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Attribute pricing strategies in the road bike market

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Table of contents

Summary

In this research, we combine hedonic price regression and conjoint analysis to investigate the pricing strategies in the road bike market. With hedonic price regression, we investigate the effect of attributes of a bike on the retail price and with conjoint analysis, we investigate the effects of the attributes on the willingness to pay. The results of this combination show that customer value-based pricing, which is the most optimal pricing strategy, is not completely applied in the road bike market.

We find the following improvements which are easy to implement for retailers of road bikes. First, the weight of a bike should be one of the most important factors in determining the retail price, since it is one of the most important variables in determining the willingness to pay of a bike. Second, groupsets from the brand Shimano are the cheapest and also the most preferred. Therefore, retailers should focus mainly on bikes with these groupsets and they can higher the prices of bikes with a Shimano groupset. Third, for bikes above €1500, the willingness to pay for a bike from 2019 is almost the same as for a similar bike from 2020. Therefore, we advise to reduce/remove discounts for models which are only 1 year old. Beside these general improvements, we also present a lot of smaller improvements which are only valid for budget bikes (€500-€1500), mid-range bikes (€1500-€4000) or expensive bikes (€4000+).

Finally, we segment the market based upon demographic and psychographic variables. We find that whether people participate in races is the best segmentation variable. People who participate in races are more price sensitive, more interested in lighter bikes and more interested in Shimano or SRAM groupsets compared to people who do not participate in races. Also, the demographic variable gender is a possible segmentation variable regarding brands. Men prefer the brands Bianchi and Wilier and women prefer Bianchi and Cube. With this information, a road bike retailer can target their Wilier bikes completely to men and their Cube bikes completely to women and slightly increase the prices of these brands.

Introduction

During the corona crisis, the demand for (road) bikes exceeded the supply of the bike shops in The Netherlands and the rest of Europe (Nu.nl, 2020). This is quite remarkable because big online bike shops have a lot of road bikes in their assortments, for example, on 25 March 2020 online bike shop 12gobiking.nl (2020) had 297 different types of road bikes and another online retailer (mantel.com, 2020) had 249 different road bike models for sale. Also before this corona crisis the market of road bikes was expanding. The total of all bikes sales reached a new maximum with total revenue of 1.25 billion euros in 2019 (RTL Z, 2020). However, the biggest part of this 1.25 billion dollars was generated by electric bikes and city bikes. Only 10% of the revenue was created by mountain bikes, road bikes and folding bikes.

Due to the fast expanding market size and the high amount of supply divided over couple of big and a lot of small (web) shops, the market for road bikes is expected to be very competitive. Therefore, choosing the right prices for the right bikes is a crucial part of the marketing strategies of retailers which are operating in this market. The goal of this research is to give recommendations about the pricing strategy to road bike retailers regarding the different attributes of road bikes by answering the following research question:

How can retailers of road bikes improve their pricing strategies regarding the different attribute levels of road bikes?

To answer this question, first, the current prices in the market are analysed. This is done with a hedonic price regressions on data scraped from the websites of 9 big road bike retailers. With this data, the effect of different attributes of road bikes on the retail price is analysed. Then the attributes which are the most important for the retail prices are used in a conjoint analysis. The results of this study show whether the attribute levels have the same level of importance for the willingness to pay as for the retail prices. The combination of these two analyses is interesting in investigating whether companies use customer value-based pricing or another pricing method since both the supply and demand side of the market are analysed.

The results of the conjoint analysis are useful in finding improvement in the pricing strategy of road bikes. This helps us understand which attributes of road bikes are the most important for customers. Retailers of road bikes can base their prices upon the information from this conjoint analysis. Finally, the results of the conjoint analysis are used to determine whether there are different segments in the market. Segments based upon demographic and psychographic variables are important for applying different pricing strategies to different groups of customers with their own preferences.

The combination of hedonic price regression and conjoint analysis for marketing purposes is something which is not commonly used in marketing research. Combining these two approaches, however, leads to valuable marketing insights from both the supply and the demand side of the market. Therefore, this paper, which is a case study of the road bike market, can also be seen as a stepping stone for the combination of hedonic price regression and conjoint analysis in a marketing-related context.

To help answering the research question and to gain more insight into pricing strategies in general, first, the theoretical framework discusses existing literature relating to this subject. Furthermore, literature about perceived value, segmentation and the approaches of conjoint analyses is discussed. Then in the data section, the collection process of the web scraping data is explained and the design of the conjoint study is discussed. In the method section, all methods used to analyse these datasets are explained in detail. Next, the results are presented in the results section and the marketing implications for the retailers of these results are given. Finally, in the conclusion and discussion, the research question is answered and the main limitations of this research are discussed.

Theoretical framework

Customer value-based pricing

In marketing, a lot of different and complex price strategies are available (Mullins & Walker Jr, 2013). However, all those strategies can be roughly divided into three classes. The first strategy is basing the retail prices upon the cost of the product. A company which is using this strategy calculates the costs of a product, then adds a fixed profit margin to the costs and uses this as the final retail price. The second method is determining the prices based on competitors' prices. This means that the company is setting the prices so that it can be competitive in the market. The final approach is customer value-based pricing, this means that a company bases its prices upon the perceived value and the willingness to pay of their customers. It is important to realise that almost all companies use a combination of these three methods, but most of the time one or two of these methods dominates the others.

The three commonly known basic strategies are known as cost-based pricing, customer value-based pricing and competition-based pricing. From these three strategies, customer value-based pricing is often considered as the best strategy for retailers. For example, Cannon and Morgan (1991) argued that customer value is the most important in setting a price when profit maximisation is the main objective of a firm. In their book, Docters, Reopel, Sun and Tanny (2004) stated that customer value-based pricing is one of the best pricing strategies, when feasible. They argued that basing the price upon the added value for its customers leads to higher margins compared to other pricing methods, but still, a lot of customers will buy the product due to the value of the product.

In an empirical study Ingenbleek, Debruyne, Frambach & Verhallen (2003) proved that customer value-based pricing is optimal for new products. They proved this with the use of questionnaires which were answered by general managers or marketing managers of 78 companies. In this questionnaire they asked multiple questions about the price setting strategy of new products and to which degree the product is successful since the launch. They found that value-based pricing has a positive significant effect on new product performances and the other two strategies did not show this significant effect.

In theory, customer value-based pricing seems to be the best pricing strategy. However, 80% of the companies priced their products or services based mainly upon cost and competition (Hinterhuber, 2008). Hinterhuber found five main obstacles for companies to implement value-based pricing. The first obstacle is the difficulty to determine the value of a product. When for the company itself it is not clear what the value of a product to a customer is, then it is hard to put customer value-based pricing into practice. The second difficulty is communicating the value of a product. In this case, the company is aware of the value of a product, but the customer is not. In cases like this, the customers are not aware of the value of a product to themself, therefore, they will not pay a price based on the true customer value.

The third problem (Hinterhuber, 2008) is related to market segmentation, in each market, there are different groups of consumers and some groups care more about the price and others less. For a company, it is essential to know these different segments and their needs to be able to apply a pricing strategy based on customer value. For example, there exist segments in most markets which perceive higher customer value than other segments, which is likely caused by the characteristics of the segment. The fourth difficulty in customer value-based pricing is about sales force management. For example, discounts which were given by the sales team, to increase the number of sales in the short term, can cut significantly in the margins and decrease the profit in the long term. When these discounts are given, customers are in most of the cases paying less than the customer value of the product, so more profit could have been made if the customer value-based price was maintained. The final and last problem which is discussed in this paper are the problems with senior management support. These problems are related to strict targets by the senior management of companies. The senior management of almost all companies wants price premiums and profit maximisation, but on the other side, they do punish people for failing their volume quotas. Because this punishments on volume quotas, most of the prices are lower than the value of the customers and therefore the margins per product are lower compared to a situation in which customer value-based pricing is applied.

Due to the problems described by Hinterhuber (2008), most of the companies base their prices upon cost and competition. Our research first identifies whether the problem of failing to implement customer value-based pricing is also present in the market of road bikes. Then, the effect of different attribute levels on the retail price is investigated and also the effect of different attribute levels on the willingness to pay of the customers is investigated. If companies in the road bike market face the same problems as described by Hinterhuber (2008), the effects of the attribute levels on the retail prices are smaller than the effect of the attribute levels on the willingness to pay, which means that retailers can increase the prices without exceeding the customer-value of most customers.

Perceived value

When a company would like to implement customer value-based pricing, it is important to know the value which is perceived by the customers of all products/attributes that are being sold. However, the perceived value of a customer can depend on a lot of different factors (Zeithaml, 1988). The perceived value is logically dependent of the perceived quality of a product, which is influenced by the intrinsic (for example, colour) and the extrinsic (for example, brand) attributes of a product. But also the price and more complex concepts like high-level abstraction can influence the perceived value of a customer. The last has to do with the beliefs in the mind of the customers instead of the products/attributes itself.

Sweeney and Soutar (2001) investigated which factors influence the perceived value. They created a measurement of perceived value which is based upon four different factors which are similar to the factors as described by Zeithaml (1988). The four factors used by Sweeney and Soutar (2001) are emotional, social, quality/performance and price/value.

First, the effect of the intrinsic attributes (quality/performance) on the perceived value is discussed. Ravald and Grönroos (1996) stated that there are two main approaches to increase the perceived value of a customer. The first one is adding benefits to the product, to create more unique value to the product. These benefits could relate to the core attributes of a product, but they can also relate to extra services which can be added to the products. The second approach is reducing the sacrifice of a customer. This means that it becomes easier for a customer to buy a product, by reducing the effort of purchasing a product. Some examples of reducing the sacrifice are lowering the price, changing the openings hours of the shop or improve the delivery service of the product.

Chen and Hu (2010) tested with the use of surveys whether attributes related to the product and the services lead to a higher perceived value in coffee outlets. They found that adding extra quality or extra services to the coffee increase the perceived value of the coffee. Only the attribute atmosphere in the coffee outlet did not show a positive significant result in this research, but all other attributes did. This implies that adding better attributes increases the perceived value of a customer. Similarly, Sanchez, Callarisa, Rodriguez and Moliner (2006) investigated the perceived value in the tourist branch. They found that quality and price play an important role in the perceived value of a tourist, however, also less tangible factors play a role.

For the road bike market, we expect that the perceived value of a customer is higher when a bike has better attribute levels. This can, of course, be logically explained because bikes with better attributes also have a higher real value. An example, is the frame of a bike, research has shown (Rontescu, Amza, Chivu & Dobrotă, 2015) that titanium is the best material, but very costly. Then carbon is the second-best material and aluminium (alloy) is least optimal. With these results in mind, it is expected that the willingness to pay for carbon bike parts should be higher compared to aluminium parts and more in general, the willingness to pay for attribute levels with the higher quality should be higher.

However, also less intrinsic attributes (Zeithaml, 1988) influence the perceived value of a customer, this might be more related to emotions (Sweeney & Soutar, 2001). An important factor in these intrinsic attributes is the brand. According to Christopher (1996), companies can add a lot of perceived value through branding strategies, while the true value of the products remains unchanged.

The differences between global brands and smaller more local brands are an example of the perceived value which is created by the brand. Steenkamp, Batra & Alden (2003) showed that consumers perceive more value from big global brands than from smaller brands. This is likely to be caused by the belief of consumers that global brands are better in delivering quality and that global brands give them a higher level of prestige.

A research in China (Li, Li & Kambele, 2012) proved that people were willing to pay more for luxury brands. One of the factors they found as an explanation was the emotional/social value of these brands. Which means that the perceived value of these brands is not only caused by intrinsic attributes like quality, but also by extrinsic attributes like the image of the brand.

For the road bike brands, no information is available of their branding strategies. However, it is almost certain that the branding strategies differ per brand and therefore the perceived value should differ between brands. Therefore, we expect to see differences in the willingness to pay of customers for different road bike brands.

Besides the intrinsic and extrinsic attributes also the price itself could influence the perceived value. Erickson and Johansson (1985) investigated this relationship in the car industry. They found that higher-priced cars have a higher perceived value, which is called the price-quality relationship. Further research to this subject (Oh, 2000) found that customers use the price of a product as a signal for quality and most customers also consider the prices of competing products as a reference.

Due to this relationship between price, quality and perceived value, we expect that the price of a road bike influences the perception of quality and the perceived value of the bike. However, considering the traditional demand curve (Frank & Cartwright, 2016) a higher price leads to less demand and thus fewer people are willing to buy the product. So the relationship between the price and whether someone is willing to buy the product is expected to go into two directions. We still expect that the price has some influence on the decision to buy a product, but other attributes might be more important because of the two directions of the effect. Since the willingness to pay is calculated via the effect of the price, the presence of this effect is likely to lower the willingness to pay of all other attribute levels.

Segmentation

Hinterhuber (2008) described that difficulties in segmenting a market (for example, a lack of information) could be one of the problems in applying customer value-based pricing. Customers in different segments experience different values for a product and when this is not recognised correctly, customer value-based pricing could not be applied to all the different groups of customers.

The importance of market segmentation was already described by Smith back in 1956. He described that market segmentation is essential for the planning of successful marketing activities. Later, Dickson and Ginter (1987) described how market segmentation can lead to product differentiation and that enrolling different strategies to the different segments in the market can be beneficial.

Lin (2002) stated that demographic variables are the most important building blocks of segmentation. However, he also admitted that demographic variables are a very rough instrument which does not tell anything over the behaviour of people. Adding psychographic variables (for example, interest) can, therefore, improve the results of the segmentation process so more accurate market segments can be detected. To test whether there are interesting segments based on demographic and psychographic variables in the road bike market, a few demographic and psychographic questions are asked after the conjoint analysis survey and used to determine different groups of customers in the analysis.

Bruwer & Li (2007) investigated segmentation of wine drinkers. They made segments within wine drinkers with the use of demographic and psychographic variables. They found five segments which were based upon the following variables: age, education, employment, gender and interests in wine. Similarly, Johns and Gyimóthy (2002) segmented tourist which visited the Danish island Bornholm. They found that the following variables were important for segmenting the tourists: importance regarding the facilities, nationality, age, participation within activities, the amount of planning they do, attractions they visit, autonomy and gender.

In the road bike market, we expect that segments can be created with the use of demographic and psychographic variables. To make sure that the survey does not become too long, just a couple of variables are asked. Regarding the demographic variables, age and gender seem to be the most important, because they appear in both of the previously discussed empirical studies. Regarding the psychographic variables, in both studies, they are related to the market itself, so in this research, we also use psychographic variables related to someone's interest in cycling and road bikes. With the use of these segments road bike brands and shops can better serve the preferences of the different segments in the market and try to optimise the customer value-based pricing for each segment. For example, retailers can target some bikes particularly to men or to women when there is a big difference between them. They can create a bike which fulfils the preferences of one of the groups and set a price which is in line with the customer value of this group. Similarly, retailers can segment based upon whether people do or do not participated in races/touring events or club rides.

Conjoint analysis

To measure the willingness to pay and the preferences of the customers for the different attributes as described in the previous paragraphs conjoint analysis is used. Conjoint analysis as it is known today was first introduced by Luce and Tukey (1964), they developed this method to measure the effect of the combination of multiple attributes on the preference of customers. Through the years conjoint analysis has had a lot of developments and changes (Green, Krieger & Wind, 2001) but the main idea, that it can deal with situations in which there is variation between two or more attributes, remains the same. Also, changes are expected in the future of conjoint but presumably this will not change the main idea of conjoint.

Nowadays, there are four main methods of conjoint analysis which are commonly used (Rao, 2010). The first method is traditional conjoint which makes use of ratings. Secondly, choice-based conjoint is available which lets respondents choose between multiple products. An adaptive based conjoint is a more advanced technique, which adapts itself to the respondents and could handle more attribute and attribute levels in this way. The last method has a different approach, self-explicated conjoint let people estimate directly their preferences for each single attribute level.

In the traditional conjoint analysis, a product with some attributes and its levels is shown. Then the respondent is asked to rate the product on a scale (Rao, 2010). With the use of all the ratings of all customers on all questions, it is possible to make a (simple) regression model to predict which attribute levels are the most important for a customer. The advantage of this method is that it is pretty simple but due to this it might be not very realistic.

A more realistic approach of conjoint analysis is choice-based conjoint. This method is based upon the behavioural theory of random utility maximization (McFadden, 1973). This theory makes it possible to model individual choices based upon sampling of a population. The choice-based conjoint shows multiple products with different attribute levels per question and people have to choose which of the options they prefer. The results of this approach are most often analysed with the use of a multinomial logit model (Louviere, Henser & Swait, 2000) which has as advantages that is still quite simple, the performances of these models are often acceptable or good and it is more realistic compared to the traditional conjoint analysis.

The third method that is discussed is self-explicated conjoint. In this conjoint approach, the respondent has to indicate what their preferences are for each different attribute level (Green & Srinivasan, 1978). This is a for the respondents a simple task which minimises the effort. However, Srinivasan and Park (1997) compared this method with the choice-based conjoint and they found that self-explicated conjoint was surprisingly robust.

The last conjoint method is adaptive based conjoint (Johnson, Huber & Bacon, 2003). In this method first, a couple of self-explicated questions as described before are asked. Based upon the answers to those questions the conjoint design adapts to the respondent. This makes it possible to have a customised design for each respondent so that the questions which suit this respondent the most are asked. By using this method it is possible to use more attributes and attribute levels compared to traditional or choice-based conjoint. However, to perform this type of conjoint analysis specific software is needed, which is expensive.

In this research choice-based conjoint has been used, because it better represents realistic decision tasks compared to traditional and self-explicated conjoint. Creating a complete adaptive choice-based conjoint survey would be the most effective. However, creating a complete adaptive conjoint survey is complicated or expensive, therefore, the decision has been made to use one adaptive question before the survey which asks in which price segments of bikes the respondent is interested. We use this answer to make sure that the respondent only has to make decisions between bikes in the price segment in which he is interested.

