4 On Estimating Pricing Models from End-Consumer Internet Car-Configuration Data

Tino Fuhrmann, Marvin Schweizer, Andreas Geyer-Schulz
Information Services and Electronic Markets
Karlsruhe Institute of Technology (KIT)
Karlsruhe, Germany
Tino.Fuhrmann@student.kit.edu,
Marvin.Schweizer@student.kit.edu,
Andreas.Geyer-Schulz@kit.edu, and
Peter Kurz
TNS Deutschland GmbH
München, Germany
Peter.Kurz@tns-infratest.com

Abstract

In this contribution we report on our first attempts of extracting a pricing-model from an anonymous end-consumer Internet car configurator data set made available from TNS Infratest for a data mining competition of the special interest group for data analysis of the German Classification Society (GfKl e.V.) in Karlsruhe on 20.-21. November 2015. In this report, we concentrate on the simplest possible rational pricing model – a linear part-worth utility function. We introduce a new data-transformation for product configuration data in general: the elimination of "irrational" product configuration types. We combine this transformation with an elimination of configuration types which are price outliers. Our second contribution is the analysis of the null space of the pricing model in a post-processing phase to improve the interpretation of the pricing model.

Introduction and Motivation

"A product configurator is a software-based expert system that supports the user in the creation of product specifications by restricting how predefined entities (physical or non-physical) and their properties (fixed or variable) may be combined." (A. Haug [3, p. 19])

Modern product configurators are the car industry's response to increased global competition, because they enable mass customization at an industrial scale [8]: *"The customer should get what he wants, when he wants it at an attractive price."* Product configurators enable the customer to build his own product autonomously – even if the product is complex. Figure 20 shows that product configurators play a key role across several functional areas of a company: Empirical configuration data improves e.g. strategic product portfolio planning, offer generation in the operative sales process, production planning, and, last but not least, the pricing of product lines. Researchers at Sawtooth Software Inc. investigated product

