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Beklädnadsvaror i KPI: Varumärken i de hedoniska modellerna

För information

Under 2012 har ett utvecklingsprojekt pågått där kvalitetsjusteringsmetoden för beklädnadsvaror i KPI har utvärderats. Sedan 1993 har en hedonisk kvalitetsjusteringsmetod använts för kläder, och en mängd data för produktegenskaper har samlats in månadsvis för att kunna användas i de hedoniska modellerna. Projektets syfte har varit att göra en översyn av de modeller som används och de egenskaper som samlas in. Utvärderingen har omfattat åren 2001-2009.

Varumärket är en av de viktigaste förklaringsvariablerna i de hedoniska modeller som används. För att kunna använda varumärket i kvalitetsjusteringen måste dock varumärket grupperas utifrån kvalitet. I nuläget används en subjektiv metod för detta. För att undvika systematiska felgrupperingar av varumärken och säkerställa en effektiv användning av data testas en alternativ metod för att bedöma ett varumärkes kvalitet; ett oberoende datamaterial används för att uppskatta konsumenternas värdering av ett varumärke. Det visar sig att den alternativa metoden ökar de hedoniska modellernas förklaringsgrad, samtidigt som systematiska felskattningar av varumärken undviks. Samtidigt innebär denna alternativa metod begränsningar på data, jämfört med en subjektiv metod, om metoden ska kunna användas i produktion.

Följande PM redovisar ett urval av preliminära resultat och slutsatser från projektet, och rör främst den del av projektet som behandlar gruppering av varumärken.

Introduction

In the Swedish consumer price index (CPI), hedonic methods are regularly operationally used since several years for adjusting apparel indexes for quality differences. The method used for quality adjustment, in combination with local price collection, makes the cost for producing indexes for apparel high relative to other groups in the CPI.[1] Also, the uncertainty resulting from the sampling

[1] Arvidsson (2004) estimated the cost per price observation and year at 390 SEK. Nilsson et al. (2010) further estimated the total cost for price collection for apparel at around one

of apparel is high; calculations indicate that the sample error for total CPI is about ± 0.4 percentage points for a year link, where sampling error from apparel contributes with ± 0.1 percentage point (Nilsson et al, 2010). Further, estimations of variance for the CPI by Norberg (2004) reveal that apparel contributes to around half of the total variance for an index based on locally collected prices. Norberg (1993) and Nilsson et al. (2010) also conclude that the use of a hedonic method for quality adjustment for apparel has not resulted in less variation in the price index for apparel used in the CPI. However, the method might serve to adjusts for any long term change of quality in the supply of apparel goods.

In an international comparison the method used for quality adjustment for apparel in the CPI is ambitious.[2] Any adjustment in the scope of the method used might free resources and these resources can be used to reduce uncertainty by increasing the sample size for apparel goods in the CPI. The aim of this paper has been to evaluate the method that is currently used for quality adjustment of clothing in the CPI, i.e. the hedonic approach. More specifically, the hedonic regression models that are used are evaluated for the period 2001-2009 in order to identify irrelevant characteristics that are collected at present and to ensure an effective use of collected data. Thus, any addition of new characteristics to the models are not prioritized. No study has previously been made that evaluates the hedonic regression models in long term.

Brand is a highly influential factor in determining the price of a specific product for apparel. In order to ensure a efficient use of the brand variable, this paper explores an alternative approach towards grouping the brands in different segments, or quality classes. This alternative, *explicit*, approach uses a independent dataset in order to group the brand variable, in contrast to the presently used method which is based completely on subjective judgment of quality of brands. The paper also recognizes a potential risk of bias from using

million SEK, which can be put in relation to the total yearly cost of local price collection at 5-6 million per year.

[2] To the authors knowledge, only the U.S. uses a similar approach, e.g. see Fixler et al. (1999).

the subjective method of grouping emerging brands in the sample; the assessed quality of a emerging brand may be dependent on the single price observation that is associated with the first observation of that specific brand. The explicit approach avoids this potential problem.

The main finding from the paper is that there are several characteristics that easily can be excluded from the data collection. Also, by using historical data a more consistent grouping of the brand variable can be made, which increases the explanatory power of the models used and reduces the risk of potential bias from grouping the brands subjectively. However, the explicit approach has some implications on data if used in production. Further, in order to ensure a representative sample, reduce variance and to avoid long term bias, the instructions to the price collectors must be revised or clarified.

The results that are presented in this report are somewhat reduced, as the results are restricted to mainly include the analysis of the different approaches towards grouping of brands. Hence, only results for women's wear are presented. Further, the conclusions are incomplete as the results are still being discussed. This report is organized as follows. Section 2 presents the method used for quality adjustment of apparel in the CPI as well as some theoretical considerations. Section 3 presents the empirical models and the data that is used for estimation. Section 4 presents the results and section 5 provides some preliminary conclusions of the findings.

Background and Conceptual Framework

Hedonic Analysis

One basic problem that arise when calculating index numbers for consumer goods and services are how to deal with quality changes in a product. There exist a variety of methods, implicit and explicit, that aims to adjust for the change of quality in the product when calculating an index. The hedonic approach is used in order to obtain an estimate of the market valuation of product characteristics or quality.

Rosen (1974) formulates a theory of hedonic prices where goods are valued for their utility-bearing attributes or characteristics. Utility-maximizing consumers and producers observes prices of differentiated products and the specific amounts of characteristics associated with them. Hedonic prices are defined as the implicit prices of these attributes. The model assumes a competitive equilibrium for a range of possible product differentiations where both consumers and producers locate. Any specific differentiation, or package, can be represented by a vector of specific characteristics, which in turn determine a market clearing price. The price is fundamentally determined by consumer tastes and producer costs.

A hedonic function can be given by $p(\boldsymbol{z})$ where **z** is vector of characteristics for each good. The function is defined for each package of characteristics bought and sold on the market. An estimation of the function $p(\boldsymbol{z})$ denoted $\hat{p}(\boldsymbol{z})$ then gives a set of implicit marginal prices $\hat{p}_i(\boldsymbol{z}) = \frac{\partial \hat{p}(z)}{\partial z_i}$ for characteristic *i*. One way of using hedonic prices in the context of price indexes is to use the hedonic function estimated in the base period to estimate the price of a product in a comparison period. Following Fixler et al. (1999), let p_t and p_{t-1} be the price in period *t* and *t-1* respectively. The measure of the price change after adjusting for any quality change, i.e. any change in the package of characteristics, can be shown as

$$\frac{\frac{p_t}{p_{t-1}}}{\frac{\hat{p}(z)}{p_{t-1}}} = \frac{p_t}{\hat{p}(z)}$$

The use of a hedonic functions relies on some assumptions, both theoretical and practical. The model outlined above presumes competitive markets and market clearing prices. Fixler et al. states that the characteristics of a product must be quantifiable in order to be measured and estimated by a hedonic function. In particular, this is problematic for characteristics that are intangible, e.g. perception or general “feeling” of a product. However, such characteristics can often be captured by the inclusion of other characteristics, e.g. brand name. Further, hedonic techniques assume that the changes in the characteristic package is non-drastic and they should also be able to distinguish between the demand and supply of characteristics.

The Hedonic Index for Clothing in the CPI

For clothing in the Swedish CPI, a hedonic model is used for quality adjustment since 1993. The quality between products are adjusted by the hedonic method when products are replaced within a specific description.

