# Analyzing Socio-Demographic Determinants for Fair Trade Label's Price Premia: A Practical Approach

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**Abstract** The adequate skimming of consumers' willingness-to-pay (WTP) for social product enhancements is key for companies' monetary benefits, because an increasing WTP translates to increasing price premia. We investigate consumers' WTP for the fair trade label in the jeans category and explore WTP differences between several socio-demographic segments. We conduct a discrete choice experiment and derive a segment-specific WTP by averaging individual WTP estimates for socio-demographic segments. This approach enables statistic testing of segment-specific WTP-differences. We found substantial differences in WTP for varying income- and household-based segments and segments built from consumers' awareness of the fair trade label. This information enables companies to derive adequate pricing strategies, i.e., second- or third-degree price differentiation strategies, when a social attribute enhances a product.

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# 1 Motivation

The adequate skimming of consumers' willingness-to-pay (WTP) is key for companies' monetary benefits. The determination of consumers' individual WTP and the subsequent use of first-degree price differentiation, i.e., offering individual prices, constitutes an optimal skimming strategy. However, one-to-one marketing is highly cost-intensive and, therefore, unrealistic in most markets. On the contrary, a complete abandonment from price differentiation, i.e., offering one price for all consumers, obviously does not satisfy the prevalent consumer heterogeneity and leads to reduced profits of the company. The application of market segmentation strategies and the use of varying price levels for different segments, i.e., third-degree price differentiation, could be regarded as a compromise between these two extremes and is heavily applied in practice.

Market segmentation divides a market into homogeneous sub-markets by using varying market segmentation variables such as consumers' socio-demographics, e.g. gender, age, income. If market segmentation is used for price differentiation, the knowledge of relationships between consumer's individual background variables and consumers' WTP is very important. Obviously, only if consumers' WTP varies significantly between different (socio-demographic) segments, companies are recommended to offer varying prices for their products to skim consumers' different WTPs. Consider, e.g. a company, that wants to enhance its current product, e.g. jeans, with a social product enhancement like the fair trade label, i.e. employ product differentiation. The knowledge about the consumers' WTP for the fair trade label and the appropriate clustering of consumers into segments is crucial to derive segment-specific price premia for the fair trade label and to finally gain profits from the introduction of the social product attribute. The introduction of a fair trade label both attracts new consumers that are willing to buy a more expensive product with the fair trade label and skims the WTP of existing consumers who switch to the fair trade product variant.

Recent literature has extensively studied relationships between consumers' preferences (or WTP) for a social product attribute and consumers' individual background variables. For example, the literature reviews in the meta-studies of Andorfer and Liebe (2012) and Tully and Winer (2014) give excellent overviews of the relevant literature. In most instances, recent literature examined socio-demographic drivers for consumer's WTP for the fair trade label attribute on an individual level and/or uses fast moving consumer goods (FMCG) such as coffee, chocolate, orange juice or paper towels within their study (cp. e.g. Rotaris and Danielis 2011; Rousseau 2015; Paetz and Guhl 2017a). From the literature review of Tully and Winer (2014), we observe that less than half of the studies deal with durable goods, e.g. furniture, electronics, clothes, etc. Haase et al. (2016), for example, analyzed the computer mice category and calculated the WTP for the fair trade label attribute. However, jeans within the clothing category are underrepresented in the context of WTP for the fair trade label. Tully and Winer (2014) do not report any study that considered the product category of jeans.

The purpose of our study is to further contribute to a deeper understanding of consumer's purchase drivers within the durable product category. In particular, we highlight the underrepresented jeans category. Using an empirical data set in the jeans category, we investigate whether relations between consumers' socio-demographic background variables and their (segment-specific) WTP for the fair trade label in the jeans category exist. Therefore, we use a practical segmentation approach, where we determine individual respondent's (preferences and subsequently) WTP and segment respondents into segments by using socio-demographic variables such as gender, age, etc. By averaging the individual WTP estimates of the associated segment-members, we achieve segment-specific WTP estimates. Finally, we check for segment-specific differences in WTP and draw conclusions on relations between price premia for the fair trade label and consumer's socio-demographic background variables. In contrast to an apriori segmentation approach, where aggregated WTP calculations are derived for predefined (e.g. gender-specific) segments, our practical segmentation approach enables inferences on statistically significant differences in WTP between segments by using one-way ANOVA.

