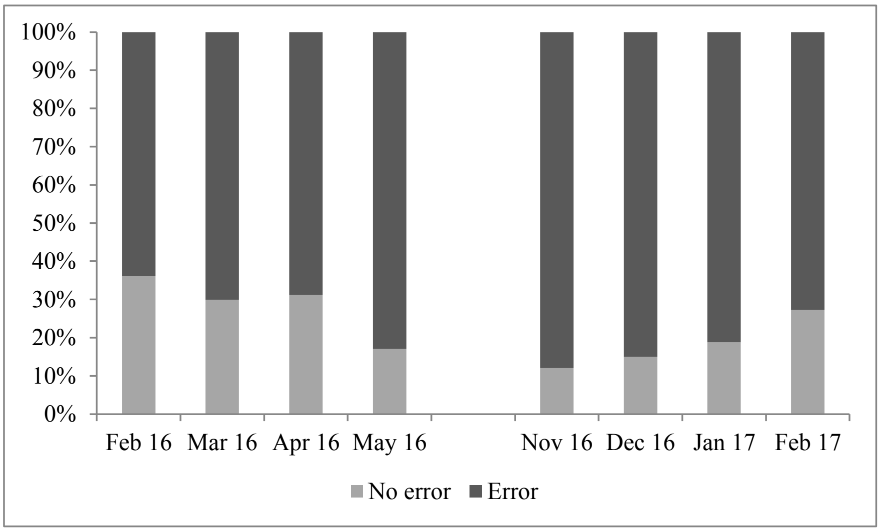

Figure 2 Development of Errors and No Errors (High-frequency Customers)

Figure 3 takes a closer look at different customer groups formed on the basis of the average number of trips per month (i.e., trip frequency) for the cohort active in all of the months of the sample period. We would expect that customers with a higher total trip frequency are more aware of their usage and thereby make fewer errors than other customers due to their experience. However, Figure 3 again shows the opposite result – that the most experienced customers (in terms of trip frequency) make the most errors.

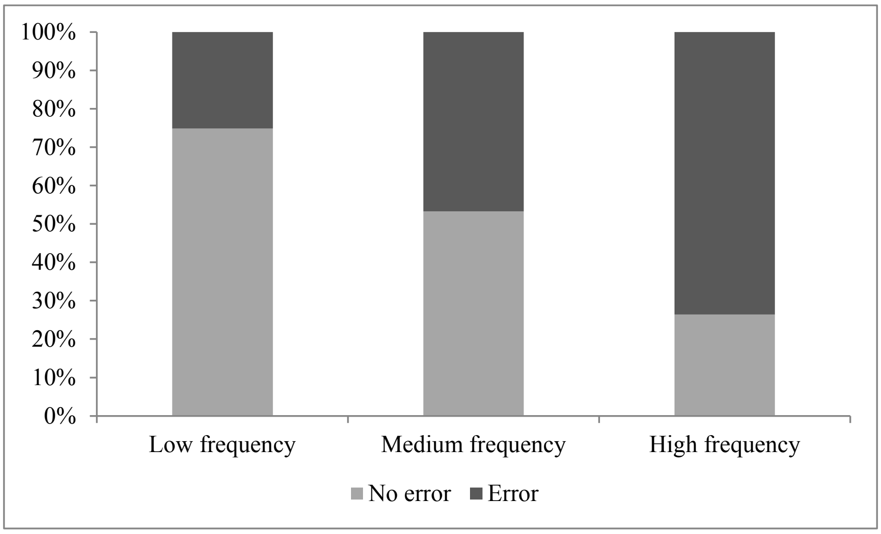

Figure 3 Different Customer Groups based on Trip Frequency

Note: High-frequency customers are above the 75th percentile of mean trips/month/user. Medium-frequency customers are above the 50th percentile to ≤ 75th percentile of mean trips/month/user.

4.2 Possible Explanations for the Pay-Per-Use Bias

Next, we examine three possible explanations for the existence and persistence of the pay-per-use bias: underestimation, the preference for flexibility, and the physical context. We do so by looking at the data patterns for each explanation individually.

Underestimation

The first potential explanation for the observed pay-per-use bias is that customers underestimate their usage (Lambrecht & Skiera, 2006; Uhrich et al., 2013). Since the pay-per-use bias is persistent over time with little evidence that learning occurs, it seems plausible that underestimation is driven by overconfidence (a similar argument is made by Szymanowski & Gijsbrechts, 2013). As in Grubb and Osborne (2015), we can assume that the customers are overconfident because they underestimate the noise in their own forecasts about their future requirement for using car sharing. Specifically, the customers underestimate the variance in their future consumption. This is supported by the descriptive statistics of monthly trips without a package for different error categories (see Table 5).[17] The variance in trips strongly increases between categories without errors and categories with errors. These results indicate that the customers in the categories that are *sometimes wrong* and *always wrong* are overconfident, as these customers underestimate the variance in their usage behavior and as a result, make more errors.

Error category	Mean	Variance	Median	SD	No. of obs
Cannot be wrong	1.85	1.99	1	1.41	4,713
Never wrong	1.37	7.20	1	2.68	732
Sometimes wrong	5.31	41.09	3	6.41	7,718
Always wrong	10.36	104.37	8	10.22	812
Total	4.23	34.96	2	5.91	13,975

Table 5 Descriptive Statistics: Monthly Trips without Packages for Different Error Categories

[17] Table 5 shows the statistics for all month–customer combinations. The results also hold for high-frequency customers only, when controlling for trip frequency.

To support this finding, we evaluate two alternative explanations that could also result in similar data patterns. First, the customers may simply lack the mental capacity to correctly predict their car sharing usage given multiple transportation alternatives and thus make errors. However, this is unlikely to be an issue because the accrued car sharing cost is made very transparent to customers. Customers receive emails with detailed cost overviews, and the invoices are also visible in the dedicated app at all times. Additionally, although alternatives to car sharing might exist, no other free-floating car sharing provider operated during the sample period in our location, and therefore, the usage prediction does not have to be divided between several free-floating providers.