DOI 10.20347/WIAS.REPORT.29

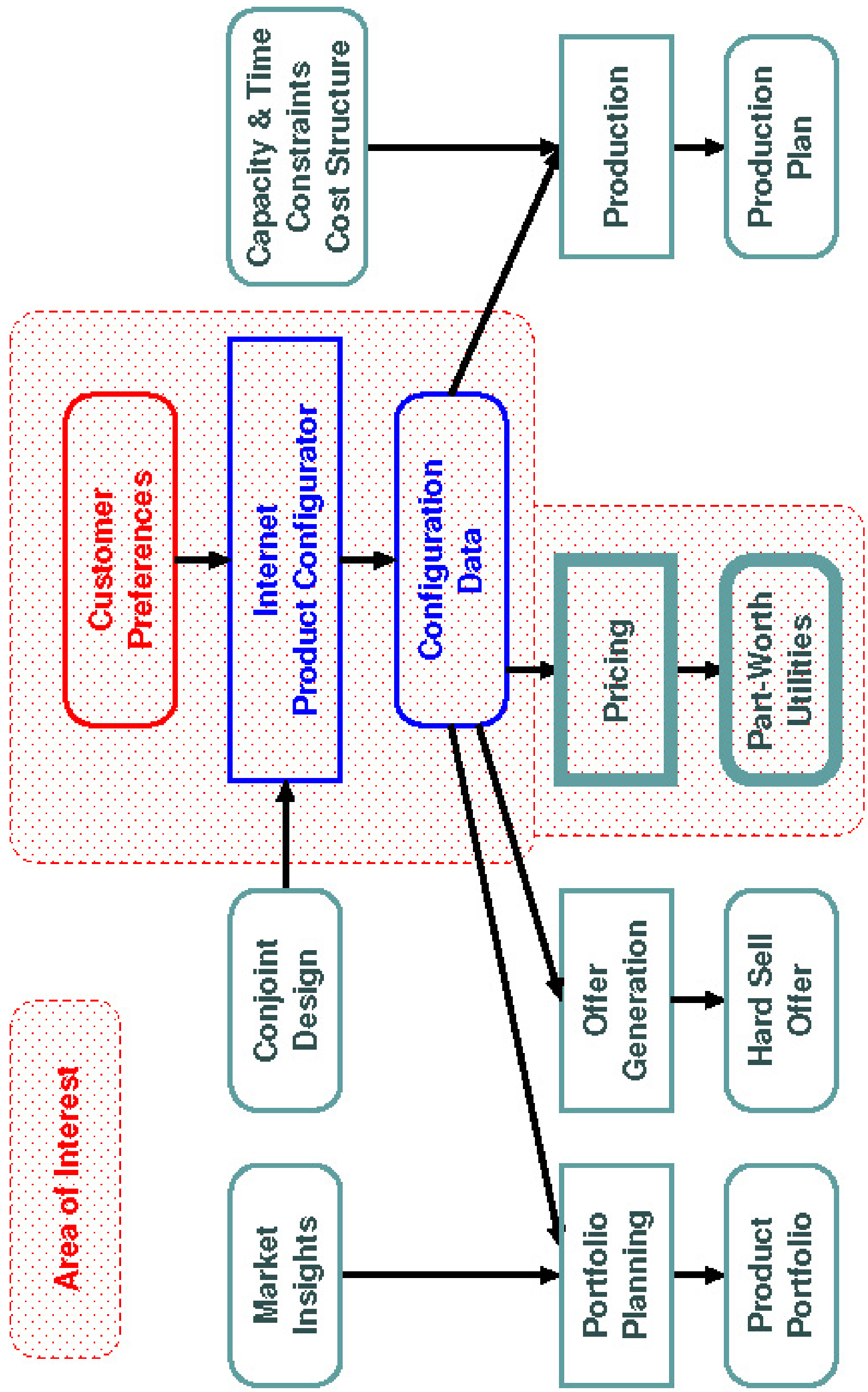

Figure 20: Pricing and Product Configurators

configurators as part of adaptive choice-based conjoint analysis as early as 2006 (see [4], [9], and [7]).

The car industry has reacted to this strategic challenge only recently. In 2013 the international benchmark study on mass customization companies of Walcher and Piller [10] did not yet contain a single car configurator. However, the Configurator Database Project (as of December 29th, 2016) listed 87 end-consumer Internet car configurators with all global players (and their major brands) present. Despite the intensive use of car configurators by the car industry, academic research on datasets of end-consumer car configurators is practically non-existent, because of the lack of publicly available datasets of this type. In a recent survey on consumer decision-making and configuration systems (see [5]), the main emphasis is on consumers' behavioral deviations from rationality and their causes.

While we may safely assume that each global player knows his own pricing models (and considers them a strategic secret), it is nevertheless interesting to investigate methods of extracting pricing models from large end-user Internet car configuration data sets and to know the limits of these methods. In addition, the assessment of the quality and information content of such Internet data sets remains an open problem.

Our contribution is structured as follows: In Subsect. 4.1 we describe the end-consumer car configuration data set used in this investigation. Next, we introduce the basics of linear part-worth utility functions and their estimation by weighted least-squares (WLS) in Subsect. 4.2. In the next two Subsects. (4.3 and 4.4) we introduce the data transformations used in preprocessing and the analysis of null space of the models used for computing a canonical model representation. We discuss first results in Subsects. 4.2, 4.3, and 4.4, respectively. In Subsect. 4.5 we discuss the results and limitations of the pre- and postprocessing transformations introduced.

4.1 The Car Configurator Data Set

The preprocessing of the original data set of TNS Infratest (collected from 473 819 respondents, 3 days from the first half of 2012 with 962 799 configurations) is described in [2] and reduces the data set by a lossless transformation to a data set of 943 (weighted) configuration types with 112 binary variables and, in addition, frequency (weight), price, line, and engine type. In the following, we use the preprocessed data set with the 112 binary attributes grouped for easier reference. Since we will concentrate on the Sports Line, we indicate all attributes which are observed in the configuration types of the Sports Line as bold:

1 6 attribute groups with mutually exclusive attributes (only one attribute in a group can be set to 1):

  1.1 4 model lines (**Sports Line**, Modern Line, Luxury Line, No Line).

  1.2 9 engine types, (**1, 2, 3, 4, 5, 6, 7, 8, 9**). We assume that engine types 1 to 4 are petrol engines, and engine types 5 to 9 are diesel engines.

1.3 12 color variants: **Hematite grey metallic, sparkling bronce metallic, alpine white, black saphire metallic, deep sea blue metallic, blue water metallic, peacock blue metallic, glacier silver metallic, orion silver metallic, mineral white metallic, black**, and **crimson red metallic**.

1.4 11 trim variants (3 observed): **Aluminum with fine longitudinal grain with accent strip in milky glass look, fine wood burr walnut with accent strip in chrome**, **aluminum with fine longitudinal grain with red accent strip**, fine wood burr walnut with black accent strip, high polish cashmere silver with accent strip in milky glass look, aluminum with fine longitudinal grain with black accent strip, fine wood fine line anthracite with intarsia and accent strip in chrome, aluminum with fine longitudinal grain and black accent strip high polish black with red accent strip, matt satin silver, and fine wood fine line porous structured with accent strip in milky glass look.