The remainder of this paper is structured as follows: In section 2 we discuss the practical segmentation approach used here. Therefore, we briefly review the determination of individual preferences by using Hierarchical Bayesian estimation and discuss the calculation of consumers' individual WTP. In section 3 we provide a brief review of selected literature and formulate hypotheses regarding the determining effects of the socio-demographic variables. Section 4 provides information on our empirical study and yields the results. Managerial implications are provided in section 5. We conclude in section 6 and draw inferences on limitations and future research.

## 2 A Practical Segmentation Approach

In the context of discrete choice experiments, the use of random utility models is common practice. In random utility models, it is assumed that a respondent behaves as a utility-maximizer. Hence, he/she prefers that alternative for which he/she has the highest utility. The scalar $u_{ijt}$, which represents the utility of a respondent $i$ for alternative $j$ in choice occasion $t$ could be given via

$$u_{ijt} = \boldsymbol{x}'_{ijt} \cdot \boldsymbol{\beta}_i - p_{ijt} \cdot \gamma_i + \varepsilon_{ijt}, \text{ where } \varepsilon_{ijt} \sim EV(0, 1). \tag{1}$$

The first two summands constitute the deterministic part of the utility, which is determined by the attributes and their levels. We separate non-price attributes (e.g. brand or fair trade label) in vector $\boldsymbol{x}_{ijt}$ and the price in $p_{ijt}$ because this later simplifies the derivation of the WTP (see eq. 2 below). Note that the products' attributes vary over all three dimensions, $i$, $j$, and $t$, because in the online choice experiment, every respondent saw different stimuli in each choice occasion. The corresponding coefficients (vector $\boldsymbol{\beta}_i$ and scalar $\gamma_i$) denote the individual part-worth utility vector and the linear price parameter. We expect the sign of the price coefficient to be negative, which means that consumers' preference for a product decreases if (ceteris paribus) its price increases.

Besides the deterministic part, the utility contains a random error term $\varepsilon_{ijt}$. This part of the utility captures all the effects which influence the respondent's utility, but are not included in the deterministic part. We use the Extreme Value Type I distribution (i.e. the Gumbel distribution), which leads to the Multinomial Logit model. We fix the scale to unity for identification as only utility differences matter in multinomial choice models (see, e.g. Train 2009 or Elshiewy et al. 2017 for more details). Depending on the data setup (dual-response or 'typical' discrete choice experiments), the choice probability of an alternative and, therefore, the estimation algorithm for the focal parameters $\beta_i$ and $\gamma_i$ looks different. To avoid exhausting technical discussions on the underlying estimation concepts and algorithm, we refer the interested reader to Diener et al. (2006), who explain the estimation approach as well as the differences of dual-response and 'typical' discrete choice experiments.

If we account for heterogeneity at the individual level and, therefore, estimate individual parameters $\boldsymbol{\beta}_i$ and $\gamma_i$ (for each respondent i), the Hierarchical Bayesian (HB) Multinomial Logit model results. We assume that the vector of individual-level parameters follows a multivariate normal distribution (i.e., $[\boldsymbol{\beta}_i, \gamma_i]' \sim MNV(\boldsymbol{\theta}, \boldsymbol{\Sigma})$). The population parameters $\boldsymbol{\theta}$ (avg. part-worth utilities in the population) and $\boldsymbol{\Sigma}$ (covariance matrix of part-worth utilities in the population) are jointly estimated with the individual-level parameters using MCMC methods (i.e., Metropolis-Hastings algorithm and Gibbs-sampling, see Sawtooth Software 2009). To avoid a reiteration of the explanation of the popular Hierarchical Bayes Multinomial Logit model, we refer the interested reader to Elshiewy et al. 2017. We employed the commercial software from Sawtooth Software Inc. (cp. Sawtooth Software 2009), but also free software (e.g. the `RSGHB` package in `R`) could be used. As prior we use typical diffuse (conjugate) priors (e.g. normal for $\boldsymbol{\theta}$ with mean zero and a variance of 1000 and standard inverse Wishart for $\boldsymbol{\Sigma}$ with 2 degrees of freedom). We ran the sampler for $20,000$ draws and discarded the first $10,000$ draws as burn-in. Therefore, we end up with $10,000$ draws from the posterior distribution of the estimated parameters. Visual inspection of trace plots confirms that the sampler converged quickly (i.e., within the burn-in phase) and had good mixing.