Second, it could be that customers with a pay-per-use bias are less price sensitive. To test this alternative, we analyze the number of discounted cars that the customers with and without errors booked. Discounted cars are usually cars in remote locations. The trip-level data show that customers have to walk longer distances to reach a discounted car than a nondiscounted car.[18] Thus, opting for the cheaper but likely more distant car can be seen as a trade-off between price and distance and thereby an indicator of price sensitivity, given that nondiscounted cars are also available. Looking at high-frequency customers, we find that customers who exhibit a pay-per-use bias book slightly more discounted cars (in 17% of months with trips) than customers without a bias (in 14% of months with trips). This finding works against the argument that these customers are less price sensitive.

Preference for Flexibility

Second, as shown by the previous literature, customers can be guided by their preferences when choosing a pricing plan (e.g., Krämer & Wiewiorra, 2012; Lambrecht & Skiera, 2006). For example, they might prefer a pricing plan because they value certain characteristics about it. In our context, we presume that customers may have a preference

[18] Looking at distances < 1 km from the location of booking to the location of the reserved car, discounted cars are on average 86 m further away than the nondiscounted cars.

for flexibility. We analyze whether customers are primarily guided by their preference for flexibility rather than price, which increases their likelihood of making an error.[19]

To analyze a possible preference for flexibility, we first calculate the premium that the customers paid on average per month for not committing to a flat rate but using the flexible pay-per-use option instead. The overall premium that the customers pay, on average, to stay flexible is 23%. When looking at only the second sample period, the average premium is 33%. As a result, the customers pay a considerable mark-up to avoid committing to a flat rate. The second indication of a preference for flexibility results from the comparison of errors made in the first and second sample periods. As indicated before, the minimum 30-day package that could be booked in the first period was 60 minutes and 125 minutes in the second period. Figure 4 shows that the proportion of errors to no errors increases significantly ($p < .01$) from 57% in the first period to 65% in the second period. This result is robust when we control for the cohort and trip frequency. The relative increase in errors in the second period is consistent with the argument that due to the higher commitment customers have to make in the second period (125 minutes instead of 60 minutes), they are even less willing to give up their flexibility and as a result, make more errors in the second period.

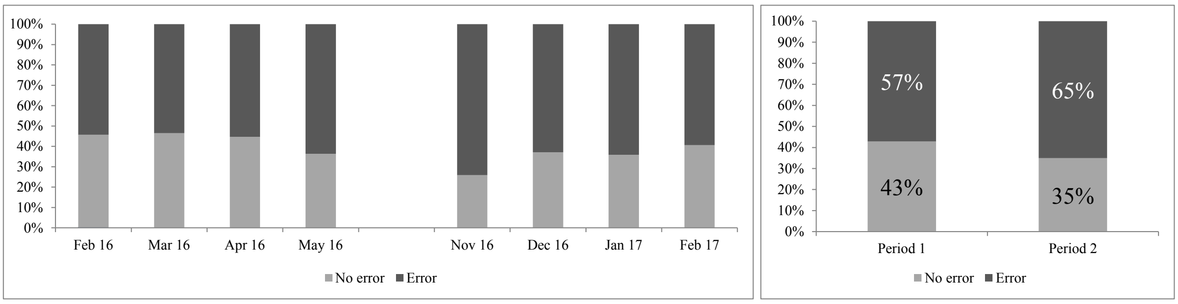

Figure 4 Comparison of Errors to No Errors across Two Sample Periods

[19] A potential alternative explanation may be risk aversion. However, risk averse consumers should choose the flat-rate instead of the pay-per-use rate. Further, given the moderate amount of money required for a car sharing trip, the customers should be locally risk neutral (DellaVigna and Malmendier 2006).

Physical Context

Finally, we suggest that the physical context (i.e., the real-world environment) can also help explain the occurrence of a pay-per-use bias. As shown by several studies, the physical context can have a significant impact on consumer behavior when consumers use their mobile phones (e.g., Andrews, Luo, Fang, & Ghose, 2016; Kannan & Li, 2017). In our context, we propose that the two main contextual factors are weather and home location. To measure the weather, we use the mean monthly level of precipitation as this is likely to affect the use of car sharing. As seen from the panel probit estimation displayed in Table 6, when we control for trips within these months, the customers made more errors in months with, on average, higher levels of precipitation than they did in months with smaller levels of precipitation. This suggests that weather, measured here by precipitation, is correlated with a higher error likelihood.

Dependent variable: 0 = No error, 1 = Error	Parameter	SE
Precipitation (mean month)	0.204***	(0.067)
Access to public transportation	-0.107***	(0.040)
Traffic (mean)	-4.62×10^{-4}***	(1.76×10^{-4})
Roundtrips per month	-0.035*	(0.018)
Total trips per month	0.081***	(0.006)
Period	0.130**	(0.059)
Southeast region	-0.083	(0.399)
Northwest region	-0.188	(0.407)
Southwest region	0.040	(0.400)
Northeast region	-0.210	(0.536)
Constant	0.432	(0.450)
Observations	3,458	
Number of customers	1,610	

Table 6 Panel Probit Regression Analysis of Physical Context

Notes. Standard errors appear in parentheses. The number of observations does not equal 5,675 because the home location is not available for all customers.
The fifth region, which is the baseline, is the region surrounding the business area.
*** p<0.01, ** p<0.05, * p<0.1

The second factor we look at is the customer's home location with regard to surrounding mobility options, specifically, access to public transportation[20] and traffic patterns. As again depicted in Table 6, we find that the error likelihood is higher when the degree of access to public transportation is low than when public transportation is more accessible. To support the previous finding that home location matters, we also analyze the impact of traffic in the vicinity of the home location. We match the location of 17 traffic counters with the customers' home locations and add average traffic data for the sample period.[21] Although we identify only a minor effect, Table 6 shows that the error likelihood is again

[20] The data on access to public transportation accurately measure the access to public transportation, taking into account walk access time and service availability. It is reported on an area level, where each area was given an average score out of 8, where 8 is the highest level of accessibility.