1.5 16 cushion (interior upholstery) variants (5 observed): **Fabric leather combination oyster, leather Dakota black with red contrasting seam, leather Dakota coral red with black contrasting seam, fabric Imola anthracite with red contrasting seam, leather Dakota black II**, leather Dakota Everest grey with black contrasting seam, leather Dakota Veneto beige I, leather Dakota Veneto beige II, fabric leather combination anthracite, fabric Imola anthracite with grey contrasting seam, leather Dakota oyster with contrasting seam in dark oyster, leather Dakota black I, leather Dakota saddle brown, leather Dakota black with contrasting seam in dark oyster, fabric Salome saddle brown anthracite, fabric anthracite.

1.6 24 rim variants (5 observed): **17 inch alu basis II, 17 inch alu sport II, 17 inch alu luxury II, 18 inch alu sport III, 18 inch alu luxury III**, 18 inch alu basis II, 18 inch alu luxury I, 17 inch alu sportI, 18 inch alu modern III, 17 inch alu modern II, 18 inch alu basis I, 17 inch alu luxury I, 17 inch alu basis III, 16 inch alu basis II, 18 inch alu modern I, 18 inch alu sport I, 18 inch alu luxury II, 16 inch alu basis I, 17 inch alu modern I, 18 inch alu sportII, 18 inch alu basis III, 16 inch steel basis, 17 inch alu basis I, and 18 inch alu modern II.

The attributes **model line** and **engine type** are used as a priori segmentation attributes for identifying iso-price segments of configuration types.

41 attributes of of the 76 binary attributes in this group are not observed for configuration types of the Sports Line.

2 36 attributes which can be combined (any subset of attributes can be set to 1) structured as follows:

2.1 4 packages: sport, **comfort, storage,** and **light interieur**.

2.2 2 types of transmission: **four wheel drive** and **automatic transmission**.

2.3 8 driving assistants: **cruise control with braking function, cruise control with stop go function, parking assistant, rear view camera, lane change warning, lane departure warning, road sign recognition,** and **head up display**.

2.4 8 attributes for steering, light, and chassis: **adaptive chassis with lowering**, sport leather steering wheel, **variable sports steering, performance leather steering wheel, xenon light, adaptive cornering light, glass sunroof,** and **sun protection blind**.

2.5 9 attributes for convenience, security, etc.: **seat heating for front seats**, sports seats for front seats, **electric seat adjustment, lumbar support for front seats, climate control, alarm system, arm rest for front seats, comfort access,** and **hitch**.

2.6 5 attributes for navigation, media, and communication: **navigation system business, hifi system, dvd changer, mobile phone prep with bluetooth usb,** and **digital radio**.

The 3 attributes sports package, sport leather steering wheel, and sports seats for front seats are not configured in the configuration types of the Sports Line.

Configuration types of the Sports Line have 68 binary attributes, 35 belong to the 6 groups of mutually exclusive attributes. For four groups of these attributes (Color, Rims, Cushions, Trims) we know the part-worths from the setup of a conjoint experiment partially contained in the data, but we do not use them. The second group of attributes contains 33 attributes which can be combined. For the second we do not know the part worths. The technical constraints of the car configurator are unknown.

4.2 Estimating a Linear Part-Worth Utility Function

The theory of choice in micro-economics and statistical utility theory formalize a general, axiomatic and normative model how rational decision-makers should act. Rational behavior is captured by the axioms of expected utility theory (EUT) introduced by John von Neumann and Oskar Morgenstern in 1944 [6, Chapter 3, pp. 15-31] and compatible with linear utility functions.

The simplest rational pricing model is a linear (part-worth) utility function $U(C)$:

$$U(C) = pw_0 + \sum_{c_j \in C} pw_j \cdot c_j$$

where the constant pw_0 is the part-worth (base price) of the configuration, C denotes the set of attributes describing the configuration and $c_j \in \{0,1\}$ the j-th attribute in C and pw_j the part-worth of the j-th attribute. Under the assumptions that the base price pw_0 is for a car configuration without configured attributes and that the presence of the j-th attribute in a configuration ($c_j = 1$) is more valuable than its absence ($c_j = 0$), all part-worths should be positive: $pw_j \geq 0, \quad \forall j$. We assume that $U(C)$ at least equals the *price* a consumer is willing to pay for a car with configuration C: $U(C) = price$.