To calculate the consumers' WTP, we use the estimated individual preferences (i.e., posterior-means of $\boldsymbol{\beta}_i$ and $\gamma_i$) and translate them into marginal units for the fair trade label attribute (cp. Tully and Winer 2014). If we consider effect-coding for the non-price attributes and a linear price parameter, the WTP will be calculated via:

$$WTP_i^{\text{fair trade label}} = \frac{\beta_i^{\text{fair trade label}} - \beta_i^{\text{no fair trade label}}}{\gamma_i}. \tag{2}$$

Thus, the WTP measures the (part-worth) utility difference of an alternative with and without a fair trade label relative to the marginal effect of price. See Chandukala et al. (2007) for more details on the economic foundations of (multinomial) choice models.

As it is well known, several approaches exist to derive the individual WTP of consumers. The approach used here constitutes an indirect approach, i.e., WTP for the fair trade label is not directly stated by the respondents, but (indirectly) derived from his/her individual preferences. Indirect approaches are known to provide more valid estimates of WTP than direct approaches and tend less to a highly inflated WTP in comparison to direct approaches (cp. Breidert et al. 2006).

Finally, we consider a practical segmentation approach (for further explanations on so-called two-step segmentation approaches in the context of discrete choice experiments, see, e.g. Desarbo et al. 1995): Once, the individual preferences/WTP estimates are achieved, we segment the respondents based on socio-demographic variables, e.g. gender or age, and average the individual estimates of associated segment members to achieve segment-specific preferences/WTP estimates. To this end, we perform one-way ANOVA analyses for each socio-demographic variable, to assess and test, whether WTP differences exist.

## 3 Literature Review, and Development of Hypotheses

Socio-demographic drivers for consumer's preferences or WTP for the fair trade label attribute have been frequently investigated in different product categories. Mostly, non-durable products, e.g. FMCG, were examined in previous research studies. Here, coffee and chocolate are by far most prominent:

De Pelsmacker et al. (2005) used conjoint analysis to determine the individual preferences of Belgian consumers for fair trade coffee. The individual results were then clustered into four segments, e.g. brand lover, flavor lovers, fair trade lovers, and fair trade likers. De Pelsmacker et al. (2005) found consumers who attach high importance to the fair trade label to be tendentiously younger and of higher education. However, no differences between genders became obvious.

The lacking influence of gender on fair trade preferences is also reported by Cailleba and Casteran (2009). The authors focused on panel data from the French fair trade coffee market and estimated latent class models. The profiling of segments yields no effects of gender and age on fair trade coffee's preferences.

This corresponds to the results of Cranfield et al. (2010). The authors examined preferences of Canadian consumers for fair trade coffee. Based on the results of a conjoint analysis, they estimated individual preferences that were subsequently clustered via K-means clustering. They obtained a 3-segment solution and estimated multinomial probit models to explain segment-membership by respondents' individual background variables. However, no variable, e.g. age, education, gender, explained segment-membership and, therefore, preferences for the fair trade label.

In contrast, Paetz and Guhl (2017b) found a discriminatory potential of gender. They conducted a discrete choice experiment with fair trade and conventionally traded orange juice alternatives in Germany and estimated finite mixture multinomial logit models. They selected a 4-segment solution and found the most social segment, i.e., the segment that attached the highest WTP to the fair trade label, to predominantly consists of female consumers. However, no discriminatory differences of respondents' age classes were found.

Rousseau (2015) conducted a discrete choice experiment in order to determine the preferences of Belgian consumers for fair trade chocolate. The author estimates latent class models as a (one-step) benefit segmentation approach. The resulting three segments were profiled with certain individual background variables, e.g. gender, age, income, knowledge of the fair trade label. Two segments were identified that value the inclusion of a fair trade label, while the members of the third segment were indifferent. The profiles of the two segments that prefer fair trade chocolate show, that these segments consist of a large proportion of female and younger consumers as well as of consumers with a higher income and those who recognize the fair trade label. However, significantly educational differences between the classes did not become obvious.

The study of Arnot et al. (2006) also examined the influence of respondents' familiarity with the fair trade label on their fair trade preferences. The authors examined purchases of fair trade coffee in an actual market setting in Canada. They estimated a conditional logit model that included several interaction terms, e.g. awareness of the fair trade label. Arnot et al. (2006) found that respondents, who are aware of the fair trade concept, are more likely to purchase a fair trade coffee and, therefore, have a higher WTP for the fair trade label attribute.