Hedonic price regression

Conjoint analysis gives insight into the willingness to pay and the demand of the customers. For analysing the supply side of the market hedonic price regression is used. Hedonic price regression is a regression model in which the price is dependent on the characteristics of a product (Rosen, 1974). This implies that the characteristics of the products are independent of each other. Which makes it possible to estimate the effect on the price of all characteristics under this assumption of independence.

An issue that we have to keep in mind with hedonic price regressions is omitted variable bias. Cropper, Deck and McConnel (1988) proved that omitted variables from a hedonic price regression would decrease the performance of a model, would increase the variance of the errors and bias the values of the estimated coefficients. In our research, it is quite likely that we do not use all characteristics of a bike which are important in a real decision-making process (for example, less tangible effects like the looks of a bike are not investigated in this research) and therefore we have to keep in mind that our model would not be perfect and that the real causal effects between the price and the attributes could differ from the effects found in this research.

Hedonic price regressions can be used for several marketing questions related to the prices. For example, Costanigro, McCluskey and Mittelhammer (2007) used hedonic price regression for a segmentation problem in the wine market. They estimated whether different attributes of red and white wine have different effects on the price in other market segments. Similarly, a study in Turkey (Selim, 2009) investigated which attributes are important for the price in the housing market in urban and rural areas. They found that several attributes are quite important, for example, the type of house, number of rooms and whether the house has a pool or not.

In this research, we similarly use hedonic price regression as in the two previous discussed empirical papers. The effect of different attribute levels of road bikes on the price is estimated. This indicates which attribute levels are most important for the determination of the price, which gives insight into the supply side of the market. Finally, combining the results of the conjoint analysis and these hedonic price regression gives us valuable insights into whether customer value-based pricing is applied in the road bike market.

Data

Web scraping data

To investigate the effect of road bike attributes on the retail prices, 9 websites of Dutch (online) bike retailers are scraped. To ensure that all big bike retailers are included, two conditions were set to decide whether a website is scraped or not. The first condition is that the website has to appear on the organic search results within the first two pages of Google with the use of the Dutch word for road bike (racefiets) on 25 March 2020. This condition makes sure that only the data of the most popular and well-known bike retailers is collected. The second condition is that the retailer should have at least a 100 different road bikes for sale on 25 March 2020, which ensures that only the bigger retailers are considered. The following nine websites met both of these conditions and are, therefore, scraped for this research: 12gobike.nl, mantel.com, salden.nl, bikester.nl, peterterlouw.nl, rullensfietsen.nl, fietsspecialist.nl, bike-x.nl and rijwielcashencarry.nl.

This results in a dataset with 1605 different bikes, however, a couple of hundred bikes are deleted because they are not road bikes (for example, gravel bikes, time trial bikes or fixed gear bikes) or the price is unknown which was most of the time caused by flexible prices of customisable road bikes. The final dataset after removing these bikes consists out of 1404 road bikes and for all these bikes information about the following attributes is present.

Price

The price of a road bike is the main variable of interest in this research. The price is a continuous variable with a range from €479 to €14100 and a median value of €2499. All observations with missing values in this variable are removed, as described above. Because a missing value in the dependent variable does not lead to any insights for the analysis.

Website & Brand

These two variables are categorical variables without any missing values which describe the website on which the bike is for sale and the brand of the bike. The websites which have the most observations in the final data are 12gobiking.nl (281), mantel.com (205) and bikester.nl (195). The brands which appear the most in the data frame are Giant (316), Cube (136) and Liv (119). Brands which appear less than 20 times are merged to the category other, this is also done for all levels in other attributes which appear less than 20 times. After merging these small brands there are 15 categories in this variable, 14 brands and the category other.

Frame & Fork

For the frame and the fork of the bike, information is collected about the material. The main materials which are used for bikes are aluminium and carbon, however, a few bikes in the dataset are made from steel or titanium. Another possibility is that some bikes are created of a combination of carbon and aluminium called composite. Some websites provide information in this but others do not and just call it carbon. Therefore, the decision has been made to classify all frames and forks which contain (partly) carbon as carbon and only frames and forks which contains completely out of aluminium as aluminium. This resulted in 339 bikes with an aluminium frame and 832 bikes with a carbon frame. Most of the forks are classified as carbon (1088) and just a couple of forks are completely made of aluminium (34).

Wheels, Saddle, Steer & Tyres

These four parts of a road bike have a lot of different attribute levels. To reduce these levels only the brand of the parts are considered. The brands of these parts can match the brand of the bike. For example, a lot of Giant bikes in the data frame are assembled with Giant wheels, saddles, steers and tyres. However, also a lot of part-specific brands are in the market. For example, the saddle brand Prologo is present on 110 different bikes and the tyres of the brand Vittoria are mounted on 314 bikes in the dataset.

Year, Model & Gender

These three variables indicate what sort of road bike we are dealing with. First, the year indicates in which year this type of road bike is launched to the market. Almost all road bikes in the dataset were launched after 2017. Therefore, three categories are created 2020 (800), 2019 (348) and 2018 or before (115). The model contains information about whether we are dealing with an aero road bike, all-round road bike, endurance road bike or a fitness bike. Not many websites contain this information, so a lot of missing values (966) are present in this variable. The gender of a road bike contains information about whether a road bike is specifically designed for a women or a men. If a road bike was specifically created for a men or both sexes it is classified as a men road bike (967) and otherwise, it was classified as a specific women road bike (200).

Colour

A couple of websites also mention the colour of the bike. If a bike has only one colour, the bike is classified to the category of that colour. Note that the colours are simplified, so all variations of a colour (for example, dark red) are classified as the base colour (for example, red). When a bike has two or more colours it is going to be very complex. A bike which is for example called black/red on a website can be a black bike with a bit of red or vice versa. Therefore, all bikes which have more than 1 colour are classified as one general category called multiple colours.

Weight

The weight of a bike is the only continuous independent variable in this research and it contains the total weight of the whole bike (the frame and all the other parts together). The lightest bike in our dataset has a total weight of 6.2kg, the heaviest bike has a weight of 18kg and the median bike weights 8.4kg. The missing variables in the category weight are predicted by a conditional inference tree using the variables frame, fork, groupset and brakes because these variables are the most logical explanations of the weight of a bike. To ensure that the variable weight is comparable in scale to all the categorical variables it is scaled to a scale from 0-1 by the following formula:

$$W_{n_i} = \frac{W_i - W_{min}}{W_{max} - W_{min}}$$

In this formula W_{n_i} is the scaled weight of bike i, W_i is the weight in kilograms of bike i, W_{min} is the weight in kilograms of the lightest bike in the dataset and W_{max} is the weight in kilograms of the heaviest bike in the dataset.

Groupset

The groupset of a bike consists out of all moving parts of a bicycle. Three brands are present with all groupsets of different qualities. The first brand is Shimano with the following groupsets (from high quality to lower quality): Shimano Dura Ace, Shimano Ultegra, Shimano 105, Shimano Tiagra, Shimano Sora and Shimano Claris. The second brand is SRAM with the following groupsets: SRAM Red, SRAM Force, SRAM Rival and SRAM Apex. The final brand is Campagnolo, which is mounted to very few bikes in our dataset, with the following groupsets: Campagnolo Super Record, Campagnolo Record, Campagnolo Chorus, Campagnolo Potenza, Campagnolo Centaur and Campagnolo Veloce.

This variable is then split into two variables. The first variable contains only the brand of the groupset, so whether a groupset is from Campagnolo, SRAM or Shimano. Then another variable with 6 categories regarding the quality of the groupset is created. In this variable, the six Shimano groupsets are used as a reference and all the groupsets of SRAM and Campagnolo are merged with the Shimano groupset which is most similar to that groupset according to Bikevision (2020). This results in six categories called level 1 to 6 which provide information about the quality of the groupsets. Due to the complexity explained by the following attributes, not for all bike information about the groupset is available.

Rear derailleur, Front derailleur, Cassette, Chain, Crank & Shifters

The previously discussed variable groupset (when present) provides general information (like a summary) about the majority of the parts of the groupset. It is possible that a groupset is a combination of parts from different groupsets. When this is the case the information of a groupset could be missing, but it could also be named to the majority of the groupset.

Therefore, these six variables which are important parts of the groupsets are specified individually. For each part, different categories are created for all the groupsets as mentioned above and for parts which do not specifically belong to a groupset. For example, Shimano produces CS/HG cassettes which do not belong to a single groupset. Also, other brands could create a part of the groupset, for example, a lot of chains are created by the brand KMC.

Some of these six variables do have a high correlation with each other and with the variable groupset and therefore they are not used in the hedonic price regressions. However, these six variables are used for the imputation of most of the missing variables in the variable groupset. This is further explained in the beginning of the results section.

Electronic shifting

The more expensive groupsets (level 5 and 6) have an option for electronic shifting instead of mechanic shifting. To capture this a dummy variable is created for if a bike has electronic shifting or not. In the dataset 274 bikes shift electronic and 1130 bikes shift mechanic.

Brakes

For the brakes two variables are created. The first variable considers the brand of the brakes and this is similar to other parts of the groupset like the derailleurs and the chain. Therefore, this variable is also only be used for the imputation of missing variables of the groupset. Besides the categories of the brakes which belong to a groupset the most common brakes are Shimano BR (94) and brakes from the brand Tektro (69). The second variable regarding the brakes, which is used for hedonic price regressions, is a dummy variable which indicates whether a bike contains disc brakes (751) or rim brakes (327).

Missing values

Because data is scraped from 9 different websites a lot of missing values are present in the independent variables. For the categorical variables, the missing values are set as an additional category, so no observations are lost. For the continuous variable weight, a conditional inference tree based on a few other variables has been used to predict the missing values of the variable. Finally, for the variable groupset, a lot of missing values are predicted with a conditional inference tree which uses all the different parts of a groupset. However, still, 80 observations are missing, because information on all parts of these groupsets were missing. These 80 observations are set as a category with missing values. The models which are used for replacing missing values are mentioned in the method section and the results are shown at the beginning of the results section.

Conjoint data

To investigate the effect of road bike attributes on the willingness to pay, three conjoint surveys are conducted. For each price segment, a different conjoint survey is created. To make sure that each respondent answers the survey which suits him the best, the first question asks to budget for a road bike so each respondent is redirected to the best suiting survey. In each survey, the respondents get 10 choice sets of 3 bikes each in which they have to decide which bike is the best purchase.

In each survey, we aim to ask the most optimal questions for estimating the effects of all the attributes in our models. For creating such an optimal survey design we have to measure the utility of the bikes which we use in the choice sets based upon the attribute levels. This can be done with the help of the utility model (McFadden, 1973). In the following formula u_i is the utility of attribute level i. β is the weight which is before creating the design is specified to attribute level x_i. Finally e_i, is the random error term which has an expected value of zero.

$$u_i = x_i\beta + e_i$$

First, we discuss an utility neutral design. In a utility neutral design, the assumption is that all $\beta's$ are zero and therefore the expected utility of all bikes is the same. For a utility neutral design there are three characteristics which have to be used in creating the design (Huber & Zwerina, 1996). The first characteristic of such a design is that there exist level balance, which means each attribute level occurs the same amount of time as all other levels of that attribute. The second characteristic is orthogonality, orthogonality means that a combination of two levels of different attributes occurs in as many times as the product of the marginal frequencies of the corresponding attributes. This means that each combination of a two-level attribute and a three-level attribute occurs in 1/6th of the choice profiles. The third characteristic is that there should be minimal overlap between attributes within a choice set.

In a utility neutral design, some choice sets can become uninformative, because in some cases all people prefer a specific choice set over the others. This would certainly happen when some attribute levels are objectively better compared to other levels of this attribute. Some examples of this in the context of road bikes are that people always prefer lower prices over higher prices, lighter bikes over heavier bikes and groupsets of better quality over groupsets with a lower quality. To counteract this problem and to ensure that all choice sets are informative the fourth characteristic of utility balance is introduced by Huber and Zwerina (1996). Utility balance is balancing the utility of the options in a choice set based upon prior knowledge of the attribute levels. Implementing utility balance with realistic prior knowledge reduces the chance of uninformative choice sets.

To satisfy the fourth characteristic of utility balance, prior knowledge about the attribute levels is needed. In this research, we do not have much information in advance to determine the importance of the attribute levels. However, the assumption is made that with the use of common sense in some attributes certain levels are preferred over others and that in other attributes this is less likely. Only for the attributes in which it seems logical that there is an obvious difference between the attribute levels prior knowledge is used to satisfy utility balance and to avoid uninformative choice sets.

To satisfy this characteristic of utility balance some $\beta's$ are manually set, taking prior knowledge into account. However, there is no detailed information about the prior knowledge of the attribute levels. Therefore, the assumptions is made that all $\beta's$ are between 0 and -1 and that the difference between all attribute levels is the same. Suppose that there is an three-level attribute with prior knowledge that the attributes can be ranked from most preferable to least preferable. The most preferable level receives a β of 0, the second preferred level a β of -0.5 and the least preferred level a β of -1. This might sound not very accurate, but Huber and Zwerina (1996) stated that determining the $\beta's$ in this way significantly improves the survey efficiency compared to a design which is made for a case where all $\beta's$ are assumed to be zero.

With all this information we create with the use of JMP software a survey design which minimally violate these four characteristics but in practice there is always a trade-off between multiple of these characteristics. Manually, adapting the $\beta's$ for utility balance could harm one of more of the other three characteristics. In the beginning of the results section of the conjoint part, the used attributes, attribute levels and the $\beta's$ are further discussed for each price segment.

To check whether the predetermined $\beta's$ are realist, we calculate the expected utilities of the choice sets. With the predetermined $\beta's$ we calculate the utilities with the use of the multinomial logit formula. This formula is explained in the methods part regarding the conjoint analysis. With this formula, it is possible to calculate the expected probability of a bike within a choice set. For a couple of choice sets, this is done and all the probabilities look realistic. For example, the three bikes in the first choice set of the budget bikes have the following probabilities 0.177, 0.481 and 0.341. This indicates that the second bike is more likely to be chosen regarding the prior information, but the probabilities are divided relatively equal over the three bikes.

The survey with the three conjoint studies was distributed via Facebook. The link to the survey was posted in 5 Dutch cycling-related Facebook groups and on my personal Facebook page. Many people shared the survey on Facebook or asked their cycling friends to participate by tagging them. Because of this sharing and tagging, a kind of snowball sampling (Goodman, 1961) took place. In other words, people were asking other people to participate which increased the number of participants. However, this makes it very difficult to recognise the exact population from which the respondents are drawn but it is likely that most respondents are cycling enthusiasts.

In the end, 703 people participated in the survey, but we deleted the answers of 4 people because of missing values in one or more of the demographic/psychographic questions. So in the end we have 699 participants divided over the three price segments. In the segment of budget bikes, the least people (114) participated, in the mid-range segment 427 people participated and in the segment of expensive bikes 158 people answered the survey.

The people who participated in this survey are between 17 and 76 years old with an average of 46.4. 90.6% of the participants are male and 9.4% female. This sounds very unevenly distributed but the sport cycling is more popular by men than by women (Wielersportmonitor, 2020), however, a percentage above 90% is still a slight overrepresentation of men in our sample. All people in our sample cycle between 0 and 40 hours per week with an average of 7.1 hours per week.

The next question asked for what types of activities people uses their road bikes. 94.3% uses their bikes for individual rides, 29.2% for rides with their cycling club, 58.7% for rides with their friends, 42.7% for participation in organised tours, 10.0% for participation in races and 24.6% for cycling holidays abroad. In the final question, we asked whether people missed some important attributes in this research, this is further discussed in the conclusion and discussion of this research.

Methods

Hedonic price regression methods

Most of the models regarding the hedonic price regression are based upon linear regression, so first the methods behind linear regression is discussed. In a linear regression we try to predict the dependent variable by the independent variables based upon a straight line. This is done by estimating an intercept ($\hat{\beta}_0$) and coefficients for each variable ($\hat{\beta}_j$), each category of a categorical variable is treated as an individual variable for this method. In a formula multiple linear regression looks like this:

$$\hat{y} = \hat{\beta}_0 + \sum_{j=1}^{m} \hat{\beta}_j \cdot x_j$$

In this formula $\hat{y}$ is the estimated value of the dependent variable, $\hat{\beta}_0$ is the estimated value of the constant which is the estimated value of $\hat{y}$ when the value of all explanatory variables is zero. Then the $\hat{\beta}_j$ is the estimated effect of the variable x_j, so $\hat{\beta}_j$ is the effect on $\hat{y}$ when x_j increases with one. This effect is estimated for all j variables by minimizing the loss function which is also called the residual sum of squares (RSS). By minimizing all the $\hat{\beta}'s$ in the RSS formula, a linear line is created which fitted the data the best:

$$RSS = \sum_{i=1}^{n} \left(y_i - \hat{\beta}_0 - \sum_{j=1}^{m} \hat{\beta}_j \cdot x_{ij} \right)^2$$

However, the best solution is not always linear and therefore using the linear regression as described above might not be optimal. A non-linear relationship can still be estimated with the use of a linear regression by adding interactions and polynomials to this formula. Adding interactions means that the multiplication of two variables becomes a new variable. So, in this cases the formula's remain the same, however, beside for each variable x_{ij} also each interaction between two variables has his own $\hat{\beta}_j$. This interaction effect could estimate an extra effect when two variables occur at the same time, so this makes the model less linear. Adding polynomials is only possible for continuous variables (only weight in this research) and this means that also polynomials of the variables get their own $\hat{\beta}_j$ which makes it possible for the continuous variables to estimate a non-linear relationship.