For the estimation of the part-worth utilities and the base price(s) of car configurations from the data set we use the following linear regression model:

$$\mathbf{price} = \mathbf{C} \cdot \mathbf{pw} + \mathbf{u}$$

where the dependent variable $\mathbf{price}$ is an $N \times 1$ vector, $\mathbf{C}$ is an $N \times J$ regression matrix (each line represents a car configuration), $\mathbf{pw}$ is the $J \times 1$ parameter vector (of part-worths), and $\mathbf{u}$ is an $N \times 1$ vector, N is the number of car configurations, J the number of boolean attributes of a car configuration. $\mathbf{C}_{i.}$ denotes the i-th line of $\mathbf{C}$ and is a $1 \times J$ vector. Since we concentrate only on car configurations of the Sports Line, there are 5 attribute groups with mutually exclusive attributes. We suppress the constant and this implies that we have one default configuration for each engine (the most important attribute). In each of the 4 attribute groups color, interior upholstery, trims, and rims one variable must be configured. This implies that we can only estimate the part-worths of $n-1$ attributes in an attribute group of n attributes. The last attributes are part of the default configuration. We use a completely specified model, because we want to extract as much information from the dataset as possible. However, this approach implies that $C^T C$ is not of full rank, because some attributes are linear dependent and others are not observed. We deal with this complication in Subsect. 4.4.

However, by moving from car configurations to car configuration types whose number we represent as T, we can reduce the computational effort considerably (by three orders of magnitude) because $T << N$ for our dataset. This implies that we move from minimizing the residual sum of squares

$$RSS(\mathbf{pw}) = \sum_{i=1}^{N} (\mathbf{price}_i - \mathbf{C}_{i.} \cdot \mathbf{pw})^2$$

of car configurations to minimizing the weighted sum of squares of car configuration types

$$WSS(\mathbf{pw}, \mathbf{W}) = \sum_{i=1}^{T} \mathbf{W}_{ii} (\mathbf{price}_i - \mathbf{C}_{i.} \cdot \mathbf{pw})^2$$

with $\mathbf{C}$ now representing the car configuration types and $\mathbf{w}_{ii}$ (a diagonal element of the diagonal weight matrix $\mathbf{W}$) the number of times the i-th car configuration type has been observed in the data set. This simply means, we solve the weighted least squares problem $(\mathbf{price} - \mathbf{C} \cdot \mathbf{pw})^T \mathbf{W} (\mathbf{price} - \mathbf{C} \cdot \mathbf{pw})$ by

$$\hat{\mathbf{pw}} = (\mathbf{C}^T \mathbf{W} \mathbf{C})^{-1} \mathbf{C}^T \mathbf{W} \cdot \mathbf{price}$$

Note, in this contribution, we use weighted least squares for parameter estimation in order to replace the computation of the $\mathbf{C}^T\mathbf{C}$ matrix for car configurations by the computation of the $\mathbf{C}^T\mathbf{W}\mathbf{C}$ matrix of configuration types to reduce the computation effort. We do not try to deal with heteroscedasticity by reweighting as suggested e.g. in [1, Chap. 4.5] and [11].

4.3 Preprocessing: The Elimination of Irrational and of Price Outlier Configuration Types

4.3.1 The Elimination of Irrational Configuration Types

But are end-consumers designing their own car in a rational manner? Obviously not, as the comparison of the attributes of two configuration types of the iso-price segment in Table 2 shows.

Table 2: The Configuration Types for Sports Line, Engine 2 of the Iso-Price Segment at 35 300 Euro: B a subset of A

Configuration Type	A	B
Color: Rims: Cushions: Trims:	Orion Silver Metallic 17 Inch Alu Sport II Fabric Imola Anthracite with Red Contrasting Seam High Polish Black with Red Accent Strip parking assistant lane change warning dvd changer	Orion Silver Metallic 17 Inch Alu Sport II Fabric Imola Anthracite with Red Contrasting Seam High Polish Black with Red Accent Strip parking assistant lane change warning dvd changer
	xenon light	

Iso-price segments are defined by choices between car configurations of the same model line and engine type with the same price under the assumption that an attribute configured adds value to a car configuration. The comparison of the attribute sets of the configurations in an iso-price segment allows us to analyze deviations from rationality, because of the axiom that a consumer always prefers more (the value provided by an additional attribute) to less. In the whole data set, 17% of the consumers have configured car configurations which are proper subsets in an iso-price segment. We call these configurations *irrational*.

When estimating rational pricing models from product configuration data, the elimination of irrational configurations is – as far as we know – a new data transformation which takes care of irrational behavior. Figure 21 shows a first, naive filter algorithm for implementing this data transformation.

1 For each iso-price segment in data set do

   1.1 Perform a subset comparison operation between all pairs of configuration types in an iso-price segment and build a list of all subset configuration types found.