Further studies assess the consumption of fair trade products in general or focus on durable products: For example, Panico et al. (2014) focused on Italian consumers and asked for both the annual frequency and average expenditures in fair trade products in several product categories. In order to determine the influence of several individual background variables, e.g. socio-demographic and psychographic variables, on fair trade consumption, they used ordered probit regression. They found that a higher income as well as smaller household size increase fair trade consumption. However, consumers' age, education and gender showed no influence on fair trade consumption.

In a durable product-category, Dickson (2001) interviewed US apparel consumers and focused on men's dress shirts. The author determined the consumers' importance for No Sweat labels in purchase decisions. No Sweat labels like the fair trade label are social labels, because both target on people, e.g. producers, workers, as beneficiaries. Using conjoint analysis, the author determined individual preferences that were then clustered into four segments. No differences w.r.t.

income and age between the segments were found. However, consumers who attached the greatest preference for the social label were more likely to be female.

As we already noticed in section 2, consumer preferences and WTP correspond to each other. Hence, ceteris paribus, a higher preference for the fair trade label leads to a higher WTP for the fair trade label. Because of this, we can use the results from the previously discussed literature and derive the following hypotheses for our study:

**H1**: If at all, the segment of younger respondents yields a higher WTP for the fair trade label.

**H2**: If at all, the segment of female respondents exhibits a higher WTP for the fair trade label.

**H3**: If at all, the segment of respondents who live in smaller households, show a higher WTP for the fair trade label.

**H4**: If at all, the segment of academics yields a higher WTP for the fair trade label.

**H5**: If at all, the segment of wealthier respondents has a higher WTP for the fair trade label.

**H6**: The segment of respondents, who are aware of the fair trade label, yields a higher WTP for the fair trade label.

These hypotheses are tested in our empirical study.

## 4 Empirical Study

We conduct an empirical discrete choice experiment in the jeans category in Germany. The jeans alternatives were described by four attributes (and associated levels), i.e., price (50 €, 90 €, 130 €, 170 €), brand (Diesel, G-Star, Levi's, Replay), design (trendy, traditional) and display of a fair trade label (yes, no). We used a dual-response design, in which each respondent faced two choice questions in several choice occasions, respectively. Figure 1 shows an exemplary choice question.

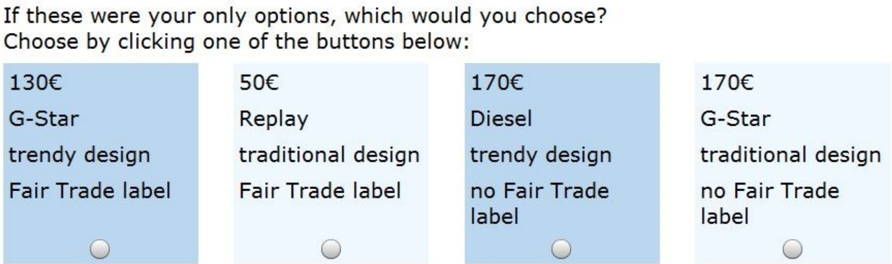


**Figure 1:** Exemplary choice question.

First, each respondent had to choose his/her favored jeans out of four jeans-alternatives. Second, each respondent was asked whether he/she would really buy the previously selected jeans alternative in the current marketplace (Yes / No) (cp. Diener et al. 2006, p. 157). We used 14 choice questions in a dual-response design for data calibration. In addition to the data of the discrete choice experiment, we collected information on several consumers' socio-demographic variables, i.e., gender, age, (household) income, household size, education level, as well as on consumers' awareness of a specific fair trade label, i.e., the label of the organization 'Transfair', which is displayed in Figure 2.

**Figure 2:** Label of the organization 'Transfair'.

The questionnaire was distributed online via a German market research institute. The final sample consisted of 353 German respondents; 49.6 % were male, 50.7 % were 43 years old or younger, 62.0 % had a monthly (household) income lower than 2600 €, 17.3 % had an academic degree. Concerning household size we considered four classes: 20.1 % lived alone, 39.9 % lived in a 2 person household, 34.8 % in a 3-4 person household and 5.1 % in a household with more than four persons. 77.1 % of the respondents were aware of the fair trade label.