In the design of the hedonic model, some practical restrictions were initially adopted. First, the hedonic functions, i.e. the regression models, should be as similar as possible for all the initial 24 product groups of clothing. Furthermore the models should be simple enough to be estimated by a standard statistical package on a PC, and the parameters of the hedonic function should need to be estimated at most once a year. Only data available through the CPI system should be needed for the estimation of the regression parameters.

Data for Estimation of the Hedonic Function

Each month about four sampled products are observed in about 20-25 outlets, giving about 100 observations for each product group. In a year, with monthly measurements, altogether 200-400 different sampled products are encountered because of forced replacements, The turnover rate can be high, especially for ready-made clothes like women´s blouses and dresses. Fewer observations are available for winter clothing. To these data are added the observations from the sample of the price reference period of the coming year.

Assuming that the outlet effects are equal for two or more product groups, for example women´s dresses, skirts and trousers, one large model for all these product groups together can be estimated, which saves degrees of freedom and thus uses data more efficiently in terms of precision. However, parameters should not be estimated in this way for very different product groups as the price formation can vary between product groups.

Updating hedonic coefficients

The hedonic coefficients are updated annually. There is a parallel updating of hedonic coefficients and weights in the CPI. The weights in the CPI are based on consumption during the year preceding the past year, while the hedonic coefficients for the coming year are estimated with data collected the past year.

The strategy is to analyze old data to find the best explanatory variables. There is plenty of time for this exploratory analysis. In the beginning of the year, when weights and hedonic coefficients must be computed on new data, it is in principle only a question of estimation, without testing different models and sets of independent variables. This is also a question of credibility by not being free to choose how to compute the index numbers in the CPI.

In the explanatory analysis the possible models and independent variables are evaluated with respect to explanatory power, statistical significance, multicollinearity and, desirably, stability of coefficients over time. However, model building of this kind must always be guided by economic theory and knowledge of products and markets.

Dependent Variable

Either regular price or actual price, i.e., price before or after any temporary sales discount, can be taken as the dependant variable in the estimation of the hedonic functions. If actual price is used as the dependant variable, "being out of season", indicated by a sales price, should in this situation be treated as a quality variable, thereby making possible better estimates of the effects of the quality variables – brands and physical properties. The explanatory variables would then need to be accompanied by a variable for type of price.

Regular price is the choice made for estimation of the hedonic functions in the Swedish application. Taking the regular rather than the actual price avoids a lot of variation in the dependant variable to be explained. Empirical studies using 1991-92 data showed that the regression coefficients are very similar whether estimated with the regular price or the actual price as the dependant variable, and the effect on price index is negligible.

Independent Variables

The independent variables in the regression models are grouped into outlet type, origin (brand and manufacturing country) and physical characteristics. A systematic search for good explanatory variables was initially made through regression analysis carried out by the Swedish Price and Competition Board in the 1980´s, pilot studies on CPI 1991-1993 at Statistics Sweden and findings from the U.S Bureau of Labor Statistics.

The outlets are grouped into eight different categories, ranging from department stores to exclusive shops. Given a specific product, different types of outlets may practice different policies regarding of markup of price, service, warranties offered etc. These outlet specific characteristics need to be controlled for in order to estimate the effects of other characteristics on the price, i.e. brand/origin and physical characteristics.

The physical characteristics that describes the products shall in principle mirror the valuation made by the consumer, hence production costs not giving consumer value shall not be considered in the model. On a competitive market the consumer prices are assumed to be proportional to production costs, therefore physical characteristics that vary in production costs may be included. Also, pure fashion characteristics are not to be controlled for in the model. As Fixler et el. (1999) points out, there are certain inherent difficulties in using hedonics for clothing that are related to possible specification bias. It is inherently difficult for a hedonic model based on survey sampling to capture all aspects of a products physical characteristics. An alternative is to let certain quality characteristics that are not captured be approximated by other variables, such as brand. However, such an approach is not perfect in any way.

Brand has proved to be highly significant in explaining price levels of clothing. Initially, Statistics Sweden utilized the service staff of the largest professional fashion magazine in Sweden to group brands into five “status classes”, as valued from a consumers point of view. The process of grouping new brands have in recent years been passed to the staff at Statistics Sweden. A new brand is grouped with respect to information received from the internet, price collectors, product knowledge of staff and exceptionally by contacting the retailer. This grouping of brands on a scale by consumer value can be put in contrast to the approach of the U.S Bureau of Labor Statistics where brands are grouped depending on type of brand, i.e. store/private, national/regional and exclusive brand. (Liegey, 1991). The American approach is thus similar to the Swedish grouping of outlet types. As a replacement product should preferably, but not necessarily, be selected among products of the same brand or the same class of brands, quality adjustment for this variable has not been the most frequent[3]. However, there is a possible risk of bias when assigning the status code to a new, emerging, brand. In the face of incomplete information about the new brand and perhaps inability to use information at hand, the new brand may be coded with the single price observation as only guidance when choosing brand status code. In that case, there is a possibility that the index level is pushed towards 100 each time new brands are coded. This potential problem would not arise when utilizing the staff at the fashion magazine, rather the risk occurs when observed price of the first observation of a emerging brand is not believed to be independent from the assessment of brand quality.

Taking account of the impact from brands for clothing seems well motivated. For clothing the brand is often a very essential component in the consumers perception of a product. It is linked to consumer satisfaction both directly by its value in itself, and indirectly by being perceived as an indicator of quality in

[3] For 2011 around 16 percent of all replacements are made *between* products of different status coding.

general. In the marketing and consumer science literature this is sometimes described as merchandise evaluative cues being *intrinsic* or *extrinsic* (Forsythe, 1991). Intrinsic cues cannot be changed without also changing the physical characteristics of the product itself, whereas extrinsic cues are product related but not part of the physical product. Consumers use both intrinsic and extrinsic cues to choose between products and to form perceptions about value and quality. Brand name can be regarded, as mentioned earlier, as an indicator of product features, including quality.

Forsythe states that there is evidence from previous studies that perception of quality is related to the price of the product when consumers lack information about the product. Forsythe also shows that there is an absence of a significant relationship between brand name and perception of quality among shoppers when confronted with physically identical products. Hence, shoppers tended to rely primarily on physical product characteristics when forming perceptions about the quality of a product. However, shoppers did expect to pay a higher price for more exclusive brands, regardless of perceived quality. Hence, although consumers may not perceive a high priced brand as having better physical quality, they are willing to pay the higher price for other reasons. In this way brands have an intangible value to the consumer, even when the information about the products quality is complete. In the same way, brand name may prove to be an important indicator of general quality of a product when information is incomplete, thereby reducing perceived risk of a purchase. For example, Liljander et al (2009) found that store image affected purchase intentions indirectly, by reducing perceived financial risk of buying a store branded product.

Independent Variables and Stability of Parameter Estimates

Fashion is to some extent a subjective concept and is not well defined in the literature. However, fashion as well as production costs not giving value to the consumer is considered by the CENEX HICP Quality Adjustment Project to be undesirable in a quality adjustment method that applies hedonic regression

(Federal Statistical Office, 2009). According to this, the selected characteristic variables should not reflect fashion in order to avoid long-term bias in the index calculations. Fashion is put in contrast to lasting quality improvements; it is only the quality related differences that is to be accounted for when evaluating the price differences in a hedonic model. As an example of a fashion characteristic, color of a laptop computer is used.