In this research, logarithms of the dependent variable are not used in the regression models because the data has no outliers regarding the price. Even the prices completely on the cheap and expensive side of the market occur relatively often. The absence of heteroscedasticity within the error term can be another reason for implementing logarithms in the model. Heteroscedasticity is violated when the random variation of price differs across bikes. The possible lack of heteroscedasticity is already solved by creating different models for different price ranges in the market, as discussed later on. Because using logarithms is not necessary regarding the reasons discussed above, we do not use them to keep the interpretation of the models as straightforward as possible.

When a linear regression has too many variables there is the risk of overfitting, overfittings means that the model predicts really well inside the sample, however the model also fit really well to the noise in the sample and therefore a model which overfits performs worse on new and unseen data. Removing variables from the linear regression reduces the probability of overfitting. The problem is that it can be hard to determine which variables have to be deleted. To solve this problem the elastic net regression (Casella, Frienberg & Olkin, 2017) is used. Elastic net regression is a linear regression with a penalty term which got the ability to shrink and delete $\hat{\beta}_j' s$. The penalty term of an elastic net regression is a combination of the LASSO and the Ridge penalty. The RSS which is minimized is the following:

$$RSS = \sum_{i=1}^{n} \left(y_i - \hat{\beta}_0 - \sum_{j=1}^{m} \hat{\beta}_j \cdot x_{ij} \right)^2 + \lambda \left(\alpha \sum_{j=1}^{m} \left| \hat{\beta}_j \right| + (1-\alpha) \sum_{j=1}^{m} \hat{\beta}_j^2 \right)$$

The first part is exactly the same as the previously discussed RSS of the linear regression. However, to this formula a penalty term has been added. The first part of the penalty term is the LASSO part which could shrink variables completely to zero and the second part of is the Ridge part which could deal better with highly correlated variables but is not able to shrink variables completely to zero. The α has a value between 0 and 1 and determines the importance of each part. So if α is 1 than the Ridge regression is neglected and the model becomes a full LASSO regression and if α becomes 0 the model becomes completely Ridge. Finally, λ determines the size of the penalty term. When λ is equal to 0, the whole penalty part becomes zero and the model becomes a standard linear model but if λ becomes bigger more variables are shrunk (close) to zero.

To determine which values of α and λ are the most efficient 10-fold cross-validation (Tan, Steinbach & Kumar, 2006) is used for the training set (75% of the data). 10-fold cross-validation means that the training dataset is split into 10 parts and that the model is estimated 10 times with a lot of different values of α and λ, each time 9 of the 10 parts is used and the remaining part is used to calculate the error in predicting for all values of the parameters. Sometimes, for λ the minimum value is not used, but the maximum value of λ which is one standard error away from the minimum because this shrinks a lot more variables with only a small reduction in predictive power. In this research we try both of these approaches. When for all different types of models the parameters are tuned with the training data the error in predicting the test dataset, which is unseen in the tuning process, is calculated so that all models can be compared based upon their predicting values.

The errors in predicting are calculated with the root-mean-squared error (RMSE). The RMSE is a simple measurement which measures the error between the predicted value ($\hat{y}_i$) and the real value (y_i) of all N observations. The RMSE has as advantages over the MSE (mean-squared error) that the square root of the squared differences makes the value of the measurement comparable with the values of the y variable. When only the training data is considered the RMSE is equal to the square root of the minimized RSS as described above.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$$

In linear regression it is possible to calculate p-value's for the coefficients ($\hat{\beta}_j' s$) and to calculate a confidence interval. In elastic net regression this is mathematically not possible, therefore to calculate confidence intervals bootstrap sampling is used. In bootstrap sampling validation (Tan, Steinbach & Kumar, 2006) a regression model is repeated many times (1000 times in this research) with a sample of the data. This sample has the same size as the original data however, the sample is drawn with replacement from the original data. The consequence of this is that each observation can appear more or less than once in each sample. When this is done 1000 times, a 95% confidence interval and the average difference between two attribute levels can be calculated with the use of all 1000 repetitions to see how stable the results based upon the original data are. It is important to note that in each bootstrap repetition the cross-validation process is not repeated, we stick with the originally found penalty parameters because otherwise, the whole process would become very time-consuming due to long running times.

Besides the linear and elastic net regressions as described before, for comparison reasons also a random forest and a conditional inference tree are used. Because these are not the most important models in this paper we discuss them briefly. A conditional inference tree is a tree-based method which is based upon the permutation test (Strasser & Weber, 1999). In this tree only splits are made, which are significant at 95% regarding the permutation test, which keeps the trees relatively small and prevents for overfitting. These kinds of trees are also used for the imputation of the missing values as described in the data section.

Finally, also for comparison, a random forest regression is used. A random forest is a combination of multiple regular decision trees, in which each tree uses a subset of the variables which are randomly chosen. The random forest regression is also used in the results section about segmentation.

Conjoint methods

In the models regarding the hedonic price regression, a linear approach is used, because the price is the dependent variable. In the data which is collected through the conjoint survey, the price is not the dependent variable but a dummy variable which indicates whether a respondent did or did not prefer a certain bike. Because this variable is either 0 or 1 a linear regression is not optimal. For these kinds of problems, different types of classification models can be used but in this research, we are interested in the interpretation of the coefficients and therefore, we use a multinomial logistic regression.

A multinomial logistic regression (Huber & Zwerina, 1996) calculates the probabilities of events occurring. In our case, the logistic regression calculates the probabilities (P_{in}) for each bike to be chosen by a respondent, where i is a bike in a choice set and n is the total number of choice sets. The probability of choosing bike in depends on the values of the variables x_{in} multiplied by all the $\beta's$, divided by the sum of the $\beta's$ for all J options in a choice set. $x_{in}\beta$ is equal to the utility of a bike as discussed in the conjoint related data section when the assumption is made that the error (e_i) is zero.

$$P_{in} = \frac{e^{x_{in}\beta}}{\sum_{j=1}^{J_n} e^{x_{jn}\beta}}$$

The $\beta' s$ in the multinomial logistic regression are estimated by plotting a line to the data and maximizing the log likelihood of this line. The log likelihood is the sum of the logarithms of all individual likelihoods. The individual likelihood is the probability of each observation (bike) to be chosen, compared to whether this bike is chosen or not by a respondent.

The individual coefficients of the multinomial logistic could be hard to interpret, therefore, for all attribute levels except the ones of the price, the willingness to pay is calculated. This is done by dividing the β of that attribute level, by the negative β of the price. For this, the assumption that the effect of price is linear over all the price levels is necessary. With the willingness to pay it is possible to compare the results of the conjoint analysis with the results of the hedonic price regressions.

Results

Missing values imputation web scraping data

As discussed in the data section, a lot of missing values are present. In most variables, all the missing values are used as an attribute level. However, for the continuous variable, we have decided to impute the missing values since this variable is continuous instead of categorical. For the variable groupset, we could also create a category with missing values, but because of the information we have on the different parts of the groupsets, we create an imputation model based upon these groupset parts.

For the continuous variable weight, the missing values are predicted by a conditional inference tree which uses the variables groupset level, frame, fork and brakes. Because these are variables which are likely to cause most of the weight differences of a bike. 75% of the observations without missing values in weight are used as train data, then for the remaining 25%, the weight is predicted and compared with the real weight to estimate the error outside the training sample. The RMSE on the test data is 0.789 which means that the average prediction differs less than a kilogram from the real value of weight. Also compared to the standard deviation of weight which is 1.48 kilograms this is quite a good score. Therefore, this model performs well enough to predict the missing values. So this time all the data without missing values in weight are used to train the conditional inference tree and based on this model the missing values are imputed.

Then for the variable groupset, the missing values are also predicted by a conditional inference tree, this tree uses all the different parts of the groupsets. Only when all the parts of the groupset were missing no prediction is made. Again 75% of the data without missing values in the variable groupset is used as the training set and the other 25% as the test set. Because the variable groupset is categorical we calculate the accuracy instead of the RMSE, the accuracy was 82.3% which means that this model predicts the groupset right in more than 4 out of 5 observations and when a prediction is wrong it is most of the time just one level above or beneath the correct level. Therefore, this model is good enough in predicting the missing values of the groupset. All the data without missing values in groupset are set as training data and they are used to predict the groupset. After this imputation based model, only 80 observations a have missing value in the variable groupset. These observations are treated as all the other variables with missing values. So all these 80 observations are put together in the category for groupsets with a missing value.

Hedonic price regressions, model selection

Now all the missing values are predicted by a conditional inference tree or classified as an additional category to the corresponding variable, so we start with analysing the data. In the first step, the price of the bikes is predicted by all the variables with the use of different regression methods to see which methods and which subsets of variables performs the best. To measure the performance by the RMSE of the models, the data is randomly divided into a 75% test dataset and a 25% training dataset. In table 1 an overview is given of the RMSE of all the models discussed below.

To set a benchmark for the RMSE, first, the RMSE of the mean price of the training data is calculated. So, we predict for each observation that the price is equal to the mean price of the training dataset. This resulted in a RMSE on the test data (outside the sample) of €2514.55 and a RMSE on the training data (inside the sample) of €2173.87. Each model we discuss now is expected to score much better (lower) on both the test as the training sample.

The first and most simple model is a linear regression with the use of all the available variables. This results in a RMSE of €1225.31 on the test data and €953.71 on the training data. This is a lot better compared to the benchmark we set. To improve this model manually subsets of the variables were tried, but this does not result in any improvements of the RMSE on the test or training data. A lot of different subsets can be used and it is nearly impossible to check them all manually. To solve this problem, the elastic net regression with the penalty term is used. For the first try, α is fixed to 0.5 which is exactly 50% ridge regression penalty and 50% lasso regression penalty, the λ is set to the biggest value that is within one standard error of the minimum value in cross-validation (Rdocumentation, 2020). Surprisingly, the RMSE of this model is worse on both the test (€1240.33) and the training (€1005.54) data compared to the linear model. Finetuning this models' α to 0.53 by cross-validation only lowers the RMSE's marginally (test RMSE: €1240.17 and train RMSE: €1005.32). Using the minimal value of λ reduces the test RMSE to €1223.05 and the train RMSE to €967.42.

To the default elastic net, interactions are added to take into account that not all variables have a linear effect. The default elastic net with interactions performs the best up to now with a RMSE of €1131.27 on the test data and €798.12 on the training data. Then polynomials of the variable weight are added to the elastic net regression with interactions. When the square root and the polynomials of degree 2 to 20 are added to the model a very small improvement is visible. The RMSE on the test set is €1130.20 and on the training set €797.95. However, these differences are so small for the complexity which is added that these polynomials are not further used in this research.

An elastic net regression with interactions is the most preferred model. To reduce the RMSE the values for α and λ were optimised. First, with the use of cross-validation, it is found that an α of 0.05 is optimal whether we would use the corresponding minimum value of λ or the maximum value which is within one standard error of the minimum value. Then finally for this model both the minimum value of λ and the maximum value which is one standard error away from the minimum are tested. First, the model within one standard from the minimum shows a RSME of €1128.82 on the test data and a RSME of €765.59 on the training data set. The model which uses the minimum value of λ does a bit better, but it also uses a lot more variables. The RMSE of this model is €1100.58 on the test data and €603.46 on the training data.

None of these models based upon linear regression is very accurate in predicting the price of a road bike. To check whether this can be solved with the use of a non-linear regression type, a random forest and a conditional inference tree are used. The default conditional inference tree predicts worse compared to most of the linear models (test RMSE: €1271.04, train RMSE: €1041.04). A default random forest with 200 trees is a bit worse on the test data (RMSE: €1184.21) compared to the elastic net models with interactions, however, this random forest is the best model on the training data (RMSE: €578.79).

__Table 1__, train and test RMSE of the different regression models, all the data

Model	RMSE (train set)	RMSE (test set)
Mean (benchmark)	2173.87	2514.55
Linear all variables	953.71	1225.31
Linear subset: groupset, electronic shifting, weight, brand, frame, groupset brand	1138.36	1351.47
Elastic net, α = 0.5, λ = 1se	1005.54	1240.33
Elastic net, α = 0.53, λ = 1se	1005.32	1240.17
Elastic net, α = 0.53, λ = min	967.42	1223.05
Elastic net + interactions , α = 0.5, λ = 1se	798.12	1131.27
Elastic net + interactions + polynomials , α = 0.5, λ = 1se	797.95	1130.20
Elastic net + interactions , α = 0.05, λ = 1se	765.59	1128.82
Elastic net + interactions , α = 0.05, λ = min	603.46	1100.58
Conditional inference tree (default)	1041.04	1271.04
Random forest (default, 200 trees)	578.79	1184.21

These two non-linear models do not perform much better compared to the linear models. Therefore, it is likely that the inaccuracy of the predictions is caused by the random variation of the data and not by the type of model which is used. The best models that are created up to now can predict whether a bike is an expensive, a mid-range or a cheap bike, but they are not precise in predicting the exact price. To be more precise the best model, the optimised elastic net regression with interactions, has a RMSE of €1100.58 on the test data, as a percentage, this is 8.1% of the whole price range. To improve the performance of the models, we divide the data, based upon the quantiles into three subsets regarding the prices. Splitting the data into price-based subsets certainly reduces the absolute value of the RMSE, however, the relative value might not decrease.

The first subset which is created is equal to the first quantile and has a range from €479 to €1499 and therefore this subset is called budget bikes. The second subset contains the second and third quantile and ranges from €1500 to €3999 and these are called mid-range bikes. The final and last subset is the fourth quantile and contains all bikes between €4000 and €14100, therefore this subset is called expensive bikes.

Budget bikes

The first subset which is discussed are the budget bikes. In table 2 all the RMSE's of all tried models are presented. First, again a prediction based on the mean is used as a benchmark. This results in a RMSE on the test set of €274.35 and on the train set of €267.08. Then a standard linear model including all variables already performs a lot better with a test RMSE of €144.80 and a train RMSE of €99.45.

All elastic net models without interactions perform as good or even worse compared to the linear model. Even when λ is set to the minimum value and α is tuned to 0.35 with the help of cross-validation the models' performance is comparable with linear regression. This is visible by the RMSE of the test set which is a little bit lower (€140.66) compared to the linear regression but the RMSE of the training set is a little bit higher (€103.53).

Finally, we take a look at the elastic net models with interactions. The first of these models uses the default value of 0.5 of α and a λ which is maximal one standard error away from the minimum. This model performs with a test RMSE of €150.81 and a train RMSE of €103.50 worse compared to the linear regression without interactions. The second model with interaction uses the value of λ which is one standard error away from the minimum and an α of 0.23. This results in a RMSE on the test set of

€151.44 and on the train set of €100.38. This is also worse compared to a standard linear model without interactions. Then the third model with interactions for budget bikes uses the minimum value of λ and an α of 0.02. Which means that the penalty term is nearly a complete ridge regression penalty. This model results in a test RMSE (€137.76) which is a little bit lower compared to the linear, but the train RMSE (€49.87) is a lot lower compared to the linear model. However, this big decrease in the train RMSE with nearly no change in the test RMSE could indicate that this model tends to overfit.

***Table 2**, train and test RMSE of the different regression models, budget bikes (€479 - €1499)*

Model	RMSE (train set)	RMSE (test set)
Mean (benchmark)	267.08	274.35
Linear all variables	99.45	144.80
Elastic net, α = 0.5, λ = 1se	118.09	155.53
Elastic net, α = 0.35, λ = 1se	119.06	156.67
Elastic net, α = 0.35, λ = min	103.53	140.66
Elastic net + interactions, α = 0.5, λ = 1se	103.50	150.81
Elastic net + interactions, α = 0.23, λ = 1se	100.38	151.44
Elastic net + interactions, α = 0.02, λ = min	49.87	137.76

In conclusion, for the budget bikes, elastic net models without interactions perform as good as models with interactions. Therefore, it is likely that there are not many interactions present in this subset of the data. When we take a look at the relative RMSE of the preferred model we see that the optimised elastic net (without interactions) has a test RMSE of €140.66, which is 13.8% of the price range of the budget bikes. So these models, perform relatively a bit worse compared to the model regarding all the data but due to the lower absolute RMSE, the models regarding this subset are nevertheless useful.

Mid-range bikes

The second subset are the mid-range bikes, this subset exists of the second and third quantile of the data and therefore it is twice as big as the other subsets. Again, to set a benchmark for the mean has been used to predict the prices. This results in a test RMSE of €658.86 and a train RMSE of €713.78. These are bigger compared to the budget bikes, but this is quite logical since the price range of the mid-range bikes is wider. All the RMSE's of this subset are presented in table 3.

The first model for the mid-range bikes is again the linear regression. This regression has a RMSE of €603.81 which is not much lower compared to the benchmark which was set. Compared to the models with the budget bikes and the models with all the bikes this is surprising because there the linear model was much lower compared to the benchmark. The train RMSE is with €407.56 much lower compared to the benchmark. All the elastic net regressions without interactions score a bit better on the test set compared to the linear model, however, they score a bit worse on the train set.

The default model with interactions scores as good as the other elastic net models on the test set (RMSE: €559.53), but a bit worse on the train set (RMSE: €477.63). Finetuning the α to 0.08 with cross-validation in combination with the standard error value of λ does lower the test RMSE a little bit to €552.11 and lowers the train RMSE to €434.83. Then the final model, with an α of 0.04 and the minimum value of λ does not score better on the test set (RMSE: €557.06), but scores much better on the train set (€282.59), however, this big decrease could indicate that this model is overfitting.

__Table 3__, train and test RMSE of the different regression models, mid-range bikes (€1500 - €3999)

Model	RMSE (train set)	RMSE (test set)
Mean (benchmark)	713.78	658.86
Linear all variables	407.56	603.81
Elastic net, α = 0.5, λ = 1se	465.58	562.21
Elastic net, α = 0.98, λ = 1se	463.47	562.45
Elastic net, α = 0.71, λ = min	431.47	564.70
Elastic net + interactions, α = 0.5, λ = 1se	477.63	559.53
Elastic net + interactions, α = 0.08, λ = 1se	434.83	552.11
Elastic net + interactions, α = 0.04, λ = min	282.59	557.06

Also in these models, the models with interaction effects do not result in notable increases in performance. This indicates that interactions between variables are not important in predicting the price of mid-range bikes. In general, the models perform worse compared to the budget bikes, a RMSE of €564.70 on the test data is equal to 22.6% of the price range, which is quite high compared to the 13.8% of the budget bikes.

