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# The price-perceived quality relationship: A meta-analytic review and assessment of its determinants

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**Abstract** The authors conducted a meta-analysis of study results on the price-perceived quality relationship published from 1989 to 2006. The findings show that the price effect on perceived quality has decreased. Furthermore, the price–quality relationship is stronger in studies that use a within-subjects design, investigate higher priced products, and use samples from European countries but weaker for services, durable goods, and respondents who are familiar with the product. A striking null result indicates that the number of cues does not affect the price-perceived quality relationship significantly.

**Keywords** Price-perceived quality relationship · Informational role of price · Meta-analysis

Marketing scholars and practitioners increasingly have recognized in recent decades that price provides an important marketplace cue (e.g., Gijsbrechts, 1993; Monroe, 2003) by indicating the amount of money consumers must sacrifice to satisfy their consumption needs. In this respect, price represents a financial burden, and higher prices negatively affect purchase probabilities (i.e., negative role of price; Erickson and Johansson, 1985). However, many consumers perceive price in a broader sense; according to theoretical and empirical evidence, they use price as a quality cue (e.g., Erickson and Johansson, 1985; Völckner and Sattler, 2005). In their influential meta-analysis, which has been cited more than 131 times according to the Social Science Citation Index, Rao and Monroe (1989) summarized research findings regarding the price-perceived quality link and thus have provided the contemporary state of knowledge about the overall relationship between price and perceived quality. However, a single meta-analysis does not provide a final statement of truth (Tellis, 1988). Recently, Bijmolt et al. (2005) presented an update of Tellis's (1988) meta-

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analysis on the negative role of price, but an update of the positive role of price remains missing, although the relationship between price and perceived quality is one of the most commonly studied extrinsic cues in marketing (Miyazaki et al. 2005). Because the most recent meta-analysis of the price–perceived quality relationship was published 17 years ago, whereas literature on the use of price as an indicator of product quality has continued to flourish, it is important to examine whether the findings of Rao and Monroe (1989) still hold or need to be updated and revised. The aim of this article is to provide an update of the positive role of price to assess the state of knowledge on this clearly important phenomenon.

This article extends empirical generalizations on the price-perceived quality relationship with a meta-analysis that integrates research from 1989 to 2006 and includes 71 effects of price on perceived product quality. Furthermore, Rao and Monroe (1989) investigated four methodological differences among price-perceived quality research studies—namely, number of cues, experimental design, price manipulation, and price level—to determine whether they are associated with outcome variations. We broaden this scope by studying several additional determinants of the observed price–perceived quality link: type of product category (fast-moving consumer goods, durables, services), the countries for which price–perceived quality effects have been reported (North American, European, and "other" countries), samples (student versus nonstudent), and respondents' familiarity with the product category.

We organize the remainder of this article as follows: First, we discuss the development of our database for the meta-analysis. Second, we use the meta-analysis to offer a quantitative summary that documents the overall magnitude of the relationship between price and perceived quality. Third, we present our findings on some substantive and methodological determinants of price–perceived quality effects. Fourth, in our closing discussion, we summarize the main findings and suggest avenues for further research.

## 1 Database development

To identify publications that report estimates of the relationship between price and perceived quality, we conducted an elaborate search. First, we used ABI/Inform, Business Source Premier (EBSCO*host*), EconLit, and ScienceDirect in a computerized bibliographic search. Second, we searched the Social Science Citation Index for studies that referred to Rao and Monroe (1989). Third, we conducted an issue-by-issue search of nine major marketing journals from 1989 forward.[1] Fourth, we searched the Web for working papers. Fifth, we examined references from articles we had already obtained to find additional studies with estimates of the price–perceived quality relationship.

[1] We inspected the following journals: *International Journal of Research in Marketing*, *Journal of the Academy of Marketing Science*, *Journal of Consumer Research*, *Journal of Marketing*, *Journal of Marketing Research*, *Journal of Retailing*, *Management Science*, *Marketing Letters*, and *Marketing Science*.

The effect size metric selected for the analysis is the correlation coefficient *r* between price and perceived quality. The coefficient was chosen because it is an easily interpretable, scale-free measure, and it is the mostly used effect size in meta-analyses in marketing literature (e.g., Rosenthal, 1994). During the search process, we recognized that correlation was the most common metric reported in the studies and provided a metric to which the reported noncorrelations could be converted. We therefore converted noncorrelations to correlation coefficients following common guidelines for meta-analyses (e.g., Lipsey and Wilson, 2001). Some studies could not be included because they only reported consumers' responses to scale-based measures (e.g., "The old saying 'you get what you pay for' is generally true" [1 = strongly agree to 7 = strongly disagree]) that could not be integrated with the effect sizes reported in the other studies (e.g., Lichtenstein et al. 1993). Furthermore, we include only articles that measured the effect of price on *perceived* product quality. That is, analogous to Rao and Monroe (1989), we exclude research on the relationship between price and objective product quality. After completing the search process, we had obtained a total of 71 effects from 23 publications (see Table 1).[2]