[21] This analysis was only carried out for customers living within the operational area of the car sharing provider, as we only have access to data for traffic counters within this area.

slightly higher when there is less traffic in the vicinity of the home location than when there is more traffic.

Among other controls, Table 6 includes “roundtrips per month”, representing trips that start and end at approximately the same location (within a 500 m radius).[22] This indicates that the error likelihood is higher when there are fewer roundtrips per month (p =. 055). Assuming that roundtrips are planned trips, as the return journey is also taken into account, one could argue that the error likelihood is higher when customers make more unplanned trips, indicating that the predictability of trips is lower for these customers than others.

To interpret the presented effects of the physical context, we draw on the unpredictability of trips and the resulting underestimation of usage, as illustrated before. Weather in general and in particular, the number of days with rain in a month, are rather unpredictable. We assume that the customers use car sharing more often when it is raining than on days when it does not rain and that they make more unplanned trips when it is raining. In terms of public transportation, we propose that having limited access to public transportation is positively correlated with the likelihood of using other mobility options more often than those who have good access to public transportation and thereby the likelihood of using car sharing. The amount of traffic may affect how often the customers use care sharing – they may be more likely to use car sharing when there is less traffic than when there is more traffic. We propose that all these context factors (i.e., rain, less access to public transportation, and less traffic) increase the uncertainty as to which mode of transportation is used and how often it is used, which probably leads customers to underestimate their usage, which increases the error likelihood.

[22] “Roundtrips per month” and “total trips per month” are correlated at .51. However, excluding “roundtrips per month” hardly changes the results, as Appendix 4 shows.

4.3 Additional Survey

To validate the possible explanations for the observed pay-per-use bias, we conducted an additional survey (see Appendix 5). We recruited 120 participants in the country in which our data originated (39.17% female, M_{age} = 31.52 years, SD = 10.33 years) from an online crowdsourcing platform where participants completed a web-based survey in exchange for a fixed fee.

We asked the participants to rate different items related to possible reasons for the observed pay-per-use bias, namely, underestimation, mental capacity, price sensitivity, flexibility, and the physical context, using 7-point scales (1 = *not difficult at all* – 7 = *very difficult*). The results provide additional support for the possible explanations previously described (see Table A2 in Appendix 5). Starting with underestimation, the results indicate that the customers might not be aware of their underestimation. However, we find support for our argument that underestimation may be driven by overconfidence and the fact that customers underestimate the variance in their future consumption. Moving to alternative explanations, the survey supports our claim that the lack of mental capacity does not explain this underestimation. Regarding flexibility, all items are highly significant in a test against the scale mean and demonstrate the highest means across all explanations. This emphasizes that the preference for flexibility is a strong driver of the pay-per-use bias. Finally, the different items with regard to the physical context (related to the weather, traffic, and access to public transportation) are also significant, providing additional support for these explanations.

To analyze the potential relationships among the different possible explanations, we examine the correlations among the different constructs (see Table A3 in Appendix 5). Several of these correlations support our prior arguments. For example, we argue that the influence of the physical context leads to the underestimation of usage, which is also reflected in the positive correlation between the physical context and underestimation (0.25, $p <. 01$). Overall, underestimation, flexibility, and the physical context are all positively correlated. This supports the conclusion that all three explanations are likely to occur together.

5 Robustness Checks

Alternative Error Calculations

The underlying approach we use for the error calculation is to calculate the errors "ex post", thereby following the typical approach used in the tariff choice literature (e.g., DellaVigna & Malmendier, 2006). As a result, we observe customer behavior and the resulting cost at the end of each month and we evaluate whether a different pricing plan (i.e., a 30-day package) would have been less expensive for the respective month or not. One could argue that the customers do not have perfect foresight and that an error calculation should take an "ex ante" approach based on the expected cost. Therefore, to ensure that our error calculation is robust, we conduct alternative error calculations based on measures of the expected cost. We analyze five different measures of the expected cost: 1) the cost of the mean number of minutes (calculated over the accrued minutes up to the current month), 2) the cost of last month, 3) the average of measures 1) and 2), 4) the cost of the first active month, and 5) the cost of the mean number of minutes of a peer customer group (depending on low, medium, and high trip frequency). To identify whether an error occurred, we compare the measure of the expected cost to the cost of the driven minutes without a savings package in the respective month. An error occurred if the cost of the monthly driven minutes was higher or 20% lower (assumed error margin) than the expected cost and if a 30-day package would have been less expensive in the respective month. The error percentages based on these five different measures are 28.12%, 26.06%, 27.17%, 27.63%, and 26.50%, respectively (see Appendix 6 for more details). The alternative error calculations vary slightly in size but are relatively similar. Our applied ex post calculation yields an error percentage of 24.77%. Given the similarity in the error percentages between the ex-ante and the ex-post calculations, we argue that the ex-post calculation is a valid (even at the lower bound) measure of the errors committed.

In addition, we analyze whether the error percentage significantly changes if we base our calculations on time windows other than the currently underlying calendar months. For example, we analyze 30-day windows starting in the middle of one month (e.g., Feb 16) and ending in the middle of the following month (Mar 16). We compare the error percentage based on our first proposed measure of the expected cost (the accrued mean minutes) for the different time windows, and the results show that the measure is slightly lower for the mid-to-mid months calculation (26.41%) than that for the calendar month calculation (28.12%). However, since the difference is rather small, we suggest that our results are robust to changing the time window (for more details, see Appendix 7).