Expensive bikes

The final subset for which the different models are discussed are the expensive bikes. These exist out of the fourth quantile and is therefore as big as the subset of budget bikes. The mean which is used as a benchmark again has a test RMSE of €1800.01 and a train RMSE of €1669.85. This is a lot higher compared to the other subsets, but this is explainable by the wider ranges of prices within this subset.

The standard linear model with all the variables predicts quite good in the sample with a train RMSE of €1042.33, however, outside the training sample, the predictions are worse (test RMSE: €1432.47). Then a default elastic net regression performs better for the test set with a RMSE of €1216.06, but on the train set the performance is worse with a train RMSE of €1377.60.

Cross-validation on this elastic net regression tells us that an α of 0 is the best for both values of λ. So this means that the penalty term in these models is completely ridge and that no variables could be shrunk to zero, only close to zero. This first ridge model performs worse to the default elastic net regression on the test set (RMSE: €1259.58), but it performs a bit better on the train set (RMSE: €1336.79). The second ridge regression (with the minimum value of λ) performs better compared to the default elastic net on both the test set (RMSE: €1150.29) as the train set (RMSE: €1163.53).

Then the interactions are added to the elastic net model. First, the default model with interactions performs the best on the test set with a RMSE of €1108.34. The train RMSE (€1093.13) is also quite low, only the train RMSE of the standard linear model was lower. Then finetuning the α by cross-validation makes nearly no differences because the optimal value of α for the standard error value of λ was 0.51. Therefore, this model RMSE's are nearly the same as the default model. The final and last model uses the minimal value of λ and the corresponding optimal α of 0.11. This results in a slightly higher test RMSE (€1123.69), but the train RMSE is a lot lower (€731.85), however, this could again be a sign of overfitting.

Table 4, *train and test RMSE of the different regression models, Expensive bikes (€4000 - €14100)*

Model	RMSE (train set)	RMSE (test set)
Mean (benchmark)	1969.85	1800.01
Linear all variables	1042.33	1432.47
Elastic net, α = 0.5, λ = 1se	1377.60	1216.06
Elastic net, α = 0, λ = 1se	1336.79	1259.58
Elastic net, α = 0, λ = min	1163.53	1150.29
Elastic net + interactions, α = 0.5, λ = 1se	1093.13	1108.34
Elastic net + interactions, α = 0.51 λ = 1se	1092.49	1107.82
Elastic net + interactions, α = 0.11, λ = min	731.85	1123.69

For the expensive bikes, an optimised elastic net with interactions performs the best. This means that interactions seem to be important in this subset of bikes. Also, the test RMSE of the best model is €1107.82, which might sound very inaccurate, but relatively this is better compared to the two previous discussed subsets since the relative test RMSE is only 11.0% of the price range.

Now we have discussed the test and train RMSE's of a lot of different models the most preferred models are chosen. Considering the models which use all the data, an optimised elastic net regression with interactions effects and a minimum value of λ performs the best within and outside the sample. However, looking at the different subsets it is visible that for the budget bikes a full linear model and an optimised elastic net (with a minimum value of λ) performs the best, adding interactions to the elastic net model has no effect on the test RMSE and increases the chance of overfitting. Because the elastic net performs as good as the linear regression, the optimised elastic net is chosen because of its ability to shrink coefficients, because the variables related to the shrunken coefficients are irrelevant for the predictive power of the model.

For the mid-range bikes, most of the models are really close to each other. For consistency with the budget bikes model and the shrinkage power the decision is made to use also an optimised elastic net regression with the minimum value of λ and without interactions. Finally, for the expensive bikes adding interactions to the elastic net regression increases the performance of the model, so therefore we use an optimised elastic net with interactions for the expensive bikes. However, to avoid overfitting, we use the maximum value of λ which is one standard error away from the minimum. As discussed later on, this model shrinks all non-interaction variables to zero and therefore, an elastic net regression without interactions is estimated, which makes it less complex to investigate the main effects.

Hedonic price regression, model results

The best models for the whole data and each subset are now chosen, so these models are estimated again with 100% of the data. First, we briefly discuss the optimised elastic net regression with interaction effects which uses all the data. With cross-validation, this model is again optimised and for the final model, an α of 0.02 and the minimum value of λ are used. Note that the α of 0.02 differs a little bit from the α of 0.05 in table 1, this is caused by running the cross-validation again with 100% of the data instead of the 75% test set. Finally, the bootstrap technique is used to calculate the 95% confidence interval and the average bootstrap differences.

The bootstrap of this model shows us in the first place that most interactions are not stable at all. For example, an interaction between a saddle of the brand Forza and a steer of a brand which belongs to the category other has a coefficient of €2442.22, which is logically too high for a saddle and a steer. The 95% confidence interval of the bootstrap is between €-829.72 and €3094.10, this shows that in

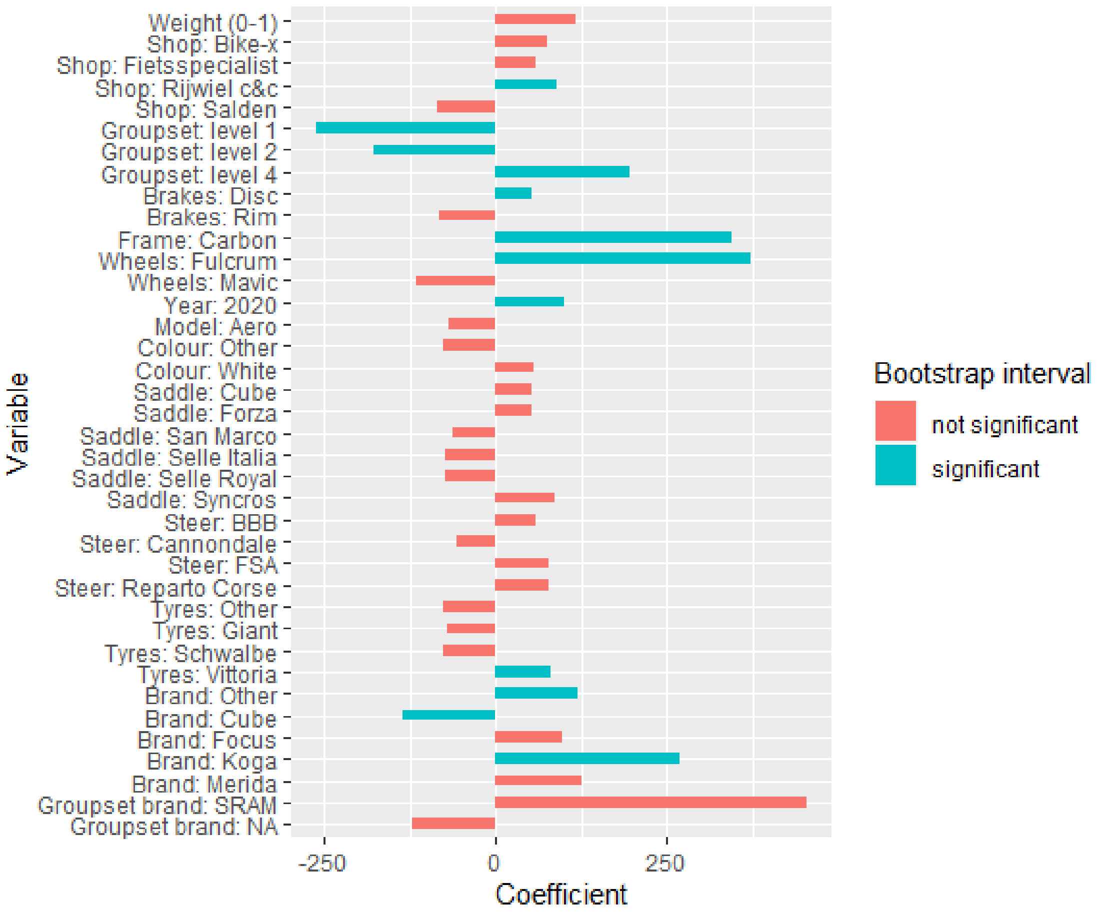
95% of the bootstrap repetitions the coefficient was in between these values and this does not significantly differ from 0. This might be caused by interactions which appear just only a couple of times in the dataset. However, there are also interactions which seem to be more logical in explaining the prices. For example, the interaction effect between a level 6 groupset and electronic shifting has a coefficient of €395.98 and the 95% bootstrap interval is between €196.08 and €511.51 and therefore it is likely that the combination of these two variables has a positive effect on the price.

Interpreting all the interactions of this model is complex and not so interesting, because we are more interested in the models based upon the subsets. Also interpreting the main effects in this model is a bit difficult because of the presence of interactions. In the previous paragraph, we showed that interaction effects only improve the predictive power of the model in the subset of expensive bikes. Therefore, we only discuss the details of the interaction effects for expensive bikes later on. Now we take a more detailed look at the models for each of the three subsets.

<u>Budget bikes</u>

To visualise the most important coefficients of the budget bikes figure 1 is created. In figure 1 all coefficients which are significantly different from 0 regarding the 95% bootstrap interval or which have an absolute value greater than 50 are presented. So when an attribute level is not present in figure 1 it has a small and insignificant effect. In table 1 of appendix A all the coefficients, bootstrap intervals and average bootstrap differences are presented. In the last column of this table, the average bootstrap difference is presented. This value indicates what the average difference of all 1000 bootstrap repetitions is between this attribute level and a reference level of that attribute.

Figure 1, *most important coefficients elastic net budget bikes*



In figure 1 we see that weight has surprisingly a positive effect on the price, which means that heavier bikes are on average more expensive but the effect is not significant. The shop 'Rijwiel Cash en Carry' has a significant positive effect, so regarding the budget bikes, this shop is significantly more expensive compared with the shops which have a coefficient of 0. Then in the variable groupset level 1, 2 and 4 differ significantly from 0 (level 3). So we conclude that groupset is one of the most important variables in predicting the price of a budget bike. Between disc brakes and rim brakes, there is a small price difference, however, the coefficient of disc brakes does significantly differ from zero. Then a carbon frame has a high and significant coefficient, which indicates a price difference between aluminium bikes (which coefficient is slightly negative) and carbon bikes.

In the variable wheels, only the brand Fulcrum has a significant positive effect, so this is the only wheel brand which significantly increases the price of a bike. The year 2020 has a small significant positive effect, which indicates that bikes from previous years are a bit cheaper which is probably caused by discounts on older models. The variables model, colour, saddle, steer and tyres have all very small and mostly insignificant coefficients, only the coefficient of tyres from the brand Vittoria is significant and positive. Looking at the brands we see that Cube has a negative significant coefficient and is, therefore, the cheapest brand in the subset of budget bikes and Koga has a positive significant coefficient and is, therefore, the most expensive brand. Finally, in the variable groupset brand, we see that SRAM has the biggest absolute value of all attribute levels but regarding the bootstrap difference, this coefficient does not differ significantly from 0 (Shimano).

Mid-range bikes

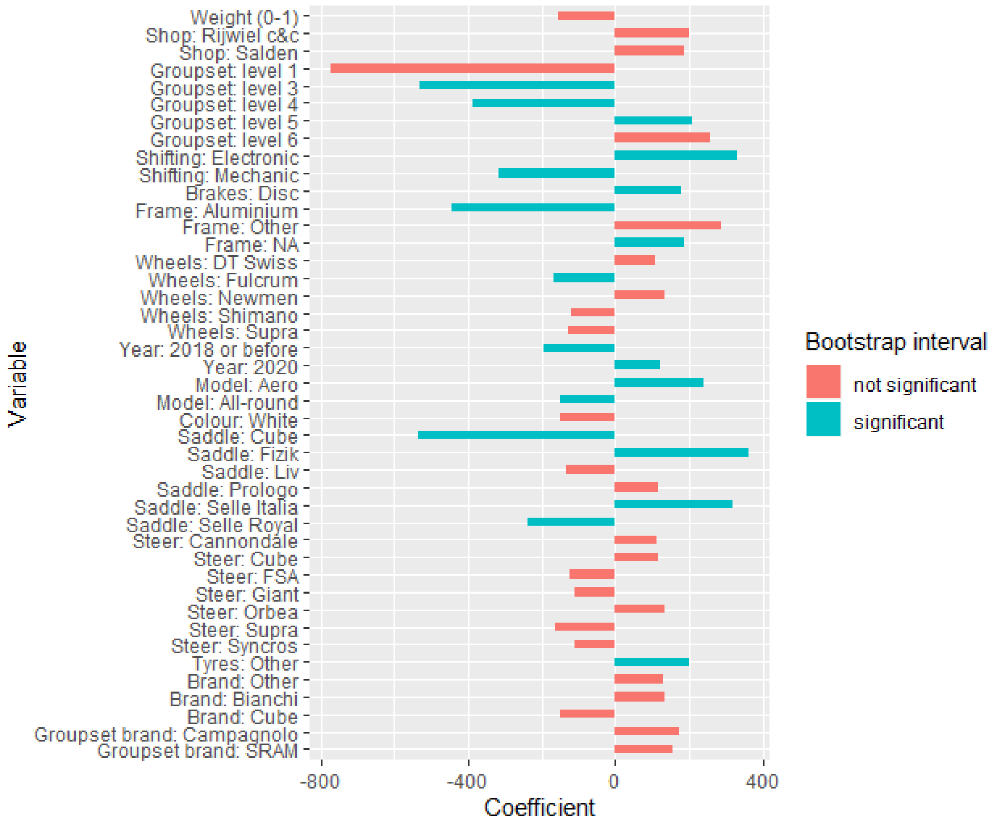
For the model of the mid-range bikes we created the same visualisation in figure 2, the only difference is that in this figure we use all the significant coefficients and the insignificant coefficients with an absolute value above 100. All the other effects are visible in table 2 of appendix A. The variable weight has a negative coefficient, which is more what we expected than the positive coefficient by the budget bikes, but the negative coefficient is not significantly different from 0 regarding the 95% bootstrap interval. Next, none of the webshops shows a coefficient which differs significantly from 0.

Then the groupset is again a very important variable, the differences are visible between all levels and all levels except 1 and 6 differ significantly from 0. A variable which is new in this model is the variable shifting because all bikes under €1500 shifts mechanically. The difference in this category between electronic and mechanic shifting is very clear. Electronic shifting differs significantly positive from 0 and mechanic shifting differs significantly negative from 0, so there is a big price difference between these two shifting methods. Then disc brakes have a significant and positive effect while rim brakes have a small insignificant (not visible in figure 2) negative effect, so there is also a price difference between these two braking systems. Similarly, aluminium bike frames are cheaper than carbon bike frames and other types of materials (titanium and steel).

Then in the variable wheels, we see that only the brand Fulcrum has a significant effect, the effect is negative which means that bikes with this brand are on average a bit cheaper compared to bikes with wheels with coefficients around or above zero. Interesting to note is that the wheels of the brand Fulcrum had a significant positive effect in the subset of budget bikes. In the variable year, we see that models introduced in 2020 are significantly more expensive and bikes from 2018 or before significantly cheaper than 0. We also see some differences between different types of road bikes, so an aero road bike is on average more expensive compared to an all-round road bike.

In the variable colour, we do not see any significant effects. Then in the variable saddle, there are some strong positive significant effects, but they are likely to be caused by the correlation with the brand of a bike. So is it likely that a bike with a saddle of the brand cube is a bike of the brand cube (correlation is 0.558). In the variables steer, tyres, brand and groupset brand only small and mostly insignificant difference are visible in this subset.

***Figure 2**, most important coefficients elastic net mid-range bikes*



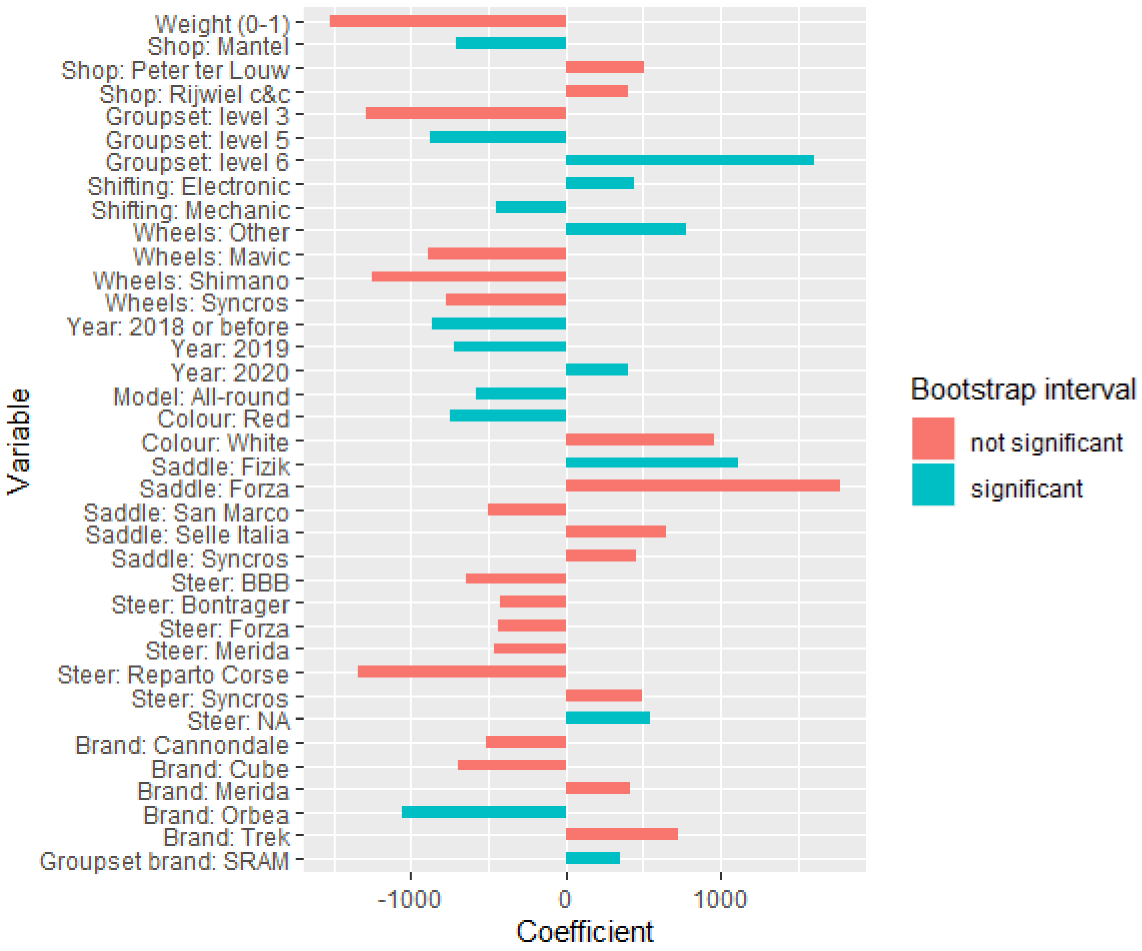
<u>Expensive bikes</u>

As previously discussed and as visible in table 4 the model with interactions performs a bit better than an optimised elastic net without interactions for the subset of expensive bikes. However, in a model with interactions, all main effects are shrunk to zero. This is not very strange, because the main effects of the attribute levels is also taken into account in all the interactions. For a simpler interpretation of the main effects, we first estimate a model without interactions which predicts a bit worse compared to a model with interactions. The main effects of this model are visible in table 3 of appendix A.