Guédès (2007) further develops the nature of this long-term bias. Guédès points out that fashion is indeed an objective and deciding element of price determination, but that it is the variability over time that distinguishes fashion from other quality characteristics. These variations are not homothetic and might lead to modifications of the absolute hierarchy of models over time for a specific product. Guédès concludes that a traditional approach with quality adjustments only at the time of replacement leads to a dissymmetrical and skewed treatment. A constant utility index would make it necessary to make quality adjustments during the time the product is in the sample, not when it is replaced.

An hypothetical example of men´s shirts can be used to highlight the potential risk of bias. Suppose that the style of a shirt is considered to be a quality indicator. More specifically, striped shirts are found to be a significant element of price determination. The problem, however, is that stripes are also an element of fashion in men´s shirts.

Diagram 1.

Evolution of regression parameters for fashion characteristics

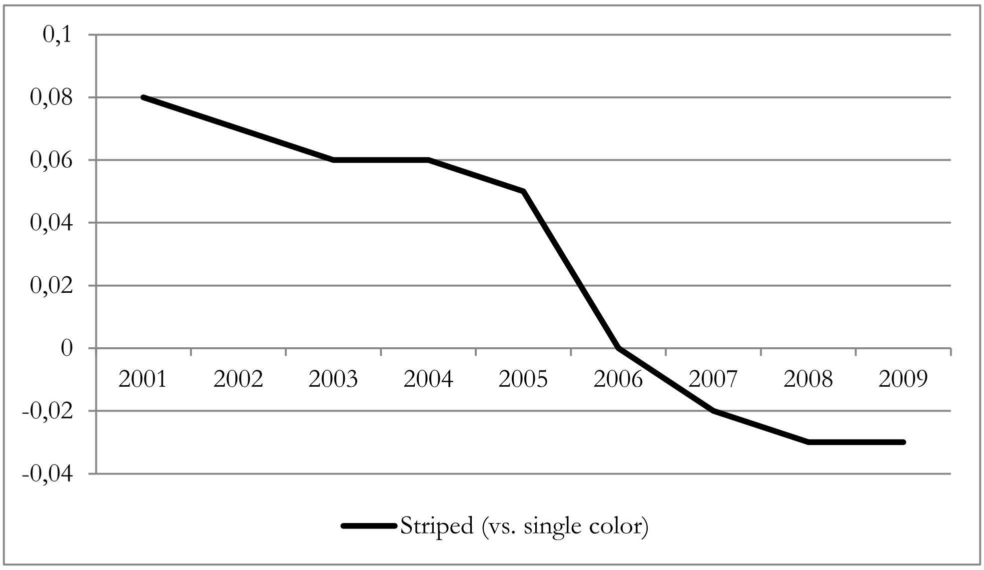


Diagram 1 above shows a hypothetical example of how a hedonic model that are used to approach the quality of men´s shirts evolves over time. It is obvious that the relative hierarchy of the model over time isn´t constant. At the beginning of the period striped shirts are estimated, ceteris paribus, to be of better quality to the consumer. In the end of the period, however, striped shirts are estimated to be of less quality.

Suppose that the quality adjustment of men´s shirts only takes place at the time of replacements. Assume further that prices for men´s shirts is stable until replacement of the product, where they rise. The quality reflected by fashion decreases over time as the shirt becomes out of fashion. At the time of replacement quality reflected by fashion is restored, as a more fashionable shirt is selected to the sample. It is obvious that the quality of the shirts in the sample is unchanged in the long run, but that prices have risen over the same period of time. A correct constant utility index would thus have to rise over time in order to reflect the true price development of men´s shirts. However, in between the replacements the quality is not constant; the fashion characteristics for a shirt tends to decline until it is replaced by a more fashionable shirt. If quality is adjusted with regard to fashion as the shirt is replaced, the replacement is considered to be of better quality. In fact, every adjustment of quality will be in this direction when quality of the shirt is actually unchanged from the introduction of the shirt in the sample until the shirt is replaced. An index that uses quality adjustments for replacements will thus we biased downwards.

Hence, the conclusion according the Guédès is that a method of quality adjustment that uses direct comparison between the product gives the same result in the long run as a continuous adjustment of quality, i.e. a constant quality index.

It is important to point out that a very different story is told when we have characteristics that expresses long term quality improvements of the product, where quality is unchanged during the life of the product in the sample. Hence, a quality adjustment at the time of replacement expresses the actual change in quality over time. The potential bias is directly connected to the inclusion of quality characteristics that varies in the short run, i.e. fashion characteristics, in a model that is used to adjust for quality differences when a product in a sample is replaced by another.

The desirability of stable parameter estimates in a hedonic regression model has been recognized in the Swedish setting by Norberg (1993). Fixler et al. (1999) also deals with the problem of unstable parameter estimates related to fashion, however the problem regarded as a risk of bias, but rather as a problem of high costs of anew specifications of the models used.

The Functional Form of the Hedonic Model

The hedonic model used in the Swedish CPI is on a semi-logarithmic functional form

$$\log(Price_i) = \alpha + \sum_k \beta_k V_{ki} + \sum_k \gamma_k X_{ki} + \sum_k \delta_k Y_{ki} + \sum_k \vartheta_k Z_{ki} + e_i$$

Where subscript i runs through all individual products in the product groups described by this hedonic function, and subscript k the levels of the factors. Furthermore, V_{ki}, X_{ki}, Y_{ki} and Z_{ki} are dummy variables for type of outlet, brand/origin, physical characteristics and month respectively. The hedonic parameter estimates β_k, γ_k, δ_k and ϑ_k may thus be interpreted as influences on the price by characteristics. Lastly, an error term e_i is included.

The Type of Hedonic Index

There exist different methods to computationally use hedonic regression results in quality adjustment, as outlined by Dalén (1992). In the present application a price adjustment approach is the natural choice. This means that either the price reference period or comparison price can be adjusted, both giving the same result. The adjusted price at time t is obtained by multiplication of the observed price with an adjustment factor

$$\exp\left(\sum_k \gamma_k (X_{ki0} - X_{kit}) + \sum_k \delta_k (Y_{ki0} - Y_{kit})\right)$$

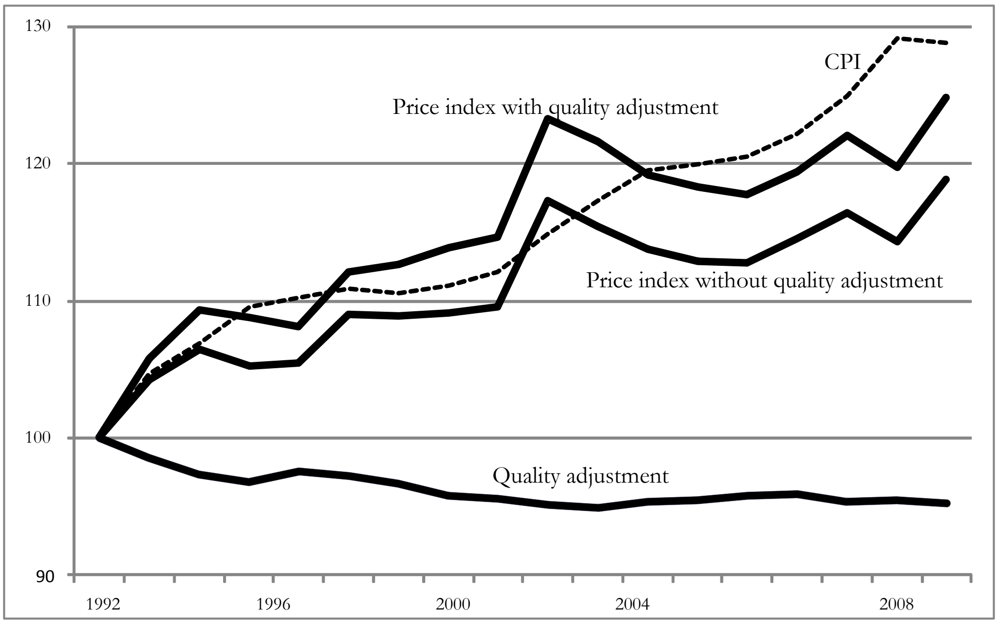
where the last subscript denotes the time period. The reason why there is no term for change of type of outlet is that replacements in the Swedish CPI always takes place within the same outlet.

