Price and Quality Segmentation of Multiproduct Firms: Some Empirical Evidence

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Abstract

Existing theory on vertical quality differentiation provides a mixed result as to the choice of market segmentation strategies of multiproduct firms. There are studies showing that firms have incentives to differentiate their products from those of its competitors, as well as studies suggesting that multiproduct firms compete "head-to-head" by making similar product choices. This empirical study uses product-test data published in consumer reports, in analyzing quality segmentation and competetion among brands. Using the same data, we investigate price-quality correlations (Spearman's rho), both on an aggregated level (across brands), and within brands of specific product tests. Under regular assumptions on existing firms' strategies to discourage new entrants, we use latent modelling to also comprise single-product brands. Our results indicate that firms, as a response to increased competition, tend to narrow their product lines, in terms of a decreasing quality variation across products. Average correlation is modest, both across and within brands, but strengthened by product test size (except for durables across brands).

Keywords: Product differentiation, product quality, price-quality correlation, multiproduct firms, market segmentation, multiple imputation.

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1 Introduction

When searching for a consumption good in a specific market, the consumer in general faces a line of alternative products, produced at different quality levels and offered at different prices. In some markets, each firm only produces a single type of product, where the quality level of the products differs across firms. However, in many markets the same firm provides a line of quality-differentiated products. In fact, it is an optimal strategy for a firm to offer a range of qualities under pure competition as well as under a monopoly/oligopoly situation (Mussa and Rosen (1978), Champsaur and Rochet (1989)). Particularly in the market for electronics and white goods, an individual firm may offer a dozen of alternatives of the same type of product, at various combinations of price and quality. Also, the increased ecological consciousness of the consumers, has led many firms in the food industry to start producing ecological alternatives, besides their regular product assortment. A strategic choice the multiproduct firm faces when deciding to produce a line of products is whether its products shall be of higher or lower quality than those of the competitors or if the products should compete head-to-head, that is, match the competitors' products.

The market segmentation strategy of multiproduct firms is a topic that is relatively well analyzed in the literature. Most of the studies are theoretical contributions, exploring how firms adjust their product lines in response to competition. (See Doraszelski and Draganska, (2006) for a shorter review of previous studies.) Depending on how competition among multiproduct firms is modeled, and what assumptions are made about the firms' costs of producing multiple products, theoretical support can be found for the emergence of both a segmented market and a non-segmented market. There exists also a significant number of empirical studies which use data from consumer reports to estimate the relationship between price and quality in various types of product tests (e.g the Spearman's rank-order correlation), but there is to our knowledge no study yet analyzing the intra-brand price-quality correlation for multiproduct brands, nor testing the market segmentation of multiproduct brands, using the same data source. Our paper is an attempt to bring forth some empirical evidence on these issues.

In this paper we analyze data collected from 132 product tests, reported in the Swedish consumer magazine Råd & Rön. The main purpose with our study is to test whether the multiproduct firm tends to narrow or to expand its differentiation of quality levels the more competition it faces from other firms. In line with previous empirical studies on the observed relationship between price and quality, we also in our study provide estimates of the Spearman's (and Kendall's tau) rank order correlation across products and brands. We also extend the price-quality analysis to fit the expected quality differentiation of individual brands in a given product test. By arguing that single-product brands are potential multiproduct brands whose additional unobserved characteristics can be modeled latently, our analysis encompass the whole market, as represented by the product test, by including all brands therein.

Our analysis of the data shows that the standard deviation of the quality scores, assigned to the commodities belonging to the same brand within a product test, decreases as the number of competing brands increases, which is consistent with a segmented pattern of quality differentiation. The outcome of the tests of the rank order correlation coefficients, corresponds to the findings in several previous studies. Price is a not a perfect indicator of quality, albeit better for durable goods than non-durable goods. Also, even within a brand's own product line, we observe a relative low correlation between price and quality. The size of product tests is associated with higher correlation, both when regressed on across tests and within brands correlations, except for durables across brands - whose correlations also are slightly higher.

We first provide a brief review of the background literature on the relationship between price and quality and on the market segmentation of multiproduct firms. This is followed in Section three by a description of the data and an analysis of the correlation between price and quality across product tests. In Section four, we estimate the price-quality rank order correlation coefficients for those commodities offered by the same brand within a product test. In order to make use of the information provided by the significant number of single product brands in the data set, we also in Section four present a method to impute missing data. Section five contains the analysis of market segmentation and Section six concludes.

2 Related literature

The economic literature on vertical product differentiation and market segmentation of multiproduct firms is relatively large. One branch of the literature examines the relationship between price and quality. The question raised in these studies, both theoretical and empirical contributions, is whether high prices signal high quality or not. Theoretical guidance, e.g. Wolinsky (1983), Milgrom and Roberts (1986), Bagwell and Riordan (1991), indicate that high prices signal high quality. The result is driven by the availability of information among consumers about product quality. Low-quality firms will lose sales volume from informed consumers by charging a high price. The more information about firms' quality diffuses, the more costly it will be for a firm to falsely signal a high quality.