Intermittent Activity

Another robustness check focuses on "intermittent activity", i.e., months with zero usage. Our current underlying sample consists of 13,975 month-customer combinations with 5,441 unique customers being active in at least one month of the observation period. For the construction of this sample, we count only active months. Thus, if customers were active in one month (e.g., Feb 16) and again active in a month not adjacent to this month (e.g., May 16), we did not count the two inactive months in between (i.e., Mar 16 and Apr 16). To analyze the robustness of our approach, we examine how our results would change if we included inactive months in our sample.

We apply three different approaches (see Appendix 8). First, we include only intermittent inactive months (i.e., months between active months as in the example above), which changes the percentage of months with errors from the current value of 24.77% (based on

13,975 month-customer combinations) to 21.46% (based on 16,131 month-customer combinations). Second, we add all inactive months for all customers that were active in Feb 16, which changed the percentage of months with errors from the current value of 24.77% to 19.97% (based on 8,493 month-customer combinations). Finally, we add all inactive months for all customers after their registration, which changes the percentage of months with errors from the current value of 24.77% to 10.17% (based on 32,445 month-customer combinations). For the second and third approaches, we assume termination after four months, i.e., after customers had been inactive for half of our observation period. When comparing the error percentages across these three approaches, the error percentage slightly decreases for approaches one and two, but it remains comparable in size. Only when all inactive months are added, as in the third approach, the error percentage significantly decreases due to the large number of inactive months added in the first period. How much the error percentages change also depends on the underlying assumptions (e.g., termination). However, since the error percentages do not significantly differ for the first two approaches, we argue that our results are robust to including some intermittent activity (potentially constituting an upper bound).

6 Conclusion

We analyze consumers' decisions among different pricing plans in a car sharing context. We observe that pay-per-use is the dominant pricing plan, and we show that more than 40% of the customers exhibit a pay-per-use bias that is persistent over time. We propose three possible explanations: The first explanation is the underestimation of usage, likely driven by overconfidence. The second explanation is that customers may be primarily guided by their preference for flexibility. As a consequence, the customers pay, on average, a premium of 23% for this flexibility. Third, we suggest that physical factors, specifically weather and the home location, help explain the occurrence of a pay-per-use bias. The error likelihood increases as the average level of precipitation increases and decreases as access to public transportation and the level of traffic decrease.

Our results suggest that a considerable proportion of car sharing customers make errors in their pricing plan decisions, which could potentially prevent them from using or recommending car sharing services in the long term. Thus, policy makers should help consumers avoid underestimating their usage of car sharing services. This could, for example, be achieved by offering and promoting apps in which the usage and cost of different modes of transportation could be tracked. On a broader scale, policy makers should educate consumers about which modes of transportation are optimal for them given their preferences and home locations. This may be achieved by providing customers with decision aids facilitating the calculation of their costs and optimal mode of transportation choice.

We believe that our findings are (to some extent) generalizable to other parts of the Sharing Economy. The choice between flat-rate and a pay-per-use options can be found in many other sharing industries, such as fashion, work spaces, and consumer electronics. Given that consumers' usage motivations and expectations in the Sharing Economy differ from those in traditional usage settings (e.g., car sharing vs. car buying), our findings of a more prevalent pay-per-use bias may apply across different Sharing Economy business models. We therefore expect that a pay-per-use bias may be the prevalent tariff choice bias in the Sharing Economy.[23]

Our study has some limitations. First, we observe situations in which customers make a trip, but we do not know if or how often they considered using car sharing but then opted

[23] It may be possible that the finding of the pay-per-use bias in this paper is related to the context of (public) transportation usage rather than the Sharing Economy setting (which is in the realm of transportation). However, this is unlikely as previous research documents that customers exhibit a flat-rate bias in the context of public transportation; see Uhrich et al. (2013).

for a different mode of transportation. Second, in a similar vein, we do not observe the competition (i.e., substitute modes of transportation, such as ride sharing or public transportation). Third, our dataset is limited to one city and one car sharing provider. Finally, we acknowledge that our results are descriptive as opposed to causal and that we cannot choose among the likely explanations that cause the bias. We hope that future works will be able to address these limitations.