   1.2 Flag all configuration types which are proper subsets as irrational.

2 Delete all irrational configuration types from data set.

Figure 21: A Naive Filter Algorithm for the Elimination of Irrational Configurations

This algorithm identifies 91 configuration types of the 416 configuration types (with 220 514 configurations) of the Sports Line and leaves a total of 325 rational configuration types (with 179 545 configurations (81%)). The effects of this transformation on the weighted residuals of a linear path worth utility model can be seen in line 3 of Table 3 and in the 3rd boxplot of Fig. 22 on the right hand side, both labelled *Rational*.

4.3.2 The Elimination of Price Outlier Configuration Types

It is well known that linear regression results are sensitive to outliers. The boxplot of configuration prices of Fig. 22 shows that all configuration types with a configuration price higher than 55000 Euro should be considered as outliers. By checking the residual errors of the configuration types we have verified that the price outliers are also the outliers in the boxplot of the weighted residuals.

Elimination of all configuration types with a price above 55000 Euro should improve the estimates of the linear part-worth utility function. The effects of this transformation on the weighted residuals of a linear path worth utility model can be seen in line 2 of Table 3 and in the 2nd boxplot of Fig. 22 on the right hand side, both labelled *No Outliers*.

4.3.3 The Effects of the Transformations on Weighted Residuals

Figure 22 on the right hand side and Table 3 allow us to compare the effects of the two data transformations and their joint effect on the residuals and the weighted residuals of the linear part-worth utility functions of Subsect. 4.2. We see that the joint effect of both data transformations eliminates most of the outliers of the residuals and leads to a more symmetric distribution of the residuals.

4.4 Postprocessing: Analyzing the Null Space of the Model

Unfortunately, not all parameters of a linear part-worth utility function can be estimated. In R, these parameters are flagged with NA (Not Available). We distinguish the following cases:

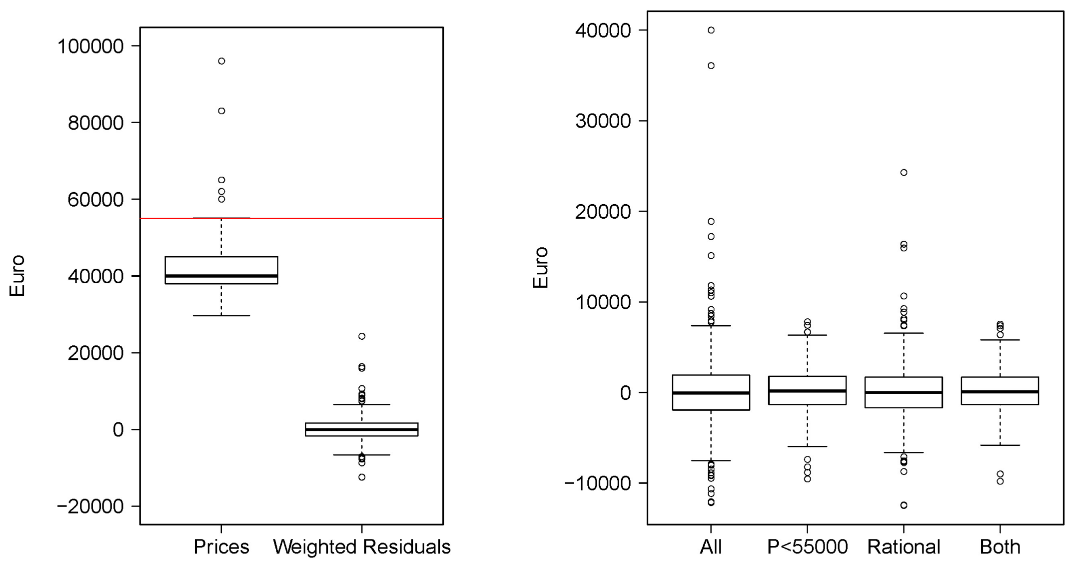

Figure 22: Boxplot of Configuration Prices and Residuals (left). Outliers have prices above $55\,000$ Euros. Boxplot of Residuals after Transformations (right).

Table 3: Effects of Transformations on Weighted Residuals of Sports Line Configuration Types

Configuration Types	Min	1Q	Median	3Q	Max
All	-385 345	-36 153	-1 145	36 614	768 514
No Outliers	-282 421	-26 019	2 973	34 423	205 543
Only Rational	-396 824	-34 695	0	37 919	517 244
Both: No Outl. & Only Rat.	-287 586	-26 993	1 523	30 758	181 377

1 Some attributes of a car configuration type of a line have not been selected by consumers. These attributes remain unobserved. The $\mathbf{C}^T\mathbf{W}\mathbf{C}$ matrix does not have full rank and these attributes form one part of the null space of the model. In addition, in our data set the unobserved attribute j has the property that $\sum_{i=1}^{T}\mathbf{C}_{i,j} = 0$. For configuration types of the Sports Line we have identified 44 attributes of this type which have been reported in Subsect. 4.1.