There is also a row of empirical studies examining the relationship between price and quality. The data in these studies is in many cases collected from product tests of consumptions goods, published by various consumer magazines. (See for example Steenkamp (1988) for a review of previous studies, or Kirchler et. al (2010) for a more recent study of the Austrian market). The general finding is that price is a poor signal of quality. The average correlation between price and quality across groups of products - frequently computed as the Spearman's rho - is often found to be between 0.2-0.3. The percentage of significant (positive) correlation coefficients is around 20%-30%. A number of studies, examining the relationship between price and quality ratings of wine, apply hedonic price models to identify partial correlations between price and different quality attributes. Oczkowski and Doucouliagos (2015) adopt a meta-regression analysis, using data from 43 published studies, where the relation between price and wine sensory rating has been estimated. They find that the partial correlation between wine prices and sensory quality ratings is about 0.3, where quality ratings seem to be far less important than wine reputation.

Another branch of the literature on product differentiation explores the behavior of multiproduct firms. In a model with two firms, where each firm first decides on the interval of quality before choosing price, Champsaur and Rochet (1989) derive a Nash equilibrium where firms offer non-overlapping quality lines in order to reduce price competition. Klemperer (1992) put forth a model where firms have an incentive not to differentiate their products from their opponents, but instead choose very similar product lines. Gilbert and

Matutes (1993) explore the firm's incentives for choosing different product lines in a model with both vertical and horizontal differentiation, that is, consumers have idiosyncratic preferences for brands. Depending on the assumption about the extent of brand-specific differentiation and the commitment of firms to exclude products from their production, their model produces different outcomes concerning product specialization and product proliferation. Johnson and Myatt (2003) analyze an entry game, where a single multiproduct firm enters a market which is originally dominated by a monopolist. How the incumbent firm decides to respond upon the entry in terms of changing its line of products, depends on the shape of marginal revenue in the market. If the marginal revenue is decreasing, and the entrant offers a low quality product, then the incumbent firm has an incentive to reduce its output in the low-quality segment and even refrain from producing low-quality products.

Doraszelski and Draganska (2006) identify three additional determinants of market segmentation beside the cost structure of offering additional products: i) the degree of fit; ii) the degree of misfit; (iii) the intensity of competition. Their point of departure is an environment where firms either offer a general purpose or tailor their products to consumers' needs. From the consumer's perspective, the up side of market segmentation is when the firm offers a product that exactly fits her needs (segmentation fit). Consequently, the down side of market segmentation is when the consumer's preferred product is not offered. She would then buy a general purpose product, rather than a product that is targeted at another segment. This is denoted as misfit. Given that consumers have idiosyncratic preferences, the authors provide various conditions and equilibria under which firms either refrain from market segmentation or engage in segmentation.

Modelling the competition of multiproduct firm as a two stage Cournot game, where firms simultaneously choose the number of products and their qualities at the first stage and then compete in quantities at the second stage, Cheng and Peng (2012) find an equilibrium where firms engage in non-segmentation. The explanation is that firms try to avoid a cannibalization effect, that is, a potential competition among the products provided by the same firm. In a subsequent paper, Cheng and Peng (2014) suggest a two stage duopoly model, in which firms simultaneously in a first stage choose the number of products and their associated qualities, and then, in a second stage, compete in prices. The equilibrium outcome of their model is that the firm chooses a segmentation strategy, that is, differentiating the products from those of its competitors in order to avoid keen price competition. In an empirical study, Dunn (2008) examines the behavior of multiproduct firms in airline markets. The study finds evidence for non-segmentation, that is, airlines are more likely to enter the market with products of higher quality (nonstop service) if their existing products in the market is of lower quality (one-stop service).

Related to our study is also the literature on entry deterrence strategies in a vertically differentiated product market. The general wisdom is that a monopolist can optimally use product proliferation to deter entry (Schmalensee (1978)). However, in a model where the incumbent firm's marginal cost to improve quality is assumed to be increasing, Noh and Moschini (2006) show that it is the incumbent's optimal strategy to accommodate entry if the entrant's fixed cost is sufficiently low. If the entrant's cost is moderate, then the incumbent firm deters entry by increasing product quality before the entrant enters the market. In the case when the market consists of several established firms, the rivalry among the incumbent firms, taking the form of less differentiated products, effectively serves as a device to prevent entry from new firms (Donnenfeld and Weber (1995)).

The contribution of our empirical paper to the existing literature is twofold. Using data from products tests provided in consumer reports, we examine the patterns of quality differentiation of multiproduct firms. We also investigate to what extent price signals quality for brands represented by multiple commodities in the same product test.

3 The relationship between price and quality - aggregated level

The data analyzed consists of 132 product tests, comprising 2,957 commodities from 667 brands. The tests were published in the Swedish consumer magazine Råd & Rön in spring 2015 and involved products from various categories, e.g. electronics, tools, white goods, food, clothes and cosmetics. The tests have been carried out within the cooperation of ICRT (International Consumer Research and Testing), a global consortium, gathering about 35 consumer organizations. The ICRT provides test programmes, evaluation methods and runs thousands of product tests each year. Besides commodity name, for each commodity (indexed by h) we have information about the test (j), brand (i), price in SEK 100 ($PRICE_h$) and assessed quality score ($QUALITY_h$). On test level we compute the number of commodities ($GOODS_j$) and brands ($BRANDS_j$), mean, standard deviation and coefficient of variation in price ($\overline{PRICE}_j$, $\hat{\sigma}(PRICE)_j$, $\hat{cv}(PRICE)_j$) and quality ($\overline{QUALITY}_j$, $\hat{\sigma}(QUALITY)_j$, $\hat{cv}(QUALITY)_j$), and Spearman's rho ($\hat{\rho}_j$) and Kendall's tau-b ($\hat{\tau}_j$) correlation between price and quality. We have defined 86 product tests as being tests of durables[1], and 46 tests concern consumables.