Appendix

Appendix 1 Number of Total Trips and Trips without Savings Package

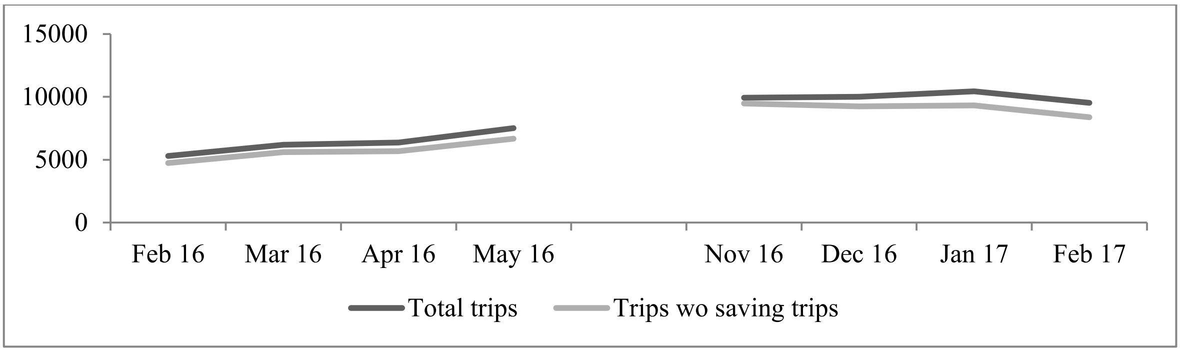

Figure A1 Number of Total Trips and Trips without Savings Package

Appendix 2 Number of New Customer Registrations

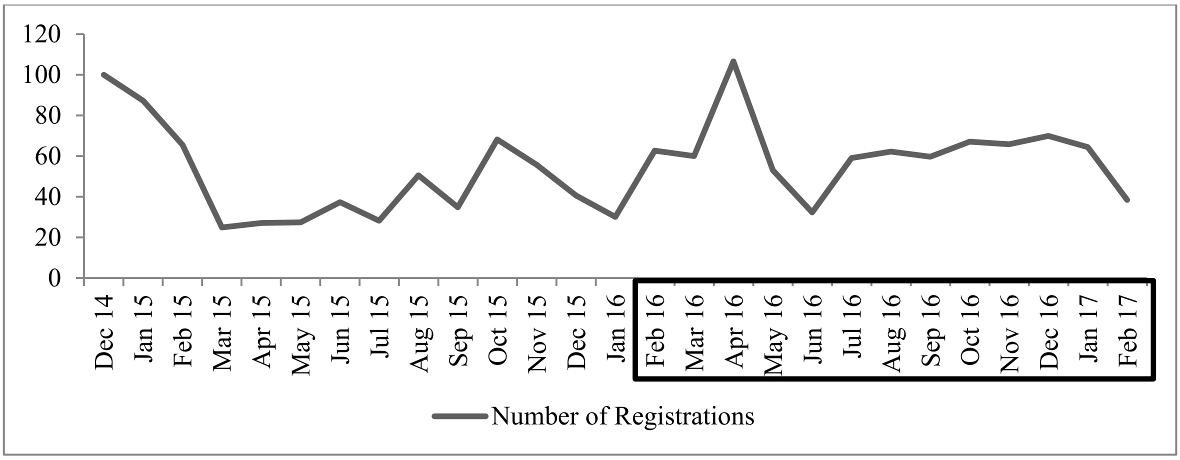

Figure A2 Number of New Customer Registrations (indexed, Dec 14 = 100%)

Appendix 3 Number of Active Customers

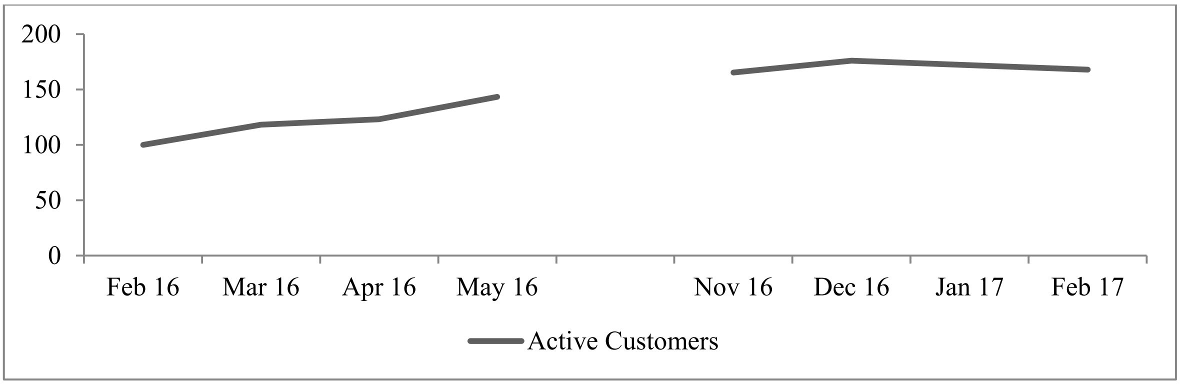

Figure A3 Number of Active Customers (indexed, Feb 16 = 100%)

Appendix 4 Panel Probit Regression Analysis

Dependent variable: 0 = No error, 1 = Error	Parameter S.E.	Parameter S.E.
Precipitation (mean month)	0.206*** (0.0666)	0.204*** (0.0666)
Access public transportation	-0.103*** (0.0394)	-0.107*** (0.0395)
Traffic (mean)	-4.78×10^{-4}*** (1.76×10^{-4})	-4.62×10^{-4}*** (1.76×10^{-4})
Roundtrips per month		-0.0354* (0.0184)
Total trips per month	0.0767*** (0.00521)	0.0810*** (0.00574)
South-east region	-0.0933 (0.399)	-0.0834 (0.399)
North-west region	-0.215 (0.406)	-0.188 (0.407)
South-west region	0.0273 (0.400)	0.0403 (0.400)
North-east region	-0.242 (0.536)	-0.210 (0.536)
Period	0.125** (0.0592)	0.130** (0.0593)
Constant	0.422 (0.450)	0.432 (0.450)
Observations	3,458	3,458
Number of customers	1,610	1,610

Table A1 Panel Probit Regression Analysis on Physical Context

Notes. Standard errors in parentheses. Number of observations not equal to 5,675 as home location is not available for all customers. The fifth region as the benchmark is the region surrounding the business area.
*** p<0.01, ** p<0.05, * p<0.1