In figure 3 all significant variables and all insignificant variables with an absolute value of 400 and above are presented. First, the variable weight has a strong negative effect on the price, but it is not significant. Then looking at the shops, we see that only Mantel has a significant negative effect. The groupset levels are again very important in predicting the price, just as whether a bike has mechanic or electronic shifting. In the variable wheels, only the merged category other has a significant effect, but this is a bit hard to interpret because it is a combination of different brands. The variable year shows approximately the same as in the previous categories but the differences are a bit bigger. Then an all-round road bike is again cheaper compared with the other categories aero and endurance, which are not in figure 3.

For the first time, we see that a colour has a significant coefficient. Expensive bikes coloured red are on average significantly cheaper compared to all colours with coefficients of 0 and above. Then in the variables saddle and steer we see again some high coefficients what is quite strange. However, most of the coefficients are not significant and also a high correlation with for example the brand of a bike could raise these coefficients. Regarding the brands, only the brand Orbea shows a significant negative effect which indicates that it is one of the cheaper brands in this category. Finally, in the variable groupset brand, SRAM has a positive significant effect, so on average bikes with this groupset brand are more expensive compared to bikes with Shimano or Campagnolo.

***Figure 3**, most important coefficients elastic net expensive bikes (model without interactions)*



<u>Expensive bikes interactions</u>

Finally, the model of expensive bikes with interactions is estimated. In this model, all main effects are 0, which makes it much easier to interpret the interaction effects of this model. In table 4 of appendix A, all interaction effects which are not shrunk to 0 are presented. The first thing we notice when looking at these interactions is that some attribute levels are present in multiple interactions were others are not present at all. For example, groupset level 6 is present in 11 interactions and all these effects are positive. This implicates that bikes with a groupset of quality level 6 are on average more expensive than bikes with groupsets of lower quality. Which is quite logical since groupset level 6 is the best quality groupset and, therefore, the bikes with this groupset are much more expensive.

Only three of the interaction effects have an effect which significantly differs from 0, regarding the 95% bootstrap interval. All these three interactions include groupset of level 6. The first one is a groupset of level 6 in combination with electronic shifting. So, the best groupset of a brand in an electrical version has logically a big positive effect on the price of a bike. Then secondly, a groupset level 6 combined with the year 2020 has a positive effect on the price. Which means that a new bike with the best quality groupset has also a big positive effect on the price. Finally, the level 6 groupset also interacts with the variable year not available, but this is hard to interpret because of the missing values. All the other effects can be interpreted in the same way, however, their effects do not differ significantly from zero, so these effects are less certain than the three discussed above.

Conjoint survey, attribute selection

In the previous part, the hedonic price regressions of the three price segments were discussed. The variables which seem to be the most important in these regressions are used as attributes in the conjoint survey, however, the attribute levels differ per price segment. The attributes which are used for creating the designs are price, weight, groupset, frame material, whether a bike has electronic or mechanic shifting, brakes, year, brand and groupset brand. The other variables of the hedonic price regression are left out of the survey designs because they seem to be less important compared to the chosen attributes, however, this is a subjective decision and this is also partly based upon my own knowledge of the road bike market so other researchers would maybe make slightly different decisions which can affect the results of this study. Finally, in the attributes in which the preference of a consumer is obvious, prior information is specified by modifying the $\beta's$ to satisfy the characteristic of utility balance (Huber & Zwerina, 1996). In table 1, 2 and 3 of appendix B an overview of the used attribute levels and the corresponding $\beta's$ per subset is presented.

Conjoint survey, model results

Now we discuss the multinomial logistic regressions of the three conjoint surveys. In table 5, 6 and 7 these results are presented and compared with the average bootstrap difference of the corresponding hedonic price regression. For the variable weight, which was scaled in the hedonic price regression, calculating the average bootstrap difference is not that straightforward. Therefore, we take the average bootstrap coefficient and calculate the price effect of the highest weight asked in the survey and compare all other weights to this weight. We first discuss the models with only the main effects, then we add some interactions in the expensive category and finally we add some demographic/psychographic variables for the use of segmentation.

<u>Budget bikes</u>

In table 5 the results of the budget bikes model are presented. The assumption is made that the effect of price is linear because this is necessary to calculate the willingness to pay. The interpretation of the willingness to pay is as follow. Suppose we have a bike with a weight of 11 kg and the price of this bike is x, then an average customer is indifferent between this bike and a bike of 10 kg with a price of x + €87.22.

First, we see that price has a negative effect which means that people prefer lower prices over higher prices. The effect may seem very small, but it is important to realise that this coefficient is the difference per euro. So if we compare a bike of €500 with a bike of €1500 the price is more important than all other variables except the groupset.

Then, if we look at the weight, people are willing to pay more for lighter bikes. Especially, bikes of 8 and 9 kg are much more popular compared to 10 and 11 kg. However, this result is not visible in the results of the hedonic price regression, in those results the weight of a bike does not play an important role in determining the price.

Next, the groupset level is the most important variable for budget bikes. The willingness to pay is higher compared to the hedonic price regression, but the direction of the effect is the same. Also, the brand of the groupset is important, people prefer by the same level (so approximately the same quality) Shimano over SRAM which is in contradiction with the price difference since groupsets of SRAM are more expensive compared to Shimano according to the hedonic price regression.

Then, people prefer carbon frames over aluminium frames and the difference in willingness to pay is almost equal to the difference found in the hedonic price regression. So this implicates that the price difference between these two frame materials is equal to the customer value between these two types of frame materials. In the variables brakes and year, there are also some differences, however, they are not significant at 5%.

Finally, we look at the brands of bikes. There are some small differences visible, Koga and Cube are the most preferred brands which is quite interesting since Koga is an expensive brand in the hedonic price regression but Cube is the cheapest brand. So people have approximately the same willingness to pay for an expensive brand as for a cheaper brand.

In conclusion, for the people interested in budget bikes the variables price, groupset level, groupset brand, weight, frame and brand are the most important. In some variables, the willingness to pay is approximately equal to the results of the hedonic price regression but in some other variables, some differences are visible. This implies that the prices of budget bikes are partly based upon customer value-based pricing but also partly upon other pricing strategies. The implications for these results are further discussed in the paragraph about marketing implications.

Table 5*, multinomial logistic regression budget bikes*

Variable	Multinomial logit coefficient	Willingness to pay	Hedonic price regression, average bootstrap difference
Price (linear)	-0.0016***	n/a	n/a
Weight: 11 kg	Reference		
Weight: 10 kg	0.14	87.22	-9.95
Weight: 9 kg	0.61***	373.77	-19.89
Weight: 8 kg	0.67*	413.96	-29.84
Groupset: Level 1	Reference		
Groupset: Level 2	0.79***	489.29	89.97
Groupset: Level 3	2.41***	1486.46	270.06
Groupset: Level 4	3.01***	1856.03	463.74
Groupset brand: Shimano	Reference		
Groupset brand: SRAM	-0.67***	-412.57	356.93
Brakes: Rim	Reference		
Brakes: Disc	0.11	70.27	126.99
Frame: Aluminium	Reference		
Frame: Carbon	0.55***	335.91	345.49
Year: 2018	Reference		
Year: 2019	0.02	9.96	2.64
Year: 2020	0.22	133.26	96.70
Brand: Cube	Reference		
Brand: Focus	-0.55**	-337.40	178.03
Brand: Koga	0.16	95.57	378.67
Brand: Merida	-0.48***	-294.08	235.92

** indicates $p < 0.05$. ** indicates $p < 0.01$. *** indicates $p < 0.001$.*

Mid-range bikes

For the mid-range bikes, we see in table 6 that price is still significant but the coefficient is three times as small. However, this can be explained by the wider range of the price. Then, all the attribute levels show a significant difference from their reference levels. So do people prefer lighter bikes, better quality groupsets, the groupset brand Shimano, electronic shifting, disc brakes, carbon frames, bikes from the years 2019 and 2020 and the brands Bianchi and Wilier.

From the hedonic price regression, we see that the weight of a bike is relatively unimportant for the price in the category of mid-range bikes. However, the willingness to pay is much higher for lighter bikes compared to a bike of 10 kg. Next, in the groupset levels we see that people have a higher willingness to pay for better quality groupsets and also the price is higher regarding the hedonic price regression but the difference in prices is smaller compared to the differences in willingness to pay. In the groupset brands, we see the same as in the subset of budget bikes. Shimano is the most preferred brand and it is also the cheapest brand. The final attribute of the groupset is whether the shifting is electronic or mechanic. Electronic shifting is preferred but the difference is small compared to other variables. The difference in the willingness to pay for electronic shifting and the effect on the price is relatively small.

The next variable is the brakes of the bike, disc brakes are preferred strongly over rim brakes however the price differences between those two brakes systems is relatively small. The same thing applies to the frames, carbon frames are preferred over aluminium frames, but the price difference regarding the hedonic price regression is much smaller compared to the difference in willingness to pay.

Then in the variable year, we see something really interesting. The difference between a bike from 2018 and 2019 is quite noticeable, but the difference between 2019 and 2020 is very small. When we take a look at the results of the hedonic price regression we see that the prices of bikes from 2019 are quite a bit cheaper compared to bikes from 2020. This implies that bike shops can reduce the discount of bikes from the previous year because people seem to have the same willingness to pay as for new bikes. Only bikes which are 2 years old or older should be sold with an interesting discount.

Then the final variable is again the brand, Sensa and Cube are the cheapest brands and their willingness to pay is also the lowest. Wilier and Bianchi are the more expensive brands and also the willingness to pay for these brands is the highest. However, the difference in willingness to pay is much bigger than the price difference. For example, people are willing to pay €1366.82 more for a Bianchi than for a Cube but the price difference is just €290.62.

In conclusion, all variables have a significant effect so all variables are important for the preference of customers. The groupset levels are again the most important and the effect of the year is the smallest effect. In some attributes, the willingness to pay and the hedonic price regression results are quite similar but in other attributes, the differences are quite big and sometimes the effect is moving in the opposite direction (e.g. groupset brand).

***Table 6**, multinomial logistic regression mid-range bikes*

Variable	Multinomial logit coefficient	Willingness to pay	Hedonic price regression, average bootstrap difference
Price (linear)	-0.0005***	n/a	n/a
Weight: 10 kg	Reference		
Weight: 9kg	0.58***	1097.71	20.78
Weight: 8 kg	0.66***	1249.83	41.57
Weight: 7 kg	1.25***	2366.87	62.35
Groupset: Level 4	Reference		
Groupset: Level 5	0.99***	1860.65	589.53
Groupset: Level 6	1.61***	3046.74	635.12
Groupset brand: Shimano	Reference		
Groupset brand: SRAM	-0.76***	-1442.08	175.17
Groupset brand: Campagnolo	-0.81***	-1522.91	221.30
Shifting: Mechanic	Reference		
Shifting: Electronic	0.43***	814.11	653.28
Brakes: Rim	Reference		
Brakes: Disc	1.18***	2235.71	205.97
Frame: Aluminium	Reference		
Frame: Carbon	0.69***	1303.35	430.29
Year: 2018	Reference		
Year: 2019	0.20***	384.51	105.97
Year: 2020	0.22*	413.76	313.39
Brand: Cube	Reference		
Brand: Sensa	-0.17**	-319.15	101.32
Brand: Wilier	0.30***	559.35	281.88
Brand: Bianchi	0.72***	1366.82	290.62

** indicates p < 0.05. ** indicates p < 0.01. *** indicates p < 0.001.*

Expensive bikes

For the expensive bikes, we first discuss a multinomial logistic regression without interaction and compare this with the hedonic price regression without interactions (table 7) and afterwards, we add the most important interactions regarding the hedonic price regression to the model. In the model without interactions, the coefficient of price has decreased compared with the previous models but the range of the price is bigger than in the previous subsets.

The first variable is the weight. We see an increase in preference between 9, 8 and 7 kg but people prefer a bike of 7 kg over a bike of 6 kg. At first, this looks a bit strange, however, the UCI (Union Cycliste Internationale) rulebook might have a valid solution to this phenomenon. Article 1.13.019 (UCI, 2020) states that the weight of a bike in an official UCI event cannot be less than 6.8 kg. Despite that most people do not have to follow these rules, because they do not participate in these type of international events, they might still have this well-known official weight limit in their minds when they are making purchase decisions regarding new bikes. Because we treat weight as a linear variable in the hedonic price regression we are not able to compare this result with the hedonic price regression. However, the increase in price from 9 kg to 7 kg is a lot smaller compared to the increase in willingness to pay.

In the groupset, we see something that is in contradiction with the previous subsets. The groupset level 6 has a small but insignificant effect, which means that an increase from a groupset of level 5 to a groupset of level 6 does not significantly increase the preference. The estimated price difference from the hedonic price regression is much higher compared to the willingness to pay. Then the groupset brand is very similar to the previous subsets, Shimano is the cheapest but also the most preferred groupset brand. Next, electric shifting is way more popular than mechanic shifting and this implies that people prefer level 5 electric groupsets over level 6 mechanic groupsets.

Again disc brakes are preferred over rim brakes and the effect on the price of the brakes type is relatively small. The variable frame is not used, because almost all bikes over €4000 have a carbon frame. Next, in the variable year, we see the same as by the mid-range bikes. There is very little difference in preference and willingness to pay between bikes from 2019 and 2020 but bikes from 2019 are on average €1000 cheaper compared to 2020 bikes. So also for bikes above €4000 reconsidering these discounts for models of just 1 year old is interesting.

The final variable is the brand of a bike, Orbea is the cheapest brand but not the least preferred. Trek and Cannondale are the most preferred brands with the highest willingness to pay. Trek is also the most expensive brand regarding the hedonic price regression, Cannondale is somewhere in the middle. Therefore, on average Cannondale bikes are sold below the customer-value.

***Table 7**, multinomial logistic regression expensive bikes*

Variable	Multinomial logit coefficient	Willingness to pay	Hedonic price regression, average bootstrap difference
Price (linear)	-0.0002***	n/a	n/a
Weight: 9 kg	Reference		
Weight: 8kg	0.47***	2375.01	121.27
Weight: 7 kg	0.75***	3792.97	242.53
Weight: 6 kg	0.53**	2678.64	363.80
Groupset: Level 5	Reference		
Groupset: Level 6	0.16	816.17	2470.68
Groupset brand: Shimano	Reference		
Groupset brand: SRAM	-0.78***	-3915.42	657.05
Groupset brand: Campagnolo	-1.04***	-5225.27	401.19
Shifting: Mechanic	Reference		
Shifting: Electronic	1.53***	7686.28	902.64
Brakes: Rim	Reference		
Brakes: Disc	0.67***	3392.62	294.64
Year: 2018	Reference		
Year: 2019	0.56***	2825.13	44.92
Year: 2020	0.48**	2435.74	1032.51
Brand: Cube	Reference		
Brand: Merida	0.45***	2275.97	952.21
Brand: Orbea	0.46**	2316.23	-468.56
Brand: Trek	1.10***	5511.23	1103.08
Brand: Cannondale	1.03***	5189.77	112.05

** indicates $p < 0.05$. ** indicates $p < 0.01$. *** indicates $p < 0.001$.*

Expensive bikes, interactions

First, we take the model without interactions (table 7) and try to add the two interactions which differ significantly from 0 in the hedonic price regression. This are the interactions between a level 6 groupset and electronic shifting and between a level 6 groupset and the year 2020. Unfortunately, the model with the interaction between a groupset of level 6 and 2020 was not able to run due to computational singularity. Which means that the correlation between this interaction and one of the other variables was too high to calculate the coefficient of this interaction. This problem is created by the survey design, the survey design is created to optimise the 4 characteristics and to estimate all main effects, but the estimation of all possible interactions is not taken into account in creating the design, since this would result in a very complex design for which a lot of questions or respondents are needed. Therefore, we estimated the model with all the main effects and only the interaction between a level 6 groupset and electric shifting. The relevant coefficients of this model are presented in table 8.