The variation in the collected variables is relatively large. Figures for goods, price and correlations are lower among consumables compared to durables, see Table 1 (and the aggregated Table A1 in Appendix). The number of commodities in each product test ranges from a handful to 147. Also, $GOODS_j$, and $\overline{PRICE}_j$ and $\hat{\sigma}(PRICE)_j$ are strongly right skewed albeit not as accentuated in $\hat{cv}(PRICE)_j$. In 106 of the 132 product tests, there is at least one multiproduct brand present, producing at least two of the goods tested. The results on correlation coefficients are in line with previous findings in the literature, that is, price is a poor signal to infer quality from.[2]

3.1 Regression on price-quality correlation

In order to examine variables that possibly affect the strength of the price-quality correlation, we regress the other variables listed in table 1 on the correlation coefficient. Since the variables are non-negative and mainly right skewed (except $\overline{QUALITY}_j$), we allow for square-root transformations to avoid skewed regression residuals and allow for nonlinear (quadratic) relationships. We also use a durables indicator variable CD to address potential difference between consumables (coded as 0) and durables (1) and allow for interaction with the other variables. The regression model on $SPEARMAN'S\ \hat{\rho}_j$ is summarized in equation (1) where matrix $\mathbf{Z}$ includes the explanatory variables.

[1]About 80% of the total of number of goods tested are defined as durables.

[2]Our estimates of the median values are very similar to those obtained in Steenkamp (1988). The median values of the Spearman's ρ and the Kendall's τ in his study, based on 413 product tests in the Netherlands 1977-1986, were 0.32 and 0.25, respectively.

Table 1: Summary statistics from 132 product tests, consumables and durables

	Consumables (46 obs)					Durables (86 obs)				
	mean	std	min	md	max	mean	std	min	md	max
$GOODS_j$	13.1	3.07	7	12	20	27.4	27.5	6	15	147
$BRANDS_j$	10.4	3.03	3	10	16	10.4	4.59	2	9.5	24
$\overline{PRICE}_j$	2.54	3.28	0.01	0.91	12.5	27.7	25.6	1.05	16.5	108.9
$\overline{QUALITY}_j$	57.2	9.73	21.9	58.2	69.5	61.8	7.54	42.0	62.1	77.5
$\hat{\sigma}(PRICE)_j$	0.82	1.09	.003	0.38	4.66	12.4	12.2	0.61	9.09	79.6
$\hat{\sigma}(QUALITY)_j$	11.8	5.22	3.94	10.3	22.7	10.7	5.35	2.96	9.38	27.0
$\hat{cv}(PRICE)_j$	0.40	0.26	0.09	0.32	1.22	0.52	0.21	0.13	0.53	1.17
$\hat{cv}(QUALITY)_j$	0.21	0.09	0.06	0.20	0.45	0.18	0.11	0.04	0.15	0.50
$^*SPEARMAN'S\ \hat{\rho}_j$	0.15	0.44	-0.75	0.22	0.93	0.35	0.29	-0.42	0.38	0.84
$^{**}KENDALL'S\ \hat{\tau}_j$	0.11	0.34	-0.58	0.14	0.81	0.27	0.22	-0.37	0.27	0.70

* 24% consumbles and 48% durables significant in approx. t-tests, H_0: $\rho_j \leq 0$.

** 28% consumbles and 48% durables significant in approx. z-tests, H_0: $\tau_j \leq 0$.

$$\hat{\rho}_j \sim N(\alpha_0 + \mathbf{Z}_j\boldsymbol{\alpha}, \sigma^2_{\hat{\rho}}) \tag{1}$$

The more commodities available to consumers, as measured by $\sqrt{GOODS}_j$, the stronger we expect the relationship to be. We also consider the number of brands ($\sqrt{BRANDS}_j$) included in the same product test. Assuming that the firm incurs a higher cost when producing an alternative good of superior quality of the same brand, the price-quality rank correlation would strengthen as more brands enter the product test. The variable $\sqrt{\overline{PRICE}}_j$ captures the average price level in each product test. It is expected that the rank correlation is stronger when the cost for the products is higher. The variables $\sqrt{\hat{\sigma}(PRICE)}_j$ ($\sqrt{\hat{\sigma}(QUALITY)}_j$) and $\sqrt{\hat{cv}(PRICE)}_j$ ($\sqrt{\hat{cv}(QUALITY)}_j$) are standard deviation and coefficients of variation of prices and assessed qualities in a product test. The larger the dispersion of prices and quality, the stronger the price-quality relationship will be. Finally, a durable product is expected to provide the consumer quality over a longer period of time, inducing the consumer to collect more information about products and prices. Hence, durables strengthen the price-quality relationship.

In table 2, we provide the regressions results. [3] The univariate regressions summarizes the linear relationship between Spearman's rho and each of the explanatory variables separately, while the full model contain all the linear effects. We also present a refined model which better fits the data, excluding insignificant effects, and accounting for an observed quadratic relationship between Spearman's rho and $\sqrt{\hat{cv}(PRICE)}_j$, where the vertex is reached at predicted rho of roughly 0.5 when $\sqrt{\hat{cv}(PRICE)}_j$ is about 0.75.