Quality Adjustments for Clothing

Diagram 2 below shows the price development of clothing with and without quality adjustments for the period 1993-2001. Also, the aggregated level of quality adjustments are included together with the actual CPI for the period.

Nilsson et al. (2010) concludes that a analysis of the period 1995-2003 reveals that the estimated variance for an index with and without quality adjustments respectively, are very similar for the period studied. Indeed, this could be interpreted as if the quality adjustments made has not explained the variation in price within each product group to any greater extent. However, the quality adjustments may also adjust for any long term change in the quality of the supply; the quality has actually decreased with 0.3 percent per year in average for the period. The largest drop was between 1992 and 1999, as quality decreased by 0.6 percent. After 1999 quality remained practically unchanged.

Diagram 2.
Price development, with and without quality adjustment, 1992-2009 *(Nilsson et al., 2010).*



Data and Empirical Models

Monthly data for each product group for clothing in the CPI are used to study the effect of the alternative grouping of brands and the impact of the different independent variables. The data span a nine-year period from December 2000 to December 2009. The full sample consists of 29 250 unique observations for women's wear, 26 704 unique observations for men's wear (including sportswear) and 5944 unique observations for children's wear.

As the purpose of this paper is to compare two alternative methods of grouping the brand variable which is used in the hedonic regression model for clothing in the CPI, two empirical models will be estimated. Each model differ only in the way the independent variable containing brand name is grouped. Also, a third model is estimated that is used to evaluate the independent variables describing physical characteristics. The models are presented in the following, together with some notes regarding implications on the data used for estimation.

The models are identical regarding which independent variables describing physical characteristics that are included. Basically, the models contains all the independent variables, all dummies, that were defined in 2007. However, the data has been checked for inconsistencies regarding variable specifications and correlations between the included independent variables.

Model with Subjective Grouping of Brands

This model uses the actual grouping of the brand variable that was done in the CPI production process during the period 2001-2009. Hence, the method for grouping the brands is a mixture between the earlier described approaches, that is, using experts and staff respectively to group brands on a subjective scale ranging from one to five.

Using the semi-log form the model can be written as

$$\log(PRICE_i) = \alpha + \sum_k \beta_{1k} PGROUP_{ki} + \sum_k \beta_{2k} PHYSICAL_{ki} + \sum_k \beta_{3k} BRAND_{ki} + \sum_k \beta_{4k} OUTLET_{ki} + \beta_5 \log(CPI_i) + \beta_6 SALE_i + e_i$$

Where subscript *i* runs through all individual observations in the product groups in women's, men's (including sportswear) and children's wear respectively. Subscript *k* runs through the levels of the factors. The dependent variable $PRICE_i$ is the regular price. Furthermore, $PGROUP_{ki}$, $PHYSICAL_{ki}$, $BRAND_{ki}$ and $OUTLET_{ki}$ are dummy variables for product groups, physical characteristics, brand and outlet. CPI_i contains the individual month's index number for the price observation. $SALE_i$ indicates whether the observed price for observation *i* was actually a sales price. Lastly, an intercept α and an error term e_i is included in the model.

For *type of outlet* the following levels are recognized:

- Department stores
- Hypermarkets
- Outlets in any of four big chains
- A few exclusive shops
- One extremely cheap outlet
- Discount stores
- Outlets in other big chains
- Other outlets

For *brand* the following levels are included:

- Brand status 1
- Brand status 2
- Brand status 3
- Brand status 4

- Brand status 5

Physical characteristics are represented by a number of dummy variables for each product group. As an example, for women's dresses the following characteristics are taken account of:

- Lining, vs. no lining
- Knitted, vs. other
- At least 30 percent wool/flax, vs. other
- At least 65 percent cotton, vs. other
- Dress ha two pieces, vs. other
- Sleeveless, vs. with sleeve

Product groups ranges over the specific product groups, from Women's dresses to Men's coats. It may be noted that this model, and all subsequent, are estimated for Women's, Men's and Children's wear separately. Thus, an assumption is that the impact of the independent variables (except physical characteristics) included in the models are identical over all product groups in these three categories.

Model with Explicit Grouping of Brands

This model uses an alternative method of grouping the brand variable, in all other aspects the model is identical to that previously labeled *Model with subjective grouping of brands*. The idea is to use historical data from an independent dataset in order to estimate the market valuation of each brand. In this way, the hedonic approach is expanded to the grouping of the brand variable.

Consider the following (full) semi-log form model estimated in time *t*

$$\log(PRICE_{it}) = \alpha + \sum_k \beta_{1k} PGROUP_{kit} + \sum_k \beta_{2k} PHYSICAL_{kit} + \sum_k \beta_{3k} BRAND_{kit} + \sum_k \beta_{4k} OUTLET_{kit} + \beta_{5k} \log(CPI_{it}) + \beta_6 SALE_{it} + e_{it}$$

Where subscript *i* runs through all individual observations in the product groups in women's, men's (including sportswear) and children's wear respectively, for time *t*. Subscript *k* runs through the levels of the factors. The dependent variable $PRICE_{it}$ is the regular price. Furthermore, $PGROUP_{ki}$, $PHYSICAL_{ki}$, $BRAND_{ki}$ and $OUTLET_{ki}$ are dummy variables for product groups, physical characteristics, brand and outlet. CPI_{it} contains the individual month's index number for the price observation. $SALE_{it}$ indicates whether the observed price for observation *i* was actually a sales price. Lastly, an intercept α and an error term e_{it} is included in the model.

Also, consider another (reduced) semi-log form model estimated in time *t-1*

$$\log(PRICE_{it-1}) = \alpha + \sum_k \beta_{1k} PGROUP_{kit-1} + \sum_k \beta_{2k} PHYSICAL_{kit-1} + \\ + \beta_3 \log(CPI_{it-1}) + \beta_4 SALE_{it} + e_{it-1}$$

The grouping of the brand variable and thus the dummy variables contained in $\mathrm{BRAND}_{\mathrm{kit}}$ is a function of the residuals from the latter model estimated at time t-1.

$$BRAND_{kit} = f(e_{it-1})$$

All other variables, dependant and independent, are identical to the model previously labeled *model with subjective grouping of brands.*