Appendix 5 Additional Survey

	Test vs. scale mean (4)		
Constructs	**Mean**	**S.E.**	**t-val**
Underestimation			
U1 I underestimate my monthly usage.	4.09	0.15	0.61
U2 The probability to use car sharing less than 125 minutes in 30 days is higher than the probability to use car sharing more than 125 minutes in 30 days.	4.79***	0.15	5.27
U3 The risk of using car sharing less than 125 minutes is higher than the risk of using car sharing more than 125 minutes.	4.51***	0.17	3.04
U4 I think that I am better than others at estimating my monthly car sharing costs.	4.53***	0.14	3.67
Mental capacity			
M1 I find it difficult to calculate my monthly costs.	4.17	0.16	1.05
M2 I find it difficult to estimate the variation in trips between months	4.88***	0.14	6.17
Price sensitivity			
P1 I do not care much about prices of car sharing services.	3.51	0.18	-2.77
P2 It is too much trouble to compare prices of car sharing services.	4.02	0.17	0.10
P3 It takes so long to figure out which pricing plan is better that the effort normally isn't worth it.	4.01	0.16	0.05
P4 I do not pay much attention to discounts.	3.2***	0.17	-4.65
Flexibility			
F1 It bugs me when the 30-day package wasn't profitable in a month.	5.23***	0.14	9.05
F2 It feels like a deficit when pay-per-use pricing would have been cheaper than the 30-day package in a month.	4.98***	0.14	7.21
F3 It matters to me to max out the 30-day package.	5.23***	0.14	8.88
F4 I do not want to commit to a fixed amount of car sharing minutes at the beginning of the month.	5.01***	0.15	6.88
F5 I want to remain flexible in what means of transport I use (e.g., car sharing, ride sharing, public transportation, taxi).	5.32***	0.13	10.03
F6 I am willing to pay a little more in order to remain flexible.	5.11***	0.12	9.28
Physical context			
C1 I use car sharing more often when it is raining. However, it is difficult to predict the weather at the beginning of the month, which is why I prefer pay-per-use pricing.	4.73***	0.15	4.73
C2 If in one month I expect many trips during peak hours with increased traffic, I prefer other modes of transport and refrain from booking a 30-day package.	4.85***	0.16	5.48
C3 Since I am poorly connected to public transportation, I own a car. This prevents me from frequently using car sharing, which is why I prefer pay-per-use pricing.	4.59***	0.19	3.17

Table A2 Additional Survey Single Items
Notes: N = 120, *** p<0.01, ** p<0.05, * p<0.1

	underesti-mation	mental capacity	price sensitivity	flexibility	physical context
underestimation	1				
mental capacity	0.08	1			
price sensitivity	0.24***	0.38***	1		
flexibility	0.21**	0.10	-0.06	1	
physical context	0.25***	0.21**	0.32***	0.15*	1

Table A3 Additional Survey Correlation Matrix
Notes: N = 120, *** p<0.01, ** p<0.05, * p<0.1

Appendix 6 Alternative Error Calculations

1) ***Minutes without package compared to accrued mean minutes*** *(rolling mean of minutes in past months, first month excluded since no prior month exists, therefore N changes to 8,534)*

Error category	**Frequency**	**Percent**
No error possible	5,649	66.19
No error	485	10.99
Error	2,400	28.12
Number of observations	8,534	

Table A4 Error Calculation based on Cost of Mean Minutes

2) ***Minutes without package compared to minutes of the last active month*** *(first month excluded since no prior month exists, therefore N changes to 8,534)*

Error category	**Frequency**	**Percent**
No error possible	5,649	66.19
No error	661	7.75
Error	2,224	26.06
Number of observations	8,534	

Table A5 Error Calculation based on Cost of Last Month

3) ***Average of mean accrued minutes (1) and minutes of the last active month (2)***

Error category	**Frequency**	**Percent**
No error possible	5,649	66.19
No error	566	6.63
Error	2,319	27.17
Number of observations	8,534	

Table A6 Error Calculation based on Average of Measures 1) and 2)

4) *Minutes without package compared to minutes of the first active month*

Error category	Frequency	Percent
No error possible	9,484	67.86
No error	630	4.51
Error	3,861	27.63
Number of observations	13,975	

Table A7 Error Calculation based on Cost of First Month

5) *Minutes without package compared to mean minutes of customer group (3 customer groups based on trip frequency/month/user)*

Error category	Frequency	Percent
No error possible	9,484	67.86
No error	787	5.63
Error	3,704	26.50
Number of observations	13,975	

Table A8 Error Calculation based on Cost of Mean Minutes of Peer Customer Group

Appendix 7 Error Calculation for Mid- to-Mid-Month Time Window

Minutes without package compared to accrued mean minutes *(rolling mean of minutes in past months, first month excluded since no prior month exists, therefore N changes to 8,534 and 8,227)*

Calendar months

Error category	Frequency	Percent
No error possible	5,649	66.19
No error	485	10.99
Error	2,400	28.12
Number of observations	8,534	

Table A9 Error Calculation based on Cost of Mean Minutes – Calendar Months

Mid-to-mid months

Error category	Frequency	Percent
No error possible	5,540	67.34
No error	514	6.25
Error	2,173	26.41
Number of observations	8,227	

Table A10 Error Calculation based on Cost of Mean Minutes – Mid-to-Mid Months

Minutes without package compared to minutes of the last active month *(first month excluded since no prior month exists, therefore N changes to 8,534 and 8,227)*

Calendar months

Error category	Frequency	Percent
No error possible	5,649	66.19
No error	661	7.75
Error	2,224	26.06
Number of observations	8,534	

Table A11 Error Calculation based on Cost of Last Month – Calendar Months

Mid-to-mid months

Error category	Frequency	Percent
No error possible	5,540	67.34
No error	647	7.86
Error	2,040	24.80
Number of observations	8,227	

Table A12 Error Calculation based on Cost of Last Month – Mid-to-Mid Months

Appendix 8 Intermittent Activity

1) Include intermittent months (only between active months)

In this setting, there are no inactive months in the first month of our observation period (Feb 16), since we only "fill up" inactive months between active months within the observation period. Following this approach, the percentage of months with errors changes from currently 24.77% to 21.46%, as can be seen below (including new category "Not active").