Table 2: Summary of linear regression on SPEARMAN'S $\hat{\rho}_j$

	Univariate		Full model		Refined model	
	$\hat{\alpha}$	$t_{\hat{\alpha}}$	$\hat{\alpha}$	$t_{\hat{\alpha}}$	$\hat{\alpha}$	$t_{\hat{\alpha}}$
$Intercept$	0.284	9.110	-1.271	-2.380	-2.095	-3.429
$\sqrt{BRANDS_j}$	-0.018	-0.366	-0.063	-1.176		
$\sqrt{GOODS_j}$	0.041	2.457	0.386	3.068	0.377	3.091
CD_j	0.203	3.209	1.413	3.068	1.431	3.184
$CD_j\sqrt{GOODS_j}$	-0.010	-0.344	-0.363	-2.846	-0.365	-2.932
$\sqrt{\overline{PRICE}_j}$	0.028	2.350	0.009	0.535		
$\sqrt{\hat{\sigma}(QUALITY)}_j$	-0.004	-0.095	0.011	0.267		
$\sqrt{\hat{cv}(PRICE)}_j$	0.335	1.857	0.317	1.482	2.563	2.283
$\hat{cv}(PRICE)_j$	0.187	1.428			-1.636	-2.057
R^2_{adj} Pred. error			0.113	0.121	0.141	0.116
AIC BIC			97.5	123.1	91.0	111.2

The assumed relationships are mainly confirmed in the final model. The effect of the number of commodities ($\sqrt{GOODS_j}$) is positive if the commodities are consumables (0.386), though much weaker (0.012) for durables, which are already at a higher level. Our estimated positive effect of durables upon the price-quality rank correlation is found in most studies (see for example Kirchler et al (2010) for a shorter survey). However, though significant univariately, in contrast to other studies, our full model does not include a significant coefficient for the variable price level ($\sqrt{\overline{PRICE}_j}$), that is, expensive product categories do not strengthen the price-quality rank correlation. Also, both $\sqrt{BRANDS_j}$ and

[3] No substantial differencies are found if Kendall's $\hat{\tau}_j$ is used as dependent variable.

$\sqrt{\hat{\sigma}(QUALITY)}_j$ are weakly associated with rho. The refined model fits better, both by excluding the three weak effects, and by including $\hat{cv}(PRICE)_j$ to allow for the quadratic relationship.

4 The relationship between price and quality - brand level within test

In this section we consider the question to what extent product prices signal quality within a brand. If the firm's cost varies with quality, a priori we would in a product test expect a much stronger price-quality rank correlation for commodities within the same brand than for commodities across brands. To account for the the hierarchical structure, with brands nested within product tests, in section 4.1 we examine the price-quality variation on brand level within test by use of a multilevel regression model (Gelman & Hill, 2007).

In 109 of the 132 product tests, at least one brand have a set of products included in the same test.[4] For example, in the product test of blue-ray players, Panasonic is represented by eight products. It is common today that firms own multiple competing brands in many areas, that is, similar products are offered under different brands. Sometimes a firm's brands are marketed as representing different qualities (e.g. Audi and Skoda in the Volkswagen group), and sometimes the products within two competing brands are regarded as more or less substitutes (e.g Adidas and Reebok in the Adidas group). In order not to run into queries about companies owning various brands, we focus entirely on brands when examining the price-quality relationship and segmentation.

A number of brands have multiple products included in several tests.[5] To exemplify, Bosch is represented by multiple products, ranging from 2 to 11 products, in 20 different tests. Across the product tests we observe 467 brands, having at least two (and on average 4.39) of their products included in the same test. However, as illustrated in table A3 in Appendix, the distribution of the number of products in a test from the same brand is much skewed, with 218 cases of only two (and a median of three) products, ranging up to

[4]In 11 of the product tests there are no single-product brands at all.

[5]In total, 254 of the 667 unique brands have multiple products included in a product test.

48 products.

As was seen in table 1, the variation in both quality and price between product tests is large, where $\hat{cv}(PRICE)_j$ is smallest(.09) for car tires 195/65 and largest(1.22) for washing powders[6], and $\hat{\sigma}(QUALITY)_j$ is smallest(2.96) for espresso machines and largest for tablet cases(27.0). We account for these differences by standardizing the quality and price variation on brand level by the variation on product test level, defining the standardized product test standard deviation as $\hat{\sigma}(tQUALITY)_i = \frac{\hat{\sigma}(QUALITY)_i}{\hat{\sigma}(QUALITY)_{j[i]}}$ and standardized coefficient of variation as $\hat{cv}(tPRICE)_i = \frac{\hat{cv}(PRICE)_i}{\hat{cv}(PRICE)_{j[i]}}$.

Due to the limited number of products on brand level within test, either $\hat{\sigma}(tQUALITY)_i$ or $\hat{cv}(tPRICE)_i$ is zero for 58 brands, so there are only 409 observations of Spearman's rank order correlation $\hat{\rho}_i$ between price and quality, see summary statistics in table 3. Also, only two unique prices and qualities are observed for 202 cases, yielding correlations of ± 1 and thus a bimodal distribution, as seen in figure 1. In addition, second order moments can not be calculated for the 906 brands across the product tests that only have one product.[7]