2 The rest of the null space are attributes which are linear dependent on other attributes. The structure of this linear dependency must be analyzed completely. We treat this case in the following.

Mathematically, the existence of linear dependent attributes implies that the weighted least squares problem does not have a unique solution, but a set of equivalent solutions exist. The complete set of solutions can be represented completely as a canonical basis together with a set of linear change of basis operators. Equivalent means equivalent with regard to the optimization criterium of the regression problem.

For product configuration data not all attributes in a group of mutually exclusive attributes can be identified: At least one attribute of such a group must be configured in each configuration and, therefore, a linear dependency with the constant of the regression model exists. The pricing model's constant is interpreted as the price of a default configuration for which the default attributes (one for each group of mutually exclusive attributes) which we can not estimate are set. The prices of the other attributes in such a group indicate the cost of replacement of the default attribute by the other attributes of the group. The signs of these relative prices depend on the choice of the default configuration. In the car configuration data set, 6 groups of such mutually exclusive attributes exist: model lines, engine types, colors, interior upholstery, trims, and rims.

In order to make part-worth utilities easily interpretable and comparable, we define a **canonical product configuration** as the configuration type with a set of mutually exclusive (must-be-configured) default attributes of lowest price. From a mathematical point of view, the canonical product configuration is the canonical basis. Relative to the default attribute, all other part-worths of attributes of such a group of mutually exclusive attributes are always positive.

Weighted linear regression in R as implemented by `lm` uses a deterministic algorithm which assigns variables to the basis in the sequence in which they are listed in the model specification of `lm`. We start with a regression model specification with the independent variables in arbitrary order. For each group of mutually exclusive variables, we check the signs of the parameters. If negative signs exist, we choose the variable with the most negative parameter and we exchange this variable with the last variable of the group.

For example, for the color attributes, we get the parameters shown in Table 4: **Crimson Red Metallic** is the color of the default car configuration. Only one color attribute (**Mineral White Metallic**) is slightly significant. And **Deep Sea Blue Metallic** is the color attribute with the most negative value.

Table 4: Estimation of Parameters for Color Attributes. Significance Code: $. = 0.1$.

Attribute	β	Std. Error	t-value	$P(>\mid t\mid)$	Sign.
HematiteGreyMetallic	324.85	1 041.72	0.312	0.755420	
SparklingBronceMetallic	-100.24	1 032.38	-0.097	0.922725	
AlpineWhite	635.43	1 003.40	0.633	0.527129	
BlackSaphireMetallic	44.73	1 089.34	0.041	0.967280	
DeepSeaBlueMetallic	-1 043.27	1 042.96	-1.000	0.318120	
BluewaterMetallic	673.50	1 114.82	0.604	0.546298	
PeacockBlueMetallic	743.47	1 392.23	0.534	0.593801	
GlacierSilverMetallic	1 776.48	1 164.84	1.525	0.128485	
OrionSilverMetallic	-844.81	1 094.14	-0.772	0.440765	
MineralWhiteMetallic	2 525.75	1 467.92	1.721	0.086541	.
Black	944.33	1 406.65	0.671	0.502622	
CrimsonRedMetallic	NA	NA	NA	NA	

To obtain the canonical parameters of the color attributes we moved the attribute **Deep Sea Blue Metallic** to the last position of the color attributes. Compare the parameter estimates of the color attributes shown in Table 4 with the canonical solution shown in Table 5 and observe how signs and significance of the part-worths change.

However, linear dependencies can be more complicated: For the group of rims, we have discovered three groups of linear dependencies by permutation of the model specifications: For all configuration types of engines 3, 4, 7, 8, and 9 only the rim X18InchAluLuxury has been selected and is linear dependent on the engine attribute. For engines 2 and 6, only the rims X17InchAluLuxuryII and X17AluBasisII have been selected and they are linear dependent. The same dependency exists between the rims X18InchAluSport III and X17InchAluSport II for engines 1 and 5.

At the moment, we have only analyzed the linear dependencies of the mutually exclusive attributes.

4.5 The Canonical Model After Both Transformations

The canonical model (and all equivalent models) are highly significant and explain more than 99 percent of the variance: The residual standard error is 59940 on 253 degrees of freedom (DF), R^2 is 0.997 and the adjusted R^2 is 0.996. The F-statistic is 1361 on 61 and 253 DF with a p-value less than $2.2e-16$.