First, we used the commercial software tool CBC/HB from Sawtooth Software Inc. to assess respondents' individual preferences. CBC/HB reports the percent certainty, also known as likelihood-ratio index or pseudo-$R^2$, of 0.6995. This argues for an excellent model fit. The percent certainty can be easily translated into the log-likelihood value by considering (Paetz et al. 2019, p. 7)

$$R^2 = 1 - \frac{LL}{LL_0}, \tag{3}$$

and a value of the log-likelihood of the null model ($LL_0$) of $353 \cdot 14 \cdot \log(1/5) = -7953.842$. The log-likelihood, therefore, has a value of $-2390.209$.
We scanned the data and eliminated the data of those respondents who showed no economically meaningful price parameter. The final sample then consisted of 267 respondents. Subsequently, we used formula (2) to determine individual consumers' WTP estimates and averaged the results. Overall, we found an average WTP for the fair trade label attribute of 23.13 €. However, 18.4 % of the respondents have a negative WTP for the fair trade label. This argues for a sound basis of heterogeneity within our sample and contributes to the purpose of our study to further investigate (segment-specific) socio-demographic drivers for the fair trade label. Second, we segmented the consumers based on individual socio-demographic variables and calculated segment-specific WTP by averaging individual WTPs of the associated segment members. Finally, we conduct one-way ANOVA to test for segment-specific differences in WTP for the fair trade attribute. Table 1 displays the segment-specific WTP estimates for each category of the socio-demographic variables as well as the F-values and associated p-values resulting from one-way ANOVA.

The results from Table 1 maintain varying influences of consumer's individual background variables on his/her WTP for the fair trade label. No significant segment-specific differences could be observed between different gender, age classes, and education levels. The lacking explanatory power of these variables for the durable good 'jeans' comes not unexpected, since it is also frequently reported in the relevant literature on WTP for the fair trade label assigned to FMCG (see section 3.) Therefore, we have to reject our hypotheses H1, H2 and H4.

**Table 1:** WTP estimates in socio-demographic segments.

| Segmentation variable | # respondents | Segment-specific WTP | F-value (p-value) |
|---|---|---|---|
| *Gender* | | | |
| Female | 139 | 25.50 € | $F = 0.717$ |
| Male | 128 | 20.56 € | ($p = 0.398$) |
| *Age class* | | | |
| 43 years or younger | 101 | 21.09 € | $F = 0.430$ |
| Older than 43 years | 166 | 24.93 € | ($p = 0.512$) |
| *Income* | | | |
| Lower than 2600 € | 167 | 16.93 € | $F = 7.752$ |
| 2600 €or more | 100 | 33.49 € | ($p = 0.006$) |
| *Education* | | | |
| No academic degree | 223 | 21.93 € | $F = 0.858$ |
| Academic degree | 44 | 29.21 € | ($p = 0.355$) |
| *Household size* | | | |
| 1 person | 54 | 15.25 € | |
| 2 persons | 109 | 24.09 € | $F = 3.335$ |
| 3-4 persons | 88 | 31.78 € | ($p = 0.020$) |
| More than 4 persons | 16 | - 4.35 € | |
| 1-4 persons | 251 | 24.88 € | $F = 5.766$ |
| More than 4 persons | 16 | - 4.35 € | ($p = 0.017$) |
| *Fair trade label awareness* | | | |
| Yes | 214 | 26.90 € | $F = 6.902$ |
| No | 53 | 7.91 € | ($p = 0.009$) |

ANOVA tables are provided in the Appendix.

However, the trend within a variable's levels supports our hypotheses H2 and H4: Respondents who are female (+4.94 €) or have a higher education level (+7.28 €) yield a higher WTP for the social product attribute than their counterparts. The trend, that older respondents yield a higher WTP for the fair trade label attribute

(+3.84 €) within the jeans category than younger respondents contradicts our hypothesis H1 and the results from the FMCG-literature. For example, Rotaris and Danielis (2011) found a significantly higher WTP of young consumers in the the coffee category. On the other hand, Carrigan et al. (2004) observed a sense of moral responsibility within purchase behavior of older consumers, which fits the trend observed in our analysis.