Table 3: Summary statistics of brand level within test

	Completely observed values (409 obs.)					Including average imputed values (1367 obs)				
	mean	std	min	md	max	mean	std	min	md	max
$GOODS_j$	38.93	31.48	6	28	147	25.47	23.13	6	15	147
$BRANDS_j$	11.77	4.87	2	11	24	12.01	4.44	2	11	24
$GOODS_i$	4.67	5.05	2	3	48	2.15	3.23	1	1	48
$\overline{PRICE}_i$	25.21	27.12	0.01	15.47	139.9	18.01	24.95	0.01	6.99	159.6
$\overline{QUALITY}_i$	61.74	11.15	13.67	63.50	87.00	59.29	13.86	6.00	62.00	93.00
$\hat{cv}(PRICE)_i$	0.36	0.22	0	0.33	1.23	0.33	0.24	0	0.29	1.23
$\hat{\sigma}(QUALITY)_i$	7.76	7.47	0.55	5.00	38.18	7.29	7.37	0	4.95	38.18
$\hat{cv}(tPRICE)_i$	0.70	0.39	0	0.67	2.03	0.62	0.29	0	0.59	2.03
$\hat{\sigma}(tQUALITY)_i$	0.71	0.48	0.03	0.61	2.70	0.68	0.33	0	0.68	2.70
$SPEARMAN'S\ \hat{\rho}_i$	0.30	0.78	-1	0.68	1	0.15	0.50	-1	0.14	1

[6] Mainly due to an outlier with a somewhat specialized area of use, Fibertec wool wash.

[7] The proportion of single-product brands in a test is slightly related (Pearson's $\rho = 0.21$) to the number of brands, and moderately (Pearson's $\rho = -0.50$) to the total number of products.

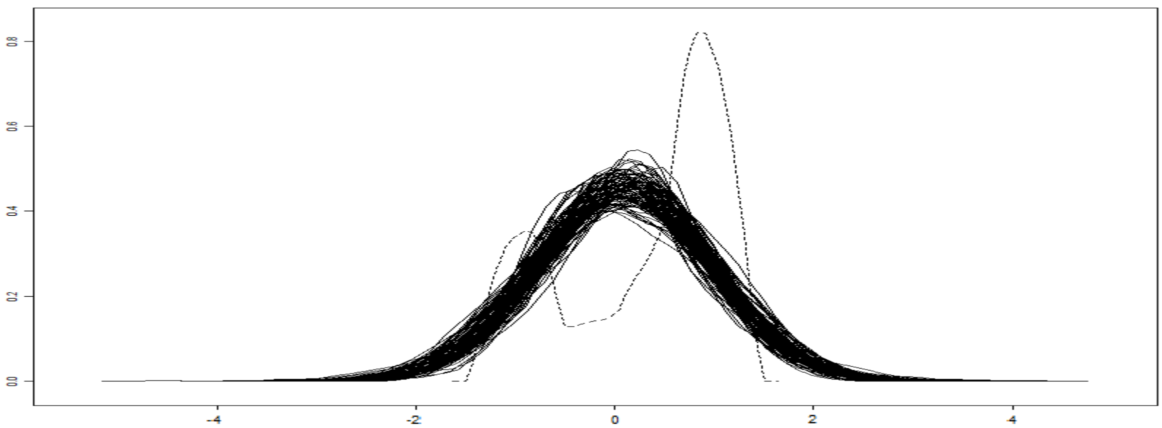

Figure 1: Estimated densities of $SPEARMAN'S\ \hat{\rho}_i$ for the 100 sets of imputed values (958 observations, solid lines) and complete values (409 observations, dashed line).

However, by assuming that in principle all brands (including those with only a single-product at present) have a counter-strategy to prevent new competitors from entering the market by (or at least threaten to) expanding their own product range, this implies that unobserved values exists latently. Therefore, we set up a model for $\hat{\rho}_i$, $\hat{\sigma}(tQUALITY)_i$ and $\hat{cv}(tPRICE)_i$. We then multiply impute the unobserved values in 100 datasets under a missing at random (Rubin, 1978) multilevel data model (Schafer and Yucel, 2002), as implemented in the software R (R Core Team, 2014) with packages MICE (vanBuuren and Groothuis-Oudshoorn, 2011) and PAN (Schafer and Zhau, 2015). The prediction variables used in imputation are found in table A2 in Appendix. Our analysis is then undertaken on each of the 100 datasets separately, and then the results are pooled.

When imputed, the high degree of bimodality in $\hat{\rho}_i$ is to a large extent reduced, since the large amount of imputed values tend to fall in between, see figure 1. Among the averages of the 958 imputed values of $\hat{\rho}_i$, six were less than possible minimum (-1).[8] The observed quality of these single-product brands were all the minimum rank 1, not because all their product characteristics were poor, but rather due to some fundamental flaws that pulled

[8]However, no average value of $\hat{\sigma}(tQUALITY)_i$ and $\hat{cv}(tPRICE)_i$ were smaller than 0.

down the overall rate, e.g. insufficient safety of child car seats. We find it reasonable to exclude these six observations from our data, due to the irregularity of the ranking function, giving all the weight to a single (though essential) characteristic.