Implications on Data

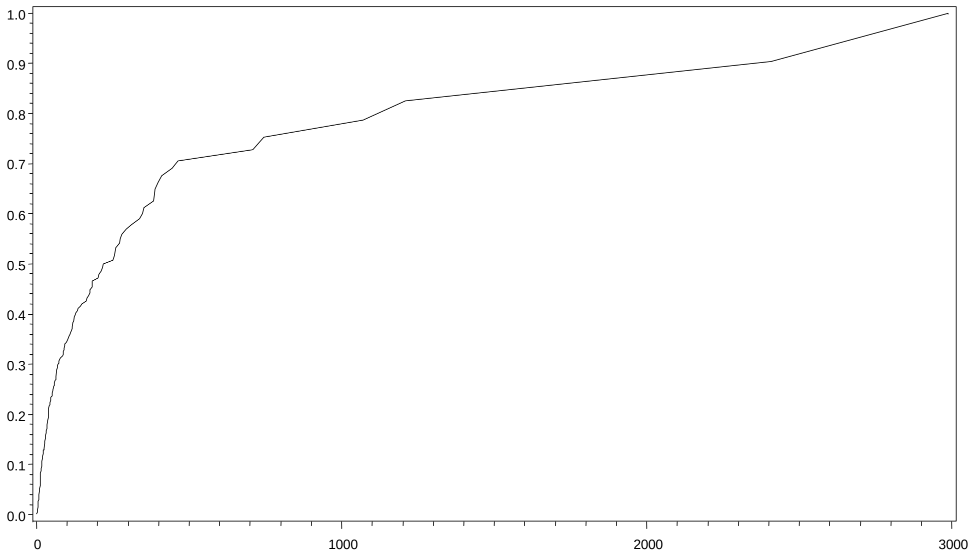
In practice, the method described above needs two datasets. One dataset is used to group the brand variable, and one dataset is used to estimate the full model. How to chose the datasets is a question of judgment and often practical limitations. In this setting, the full model is estimated for one year's data, and the reduced model is estimated on a dataset containing data for all available past years, that is *t-1, t-2…t-j* where *j* is the available number of yearly datasets and $j \geq 3$. The direct implication of this approach is that the *Model with explicit* *grouping of brands* is only possible to estimate for the year 2004 and forward, since data for the years 2001-2003 is used to group the brand variable used in the model estimated on data from 2004.

Also, this approach has the implication that brands that are introduced for the first time in the year used for estimation are omitted. In order to group a brand in time *t,* at least one observation is needed in the previous period *t-1,t-2 or t-3*. The number on observations on each brand that is desirable in order to group the brands in a coming period is a question of judgment, however with the direct price of lost observations in the data used for estimation of the full model. When estimating the *Model with explicit grouping of brands*, at least five observations is demanded in order to group a specific brand. *Diagram 3* below plots the number cumulative number of observations per unique brand to the total proportion of lost observations for 2011. The restriction to at least five observations leads to the omission of around 1 percent of the observations when using data from 2011. Further, around 7 percent of the observations are omitted from 2009 data for women's wear when new brands are omitted. Also, all unknown brands and brands labeled "brand less" are excluded from the dataset used for estimation. All to all, 17 percent of the observations for women's wear in 2009 are omitted in the dataset used for estimation of the hedonic model.

It may be noted however, that brands with very few observations can be considered outliers and may not to be included in a hedonic model that evaluates specific characteristics, even in the case of a subjectively grouping of brands where all data can be used. By the same reasoning, unknown brands may also be considered to be outliers. In the estimation of both models, identical datasets are used. That is, the restrictions on the data used for the model with explicit grouping are also considered when estimating the model with subjective grouping.

Diagram 3.

Cumulative observations per unique brand and proportion of total sample, 2011 (*women's, men's and children's wear*)



Results

Explicit vs. Subjective Grouping of Brands

Table 1.1. below presents the results from the estimation of the models presented earlier, with respect to explanatory power, for women's wear. Results for men's and children's wear are found in the appendix. The models previously presented are presented in five steps, as independent variables are included in each step. The last two columns of each table gives the results for the full models and may be used for comparisons of the different methods used for grouping of brands. Also *Table 1.2.* presents the results for 5 or 10 brand classes for the explicit method of grouping brands. The results are presented for year 2004 to 2009.

Appendix 1 presents plots of residuals from the estimations against predicted and observed value for the dependant variable, respectively. Only results for the year 2009 are presented, as these results may be regarded as representative for the whole period studied. Residuals are also plotted against different brands classes.

Table 1.1.
Regression results from different model specifications for women's wear (*coefficients of determination*)

	PRGROUP	PRGROUP OUTLET	PRGROUP OUTLET BRAND/SUBJ	PRGROUP OUTLET BRAND/10	PRGROUP OUTLET BRAND/SUBJ PHYSICAL	PRGROUP OUTLET BRAND/10 PHYSICAL
R^2_{2004} N=2367	0.55	0.77	0.80	0.88	0.83	0.90
R^2_{2005} N=2348	0.52	0.75	0.85	0.87	0.88	0.90
R^2_{2006} N=2265	0.58	0.76	0.86	0.89	0.89	0.91
R^2_{2007} N=2955	0.56	0.77	0.88	0.89	0.90	0.91
R^2_{2008} N=2987	0.59	0.77	0.87	0.88	0.89	0.89
R^2_{2009} N=2702	0.58	0.78	0.88	0.89	0.89	0.91

Note: log(CPI) and an indicator for sales are included in each model specification, together with an intercept. Adjusted R^2 values are used. Dependant variable is regular price, on a logarithmic scale. BRAND/10 indicates that 10 brand classes have been used for the explicit grouping of brands. BRAND/SUBJ refers to subjective grouping of brands.

Table 1.2.
Regression results from different model specifications for women's wear (*coefficients of determination*)

	PRGROUP OUTLET BRAND/SUBJ PHYSICAL	PRGROUP OUTLET BRAND/5 PHYSICAL	PRGROUP OUTLET BRAND/10 PHYSICAL
R^2_{2004} N=2367	0.83	0.88	0.90
R^2_{2005} N=2348	0.88	0.89	0.90
R^2_{2006} N=2265	0.89	0.91	0.91
R^2_{2007} N=2955	0.90	0.90	0.91
R^2_{2008} N=2987	0.89	0.89	0.89
R^2_{2009} N=2702	0.89	0.90	0.91

Note: log(CPI) and an indicator for sales are included in each model specification, together with an intercept. Adjusted R^2 values are used. Dependant variable is regular price, on a logarithmic scale. BRAND/5 and BRAND/10 indicates if 5 or 10 brand classes have been used.

Some general results may be noticed. *First*, and not surprising, the explanatory power of the models tend to increase as more independent variables are included. The "baseline" model of with only product group and type of outlet explains a major part of the variation in the data. As the brand variable is included the explanatory power rises with around 10 percentage points on the marginal. The inclusion of the independent variables for physical characteristics tends, on the marginal, only to explain a small amount of the price variation in the data, with around 1-2 extra percentage points of variation explained. Alternatively, the physical characteristics explain around 15 percent of the remaining variation in the data. *Second*, the brand variable grouped with the explicit method tends consistently to do a better job in explaining the price variation, compared to the brand variable with subjective grouping of brands. However, the difference is relatively small and becomes even smaller as less groups are used, as seen in *Table 1.2*. *Third*, the model for children's wear suffers from poorer fit compared to the models for women's and men's wear, as seen in the Appendix.

Table 2.1.
Parameter estimates for women's wear using subjective grouping of brands.

	2004	2005	2006	2007	2008	2009
Brand status 1	0.43*	0.23*	0.73*	0.47*	0.42*	0.52*
Brand status 2	0.99	0.66*	0.66*	0.59*	0.61*	0.55*
Brand status 4	1.52*	1.63*	1.61*	1.53*	1.60*	1.53*
Brand status 5	2.84*	2.10*	1.93*	1.95*	2.04*	2.16*

Note: * indicates statistical significance at the 0.05 level. Exponentiated values of parameter estimates. Dependant variable is regular price, on a logarithmic scale. Brand status 3 is reference.