Furthermore, we found a significant differences in WTP for varying sizes of households (4 classes). Households with up to 4 persons show the positive WTP, and households with more than four persons yield a negative WTP for the fair trade label attribute (-4.35 €). To gain further insight in this trend, we built new household classes, i.e., one class comprises all households with 4 or fewer persons, while the other class contains those households with more than 4 persons. We conducted one-way ANOVA again and found significant differences as expected; households with four or fewer persons yield a significantly higher WTP for the fair trade label (+29.23 €) than households with more than 4 persons. Hence, we can accept hypothesis H3. One explanation might be, that households with one or two children attach higher importance (and therefore a higher WTP) to the fair trade label within their choice decision. Eventually, these kinds of households interpret the fair trade label as a sign for a higher quality of products (e.g. less harmful substances in cotton used for jeans' production). This drives these households to higher WTP, since they might want to favor their children with fair trade jeans. In contrast, households with more than two children, are likely to be more concerned about other (more essential) topics, e.g. the price of a product. In this case, the fair trade label attribute's importance dilutes, while the price sensitivity of these households increases. An inspection of the (averaged) household-specific price coefficients supports this assumption. While households with four or fewer persons show in absolute a smaller price coefficient (−0.16), households with more than four members are highly price sensitive (−0.24).

WTP differences between income-based segments are significant ($p < 0.01$). Higher (monthly household) income conforms to a higher WTP (+16.56 €) for the fair trade label attribute. This finding is in accordance with the recent literature, which reports the same interdependency for income and fair trade WTP for non-durable products and we can accept our hypothesis H5.

A large difference in WTP could be observed for those segments, which emerges from a different awareness of the fair trade label ($p < 0.01$). While those respondents, who are aware of the fair trade label yield a substantial price premium of 26.90 €, respondents who are not familiar with the fair trade context showed a significantly smaller WTP of 7.91 €. Hence, we can accept hypothesis H6.

In summary, we found an overall positive WTP for the fair trade label attribute of approximately 23 €, which translates into a relative price premium of approximately 21 %. Hence, companies may offer a 21 % higher price for a fair trade jeans in comparison to a traditional traded jeans. This result conforms to results from a meta-analysis of Tully and Winer (2014), who report a relative price premium of approximately 24 % for the fair trade label restricted to the clothing category.

# 5 Managerial Implication

Due to lacking significant differences in WTP, it is not recommended to build segments based on the variables age, gender or education level, if the derivation of segment-specific pricing strategies is in focus. Companies could use the information of significant differences between income-based, household-based and fair trade awareness-based segments for pricing policies. If consumers have a higher income or live in households with four or less members or are aware of the fair trade context, companies may increase the price by approximately 17 € / 29 € / 22 € which translates into relative price premia of 15 % / 26 % / 20 %. Apparently, these price premia seem to be (slightly) inflated. However, even higher price premia are reported in the relevant literature: For example, Levinson (2010) found price premia for the fair trade label of 46 % to 62 % for T-shirts.

Besides the variables 'size of household' and 'income', the variable 'awareness of the fair trade label' provides a sound basis for managerial implication with respect to price differentiation strategies. It seems to be advisable for jeans companies to simultaneously offer a fair trade jeans and a traditional traded jeans (without a fair trade label) to skim consumers WTP and increase profits adequately. For the latter variables, this results in second-degree price differentiation, where consumers self-select themselves into different segments, rather than in a 'real' segmentation of consumers and segment-specific prices.

# 6 Conclusion

An adequate skimming of consumers' willingness-to-pay (WTP) is key for companies' monetary benefits. In order to accommodate consumers' WTP heterogeneity, the use of market segmentation strategies and segment-specific pricing is nowadays common management practice. If segments are inferred from (socio-demographic) consumer characteristics, the knowledge of relationships between consumer's individual background variables and consumers' WTP is important to derive optimal segment-specific prices. Obviously, only if consumers' WTP varies significantly between different (socio-demographic) segments, companies are recommended to offer varying prices for their products to skim consumers' varying WTPs.

We investigated consumers' WTP for a social product attribute in the jeans category, which is underrepresented in the recent literature so far. In particular, we searched for WTP differences between several socio-demographic segments. Therefore, we conducted a discrete choice experiment in the product category of jeans and determined individual preferences by using a Hierarchical Bayesian approach. Based on the individual preference estimates, we calculated consumers' individual WTP for the fair trade label attribute. Subsequently, respondents were segmented by gender, age, monthly (household) income, size of household, education level and awareness of the fair trade label, respectively. Segment-specific WTP (and therefore price premia) for the fair trade label results from an averaging of individual WTP estimates. Using one-way ANOVA, we checked for segment-specific differences in WTP.