4.1 Regression on price-quality correlation $\hat{\rho}_i$

By using a multilevel regression to model the correlation coefficient $\hat{\rho}_i$ within brands, both brand and product test level variables are considered. As on aggregated level in section 3.1, due to non-negative right skewed variables we apply square-root transformations both on brand level and product test level. The regression model on $SPEARMAN'S\ \hat{\rho}_i$ is summarized in (2), where matrix $\mathbf{X}$ are all variables on brand level, and matrix $\mathbf{Z}$ variables on product test level.

$$\begin{aligned} \hat{\rho}_i &\sim N\left(\beta_{j[i]} + \mathbf{X}_i\boldsymbol{\beta}, \sigma^2_{\hat{\rho}}\right), i = 1, ..., 1367 \\ \beta_j &\sim N\left(\gamma_0 + \mathbf{Z}_j\gamma, \sigma^2_{\beta}\right), j = 1, ..., 132 \end{aligned} \tag{2}$$

On brand level, the larger the dispersion of quality ($\sqrt{\hat{\sigma}(QUALITY)_i}$) and prices ($\sqrt{\hat{cv}(PRICE)_i}$), possibly mediated through a higher average price ($\sqrt{\overline{PRICE}_i}$), the larger we expect $\hat{\rho}_i$ to be. Given a segmented market, with more competing brands the individual brands have smaller market space, implying less opportunities for quality-price differentiation. A negative association is therefore expected from $\sqrt{BRANDS_j}$ on $\hat{\rho}_i$. The more goods within a brand ($\sqrt{GOODS_i}$), or the strongly correlated number of goods in test $\sqrt{GOODS_j}$, the stronger correlation we expect within brand. However, $\sqrt{BRANDS_j}$ and $\sqrt{GOODS_j}$ are naturally intertwined[9] since an additional brand implies that the total number of products, ceteris paribus, is increased. Therefore, it may not be possible to completely separate their effects on $\hat{\rho}_i$, but both are potentially important factors.

In table 4, the univariate results are consistent with our expectations except $\sqrt{\overline{PRICE}_i}$, which is insignificant in all models. When considering the imputed data, the considerable drops in coefficient of $\sqrt{GOODS_i}$ is a natural consequence of including the single-product brands, as seen in table 3. In the multivariate models, the number of goods and brands on product level do interplay so that their own effects are strengthened compared to if only one

[9] Pearson's ρ between $\sqrt{GOODS_j}$ and $\sqrt{BRANDS_j}$ is moderate (0.42).

Table 4: Fixed effects from regression on SPEARMAN'S $\hat{\rho}_i$

		Univariate		Full model		Reduced Model	
		$\hat{\beta}$	$t_{\hat{\beta}}$	$\hat{\beta}$	$t_{\hat{\beta}}$	$\hat{\beta}$	$t_{\hat{\beta}}$
Completely observed data (409)	$Intercept$	0.297	6.486	0.026	0.092	-0.005	-0.019
	$\sqrt{GOODS}_j$	0.033	1.657	0.065	2.227	0.058	2.797
	$\sqrt{BRANDS}_j$	-0.111	-1.727	-0.161	-2.257	-0.155	-2.297
	$\sqrt{GOODS}_i$	0.107	2.218	0.002	0.030		
	$\sqrt{\overline{PRICE}}_i$	0.004	0.217	-0.013	-0.693		
	$\sqrt{\hat{cv}(tPRICE)}_i$	0.402	2.561	0.301	1.865	0.288	1.824
	$\sqrt{\hat{\sigma}(tQUALITY)}_i$	0.390	2.911	0.311	2.260	0.330	2.455
	$^*R^2_m$ $\quad$ $^*R^2_c$			0.061	0.114	0.059	0.111
	AIC $\quad$ BIC			951.4	987.5	947.9	976.0
Including imputed data (1367)	$Intercept$	0.166	2.604	-0.064	-0.199	-0.104	-0.330
	$\sqrt{GOODS}_j$	0.038	1.477	0.068	2.018	0.066	2.391
	$\sqrt{BRANDS}_j$	-0.110	-1.361	-0.161	-1.806	-0.157	-1.813
	$\sqrt{GOODS}_i$	0.020	2.165	0.003	0.317		
	$\sqrt{\overline{PRICE}}_i$	-0.004	-0.210	-0.011	-0.490		
	$\sqrt{\hat{cv}(tPRICE)}_i$	0.365	2.111	0.253	1.456	0.252	1.459
	$\sqrt{\hat{\sigma}(tQUALITY)}_i$	0.459	3.130	0.390	2.608	0.401	2.694
	$^{**}\overline{R^2_m}$ $\quad$ $^{**}\overline{R^2_c}$			0.078	0.227	0.075	0.227
	$^{**}\overline{AIC}$ $\quad$ $^{**}\overline{BIC}$			3236.3	3283.3	3235.4	3271.9

* Marginal R^2_m refers to fixed effects, and conditional R^2_c to fixed and random effects, see Nakagawa & Schielzeth (2013).

** R-squares and information criterias are averages over the 100 imputed datasets. AIC(BIC) is smallest for Reduced model in 88(100) sets.

of them were included [10] The positive effect of number of own goods are essentially absorbed by the number of goods on product level. When allowing for imputed values, basically the relative size of effects is slightly redistributed from $\sqrt{\hat{cv}(PRICE)}_i$ to $\sqrt{\hat{\sigma}(QUALITY)}_i$.

[10] Likelihood-ratio-tests rejects excluding neither of them from the model.

5 Segmentation - regression on variation in quality at brand level

To examine the characteristics of quality segmentation within brands, we utilize the data from previous section, and adopt the same type of multilevel model, replacing correlation coefficient $\hat{\rho}_i$ by variation in quality $\sqrt{\hat{\sigma}(tQUALITY)_i}$ as the dependent varible on brand level in equation 2. The summary statistics for the average imputed data are given on the right side in table 3. With $\hat{\rho}_i$ left out, the complete observations underlying the summary statistics on the left hand side of table 3 are supplemented by 58 observations for which $\hat{\sigma}(tQUALITY)_i$ or $\hat{cv}(tPRICE)_i$ are equal to zero. The main differences in comparison to table 3 are related to these two variables, see table A3 in Appendix.