Table 8*, multinomial logistic regression expensive bike + groupset level 6 * electric shifting*

Variable	Coefficient without interaction	Coefficient with interaction
Groupset: Level 6	0.16	0.97***
Shifting: Electronic	1.53***	-0.04
Interaction effect	n/a	-1.76***

** indicates p < 0.05. ** indicates p < 0.01. *** indicates p < 0.001.*

This added interaction does also change the original coefficients. In the first column of table 8, the coefficients as in the first model (table 7) are visible and in the second column, this is compared with the new coefficient. From the model with only main effects, we predict that a bike with level 6 electronic groupset is relatively popular because both attribute levels have a positive coefficient. But the interaction shows us that this is a very unpopular combination. However, also the main effects have changed significantly by adding the interaction to the model.

Adding this interaction to the model does not influence the performance of the model. To test this we let the model predict the probabilities for each bike in a choice set to be chosen and take the highest probability per choice set as the prediction, so no threshold is used. This forces the prediction to predict 1/3 of the observations true and the remaining 2/3 false. From the 1/3 which is predicted as chosen 56.3% of the predictions are true for both models. Finally, we added some interactions to the model which show an insignificant effect in the hedonic price regression but which are not completely shrunk to zero. Again, we cannot include all interactions because of computational singularity.

The interactions which are added to the model are groupset level 6 * electric shifting, groupset level 6 * brand Trek, electric shifting * disc brakes and year 2020 * groupset brand Campagnolo. Again this does not lead to any improvements in the performance of the model and therefore we dive not further into these interaction effects. For any further research, it is interesting to investigate these interaction effects with some kind of regularisation model combined with multinomial logistic regression, but this should be considered before the conjoint design is created since estimating interactions requires more respondents/questions and more variation in the choice sets.

Segmentation

As described in the theoretical framework, a lack of segmentation can be a cause of failing to apply customer value-based pricing (Hinterhuber, 2008). In the survey, we asked some demographic and psychographic questions. For each possible segmentation variable, we first analyse what the diffusion over the three different price categories is. Next, we further analyse the mid-range segment, because this is by far the biggest segment in our samples. Since 50% of the bicycles are in this price range and 61.1% of the respondents are interested in bikes in this range.

First, to see which variables predict the best in which price segments people are interested, a random forest is used. In this random forest, the interested price segment is the dependent variable and the answers to all the demographic and psychographic questions are used as independent variables. Age and the hours of cycling per week seem to be the best predictor variables, however, this could also be caused by the fact that both variables are numeric and so more splits are possible in the trees of the random forest. The most important variable from the dummy variables is whether people use their bike for riding with friends or not, however, the difference between this answer and the other activities and the dummy of gender is very small.

<u>Gender</u>

The first variable we discuss is gender. When we take a look at the proportion of women in each price category, we see that 14.9% of the respondents in the budget category are women, 10.1% of the midrange category and only 3.2% of the expensive category. This indicates that women are on average more interested in budget and midrange bicycles. Next, we take a look at whether women have different preferences compared to man for mid-range bikes. The multinomial logit model with the interactions with the variable gender is presented in table 1 of appendix C.

In table 1 of appendix C, we see that the only significant interactions effects are two brands. The brand Sensa is for men the least preferred brand with a coefficient of -0.13, however, women have a coefficient of -0.36 by this interaction, which means that the total coefficient for women is -0.49. Similarly, Wilier which has a positive main effect shows a negative coefficient of -0.60 in the interaction with women, which implies that women prefer this brand much less compared to men. Also in the other variables, we see some interesting differences, but these are not significant at 5%.

In conclusion, women seem to be less interested in more expensive bikes and women have different preferences regarding the brands of bikes. The most preferred brands (from our research) for women are Bianchi and Cube and for men, these are Bianchi and Wilier.

<u>Age</u>

When we look at the age distribution over the three subsets, we see that the mean and the median of age are a bit higher for the midrange and the expensive subset compared to the budget subset. People who are interested in budget bikes are on average 41.35 years old and the average of the mid-range and expensive subsets is respectively 46.45 and 49.95 years old.

For the analysis of the variable age in the mid-range subset, we could, in theory, make a possible splitting point for every year and then optimise for the best splitting points to create two or more age groups. However, this would not benefit any retailer in determining their marketing and pricing strategy. Therefore, we create three ages groups which are easier to use for strategic approaches. The first group is the group with relatively young people (17-35), the second group which is used as the reference group are people aged from 36 to 50 and the final group are the more older people which are more than 50 years old.

In table 2 of appendix C, the results of the model with interactions with these age groups are plotted. We see that for the age group 17-35 no interaction effects are significant at 5%. In the age group 50+ only the interaction with groupset level 5 is significant. The main coefficient for groupset level 5 is 1.18 and the interaction between groupset level 5 and 50 years and older is -0.49. This means that the difference in preferences is smaller between groupset level 4 and 5 but bigger between level 5 and 6 for people older than 50 years old.

We conclude that age is not an important variable for segmentation. Only one attribute level shows a significant interaction for the age group 50 years and older. Therefore, we do not recommend using age as a segmentation variable.

<u>Hours of cycling per week</u>

Gender is a little bit useful in creating segments and age is not useful at all. Now we investigate whether psychographic variables are better for segmenting this market than these demographic variables. In this variable, we see in general that people who cycling more hours per week are on average interested in more expensive bikes.

For this variable, we make two groups, people who cycling 0 to 8 hours per week and people who cycling 9 to 40 hours per week. So we have two groups which are quite different, people who cycle regularly and people who cycle very often. The first group(0-8) is used as the reference group and with the group 9-40 the interactions are created. In table 3 of appendix C, we see that only the interaction with the variable price is significant. This main effect of price is -0.0006 per euro and the interaction is 0.0003 per euro. This means that people who cycle more than 8 hours per week are on average half as price sensitive. However, they are not significantly more interested in one of the other attribute levels, so therefore it is difficult to use this finding in a marketing strategy.

<u>Type of cycling activities</u>

The final segmentation variable is the kind of activities for which people use their road bikes. In selecting which variables to use in the final model, we also take into account the difficulty in segmenting a real market based upon the variables. The following our activities are used in our final model: rides with a cycling club, organised touring events, races and cycling holidays. People who use their bike for rides with a cycling club are likely to be in the mid-range or expensive group. The same applies to people who use their bike for organised touring events. Then not that many people (10%) use their road bikes for racing and again most of these people are in the mid-range or expensive subset. Finally, for holiday we see again the same. So in general, people who use their bike for one of these four types of activities are much more likely to be interested in bikes in the mid-range or expensive category compared to the budget category.

In table 4, all the main effects and the interactions with these four activities are presented. Note a person can use their bike for 0 to 4 different types of activities. The coefficients of a person who do not use their bike for any of these four activities are the main effects. For people who use their bike for multiple activities, we have to add all the relevant interactions.

First, in the interactions with holiday we see no significant interactions and in the interactions with organised tours only the brand Sensa is significant positive. This means that the brand Sensa is more popular by people who participate in organised tours. However, in the main effects, Sensa was the least preferred brand and adding the interactions of organised tours and the main events still make Sensa the least preferred but it is approximately equal to Cube for this group.

In the interactions with club rides, we see that the groupset brands SRAM and Campagnolo have very negative and significant values. These two groupset brands are not preferred in the main effect, but this is even less by people who participate in club rides. A possible explanation for this phenomenon is that Shimano is the groupset brand with the biggest market share, 83.3% of the bikes from the web scraping have a Shimano groupset. So regarding spare parts, it would be easy when everyone at a cycling club uses these same popular Shimano parts.

Finally, the most interesting interactions are the interactions with participating in races. People who participate in races are much more price-sensitive than people who do not participate in races, so their willingness to pay is on average lower. This could be explained by the risk of damage through crashing in races. People who participate in races have a strong preference for bikes of 7 kg (the lowest weight used in this subset). Also, bikes of 8 and 9 kg are stronger preferred over 10 kg but only the interactions of 7 and 9 kg are significant. This implies that people who participate in races care a lot about the weight of their bikes, which is quite logical since weight is important for the performance of a bike. In the groupset brand, the interaction with Campagnolo is very negative which is similar to people who participate in club rides.

In conclusion, the variable which is the best in segmentation is whether people participate in races or not. People who participate in races have some different preferences compared with people who do not participate in races. Also, whether people participate in club rides is important regarding groupset brands. In the other variables, gender shows some differences, men do slightly prefer other brands compared to women.

Marketing recommendations

The aim of this research is to give marketing advice to retailers regarding pricing strategies of road bikes. In this section, we translate the results found in the previous section to straight forward marketing advise. First, we discuss the marketing implications for the three price-based subsets and finally, we dive deeper into the application of the found segments.

Budget bikes (€500-€1500)

For the budget bikes, retailers can base their price more upon the weight of a bike. The price difference between lighter and heavier bikes is most of the times neglectable and this can be changed without violating the customer-value of most customers. Most people have a strong preference for the groupset brand Shimano over SRAM but bikes with SRAM are more expensive. Therefore, retailers should consider stopping with selling budget bikes with SRAM, since lowering the price to the found customer-value seems to be unrealistic. Finally, people have the highest willingness to pay for the brands Koga and Cube. Cube is one of the cheapest brands found in the budget subset. Therefore, selling Cube bikes with more margin can be an interesting option for retailers to increase their revenue. In all the other discussed variables in this research, no interesting opportunities are found or changes are needed.

Mid-range bikes (€1500 - €4000)

In this category, again weight should be considered as one of the most important variables to determine the final price of a bike. Also in this category retailers should focus on selling bikes with Shimano groupsets, because they are much more preferred and cheaper compared with SRAM and Campagnolo. Also, the prices of bikes with Shimano Dura-Ace (level 6) can be increased compared to Shimano Ultegra (level 5), since people in this subset have a strong preference for the best quality groupset. Also, people have a relatively strong preference for disc brakes in this subset, so the prices of bikes with disc brakes can be set higher compared to bikes with rim brakes.

Discounts for older bike models should be removed/reduced for bikes from the previous year (2019) since people have approximately the same willingness to pay for them as for the newer models from this year (2020). Therefore, we advise to only give discounts on bikes in the mid-range category when the model is 2 years old or even older. Finally, Bianchi is by far the most preferred brand and therefore retailers can higher the prices of Bianchi bikes to increase the margin. Cube is the cheapest from the investigated brands, but not the least preferred. Therefore, retailers should also consider selling Cube bikes in their (web)shops.

Expensive bikes (€4000+)

In the final price category, we advise again that price should be an important factor in determining the price, however, bikes lighter than 7 kg (probably 6.8 kg) are less preferred and retailers can consider stopping selling bikes which are lighter than 6.8 kg. Also in this category, we advise focusing mainly on selling bikes with a Shimano groupset. The difference in preference between Shimano Dura-ace (level 6) and Shimano Ultegra (level 5) is very small, but the difference in preference between mechanic and electric shifting is very big. Therefore, retailers can sell a lot of bikes with Shimano Ultegra Di2 (level 5, electric) and take a lot of margin on these bikes.

In this subset, we found the same regarding disc brakes and the model year of the bikes as in the mid-range subset. So retailers should consider increasing the prices of bikes with disc brakes and reduce/remove the discount on bikes from the previous year. Finally, Cannondale is an interesting brand to increase the revenue, since it is most preferred and at the moment it is one of the cheaper brands.

Segmentation

The advice we give regarding segmentation is certainly valid for the mid-range bikes but presumably, the advice is also useful for the other categories. The best variable we found for segmenting the market is whether people participate in races or not. People who participate in races have different preferences compared to other people. However, how could we identify whether a person participates in races so we can offer him different prices or products?

The first option is to sell a bike which is only preferred by people who participate in races. This bike should be relatively cheap, lightweight and mounted with a Shimano or SRAM groupset. However, with only the use of these three variables also other people who do not participate in races are probably interested in this bike. A possibility for targeting a bike more towards racers and less towards other people is making the bike more aero and less comfortable, however, this is not investigated in this research it is plausible that only racers are interested in an uncomfortable and fast aero bike.

The second option is to cooperate with the KNWU (Royal Dutch Cycling Association). All the bigger races in the Netherlands are organised under the supervision of the KNWU. To participate in these races, cyclists need a KNWU license. Retailers of road bikes can give discounts on some light weighted bikes when people show their licence. However, this could lead to a situation in which people get a license only to receive a discount on their new bike. Both approaches to target specifically to racers have their advantages and disadvantages and it is up to each retailer which approach they think that is the best for their shop.

Segmenting whether people participate in club rides is not so easy to apply. People who participate in club rides prefer Shimano more than the other groupset brands. However, we find this in all our models. So people who participate in club rides prefer Campagnolo and SRAM even less compared to other people, however, we do not think that this is a reason to create a special bike towards this group.

Finally, some differences are visible between men and women. Setting different prices to men or women is of course not allowed but with the use of for example colour and geometry, it is possible to make a bike attractive for only men or women. For example, a pink bike with women geometry is presumably not purchased by a lot of men. Since Bianchi is the most popular brand for both men and women this brand should not be used for targeting specifically men or women. Wilier is the second most preferred brand for men and the least preferred brand for women, therefore, retailers should target this brand completely to men and do not need to introduce any women-specific model of the brand Wilier.

The brand Cube is more preferred by women compared to men, therefore, retailers should consider selling one or more women models of the brand Cube. Also, the price of this women bike can be slightly higher compared to a Cube bike designed for men since women have a higher willingness to pay for this brand.

In conclusion, using these segments can improve the use of customer value-based pricing. However, the differences between the different discussed groups are relatively small. Therefore, we think that optimising the prices per price segment is the most important and segmentation by these demographic and psychographic variables can be a final push to optimise the pricing strategy regarding different groups of customers.

Conclusion & Discussion

This research aims to answer the following research question: *How can retailers of road bikes improve their pricing strategies regarding the different attribute levels of road bikes?* First, in the literature study, we discussed different pricing strategies and customer value-based pricing seems to be the best pricing strategy. With the use of hedonic price regression and conjoint analysis, we combined the supply and the demand side of the market to evaluate whether customer value-based pricing is applied in the market of road bikes.

We divided the market into three price segments, budget bikes (€500-€1500), mid-range bikes (€1500-€4000) and expensive bikes (€4000+), to create more precise models. In each price segments, we found multiple improvements regarding the prices of attributes. In most of the cases, the price is lower compared to the average willingness to pay of the customers, which implies that an increase in the price does not result in a big decrease in sales. In all price categories, we found that weight should be one of the most important factors in determining the price. Furthermore, the groupset brand Shimano is strongly preferred over Campagnolo and SRAM, so it can be interesting for retailers of road bikes to sell only bikes with Shimano groupsets and to increase the margin on these bikes. For the mid-range and expensive bikes, we found that retailers are probably giving to many discounts to bikes of the previous year (2019). Therefore, we advise giving discount only on models which are two years old or even older. Per category, we found a lot of smaller improvements which are only valid in that category, these are in detail discussed in the results section and the marketing implications section.

Segmentation could also improve customer value-based pricing. Implementing segmentation can lead to different price/product strategies for different groups of customers so that each group is targeted by their own preferences. In this research, we found that whether people participate in races or not is the best segmentation variable, people who participate in races are more price sensitive, interested in lighter bikes and have a preference for Shimano and SRAM groupsets over Campagnolo groupsets. Also, the variable gender can be used in segmentation but the differences are a lot smaller. The only differences we found between men and women are some differences between brands. Men prefer Bianchi and Wilier the most and women prefer Bianchi and Cube the most.

In this research, we also found that interactions have some importance in the expensive bike category. However, in this research, we were not able to completely investigate these interactions. For further research, it is interesting to investigate these interaction effects. To investigate this it is important to collect a bigger conjoint sample for the expensive category. Furthermore, it is important to use the interactions in the process of creating the conjoint survey design.

Conjoint analysis and hedonic price regression were used to analyse the road bike market in this research. However, the combination of these two methods is not very common. This research is an example of the possibilities of combining these two methods. However, in the hedonic price regression part, we used an elastic net regression for regularisation of the variables in combination with the bootstrap but in the conjoint analysis, we only estimated a straight forward multinomial logistic regression. Therefore, to make a comparison between these two methods better in further research, creating an easy to use regularisation method for multinomial logistic regression is very useful. To further develop the combination of these two methods, more research is needed and both methods can be further optimised. For further developing the combination of these methods, a simpler market with fewer attributes per product is advisable.

The assumptions which we made in the hedonic price regression may also be a bit unrealistic. We assumed that all characteristics are independent and that only the characteristics which were scraped from the websites of the bike shops are used in making a decision. In reality, people will use a lot more characteristics and even factors which are hard to capture in a dataset, like the looks of a bike or the atmosphere in a physical store.

Also in the conjoint part, we made assumptions. We assumed that the most important attribute levels from the hedonic price regression are the best variables to use in the conjoint survey. However, maybe other attributes would be much better. In the survey, we asked which attributes respondents missed in the survey and common answers were wheels, the type of model (aero, all-round, climbing), the saddle, other brands than the brands used in this research and the looks of a bike. For any further research, these are interesting attributes to keep in mind when creating a conjoint design.

Another problem with conjoint analysis is the lack of incentives. People have to make decisions between bikes which are mostly more than €1000. However, the choices which people make in the survey do not have any consequences. Therefore, people might make some different decisions when they are in a real purchasing process of a road bike. To solve this in further research, sales data of one or more retailers should be used.

In the end, both methods are based upon assumptions which may not be completely realistic and improvements can be made in further research. However, the results found in this research give more than a good indication of improvements in the pricing strategy in the road bike market. We gave quite a couple of advices regarding the attribute pricing strategies of road bikes without any inside information from retailers. When a retailer would like to further investigate these improvements, they could use their sales data in combination with some experimental changes to further investigate these improvements.