Table 2.2.
Parameter estimates for women's wear using explicit grouping of brands, 5 groups.

	2004	2005	2006	2007	2008	2009
Brand class 1	0.71*	0.93	1.38*	0.85*	0.83*	0.86*
Brand class 3	1.07*	1.16*	1.25*	1.25*	1.28*	1.47*
Brand class 4	1.64*	1.83*	1.79*	1.88*	1.80*	1.76*
Brand class 5	2.65*	2.79*	2.86*	2.92*	3.00*	3.39*

Note: * indicates statistical significance at the 0.05 level. Exponentiated values of parameter estimates. Dependant variable is regular price, on a logarithmic scale. Brand class 2 is reference.

Table 2.3.
Parameter estimates for women's wear using explicit grouping of brands, 10 groups.

	2004	2005	2006	2007	2008	2009
Brand class 1	-	-	-	0.76*	0.93	-
Brand class 2	0.76*	0.91*	1.07*	-	0.88	0.44*
Brand class 3	0.80*	0.81	0.89	0.84*	0.84*	0.87*
Brand class 5	1.00	1.02	1.09*	1.12*	1.19*	1.20*
Brand class 6	1.26*	1.31*	1.43*	1.52*	1.44*	1.67*
Brand class 7	1.46*	1.73*	1.75*	1.84*	1.88*	1.74*
Brand class 8	1.94*	2.04*	2.32*	2.34*	1.93*	2.27*
Brand class 9	2.60*	2.58*	2.80*	2.83*	2.86*	3.16*
Brand class 10	3.24*	3.10*	3.22*	3.43*	3.35*	3.90*

Note: * indicates statistical significance at the 0.05 level. Exponentiated values of parameter estimates.

Dependant variable is regular price, on a logarithmic scale. Brand class 4 is reference.

The parameter estimates for the brand classes are presented in *Table 2.1-2.3* above. These parameter estimates may be interpreted as adjustment factors. E.g., for 2009, the regular price of a women's product of brand status 5 (grouped on a subjective scale) is on average 2.2 times higher than that of a comparable product of brand class 3. The parameter estimates are fairly stable over time. ranging from around 0.5 for the lowest brand class to around 2 for the highest brand class for subjectively grouped brands. The corresponding range for explicitly grouped brands are around 0.8 for the lowest brand class to around 3 for the highest one.

Also, some general results from the residual plots in the appendix may be commented. First, the residuals are fairly symmetrical distributed around the zero level for the predicted value for each model. However, there is some indication of a linear pattern in the residuals against the observed value, especially for children's wear. This suggests that the model lack some predicative power for cheap and expensive products respectively. This result is regardless of method used for grouping of brands. Second, the dispersion of the residuals does not vary very much between different levels for the horizontal axis, suggesting homoskedasticity. This result also holds when residuals are plotted against brand class, or status, regardless of brand grouping method.

Conclusion

The aim of this paper has been to evaluate empirically the hedonic models that are used for quality adjustment for clothing in the Swedish CPI. More specifically, the purpose has been to reduce the number of locally collected characteristics for clothing by identifying irrelevant variables.

Also, in order to reduce the risk of bias when assigning status codes to new brands and ensuring a efficient use of collected data, an alternative approach towards grouping the independent variable for brands is tested. This alternative approach uses historical data in order to group the brand variable, in contrast to the presently used method which is based completely on subjective judgment of quality of brands.

By using data from the CPI for the period 2001-2009 a number of models are estimated empirically. This section discusses and concludes the results.

The discussion below is restricted to grouping of the brand variable.

Brands

The results from this paper show that brands for clothing are the single most important characteristic besides type of outlet when trying to explain the variation in regular price for clothing. In relation to the physical characteristics the impact of brands are big; while all the physical characteristics collected explain around 1-2 percentage points on the marginal of the yearly variation in the price data, the brands explains around 10 percentage points. Indeed, a simple model that only contains product group, type of outlet and brand does a fairly good job in explaining the price variation. This raises the question of whether the resources invested in the collection of physical characteristics is really worth it; by reducing the collection of characteristics to only consist of brands, resources could be redirected into enlarging the sample size for clothing. However, there is a risk that the general quality of these physical characteristics for clothing in the sample changes over time. By omitting these variables we induce bias in the index calculation by not controlling for these systematic changes in quality. This risk could be reduced by making the definitions of each product more tight, thereby not allowing variation in relevant physical characteristics of the products. The results from this paper can be used to identify some of these relevant characteristics. Also, the increased number of missing or unfeasible replacements can be compensated by increasing the sample size.

When assessing different approaches towards grouping the brand variable it is important to separate two sources of possible error. A random error can be expected when brands are grouped wrongly at random; sometimes a high-quality brand is grouped as of lower quality, and sometimes a low-quality brand is grouped as of higher quality. Different approaches towards grouping the brands may cause such errors to different extent. However, one would expect such errors by definition to be made at random and not show any particular pattern. Systematic errors on the other hand are errors that reputedly follow a certain pattern. For example, in the case of the subjective approach towards grouping brands there is a risk of a potential systematic error when new brands are introduced in the sample; under incomplete information regarding the quality of a specific brand the observed price may be used as the main indicator of quality. In this way there is a systematic error each time a new brand is introduced in the sample, as a price index that is adjusted for quality is "pushed" towards showing no price change.

The explicit approach towards grouping the brand significantly increases the explanatory power of the models. Also, it should reduce the potential risk of systematic "failures" when grouping the brands on a subjective scale. Especially, it is a desirable feature that this alternative method avoids the use of the current price observation when assigning a status group to the new brand. Unfortunately, this alternative approach puts some restrictions on the data; new brands and brands with few observations are omitted from the data. When evaluating the models historically, as is the case here, this is not a problem. Indeed, there is good reason to treat unusual brands as outliers when estimating the hedonic models. Also, the number of omitted observations are small. However, if this approach was to be implemented in the production of the CPI new problems would arise. The most apparent is how to treat unknown or new brands that appear in the monthly data collection and in the base sampling.

When using the present approach this is trivial as a new brand is given a status class subjectively by the staff, and any difference in quality is then adjusted for by the hedonic model. When using the explicit approach of grouping brands this becomes more problematic; no prior information exists that can be used the assign that specific brand with a brand status. When discussing this problem a range of treatments or solutions have been outlined:

i. The new brand is given the same status as the brand that is being replaced. The observation is included in the index calculation.
ii. The new brand is given a status group based on type of outlet. The observation is included in the index calculation.
iii. All new brands are assigned an own status group until data exists that could be used to group the brand explicitly. The observation is included in the index calculation.
iv. The brand is assigned a group subjectively until data exists that could be used to group the brand explicitly. The observation is included in the index calculation.
v. The observation with the new brand is excluded from the index calculation until data exists that could be used to group that specific brand.
vi. Replacements between product of different brands, or possible different known brand groups, are not to be allowed at all. Brands are held constant in the sample.
vii. Replacements between unknown brands, alternatively a replacement to/from a unknown brand from/to a known brand, are not to be allowed. Replacements between known brands are adjusted for quality differences.