Our main purpose is to investigate whether having more competing brands is associated with the narrowing of a brands quality differentiation, as would be expected if the brands were segmented on quality. We also control for the number of goods ($\sqrt{GOODS_j}$) on product test level. More products or brands in a product category implies more competition and less room for quality differentiation. We expect that $\sqrt{BRANDS_j}$ has the stronger impact of the two, meaning a relatively greater impact on competition of new brands entering the market rather than expansion of product range of existing brands.[11] However, we are aware of the difficulties of separating the two effects on $\sqrt{\hat{\sigma}(tQUALITY)_i}$, as discusses in section 4.1. On brand level, more own products $\sqrt{GOODS_i}$ would imply a larger opportunity for quality differentiation. The higher the price level $\sqrt{\overline{PRICE}_i}$, the stronger incentives for quality segmentation and head-to-head competition. Finally, quality and price variation ($\hat{cv}(tPRICE)_i$) are evidently positively associated.

The expected effects are essentially confirmed univarietely, as seen in table 5. On brand level, all the univariate effects are strong and remains fairly unaffected by the other variables when considered in the full model. Due to the inclusion of 900 observations on brands with only one product each, there is a a huge reduction in effect size of $\sqrt{GOODS_i}$ when using the complete imputed data. On product test level, the signficance of $\sqrt{GOODS_j}$ is consistently weak, and decreased further when other variables are taken account of in the

[11] Average number of commodities per brand decrease slightly with the number of brands.

Table 5: Fixed effects from regression on $\sqrt{\hat{\sigma}(tQUALITY)_i}$

		Univariate		Full model		Nested I		Nested II	
		$\hat{\beta}$	$t_{\hat{\beta}}$	$\hat{\beta}$	$t_{\hat{\beta}}$	$\hat{\beta}$	$t_{\hat{\beta}}$	$\hat{\beta}$	$t_{\hat{\beta}}$
Completely observed data (409)	$Intercept$	0.758	39.764	0.730	7.483	0.745	7.757	0.624	10.923
	$\sqrt{GOODS_j}$	-0.011	-1.319	-0.010	-0.822			-0.018	-1.801
	$\sqrt{BRANDS_j}$	-0.070	-2.734	-0.039	-1.339	-0.052	-2.094		
	$\sqrt{GOODS_i}$	0.070	3.469	0.083	3.501	0.073	3.634	0.092	4.014
	$\sqrt{\overline{PRICE}_i}$	-0.023	-3.365	-0.029	-4.163	-0.031	-4.731	-0.028	-4.015
	$\sqrt{\hat{cv}(tPRICE)_i}$	0.259	5.554	0.227	4.902	0.231	5.001	0.229	4.938
	$^*R^2_m$ $^*R^2_c$			0.146	0.236	0.146	0.238	0.137	0.232
	AIC BIC			226.9	260.1	225.6	254.6	226.7	255.7
Including imputed data (1367)	$Intercept$	0.757	27.397	0.829	7.016	0.831	7.020	0.718	9.397
	$\sqrt{GOODS_j}$	-0.013	-1.183	-0.003	-0.223			-0.011	-0.854
	$\sqrt{BRANDS_j}$	-0.058	-1.753	-0.042	-1.118	-0.047	-1.452		
	$\sqrt{GOODS_i}$	0.011	3.145	0.012	3.113	0.011	3.238	0.013	3.398
	$\sqrt{\overline{PRICE}_i}$	-0.030	-3.432	-0.035	-3.992	-0.036	-4.274	-0.034	-3.907
	$\sqrt{\hat{cv}(tPRICE)_i}$	0.251	5.017	0.240	4.838	0.241	4.851	0.242	4.864
	$^{**}\overline{R^2_m}$ $^{**}\overline{R^2_c}$			0.127	0.329	0.125	0.330	0.119	0.327
	$^{**}\overline{AIC}$ $^{**}\overline{BIC}$			705.9	747.7	704.7	741.3	706.4	742.9

* Marginal R^2_m refers to fixed effects, and conditional R^2_c to fixed and random effects, see Nakagawa & Schielzeth (2013).

** R-squares and information criterias are averages over the 100 imputed datasets. AIC(BIC) is smallest for Nested I in 71(77) sets, and for Nested II in 21(23) sets.

full modell. When included in the model, it lowers the estimated effect of $\sqrt{BRANDS_j}$ confirming their intertwined relation to $\hat{\sigma}(tQUALITY)_i$. By fitting two nested models, excluding either $\sqrt{GOODS_j}$ or $\sqrt{BRANDS_j}$, we see that the first fits the data better, especially with only observed data.[12] To sum up, there is some, though weak evidence, that the number of brands on product test level is negatively associated with variation in quality, though the results are blurred by collinearity.

[12] This is also confirmed by a likelihood-ratio-test.

6 Summary and Conclusions

In this empirical paper we have analyzed price-quality ranking data from Swedish consumer reports to look into two questions. The first question examined is to what extent high prices signal high quality. We estimated the Spearman's rank order correlation coefficients both across brands (inter-brand correlation) and within multiproduct brands (intra-brand correlation). Given our estimated correlations coefficients, we then used regression analysis to test hypotheses about the determinants of these correlations. The analysis of the inter-brand relationship between price and quality shows a low correlation. Our estimated mean(median) value of the Spearman's rank order correlation coefficient is 0.28(0.34), a result in line with many previous studies. Also, our results suggest that the correlation coefficient is higher for durable goods than for consumable goods, but is unaffected by the average price level of the products.