The 9 canonical default configurations (one for each engine type) of the Sports Line have the color **Deep Sea Blue Metallic**. Their interior upholstery is **Fabric Leather Combination Oyster** with trims configured as **Aluminium with Fine Longitudinal Grain with Accent**

Strip in Milky Glass Look. Rims differ between engines: For engines 1 and 5, we have **X18InchAluSport III**, for engines 2 and 6, **X17InchAluLuxuryII** and for engines 3, 4, 7, 8, 9: **X18InchAluLuxury**. These attributes are the non-identified attributes of the canonical car configuration. The prices of the canonical default configurations are typeset in bold in Table 5. They range from 30367 Euro for the default configuration of engine 1 to 47218 Euro for the default configuration of engine 9.

The parameter estimates of the part-worth utilities of the canonical model for the attributes with mutually exclusive attributes are shown in column Both of Table 5.

The estimates for all other attributes are shown in column Both of Table 6. In the attribute groups of *Driving Assistants* and *Convenience, Security, . . .* we find 10 attributes of the 12 attributes with negative signs. This indicates that the model of a simple linear part-worth utility function does not completely explain the unknown pricing strategy embedded in the product configurator and that further analysis is required.

Conclusion

In this contribution we have presented the preprocessing method of the elimination of irrational configuration types (without reweighting) for product configuration data sets. In addition, we have shown that a partial recovery of a pricing model from product configuration data is possible with the restriction that one attribute of each group of mutually exclusive attributes can not be estimated for regression models whose constants capture the price of the default configuration. In addition, we have made progress in the analysis of the null space of regression models for complex product configuration data: We have introduced the concept of a canonical configuration as the least price configuration (in the sense that its default attributes have the lowest price in their group of mutually exclusive attributes) and we have shown how this configuration can be found with the help of permutations of the model specification. A potential improvement for the elimination of irrational configuration types is finding a proper reweighting scheme of rational configuration types.

References

[1] Cameron, A. C. and Trivedi, P. K. (2005): Weighted Least Squares. In: Microeconometrics. Methods and Applications. Cambridge University Press, 81–85.

[2] Fuhrmann, T., Schweizer, M., Geyer-Schulz, A. and Kurz, P. (2016): Mining Consumer-Generated Product-Configuration Data. *Archives of Data Science, Series A*, forthcoming.

Table 5: Canonical Parameter Estimation (CPE) of Part-Worth Attribute Utilities for Sports Line's Configuration Types. The 6 attribute groups with exclusive attributes. Prices of default configurations in bold. Significance Codes (only model Both): $*** = 0.001$, $** = 0.01$, $* = 0.05$, $. = 0.1$.

Topic	Attributes	All	Rational	$P < 55000$	Both	Sign.
Engines	Engine 1	30 444	30 333	30 072	**30 367**	***
	Engine 2	33 620	33 273	33 022	**33 458**	***
	Engine 3	40 187	39 575	39 223	**39 377**	***
	Engine 4	43 514	43 398	43 483	**43 352**	***
	Engine 5	33 680	32 890	33 360	**33 535**	***
	Engine 6	34 160	34 017	34 252	**34 602**	***
	Engine 7	39 578	39 121	38 123	**38 841**	***
	Engine 8	46 456	45 500	43 413	**44 091**	***
	Engine 9	54 116	52 006	46 426	**47 218**	***
Color	DeepSeaBlueMetallic	NA	NA	NA	NA	
	OrionSilverMetallic	-754	-620	240	198	
	SparklingBronceMetallic	865	542	1 288	943	
	CrimsonRedMetallic	-1 414	-1 105	976	1 043	
	BlackSaphireMetallic	1 102	865	1 360	1 088	
	HematiteGreyMetallic	943	1 096	1 398	1 368	*
	AlpineWhite	2 421	2 086	2 132	1 679	**
	BluewaterMetallic	4 703	2 535	2 137	1 717	*
	PeacockBlueMetallic	2 231	1 627	2 365	1 787	
	Black	2 798	2 132	2 197	1 988	
	GlacierSilverMetallic	3 131	2 799	3 421	2 820	**
	MineralWhiteMetallic	1 886	1 379	4 411	3 569	**
Interior	Fabric Leather Combination Oyster	NA	NA	NA	NA	
	Leather Dakota (LD) Black II	982	1 386	424	460	
	LDB with Red Contrasting Seam	-186	216	371	480	
	LD Coral Red with Black Contrasting Seam	959	1 493	1 347	1 498	***
	Fabric Imola Anthracite with Red Contrasting Seam	1 811	1 963	2 510	2 555	**
Trims	Aluminum with Fine Longitudinal Grain (AFLG) with Accent Strip in Milky Glass Look	NA	NA	NA	NA	
	ALFG with Red AccentStrip	-1 228	-479	-31	146	
	Fine Wood Burr Walnut with Accent Strip in Chrome	-13	-33	670	568	
Rims	X17InchAluLuxuryII	NA	NA	NA	NA	
	X17InchAluBasisII	2 638	2 121	1 885	1 719	***
	X18InchAluSportIII	NA	NA	NA	NA	
	X17InchAluSportII	2 293	2 025	1 244	1 414	.
	X18InchAluLuxuryIII	NA	NA	NA	NA	

DOI 10.20347/WIAS.REPORT.29

Table 6: CPE of Part-Worth Attribute Utilities for Sports Line's Configuration Type. Attribute Combinations. Significance Codes (only model Both): $*** = 0.001$, $** = 0.01$, $* = 0.05$, $. = 0.1$.