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Appendix

Appendix A, hedonic price regression

***Table 1**, Elastic net, budget bikes*

Variable	Coefficient	Lower bound 95% bootstrap interval	Upper bound 95% bootstrap interval	Average bootstrap difference
Weight (0-1)	117.36	-89.82	258.87	n/a
Shop: 12gobike	0	-17.82	19.48	Reference
Shop: Bike-x	74.71	-36.34	141.8	51.90
Shop: Bikester	0	-23.24	22.68	-1.11
Shop: Fietsspecialist	57.49	-61.52	151.69	44.25
Shop: Mantel	-45.19	-100.55	11.25	-45.48
Shop: Peter ter Louw	0	-74.23	73.95	-0.97
Shop: Rijwiel c&c	89.14	13.51	166.04	88.95
Shop: Rullens Wouw	-17.95	-119.77	51.51	-34.96
Shop: Salden	-86.36	-199.9	17.37	-92.09
Groupset: level 1	-262.53	-339.53	-164.13	Reference
Groupset: level 2	-179.2	-243.09	-80.64	89.97
Groupset: level 3	0	-54.45	90.91	270.06
Groupset: level 4	196.54	133.86	289.97	463.74
Groupset: level 5	-45.96	-180.91	81.81	202.28
Groupset: level 6				
Groupset: NA	46.13	-100.87	192.79	297.79
Shifting: Electronic				
Shifting: Mechanic				
Brakes: Disc	53.5	4.9	123.52	126.99
Brakes: Rim	-81.78	-125.78	0.22	Reference
Brakes: NA	0	-3.4	3.34	62.75
Frame: Aluminium	-13.08	-89.02	31.3	Reference
Frame: Carbon	344.62	236.12	397.13	345.49
Frame: Other	0	-94.9	92.57	27.70
Frame: NA	0	-6.59	5.74	28.44
Fork: Aluminium	-40.99	-92.48	14.47	Reference
Fork: Carbon	0	-9.58	9.98	39.20
Fork: NA	28.96	-23.38	84.75	69.69
Wheels: Other	-21.92	-99.52	71.49	-13.52
Wheels: Bontrager	0	-41.58	70.4	14.91
Wheels: Cube	0	-28.28	27.28	Reference
Wheels: DT Swiss	0	-109.27	67.3	-20.48
Wheels: Fulcrum	372.79	134.69	564.92	350.30
Wheels: Giant	0	-27.38	22.12	-2.13
Wheels: Mavic	-116.81	-265.26	20.92	-121.67

Wheels: Newmen				
Wheels: Shimano	36.48	-26.13	109.61	42.24
Wheels: Supra	0	-29.04	20.46	-3.79
Wheels: Syncros	0	-30.28	27.38	-0.95
Wheels NA	0	-21.01	25.05	2.52
Year: 2018 or before	-2.15	-58.03	24.61	Reference
Year: 2019	0	-53.71	25.59	2.64
Year: 2020	99.48	31.37	128.62	96.70
Year: NA	0	-46.03	32.87	10.13
Model: Aero	-67.14	-132.54	42.48	-36.00
Model: All-round	-4.97	-40.43	22.37	Reference
Model: Endurance	34.43	-18.25	81.14	40.48
Model: Fitness	-8.29	-50.4	28.67	-1.83
Model: NA	0	-12.06	11.24	8.62
Gender: Man	0	-14.46	11.8	Reference
Gender: Woman	0	-13.93	12.82	0.78
Gender: NA	10.18	-38.2	54.63	9.54
Colour: Black	0	-24.2	23.19	Reference
Colour: Blue	4	-34.21	49.2	8.00
Colour: Other	-75.85	-148.66	9.96	-68.85
Colour: Grey	-22.79	-109.88	63.54	-22.67
Colour: Multiple	9.83	-29.31	57.36	14.53
Colour: Red	0	-56.5	44.1	-5.70
Colour: White	54.35	-18.8	114.64	48.43
Colour: NA	0	-18.36	13.98	-1.69
Saddle: Other	-38.2	-109.13	32.68	34.66
Saddle: Bontrager	0	-33.89	26.76	Reference
Saddle: Cube	53.24	-36.18	122.11	46.53
Saddle: Fabric				
Saddle: Fizik				
Saddle: Forza	51.77	-61.5	151.53	48.58
Saddle: Giant	0	-30.95	35.49	5.84
Saddle: Liv	0	-39.14	59.34	13.66
Saddle: Prologo				
Saddle: San Marco	-61.9	-129.85	30.32	-46.20
Saddle: Selle Italia	-74.22	-149.54	37.98	-52.21
Saddle: Selle Royal	-74.83	-160.21	22.55	-65.27
Saddle: Supra	0	-26.87	32.94	6.60
Saddle: Syncros	84.78	-7.99	163.34	81.24
Saddle: NA	0	-25.15	22.56	2.28
Steer: Other	0.12	-56.87	108.35	27.24
Steer: BBB	57.72	-207.94	419.04	107.05
Steer: Bontrager	0	-17.36	14.36	Reference

Steer: Cannondale	-58.34	-112.36	36.6	-36.38
Steer: Cube	0	-20.39	23.83	3.22
Steer: Forza	4.64	-12.41	27.5	9.05
Steer: FSA	76.16	-72.87	187.33	58.73
Steer: Giant	17.34	-46.74	101	28.63
Steer: Merida	-41.49	-251.91	142	-53.45
Steer: Orbea	31.53	-54.16	102.61	25.73
Steer: Reparto Corse	76.35	-67.9	192.32	63.71
Steer: Supra	0	-45.31	27.86	-7.22
Steer: Syncros	-15.47	-52.24	30.12	-9.56
Steer: NA	-23.93	-51.47	23.51	-12.48
Tyres: Bontrager	0	-12.59	13.98	Reference
Tyres: Continental	25.46	-53.85	148.88	46.82
Tyres: Other	-76.98	-131.11	54.57	-38.96
Tyres: Giant	-70.48	-152.93	47.21	-53.55
Tyres: Schwalbe	-75.87	-122.09	18.42	-52.53
Tyres: Vittoria	81.01	12.33	190.64	100.79
Tyres: NA	9.32	-49.97	116.49	32.56
Brand: Other	119.56	17.64	172.58	95.67
Brand: Bianchi	11.73	-33.18	46.89	7.42
Brand: Cannondale	0	-107.82	50.65	-28.02
Brand: Cube	-136.12	-217.63	-40.51	-128.51
Brand: Focus	97.71	-84.99	182.91	49.52
Brand: Giant	25.22	-24.12	64.69	20.85
Brand: Koga	268.22	100.84	398.36	250.16
Brand: Liv	0	-53.72	30.38	-11.11
Brand: Merida	125.91	-107.14	320.82	107.41
Brand: Orbea	1.41	-18.62	24.48	3.49
Brand: Ridley	0	-51.26	64.65	7.26
Brand: Scott	-7.21	-65.35	34.14	-15.04
Brand: Sensa	0	-29.97	20.54	-4.15
Brand: Trek	0	-9.47	8.34	Reference
Brand: Wilier	0	-120.39	48.32	-35.47
Groupset brand: Campagnolo				
Groupset brand: Shimano	0	-76.3	106.38	Reference
Groupset brand: SRAM	454.01	-90.59	834.52	356.93
Groupset brand: NA	-121.67	-269.04	68.62	-115.25

***Table 2**, Elastic net, mid-range bikes*

Variable	Coefficient	Lower bound 95% bootstrap interval	Upper bound 95% bootstrap interval	Average bootstrap difference
Weight (0-1)	-155.95	-738.96	248.54	n/a
Shop: 12gobike	-15.31	-119.07	54.54	Reference
Shop: Bike-x	0	-92.75	138.24	55.01
Shop: Bikester	37.21	-58.9	116.59	61.11
Shop: Fietsspecialist	0	-130.92	101.3	17.45
Shop: Mantel	-29.44	-179.59	63.09	-25.99
Shop: Peter ter Louw	0	-171.85	86.02	-10.65
Shop: Rijwiel c&c	199.37	-10.84	327.84	190.76
Shop: Rullens Wouw	-45.79	-263.56	114.33	-42.35
Shop: Salden	187.28	-25.04	376.09	207.79
Groupset: level 1	-772.06	-1311.34	271.44	-11.24
Groupset: level 2				
Groupset: level 3	-529.79	-682.76	-334.66	Reference
Groupset: level 4	-386.5	-484.55	-236.59	148.14
Groupset: level 5	208.61	99.25	358.66	737.67
Groupset: level 6	259.44	-139.46	688.55	783.26
Groupset: NA	79.89	-137.84	355.61	617.60
Shifting: Electronic	333.34	267.86	395.53	653.28
Shifting: Mechanic	-317.79	-384.77	-258.4	Reference
Brakes: Disc	176.56	57.6	258.33	205.97
Brakes: Rim	-20.8	-148.55	52.53	Reference
Brakes: NA	0	-47.26	33.66	41.21
Frame: Aluminium	-441.55	-579.12	-281.45	Reference
Frame: Carbon	0	0	0	430.29
Frame: Other	288.15	-93.05	690.46	728.99
Frame: NA	188.42	10.48	373.01	622.03
Fork: Aluminium				
Fork: Carbon	0	-65.93	39.78	Reference
Fork: NA	0	-36.6	59.49	24.52
Wheels: Other	0	-87.16	90.62	16.52
Wheels: Bontrager	52.59	-67.85	147.01	54.37
Wheels: Cube	0	-131.67	102.1	Reference
Wheels: DT Swiss	106.37	-50.91	263.71	121.19
Wheels: Fulcrum	-167.47	-277.83	-31.41	-139.83
Wheels: Giant	0	-53.67	40.77	8.34
Wheels: Mavic	0	-247.45	242.07	12.10
Wheels: Newmen	133.25	-99.56	378.37	154.20
Wheels: Shimano	-117.59	-236.06	36.81	-84.33
Wheels: Supra	-129.67	-257.42	3.5	-112.17

Wheels: Syncros	-6.59	-179.99	111.04	-19.69
Wheels NA	22.56	-48.85	106.59	43.66
Year: 2018 or before	-194.62	-341.57	-6.65	Reference
Year: 2019	-83.53	-192.13	55.85	105.97
Year: 2020	121.14	9.23	269.34	313.39
Year: NA	0	-65.18	73.91	178.47
Model: Aero	239.16	62.46	422.51	379.54
Model: All-round	-148.15	-244.32	-29.8	Reference
Model: Endurance	0	-125.33	138.04	143.41
Model: Fitness				
Model: NA	0	-17.8	24.26	140.29
Gender: Man	0	-38.98	58.6	Reference
Gender: Woman	-73.43	-179.39	37.69	-80.66
Gender: NA	0	-66.54	112.86	13.35
Colour: Black	88.83	-23.6	209.44	Reference
Colour: Blue	17.17	-82.82	149.74	-59.46
Colour: Other	0	-129.38	197.65	-58.78
Colour: Grey	-72.82	-229.76	80.56	-167.52
Colour: Multiple	-87.59	-227.94	60.24	-176.77
Colour: Red	20.72	-160.23	264.59	-40.74
Colour: White	-151.99	-537.77	197.1	-263.26
Colour: NA	0	-39.65	28.35	-98.57
Saddle: Other	-80.46	-241.67	73.07	-90.17
Saddle: Bontrager	0	-25.65	37.4	Reference
Saddle: Cube	-533.44	-766.74	-244.43	-511.46
Saddle: Fabric	34.92	-91.69	199.51	48.04
Saddle: Fizik	362.52	99.17	599.47	343.45
Saddle: Forza	0	-203.97	101.45	-57.13
Saddle: Giant	0	-72.11	119.17	17.66
Saddle: Liv	-131.18	-344.23	71.57	-142.20
Saddle: Prologo	116.83	-27.59	265.72	113.19
Saddle: San Marco	0	-259.42	266.35	-2.40
Saddle: Selle Italia	317.08	2.06	573.5	281.91
Saddle: Selle Royal	-236.09	-405.2	-55	-235.97
Saddle: Supra				
Saddle: Syncros	0	-129.1	168.69	13.92
Saddle: NA	0	-49.98	39.8	-10.96
Steer: Other	0	-80.14	73.01	-6.79
Steer: BBB	0	-142.92	124.36	-12.50
Steer: Bontrager	0	-16.92	23.36	Reference
Steer: Cannondale	113.08	-70.78	211.18	66.97
Steer: Cube	119.03	-93.61	288.54	94.24
Steer: Forza	0	-145.4	283.18	65.67

Steer: FSA	-124.09	-338.82	85.49	-129.89
Steer: Giant	-112.67	-249.77	52.22	-102.00
Steer: Merida	0	-100.85	91.78	-7.76
Steer: Orbea	136.13	-69.39	271.35	97.75
Steer: Reparto Corse	0	-82.17	112.36	11.87
Steer: Supra	-162.18	-290.08	11.65	-142.44
Steer: Syncros	-111.5	-342.01	160.8	-93.83
Steer: NA	0	-52.66	53.22	-2.94
Tyres: Bontrager	0	-10.7	13.7	Reference
Tyres: Continental	0	-64.25	100.6	16.68
Tyres: Other	198.82	17.69	356.05	185.37
Tyres: Giant	0	-98.35	59.48	-20.94
Tyres: Schwalbe	-41.84	-161.1	78.61	-42.75
Tyres: Vittoria	56.7	-52.21	153.81	49.30
Tyres: NA	-73.55	-233.5	51.97	-92.26
Brand: Other	130.39	-47.09	251.5	101.30
Brand: Bianchi	133.38	-79.31	277.64	98.26
Brand: Cannondale	18.81	-76.2	150.49	36.24
Brand: Cube	-149.63	-430.08	47.18	-192.36
Brand: Focus	-76.65	-291.16	116.11	-88.44
Brand: Giant	0	-89.98	58.21	-16.80
Brand: Koga	-56.79	-366.08	182.88	-92.51
Brand: Liv	0	-97.83	124.71	12.53
Brand: Merida	-66.31	-272.61	101.27	-86.58
Brand: Orbea	42.3	-86.88	206.24	58.77
Brand: Ridley	-23.61	-326.24	173.84	-80.71
Brand: Scott	0	-140.07	95.16	-24.64
Brand: Sensa	-77.25	-220.26	50.78	-91.04
Brand: Trek	0	-9.13	9.9	Reference
Brand: Wilier	89.49	-144.72	330.46	89.52
Groupset brand: Campagnolo	174.25	-243.95	622.17	221.30
Groupset brand: Shimano	0	-171.28	99.26	Reference
Groupset brand: SRAM	155.35	-78.02	360.55	175.17
Groupset brand: NA	0	-94.85	74.51	24.21

***Table 3**, Elastic net expensive bikes, model without interactions*

Variable	Coefficient	Lower bound 95% bootstrap interval	Upper bound 95% bootstrap interval	Average bootstrap difference
Weight (0-1)	-1522.72	-3360.53	498.64	n/a
Shop: 12gobike	0	-150.97	176.9	Reference
Shop: Bike-x	-19.85	-522.64	230.01	-159.28
Shop: Bikester	0	-185.13	181.83	-14.61
Shop: Fietsspecialist	0	-190.4	257.5	20.59
Shop: Mantel	-710.68	-1229.44	-99.87	-677.62
Shop: Peter ter Louw	505.38	-46.76	1090.33	508.82
Shop: Rijwiel c&c	404.6	-146.02	786.53	307.29
Shop: Rullens Wouw	0	-524.99	275.31	-137.81
Shop: Salden	0	-406.61	315.33	-58.60
Groupset: level 1				
Groupset: level 2				
Groupset: level 3	-1293.28	-2246.54	15.15	-205.94
Groupset: level 4				
Groupset: level 5	-875.2	-1223.03	-596.49	Reference
Groupset: level 6	1607.29	1204.85	1916.99	2470.68
Groupset: NA	0	-180.23	121.99	880.64
Shifting: Electronic	448.02	287.78	615.85	902.64
Shifting: Mechanic	-446.71	-614.61	-287.03	Reference
Brakes: Disc	199.76	-114.52	450.44	294.64
Brakes: Rim	-69.52	-501.77	248.42	Reference
Brakes: NA	0	-273.97	152.01	65.69
Frame: Aluminium	0	-182.87	157.74	Reference
Frame: Carbon	87.24	-119.28	319.12	112.48
Frame: Other				
Frame: NA	-115.41	-398.95	153.08	-110.38
Fork: Aluminium				
Fork: Carbon	-78.18	-301.84	116.89	Reference
Fork: NA	81.18	-117.02	299.91	183.92
Wheels: Other	773.82	259.24	1198.42	727.42
Wheels: Bontrager	309.07	-315.3	951.65	316.77
Wheels: Cube				
Wheels: DT Swiss	-130.43	-568.95	222.22	-174.77
Wheels: Fulcrum	29.3	-327.86	456.41	62.87
Wheels: Giant	0	-129.39	132.19	Reference
Wheels: Mavic	-882.04	-1871.77	23.61	-925.48
Wheels: Newmen	-238.38	-1097.83	422.1	-339.27
Wheels: Shimano	-1250.95	-2408.55	305.78	-1052.79
Wheels: Supra				