At the intra-brand level, our innovative way of modeling the 900 single-product brands as potential multiproduct brands, allows a more comprehensive analysis. Based on the available information from the observed sample, we imputed data not observed for these brands. The mean(median) rank-order correlation coefficient in the observed data of 0.30(0.68) is then seen to fall to 0.15(0.14). To a considerable extent this is related to single-product brands being more frequent in product tests with fewer products.

The second question analyzed in the paper is whether multiproduct firms exhibit a segmented pattern when differentiating the quality of their products. Using standard deviation (adjusted to the product test level) of a brand's assessed quality as a measure for brand segmentation, we examined the impact of increased competition upon a brand's segmentation. The segmentation hypothesis was tested both on the observed data as well as on the data including the imputed values. The regression analysis exhibits a negative correlation between the number of competing brands and the standard deviation of quality, suggesting quality segmentation. However, the relevance of the regressed effect of competition upon segmentation is weaker when we the regression analysis also encompasses imputed values of single-product brands. There are also difficulties in distinguishing the effect of the number of brands from the related size of the product range. Hence, our analysis does not provide clear evidence of quality segmentation due to increased competition.

A test carried out by the ICRT normally comprises a large number of commodities from many producers. The result is then collected by the national consumer organizations and presented for their national markets. It goes without saying that the number of commodities in a particular test, presented in a consumer magazine on a national level, hardly represents a random draw from the total number of commodities tested by the ICRT. Due to different market conditions across countries in terms of consumer regulations, certificate requirements, technology, customs and culture, climate, etc., a national consumer organization may regard a commodity in a test not being suitable or adaptable for the national market and therefore refrain from reporting the test results - whereas another consumer organization includes the same commodity in their national consumer report. Now, this selection method does not necessarily imply that our results are biased. Rather, adaptations based on local knowledge is likely to give a better picture of the actual market conditions. Also, the entire testing process is almost completely transparent and thus open to criticism from the public, and any stronger bias would most likely undermine their credibility. Furthermore, even if certain tests could be biased, it is harder to image any overall tendency which would effect our results.

Appendix section

Table A1: Summary statistics from 132 product tests

	mean	std	min	median	max
$GOODS_j$	22.40	23.28	6	13	147
$BRANDS_j$	10.40	4.11	2	10	24
$\overline{PRICE}_j$	18.90	23.92	0.01	8.51	108.9
$\overline{QUALITY}_j$	60.17	8.62	21.88	61.47	77.55
$\hat{\sigma}(PRICE)_j$	8.37	11.26	0.003	4.09	79.59
$\hat{\sigma}(QUALITY)_j$	11.11	5.31	2.96	9.80	26.98
$\hat{cv}(PRICE)_j$	0.48	0.24	0.09	0.44	1.22
$\hat{cv}(QUALITY)_j$	0.19	0.10	0.04	0.16	0.50
$^{*}SPEARMAN'S\ \hat{\rho}_j$	0.28	0.36	-0.75	0.34	0.93
$^{**}KENDALL'S\ \hat{\tau}_j$	0.21	0.28	-0.58	0.25	0.81

* 52(40%) significant in approx. t-tests, H_0: $\rho_j \leq 0$.

** 54(41%) significant in approx. z-tests, H_0: $\tau_j \leq 0$.

Table A2: Variables included in the imputation model

PREDICTOR VARIABLES	IMPUTED VARIABLES		
	$\hat{\rho}_i$	$\sqrt{\hat{\sigma}(tQUALITY)}_i$	$\sqrt{\hat{cv}(tPRICE)}_i$
$SPEARMAN'S\ \hat{\rho}_i$	0	1	1
$\sqrt{\hat{\sigma}(tQUALITY)}_i$	1	0	1
$\sqrt{\hat{cv}(tPRICE)}_i$	1	1	0
$PRODUCT\ TEST\ INDICATOR_j$	-2	-2	-2
$Intercept$	2	2	2
$CONSUMABLES\ INDICATOR\ CD_i$	1	1	1
$\sqrt{\overline{PRICE}_i}$	1	1	0
$\sqrt{\overline{QUALITY}_i}$	1	0	1
$\sqrt{\overline{PRICE}_j}$	1	1	0
$\sqrt{\overline{QUALITY}_j}$	1	0	1
$\sqrt{GOODS_j}$	1	1	1
$\sqrt{GOODS_i}$	1	1	1
$\sqrt{BRANDS_j}$	1	1	1
$\sqrt{SINGLE-PRODUCT\ BRANDS_j}$	1	1	1

0=Not included; 1=Fixed effect; 2=Intercept; -2=Random effect

Table A3: Summary statistics of brand level within test (467 obs)

	mean	std	min	median	max
$GOODS_j$	38.23	30.83	6	27	147
$BRANDS_j$	11.81	4.97	2	11	24
$GOODS_i$	4.39	4.79	2	3	48
$\overline{PRICE}_i$	24.92	27.78	0.01	13.83	150.10
$\overline{QUALITY}_i$	61.91	11.18	13.67	63.75	87.00
$\hat{cv}(PRICE)_i$	0.33	0.24	0	0.29	1.23
$\hat{\sigma}(QUALITY)_i$	7.29	7.37	0	4.95	38.18
$\hat{cv}(tPRICE)_i$	0.63	0.42	0	0.60	2.03
$\hat{\sigma}(tQUALITY)_i$	0.67	0.49	0	0.57	2.70

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