Error category	Frequency	Percent
Not active	2,156	13.37
No error possible	8,300	51.45
No error	2,214	13.73
Error	3,461	21.46
Number of observations	16,131	

Table A13 Errors Including Intermittent Activity between Active Months

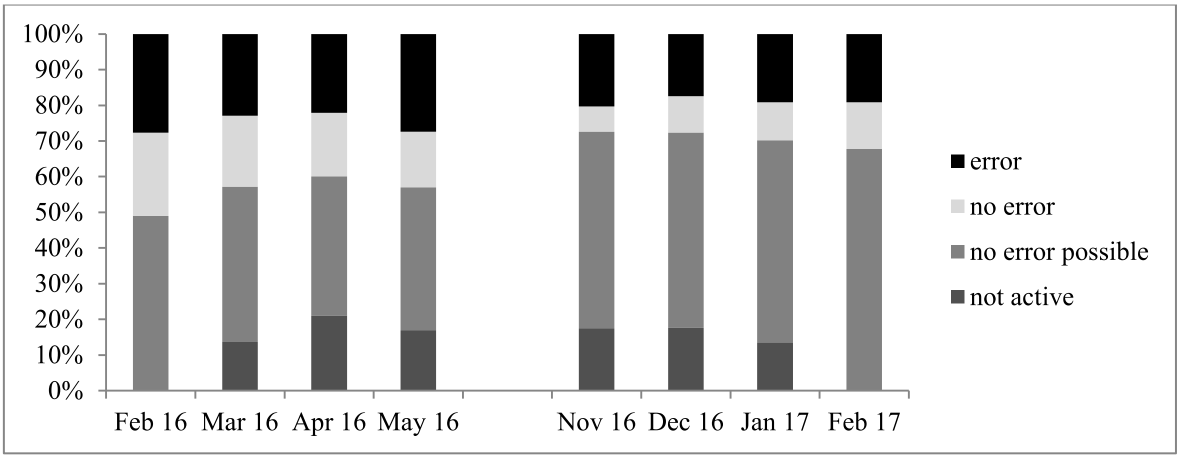

Figure A4 Comparison of Errors to No Errors including Intermittent Activity

2) Include inactive months for all customers active in the first month of the observation period (Feb 16)

In this setting, all inactive months after Feb 16 are "filled up" for all customers that were active in Feb 16. We assumed termination after four inactive months. Following this approach, the percentage of months with errors changes from currently 24.77% to 19.97%, as can be seen below (including new category "Not active").

Error category	Frequency	Percent
Not active	3,263	38.42
No error possible	2,733	32.18
No error	801	9.43
Error	1,696	19.97
Number of observations	8,493	

Table A14 Errors Including Intermittent Activity after Feb 16

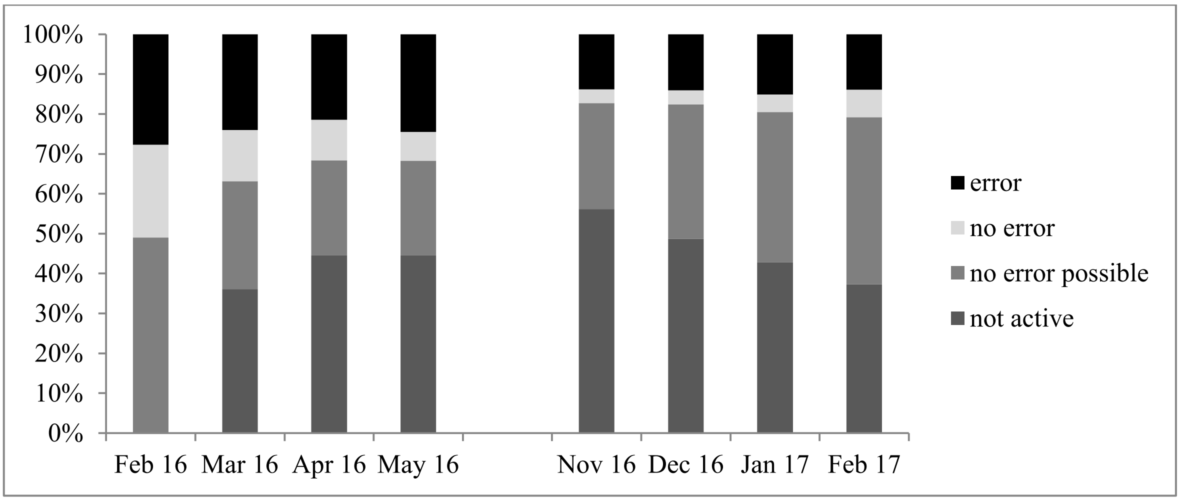

Figure A5 Comparison of Errors to No Errors including Intermittent Activity

3) Include inactive months for all customers

In this setting, all inactive months are "filled up" for all customers. We assumed termination after four inactive months. For customers that only registered after Feb 16, inactive months were naturally only added after their registration date. Following this approach, the percentage of months with errors changes from currently 24.77% to 10.17%, as can be seen below (including new category "Not active").

Error category	Frequency	Percent
Not active	19,589	60.38
No error possible	7,664	23.62
No error	1,893	5.83
Error	3,299	10.17
Number of observations	32,445	