To begin with, the **first two** solutions can be disregarded on the reason that multiple possible brand classes may exist for the same brand. Also, these treatments does not provide a solution in the case of new brands emerging in the base sample. The **third** possible solution may induce a risk of bias as all brands, high and low quality, are assigned to the same status group. In this way, the impact of that status group may be regarded as an average of all new brands. If replacements occur in outlets that are not average, e.g. exclusive boutiques, quality adjustments may be artificially regarded as occurring between average brands and high end brands, when in reality the brand statuses are unchanged. The **fourth** proposed solution solves a potential problem of randomly miss grouped brands and may thus reduce variance. However, it leaves the risk of bias from using the subjective grouping of new brands unchanged, as the method is still used for new unknown brands. The **last three** solutions solves the problem of potential bias from grouping new brands subjectively. However, if using the **fifth** solution, another risk is induced, namely the risk of bias from excluding new brands which may differ systematically from established ones. Also, observations are lost. The **sixth and seventh** proposed solutions eliminate the risk of bias from grouping new brands, as no replacements to new unknown brands are allowed. But unlike the fifth solution, unknown brands may be included in the base sampling, hereby avoiding the risk of bias from excluding unknown or new brands. These solutions have the drawback that it narrows the range of the possible sample by reducing the flexibility of replacements. However, as mentioned earlier in this paper, these replacements between different segments of brands are relatively rare. In a way, these solutions recognize the critical importance of the brand variable as a determinant of comparability. In the case of the **sixth** solution, the flexibility may be increased by allowing replacements between defined segments of brands. The method proposed in this paper could be used to define these "approved" segments. The **seventh** solution further increases the flexibility by only restricting those replacements that are made between unknown brands. Replacements between known brands are adjusted for quality differences, as usual. Replacements between unknown brands, or to/from unknown brands from/to known brands, are not allowed at all. As data becomes available, these unknown brands become known.

When trying to choose between these potential solutions one should bear in mind that the main advantage from using the explicit method comes from reducing the risk of systematic error (bias) from using the subjective method. From the results it is clear that the explicit approach of grouping brands also contributes towards explaining more of the price variation in the data; this may be interpreted as less random error. Therefore, the explicit approach is used when evaluating the models historically. The results also hint that the main difference in explanatory power between the approaches comes from allowing more groups, in this case 10, when using the explicit method; when the groups are reduced to 5 the explanatory power is reduced and becomes more comparable to that of the subjective method. From the residual plots there is no indication of systematic differences between the approaches and any patterns in the residuals are common to both approaches. Indeed, it turn out that the subjective method of grouping brands does fairly well in relation to the explicit in terms of explanatory power. In the yearly review of the hedonic quality adjustment method in the CPI the full range of brands and status codes are revised with respect to obvious misspecifications of brands. The purpose is to identify divergent brands; there is always the possibility of brands increasing their status on the market over time and thus the pricing strategies used. By doing this, the random error is reduced. However, the risk of systematic error in the quality adjusted price index is unchanged. It should be empathized that the potential risk of bias from grouping the brand variable subjectively is indeed an *potential* risk. In order to assess the implication of this risk, some sort of implicit quality index with alternative methods of grouping the brand variable should be calculated on historical data.

Lastly, there are several approaches towards grouping the brand variable that avoids this risk of bias. The previous method of grouping the brands by utilization of a fashion magazine is an example of a subjective method that avoids the risk of bias by making the assessment of brand quality independent of observed price. Further, by grouping the brands on a well defined objective scale the problem is also avoided. The approach taken by the BLS is an example, as brands are grouped on a scale ranging from “store brand” to “exclusive brand”.

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Appendix

Diagram 4.1.

Residual vs. Predicted value for women's wear *(explicit grouping of brands into 10 groups, 2009)*

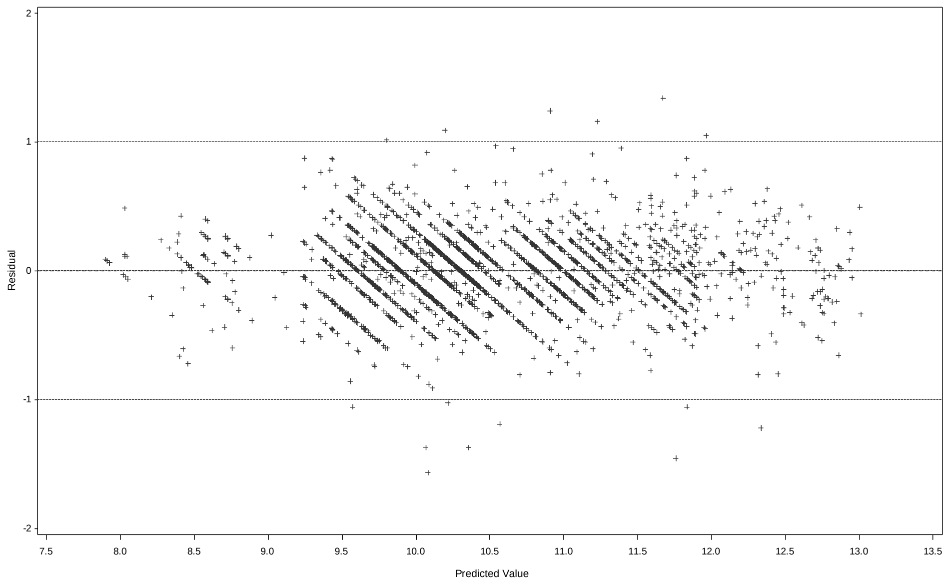


Diagram 5.1.

Residual vs. Observed value for women's wear *(explicit grouping of brands into 10 groups, 2009)*

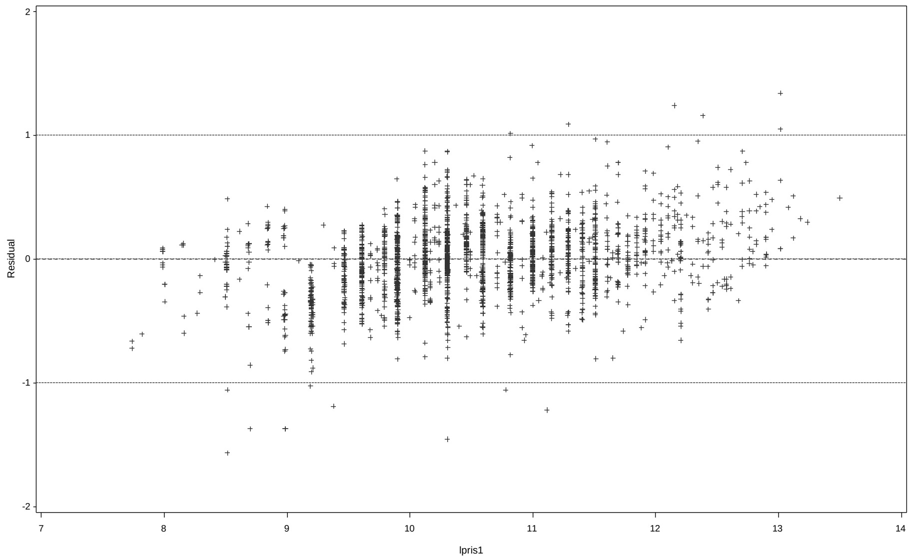


Diagram 6.1.