Wheels: Syncros	-774.84	-1726	183.6	-772.60
Wheels NA	0	-235.16	161.24	-38.36
Year: 2018 or before	-864.26	-1252.71	-54.24	Reference
Year: 2019	-715.89	-999.61	-217.48	44.92
Year: 2020	399.69	30.38	727.7	1032.51
Year: NA	0	-124.77	205.86	694.02
Model: Aero	279.61	-105.85	687	807.02
Model: All-round	-581.69	-940.39	-92.51	Reference
Model: Endurance	0	-483.27	398.46	474.05
Model: Fitness				
Model: NA	0	-38.89	49.02	521.52
Gender: Man	0	-122.88	119.26	Reference
Gender: Woman	46.48	-500.61	878.6	190.81
Gender: NA	0	-223.24	160.23	-29.70
Colour: Black	360.31	-112	732.12	Reference
Colour: Blue	180.76	-417.01	816.51	-110.31
Colour: Other	0	-339.69	274.41	-342.70
Colour: Grey	-113.88	-738.84	322.29	-518.34
Colour: Multiple	-13.25	-399.51	252.57	-383.53
Colour: Red	-743.6	-1347.27	-133.21	-1050.30
Colour: White	955.84	-124.93	1804.99	529.97
Colour: NA	0	-105.94	79.43	-323.31
Saddle: Other	-113.77	-843.38	379.31	67.96
Saddle: Bontrager	-255.12	-872.35	272.37	Reference
Saddle: Cube	-306.11	-1071.11	372.79	-49.17
Saddle: Fabric	-255.19	-1195.1	372.27	-111.42
Saddle: Fizik	1108.25	113.06	1957.99	1335.52
Saddle: Forza	1775.31	-2117.57	4994.56	1738.49
Saddle: Giant	0	-207.84	131.33	261.74
Saddle: Liv	0	-471.95	266.5	197.27
Saddle: Prologo	-89.61	-556.16	186.11	114.97
Saddle: San Marco	-498.82	-1558.46	407.75	-275.36
Saddle: Selle Italia	647.66	-234.45	1377.13	871.34
Saddle: Selle Royal	0	-255.65	247.51	295.93
Saddle: Supra				
Saddle: Syncros	458.74	-180.58	844.91	632.16
Saddle: NA	250.43	-103.48	466.21	481.36
Steer: Other	120.81	-166.22	400.9	478.37
Steer: BBB	-647.51	-1105.94	78.66	-152.61
Steer: Bontrager	-426.26	-960.09	238.02	Reference
Steer: Cannondale	0	-368.23	190.9	272.36
Steer: Cube	-203.08	-1236.82	463.17	-25.80
Steer: Forza	-439.75	-1622.23	855.79	-22.19

Steer: FSA	363.69	-465.77	1130.3	693.30
Steer: Giant	0	-206.85	132.23	323.72
Steer: Merida	-463.4	-1360.25	446.55	-95.82
Steer: Orbea	0	-575.27	393.57	270.18
Steer: Reparto Corse	-1341.03	-2422.76	2.59	-849.06
Steer: Supra				
Steer: Syncros	489.9	-183.4	829.33	683.99
Steer: NA	548.29	36.66	975.77	867.25
Tyres: Bontrager	342.76	-131.14	752.14	Reference
Tyres: Continental	-27.57	-408.32	225.45	-401.93
Tyres: Other	343.27	-300.66	872.58	-24.54
Tyres: Giant	0	-453.08	237.04	-418.52
Tyres: Schwalbe	-331.99	-1111.79	409.29	-661.75
Tyres: Vittoria	0	-182.28	115.11	-344.08
Tyres: NA	0	-145.39	185.85	-290.27
Brand: Other	-158.95	-540.18	162.17	-760.89
Brand: Bianchi	0	-728.57	599.28	-636.53
Brand: Cannondale	-517.91	-940.91	102.62	-991.03
Brand: Cube	-693.01	-1369.78	307.38	-1103.08
Brand: Focus	0	-362.11	244.7	-630.59
Brand: Giant	148.23	-216.07	530.76	-414.54
Brand: Koga	-102.93	-1038.17	759.81	-711.06
Brand: Liv	0	-541.7	359.11	-663.18
Brand: Merida	422.67	-389.31	1231.34	-150.87
Brand: Orbea	-1056.74	-1826.47	-173.05	-1571.64
Brand: Ridley	0	-460.32	495.47	-554.31
Brand: Scott	73.98	-340.52	720.2	-382.05
Brand: Sensa				
Brand: Trek	729.34	-8.87	1152.63	Reference
Brand: Wilier	0	-329.71	468.93	-502.27
Groupset brand: Campagnolo	31.43	-930.05	1264.78	401.19
Groupset brand: Shimano	-291.94	-562.86	95.21	Reference
Groupset brand: SRAM	353.54	63.37	783.07	657.05
Groupset brand: NA	0	-184.28	123.15	203.26

***Table 4**, Elastic net expensive bikes, model with interactions*

Interaction	Coefficient	Lower bound 95% bootstrap interval	Upper bound 95% bootstrap interval
Weight * Groupset: Level 5	-22.26	-1251.37	677.79
Weight * Model: All-round	-183.4	-1060.41	641.61
Weight * Tyres: Schwalbe	-321.18	-991.63	744.14
Shop: 12gobike * Shifting: Electronic	37.42	-164.08	330.93
Shop: 12gobike * Shifting: Mechanic	-16.34	-224.4	135.29
Shop: Fietsspecialist * Groupset brand: Campagnolo	1449	-418.37	1858.77
Shop: Peter ter louw * Groupset: NA	287.84	-160.72	554.51
Shop: Peter ter louw * Frame: NA	389.18	-158.35	601.12
Shop: Peter ter louw * Steer: NA	253.67	-157.3	466.69
Shop: Peter ter louw * Groupset brand: NA	324.09	-203.37	559.66
Shop: Rijwiel c&c * Groupset: Level 6	969.81	-477.92	1449.97
Groupset: Level 5 * Tyres: Schwalbe	-59.32	-181.87	120.91
Groupset: Level 5 * Groupset brand: Shimano	-307.47	-525.78	97.22
Groupset: Level 6 * Shifting: Electronic	929.76	174.84	1556.32
Groupset: Level 6 * Wheels: Other	479.37	-422.82	1269.15
Groupset: Level 6 * Wheels: Bontrager	142.18	-74.65	312.8
Groupset: Level 6 * Year: 2020	1090.56	38.96	1484.4
Groupset: Level 6 * Year: NA	1979.82	60.76	2358.67
Groupset: Level 6 * Model: NA	344.09	-219.41	904.68
Groupset: Level 6 * Colour: Black	447.19	-455.47	1257.06
Groupset: Level 6 * Steer: Bontrager	157.89	-73.69	339.6
Groupset: Level 6 * Tyres: Bontrager	171.95	-82.7	364.81
Groupset: Level 6 * Brand: Giant	31.78	-444.1	969.05
Groupset: Level 6 * Brand: Trek	148.08	-86.38	352.46
Shifting: Electronic * Brakes: Disc	137.76	-119.85	258.38
Shifting: Electronic * Frame: Carbon	22.47	-64.67	86.64
Shifting: Electronic * Year: 2020	114.21	-123.95	280.62
Shifting: Electronic * Model: NA	84.34	-107.92	188.29
Shifting: Electronic * Colour: NA	20.13	-78.6	118.02
Shifting: Electronic * Brand: Cube	-90.27	-232.25	164.27
Shifting: Mechanic * Year: 2018 or before	-160.98	-515.16	220.37
Shifting: Mechanic * Brand: Cannondale	-128.42	-206.32	141.79
Shifting: Mechanic * Groupset brand: Shimano	-189.17	-475.62	137.62
Brakes: Rim * Tyres: Vittoria	-51.61	-220.21	167.22
Frame: Carbon * Brand: Cube	-246.59	-327.36	158.39
Fork: Carbon * Model: All-round	-280.69	-440.86	177.9
Fork: Carbon * Steer: BBB	-117.98	-242.76	135.61
Fork: NA * Tyres: Continental	350.76	-512.07	1057.74
Fork: NA * Tyres: Others	1472.41	-443.68	2082.81
Fork: NA * Tyres: Schwalbe	-95.27	-342.04	216.59
Wheels: Other * Year: 2020	249.32	-219.5	487.63
Wheels: Other * Gender: NA	87.94	-240.92	414.15
Wheels: Other * Saddle: Giant	72.41	-197.7	325.24
Wheels: Other * Saddle: Syncros	321.63	-151.94	457.11
Wheels: Other * Steer: Syncros	307.09	-148.41	456.74

Wheels: Other * Steer: NA	502.56	-457.72	825.59
Wheels: Other * Tyres: Schwalbe	302.88	-150.48	475.67
Wheels: Other * Brand: Giant	47.76	-196.93	326.48
Wheels: Other * Brand: Scott	306.72	-152.35	489.38
Wheels: Other * Brand: Wilier	66.33	-677.78	1000.63
Wheels: Bontrager * Groupset brand: SRAM	552.12	-539.68	1372.14
Wheels: NA * Steer: Other	34.25	-125.18	209.65
Year: 2019 * Model: All-round	-207.56	-553.37	274.13
Year: 2020 * Model: NA	19.85	-100.61	187.64
Year: 2020 * Colour: Red	-126.49	-323.11	186.97
Year: 2020 * Colour: NA	133.33	-103.63	208.85
Year: 2020 * Groupset brand: Campagnolo	198.59	-1061.33	1872.37
Model: NA * Groupset brand: SRAM	177.08	-174.75	407.83
Gender: Man * Brand: Cube	-104.04	-222.43	121.27
Gender: NA * Groupset brand: Campagnolo	1452.37	-437.73	1870.79
Colour: Black * Brand: Scott	124.76	-619.16	1005.66
Colour: Red * Groupset brand: Shimano	-9.85	-134.53	92.49
Saddle: Selle Italia * Brand: Other	284.85	-453.82	950.42
Saddle: NA * Tyres: Bontrager	274.19	-285.06	624.24
Saddle: NA * Brand: Trek	210.52	-197.36	485.23
Steer: Other * Brand: Bianchi	754.86	-357.2	1076.14
Steer: NA * Tyres: Bontrager	549.29	-345.06	936.46
Steer: NA * Tyres: Other	974.52	-277.04	1566.21
Steer: NA * Brand: Trek	285.87	-229.23	590.55
Tyres: NA * Groupset brand: SRAM	74.93	-173.29	298.59

Appendix B, conjoint designs

***Table 1**, prior coefficients for survey design budget bikes*

Attribute	Levels	β
Price	€1500	-1
	€1250	-0.67
	€1000	-0.33
	€750	0
Weight	11 kg	-1
	10 kg	-0.67
	9 kg	-0.33
	8 kg	0
Groupset	Level 1	-1
	Level 2	-0.67
	Level 3	-0.33
	Level 4	0
Groupset brand	Shimano	0
	SRAM	0
Shifting	mechanic	
Brakes	Rim	0
	Disc	0
Frame material	Alu	-1
	Carbon	0
Year	2018	-1
	2019	-0.5
	2020	0
Brand	Cube	0
	Koga	0
	Merida	0
	Focus	0

***Table 2**, prior coefficients for survey design mid-range bikes*

Attribute	Levels	β
Price	€3500	-1
	€3000	-0.67
	€2500	-0.33
	€2000	0
Weight	10 kg	-1
	9 kg	-0.67
	8 kg	-0.33
	7 kg	0
Groupset	Level 3	-1
	Level 4	-0.67
	Level 5	-0.33
	Level 6	0
Groupset brand	Shimano	0
	SRAM	0
	Campagnolo	0
Shifting	mechanic	-1
	Electric	0
Brakes	Rim	0
	Disc	0
Frame material	Alu	-1
	Carbon	0
Year	2018	-1
	2019	-0.5
	2020	0
Brand	Cube	0
	Sensa	0
	Wilier	0
	Bianchi	0

***Table 3**, prior coefficients for survey design expensive bikes*

Attribute	Levels	β
Price	€11000	-1
	€9000	-0.67
	€7000	-0.33
	€5000	0
Weight	9 kg	-1
	8 kg	-0.67
	7 kg	-0.33
	6 kg	0
Groupset	Level 5	-1
	Level 6	0
Groupset brand	Shimano	0
	SRAM	0
	Campagnolo	0
Shifting	mechanic	-1
	Electric	0
Brakes	Rim	0
	Disc	0
Frame material	Carbon	
Year	2018	-1
	2019	-0.5
	2020	0
Brand	Merida	0
	Trek	0
	Cannondale	0
	Cube	0
	Orbea	0

Appendix C, conjoint analysis segmentation

***Table 1**, multinomial logistic regression mid-range bikes with interactions gender*

Variable	Main effect (Man)	Effect * Gender: Woman
Price (linear)	-0.0006***	0.0003
Weight: 10 kg	Reference	
Weight: 9kg	0.59***	-0.03
Weight: 8 kg	0.66***	0.05
Weight: 7 kg	1.29***	-0.34
Groupset: Level 4	Reference	
Groupset: Level 5	0.99***	0.02
Groupset: Level 6	1.63***	-0.17
Groupset brand: Shimano	Reference	
Groupset brand: SRAM	-0.75***	-0.14
Groupset brand: Campagnolo	-0.82***	0.14
Shifting: Mechanic	Reference	
Shifting: Electronic	0.46***	-0.24
Brakes: Rim	Reference	
Brakes: Disc	1.19***	-0.03
Frame: Aluminium	Reference	
Frame: Carbon	0.69***	0.002
Year: 2018	Reference	
Year: 2019	0.22***	-0.21
Year: 2020	0.24*	-0.25
Brand: Cube	Reference	
Brand: Sensa	-0.13*	-0.36*
Brand: Wilier	0.36***	-0.60**
Brand: Bianchi	0.77***	-0.44

** indicates $p < 0.05$. ** indicates $p < 0.01$. *** indicates $p < 0.001$.*

***Table 2**, multinomial logistic regression mid-range bikes with interactions age*

Variable	Main effect (36-50)	Effect * Age: 17-35	Effect * Age: 51-76
Price (linear)	-0.0006***	-0.0002	0.0001
Weight: 10 kg	Reference		
Weight: 9kg	0.67***	-0.03	-0.17
Weight: 8 kg	0.75***	-0.08	-0.10
Weight: 7 kg	1.24***	0.13	0.10
Groupset: Level 4	Reference		
Groupset: Level 5	1.18***	0.06	-0.49**
Groupset: Level 6	1.63***	0.51	-0.24
Groupset brand: Shimano	Reference		
Groupset brand: SRAM	-0.86***	0.30	0.03
Groupset brand: Campagnolo	-1.00***	-0.01	0.34
Shifting: Mechanic	Reference		
Shifting: Electronic	0.61***	-0.34	-0.23
Brakes: Rim	Reference		
Brakes: Disc	1.22***	0.06	-0.05
Frame: Aluminium	Reference		
Frame: Carbon	0.82***	-0.001	-0.21
Year: 2018	Reference		
Year: 2019	0.16	0.04	0.13
Year: 2020	0.18	-0.06	0.19
Brand: Cube	Reference		
Brand: Sensa	-0.28**	0.16	0.18
Brand: Wilier	0.24*	-0.06	0.18
Brand: Bianchi	0.68**	0.20	0.13

** indicates p < 0.05. ** indicates p < 0.01. *** indicates p < 0.001.*

***Table 3**, multinomial logistic regression mid-range bikes with interactions hours of cycling per week*

Variable	Main effect (0-8 hours)	Effect * Hours of cycling per week: 9-40 hours
Price (linear)	-0.0006***	0.0003*
Weight: 10 kg	Reference	
Weight: 9kg	0.61***	-0.09
Weight: 8 kg	0.62***	0.13
Weight: 7 kg	1.20***	0.21
Groupset: Level 4	Reference	
Groupset: Level 5	0.96***	0.09
Groupset: Level 6	1.65***	-0.13
Groupset brand: Shimano	Reference	
Groupset brand: SRAM	-0.79***	0.09
Groupset brand: Campagnolo	-0.78***	-0.09
Shifting: Mechanic	Reference	
Shifting: Electronic	0.38***	0.20
Brakes: Rim	Reference	
Brakes: Disc	1.24***	-0.21
Frame: Aluminium	Reference	
Frame: Carbon	0.66***	0.11
Year: 2018	Reference	
Year: 2019	0.20**	0.02
Year: 2020	0.12	0.33
Brand: Cube	Reference	
Brand: Sensa	-0.22***	0.18
Brand: Wilier	0.29***	0.05
Brand: Bianchi	0.68***	0.17

** indicates $p < 0.05$. ** indicates $p < 0.01$. *** indicates $p < 0.001$.*

***Table 4**, multinomial logistic regression mid-range bikes with interactions cycling activities*

Variable	Main effect	Activity: Club rides	Activity: Organized tours	Activity: Races	Activity: Holiday abroad
Price (linear)	-0.0006***	0.0000	0.0002	-0.0007***	-0.0000
Weight: 10 kg	Reference				
Weight: 9kg	0.42***	0.02	0.24	0.44*	0.14
Weight: 8 kg	0.49***	-0.02	0.18	0.51	0.31
Weight: 7 kg	0.99***	-0.09	0.18	1.32**	0.37
Groupset: Level 4	Reference				
Groupset: Level 5	0.95***	-0.07	0.02	0.06	0.19
Groupset: Level 6	1.49***	0.01	0.03	0.70	0.19
Groupset brand: Shimano	Reference				
Groupset brand: SRAM	-0.65***	-0.28*	-0.06	0.30	-0.16
Groupset brand: Campagnolo	-0.46***	-0.49*	-0.34	-0.69*	-0.12
Shifting: Mechanic	Reference				
Shifting: Electronic	0.43***	-0.21	0.05	0.37	-0.05
Brakes: Rim	Reference				
Brakes: Disc	1.11***	0.10	0.24	-0.26	0.02
Frame: Aluminium	Reference				
Frame: Carbon	0.52***	0.28	0.06	0.28	0.09
Year: 2018	Reference				
Year: 2019	0.22**	0.03	-0.02	0.03	-0.02
Year: 2020	0.06	0.24	0.07	0.29	0.05
Brand: Cube	Reference				
Brand: Sensa	-0.37***	0.15	0.33**	0.26	-0.04
Brand: Wilier	0.24**	0.02	0.16	0.13	-0.09
Brand: Bianchi	0.42*	0.38	0.21	0.24	0.50

** indicates $p < 0.05$. ** indicates $p < 0.01$. *** indicates $p < 0.001$.*