Table A15 Errors Including Intermittent Activity for all Customers

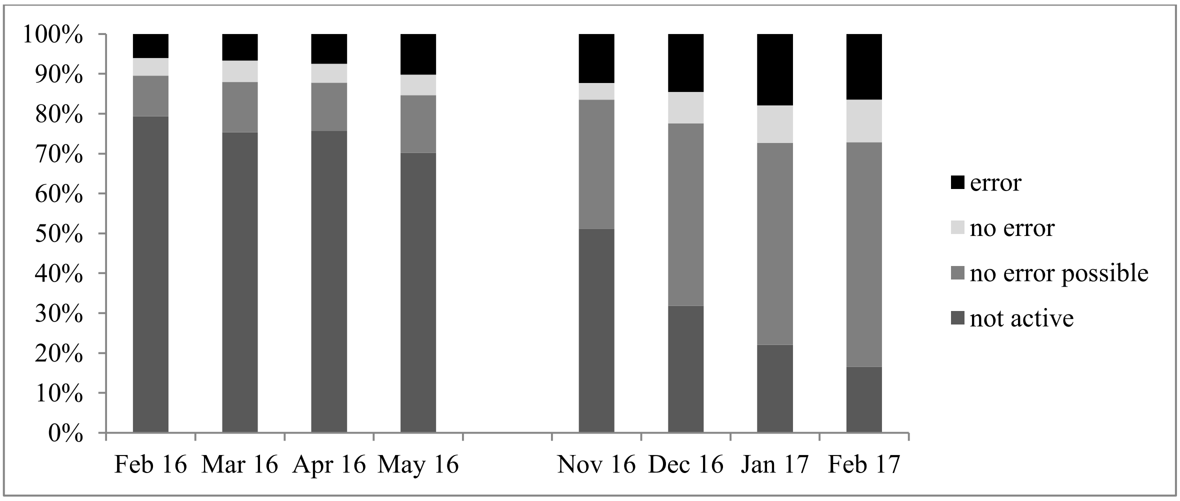

Figure A6 Comparison of Errors to No Errors including Intermittent Activity

References

Andrews, M., Luo, X., Fang, Z., & Ghose, A. (2016). Mobile Ad Effectiveness: Hyper-Contextual Targeting with Crowdedness. *Marketing Science*, *35*, 218–233.

Benoit, S., Baker, T. L., Bolton, R. N., Gruber, T., & Kandampully, J. (2017). A Triadic Framework for Collaborative Consumption (CC): Motives, Activities and Resources & Capabilities of Actors. *Journal of Business Research*, *79*, 219–227.

Conner-Simons, A. (2017). How Ride-Sharing Can Improve Traffic, Save Money, and Help the Environment. Retrieved from http://news.mit.edu/2016/how-ride-sharing-can-improve-traffic-save-money-and-help-environment-0104

DellaVigna, S., & Malmendier, U. (2006). Paying Not to Go to the Gym. *American Economic Review*, *96*, 694–719.

Farajallah, M., Hammond, R. G., & Pénard, T. (2019). What Drives Pricing Behavior in Peer-to-Peer Markets? Evidence from the Carsharing Platform BlaBlaCar. *Information Economics and Policy*, 1-17.

Gerrard, B. (2017). Is the Car Sharing Industry Finally Ready to Move up a Gear? Retrieved from https://www.telegraph.co.uk/business/2017/10/15/car-sharing-industry-finally-ready-move-gear/

Grubb, M. D., & Osborne, M. (2015). Cellular Service Demand: Biased Beliefs, Learning, and Bill Shock. *American Economic Review*, *105*, 234–271.

Hall, J., Kendrick, C., & Nosko, C. (2015). The Effects of Uber's Surge Pricing: A Case Study. *The University of Chicago Booth School of Business*. Retrieved from https://www.valuewalk.com/wp-content/uploads/2015/09/effects_of_ubers_surge_pricing.pdf

Heathman, A. (2017). These Are the Highest Valued Startups in the World Right Now. Retrieved from https://www.verdict.co.uk/top-10-startups-valuation/

Iyengar, R., Ansari, A., & Gupta, S. (2007). A Model of Consumer Learning for Service Quality and Usage. *Journal of Marketing Research*, *44*, 529–544.

Iyengar, R., Jedidi, K., Essegaier, S., & Danaher, P. J. (2011). The Impact of Tariff Structure on Customer Retention, Usage, and Profitability of Access Services. *Marketing Science*, *30*, 820–836.

Kannan, P. K., & Li, H. "A.". (2017). Digital Marketing: A Framework, Review and Research Agenda. *International Journal of Research in Marketing*, *34*, 22–45.

Kiron, D. (2013). How Next Gen Car Sharing Will Transform Transportation. Retrieved from https://sloanreview.mit.edu/article/how-next-gen-car-sharing-will-transform-transportation/

Krämer, J., & Wiewiorra, L. (2012). Beyond the Flat Rate Bias: The Flexibility Effect in Tariff Choice. *Telecommunications Policy*, *36*, 29–39.

Lamberton, C. P., & Rose, R. L. (2012). When is Ours Better than Mine? A Framework for Understanding and Altering Participation in Commercial Sharing Systems. *Journal of Marketing*, *76*, 109–125.

Lambrecht, A., & Skiera, B. (2006). Paying Too Much and Being Happy About It: Existence, Causes, and Consequences of Tariff-Choice Biases. *Journal of Marketing Research*, *43*, 212–223.

Lawson, S. J., Gleim, M. R., Perren, R., & Hwang, J. (2016). Freedom from Ownership: An Exploration of Access-based Consumption. *Journal of Business Research*, *69*, 2615–2623.

Leider, S., & Şahin, Ö. (2014). Contracts, Biases, and Consumption of Access Services. *Management Science*, *60*, 2198–2222.

Miravete, E. J. (2002). Choosing the Wrong Calling Plan? Ignorance and Learning. *American Economic Review*, *93*, 297–310.

Price, R. (2018). Toyota is Investing $500 Million in Uber at a $72 Billion Valuation as Part of a Self-driving-Car Partnership. Retrieved from https://www.businessinsider.de/toyota-to-invest-500m-in-uber-at-72b-valuation-report-2018-8?r=US&IR=T

Szymanowski, M., & Gijsbrechts, E. (2013). Patterns in Consumption-Based Learning about Brand Quality for Consumer Packaged Goods. *International Journal of Research in Marketing*, *30*, 219–235.

Train, K. E., McFadden, D. L., & Ben-Akiva, M. (1987). The Demand for Local Telephone Service: A Fully Discrete Model of Residential Calling Patterns and Service Choices. *The RAND Journal of Economics*, *18*, 109–123.

Uhrich, F., Schumann, J. H., & Wangenheim, F. von. (2013). The Impact of Consumption Goals on Flat-Rate Choice. *Journal of Service Research*, *16*, 216–230.

Zervas, G., Proserpio, D., & Byers, J. W. (2017). The Rise of the Sharing Economy: Estimating the Impact of Airbnb on the Hotel Industry. *Journal of Marketing Research*, *54*, 687–705.