Overall, we observed a positive (relative) WTP for the fair trade label attribute of approximately 21 %. Hence, if a company considers converting from traditional trading to fair trade or extending the current product line with a fair trade jeans, it could compare potential cost increases - due to fair trade - to potential price premia. If – ceteris paribus – price premia exceeds cost increases, the introduction of a fair trade label will be recommended.

The segments resulting from the variables 'gender', 'age' and 'education level' showed no significant WTP differences. However, even for those segments, we found trends (e.g. females show higher WTP for the social product attribute), that conform to results from recent literature on WTP in FMCG categories. The variable 'income' showed discriminatory potential. An increasing income leads to higher WTP for the fair trade label attribute. The largest discrepancy in

WTP between segments was observed for the variables 'size of household' and 'awareness of the fair trade label'. Those respondents, who live in a 1-4 persons household or were aware of the label, have a highly positive WTP. Households with more than four persons even have a negative WTP. As a possible explanation, we may trace this back to a higher concern of large households about more essential topics, e.g. the price of a product, which implies a dilution of the fair trade label attribute's importance.

In summary, price differentiation based on income, size of household or awareness of the fair trade label is recommended to skim consumers' WTP more adequately and further increase company profits.

We do not want to conceal limitations of this study. Although we used an indirect method to estimate consumers' WTP, the resulted WTP estimates might be slightly inflated. The inflation could be prevented by using panel data, which contain actual purchase behavior rather than stated choice behavior from a discrete choice experiment.

With this paper, we contribute to the underrepresented literature of WTP for the fair trade label of the durable good 'jeans'. Obviously, further research in this area is needed. Especially, the study of drivers of consumers' WTP for the fair trade label known from FMCG for durable goods is important to draw conclusions, whether these variables drive consumers' WTP for more expensive (durable) goods, too. This further contributes to a deeper understanding of socially responsible consumption, which is highly actual nowadays.

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# Appendix

| | sum of squares | df | mean of squares | F-value | p-value |
|---|---|---|---|---|---|
| Between groups | 1630.262 | 1 | 1630.262 | 0.717 | 0.398 |
| Within groups | 602167.936 | 265 | 2272.332 | | |
| Total | 603798.198 | 266 | | | |

**Table 2:** ANOVA table for the variable 'gender'.

| | sum of squares | df | mean of squares | F-value | p-value |
|---|---|---|---|---|---|
| Between groups | 979.107 | 1 | 979.107 | 0.430 | 0.512 |
| Within groups | 602819.091 | 265 | 2274.789 | | |
| Total | 603798.198 | 266 | | | |

**Table 3:** ANOVA table for the variable 'age class'.

| | sum of squares | df | mean of squares | F-value | p-value |
|---|---|---|---|---|---|
| Between groups | 17160.366 | 1 | 17160.366 | 7.752 | 0.006 |
| Within groups | 586637.832 | 265 | 2213.728 | | |
| Total | 603798.198 | 266 | | | |

**Table 4:** ANOVA table for the variable 'income'.

| | sum of squares | df | mean of squares | F-value | p-value |
|---|---|---|---|---|---|
| Between groups | 1947.518 | 1 | 1947.518 | 0.858 | 0.355 |
| Within groups | 601850.680 | 265 | 2271.135 | | |
| Total | 603798.198 | 266 | | | |

**Table 5:** ANOVA table for the variable 'education'.

| | sum of squares | df | mean of squares | F-value | p-value |
|---|---|---|---|---|---|
| Between groups | 22129.538 | 3 | 7376.513 | 3.335 | 0.020 |
| Within groups | 581668.660 | 263 | 2211.668 | | |
| Total | 603798.198 | 266 | | | |

**Table 6:** ANOVA table for the variable 'size of household (4 groups)'.

| | sum of squares | df | mean of squares | F-value | p-value |
|---|---|---|---|---|---|
| Between groups | 12857.767 | 1 | 12857.767 | 5.766 | 0.017 |
| Within groups | 590940.430 | 265 | 2229.964 | | |
| Total | 603798.198 | 266 | | | |

**Table 7:** ANOVA table for the variable 'size of household (2 groups)'.

| | sum of squares | df | mean of squares | F-value | p-value |
|---|---|---|---|---|---|
| Between groups | 15326.673 | 1 | 15326.673 | 6.902 | 0.009 |
| Within groups | 588471.525 | 265 | 2220.647 | | |
| Total | 603798.198 | 266 | | | |

**Table 8:** ANOVA table for the variable 'fair trade label awareness'.