Residual vs. Predicted value for women's wear *(subjective grouping of brands into 5 groups, 2009)*

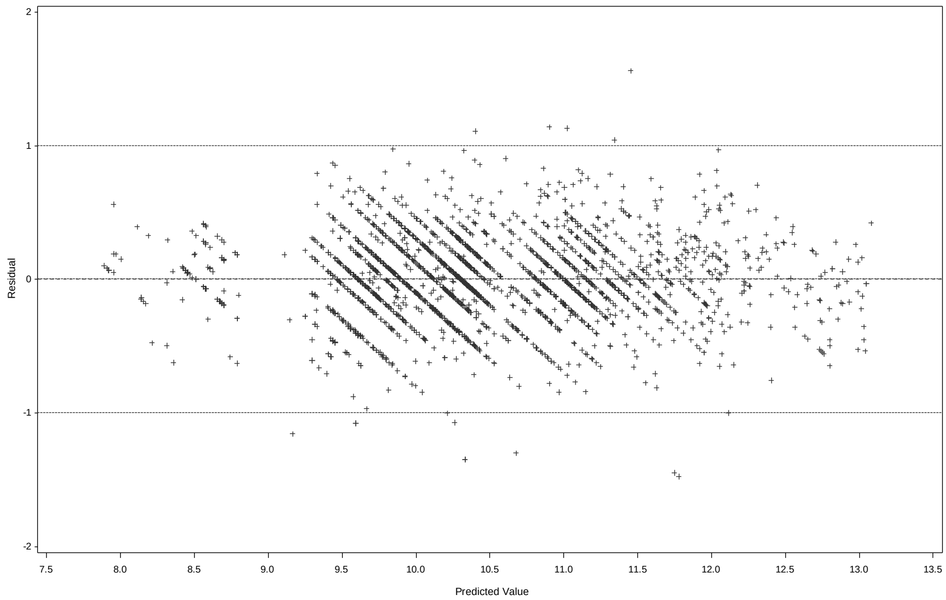
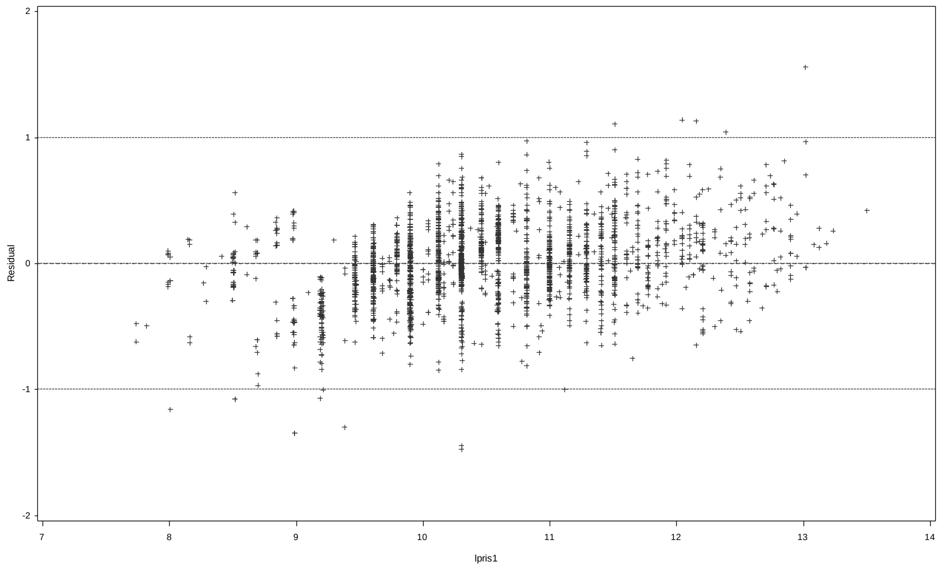


Diagram 7.1.

Residual vs. Observed value for women's wear *(subjective grouping of brands into 5 groups, 2009)*



Residual vs. Brand class for women's wear *(subjective grouping of brands into 5 groups, 2009)*

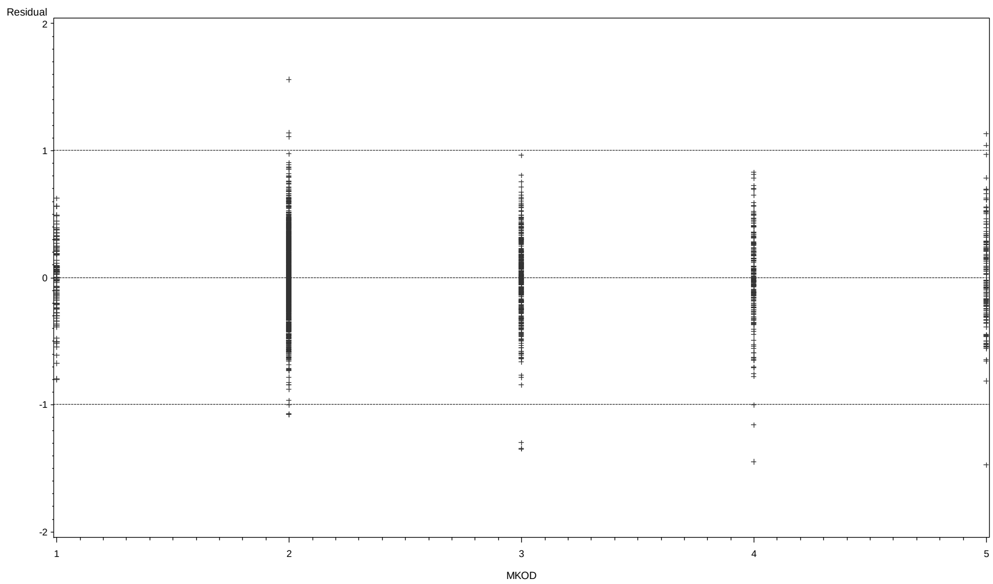
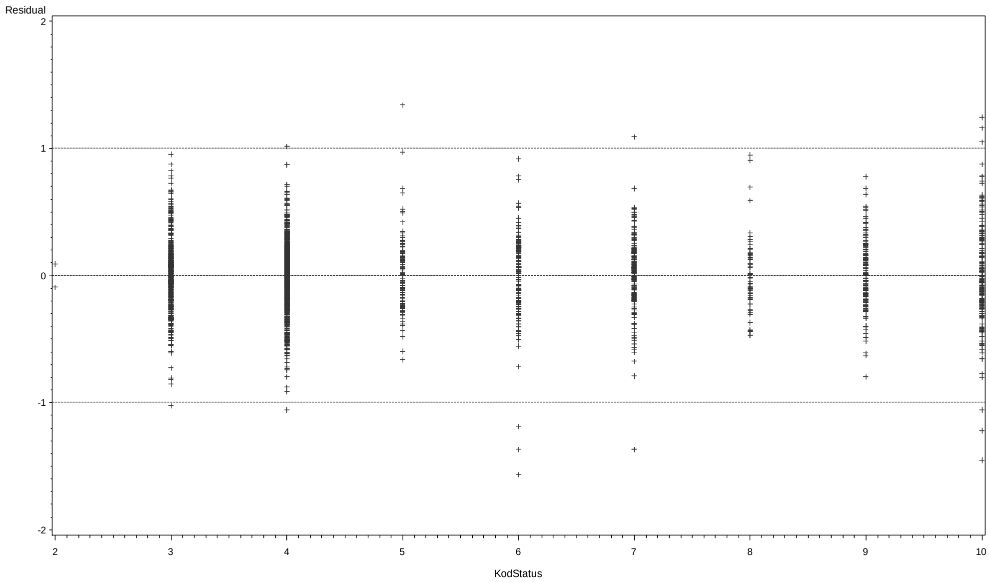


Diagram 10.1.

Residual vs. Brand class for women's wear *(explicit grouping of brands into 10 groups, 2009)*


Residual
2
1
0
-1
-2
2
3
4
5
6
7
8
9
10
KodStatus