Attributes	All	Rational	$P < 55000$	Both	Sign.
Packages					
Storage package	679	1 492	42	348	
Comfort package	782	1 545	759	1 156	**
Light package interior	3 394	3 297	835	1 452	**
Transmission					
Automatic transmission	1 346	1 402	825	1 060	.
Four wheel drive	3 316	1 878	2 049	1 450	*
Driving Assistants					
Head up display	-6 456	-4 151	-3 319	-2 432	*
Rear view camera	-525	-1 145	-1 898	-1 858	**
Lane change warning	-2 356	-3 119	-1 720	-1 553	.
Cruise control with stop go function	-184	839	-801	-605	
Cruise control with braking function	1 442	139	5	-578	
Parking assistant	398	99	342	-31	
Road sign recognition	-329	857	943	674	
Lane departure warning	2 422	1 326	3 391	2 895	**
Steering, Light, Chassis, ...					
Variable sports steering	-4 742	-4 525	-1 696	-2 255	**
Sun protection blind	8 343	7 206	-469	35	
Xenon light	901	748	617	365	
Performance leather steering wheel	1 409	1 495	945	1 109	**
Glass sunroof	1 105	1 832	1 064	1 471	**
Adaptive cornering light	-672	213	1 621	1 588	**
Adaptive chassis with lowering	1 554	91	2 707	1 669	**
Convenience, Security, ...					
Lumbar support for front seats	-622	-1 302	-1 545	-1 158	*
Electric seat adjustment	186	-466	-755	-777	
Alarm system	283	394	-531	-271	
Seat heating for front seats	-520	97	-616	-247	
Comfort access	-466	-608	177	57	
Arm rest for front seats	-109	-394	430	222	
Climate control	1 348	827	800	589	
Hitch	713	1 817	1 541	2 412	***
Navigation, Media, and Communication					
Hifi system	-415	46	-72	-122	
Digital radio	2 084	2 272	58	14	
Mobile phone prep with bluetooth usb	-1 071	-1 312	502	84	
Navigation system business	770	775	1 362	1 058	**
DVD changer	2 653	3 346	2 061	2 224	***

[3] Haug, A. (2007): Representation of Industrial Knowledge – as a Basis for Developing and Maintaining Product Configurators. PHD Thesis, Department of Manufacturing Engineering & Management, Technical University of Denmark. Lyngby.

[4] Johnson, R., Orme, B. and Pinnell, J. (2006): Simulating Market Preference with Build Your Own Data. In: Sawtooth Software, Inc. (Ed.): *Proceedings of the Sawtooth Software Conference 2006*, vol. 12, Sequim, Washington, 239–253.

[5] Mandl, M., Felfernig, A. and Teppan, E. (2014): Consumer Decision-Making and Configuration Systems. In: Felfernig, A., Hotz, L., Bagley, C. and Tiihonen, J. (Eds.): *Knowledge-Based Configuration: From Research to Business Cases*, Morgan Kaufman, Waltham, 181–190.

[6] Morgenstern, O. and Neumann, J. von (1990): *Theory of Games and Economic Behavior*. Princeton Univ. Press, Princeton.

[7] Orme, B. K. and Johnson, R. M. (2008): Testing Adaptive CBC: Shorter Questionnaires and BYO vs. Most Likelies. Tech. rep., Sawtooth Software, Inc., 530 W. Fir St. Sequim, WA 98382.

[8] Pine, B. J. (1999): *Mass Customization: The New Frontier in Business Competition*. Harvard Business School Press, Harvard.

[9] Rice, J. and Bakken, D. G. (2006): Estimating Attribute Level Utilities from Design Your Own Product Data. In: Sawtooth Software, Inc. (Ed.): *Proceedings of the Sawtooth Software Conference 2006*, vol. 12, Sequim, Washington, 229–238.

[10] Walcher, D. and Piller, F. (2013): *The Customization 500 – An International Benchmark Study on Mass Customization*. Lulu Inc., Raleigh.

[11] White, H. (1980): A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity. *Econometrica*, **48**(4), 817–838.