We prepared a coding form that specified the information to be extracted from each study. The final coding form included the authors, year, publication outlet, r-family of effect size indicators, and eight potential determinants of the observed price–perceived quality effects. As with most meta-analyses in marketing, our database contains some studies that themselves contain multiple measurements of the price–perceived quality link (e.g., effect sizes for several products) from the same population. Studies with multiple effect sizes may have a greater impact on the results of the meta-analysis than studies that only contribute one effect size. Furthermore, we must consider the dependency between effect sizes from the same study. There are two general approaches to deal with such multiple measurements. With the single-value approach, each study is represented by a single value, such as the average measurement per study (Hunter and Schmidt, 1990). In contrast, the complete set approach incorporates the values of all measurements within the studies and treats them as independent (weighted) replications (e.g., Kirca et al. 2005; Rao and Monroe, 1989; Sethuraman, 1995; Tellis, 1988). Because representing each study by a single value results in a serious loss of information and because procedures that use the complete set of measurements outperform the single value approach (Bijmolt and Pieters, 2001)[3], we include all price–perceived quality effects in our meta-analysis.

## 2 Overall magnitude of the price–perceived quality relationship

The most common metric reported in our collected studies was the correlation between price and perceived quality. We follow standard procedures employed in other meta-analyses to convert other effect size indicators (*t* statistics, *F* ratios) into correlation coefficients and compute the mean effect size (e.g., Churchill et al. 1985;

[2] Rao and Monroe (1989) use a total set of 54 price-perceived quality effects.

[3] Bijmolt and Pieters (2001) compared the single value and the complete set approaches on their ability to detect the true effect size in a Monte Carlo study.

**Table 1** Publications included in the meta-analysis

| Authors | Year | Publication Outlet | Volume, Issue, Pages |
|---|---|---|---|
| Agarwal and Teas | 2002 | *Journal of Product and Brand Management* | Vol. 11, Issue 4, pp. 213–236 |
| Chao | 1993 | *Journal of International Business Studies* | Vol. 24, Issue 2, pp. 291–106 |
| Chen, Gupta, and Rom | 1994 | *International Journal of Service Industry Management* | Vol. 5, Issue 2, pp. 23–33 |
| Cronley, Posavac, Meyer, Kardes, and Kellaris | 2005 | *Journal of Consumer Psychology* | Vol. 15, Issue 2, pp. 159–169 |
| Darke and Chung | 2005 | *Journal of Retailing* | Vol. 81, Issue 1, pp. 35–47 |
| Dodds, Monroe, and Grewal | 1991 | *Journal of Marketing Research* | Vol. 28, Issue 3, pp. 307–319 |
| Fogel, Lovallo, and Carnigal | 2004 | *Australian Journal of Management* | Vol. 29, Issue 1, pp. 45–64 |
| Gorn, Tse, and Weinberg | 1991 | *Marketing Letters* | Vol. 2, Issue 2, pp. 99–110 |
| Gotlieb and Sarel | 1992 | *Journal of the Academy of Marketing Science* | Vol. 20, Issue 3, pp. 253–260 |
| Hansen | 2005 | *Journal of Consumer Behaviour* | Vol. 4, Issue 6, pp. 420–437 |
| Kerin, Jain, and Howard | 1992 | *Journal of Retailing* | Vol. 68, Issue 4, pp. 376–397 |
| Raghubir | 2004 | *Journal of Retailing* | Vol. 80, Issue 1, pp. 1–12 |
| Rao and Sattler | 2003 | *Conjoint Measurement: Methods and Applications*, Gustafsson, Herrmann, and Huber (eds.) | 3rd ed. 2003, pp. 47–66 |
| Shiv, Carmon, and Ariely | 2005 | *Journal of Marketing Research* | Vol. 42, Issue 4, pp. 383–393 |
| Sjolander | 1992 | *European Journal of Marketing* | Vol. 26, Issue 7, pp. 34–44 |
| Suri and Monroe | 2003 | *Journal of Consumer Research* | Vol. 30, Issue 1, pp. 92–104 |
| Sweeney, Soutar, and Johnson | 1999 | *Journal of Retailing* | Vol. 75, Issue 1, pp. 77–105 |
| Taylor and Bearden | 2002 | *Journal of the Academy of Marketing Science* | Vol. 30, Issue 2, pp. 131–140 |
| Teas and Agarwal | 2000 | *Journal of the Academy of Marketing Science* | Vol. 28, Issue 2, pp. 278–290 |
| Verma and Gupta | 2004 | *Vikalpa: The Journal for Decision Management* | Vol. 29, Issue 2, pp. 67–77 |
| Völckner and Sattler | 2005 | *Marketing – Journal of Research and Management* | Vol. 1, Issue 1, pp. 1–13 |
| Völckner and Sattler | 2006 | *Proceedings of the 35th Annual Conference of the European Marketing Academy* | 8 pages |
| Yoo, Donthu, and Lee | 2000 | *Journal of the Academy of Marketing Science* | Vol. 28, Issue 2, pp. 195–211 |

D. W. Johnson et al. 1983; Rosenthal, 1994; Sethuraman, 1995). For the *t* statistics, in line with existing recommendations, we convert them into point biserial correlations and subsequently into biserial correlations (e.g., Cohen, 1988; Glass et al. 1981). Because of the underlying mathematical formula, we could obtain a biserial correlation greater than 1.0 if the point biserial correlation is larger than approximately 0.8 (e.g., Magnusson, 1967; Wherry, 1984).[4] Within the scope of our meta-analysis, we converted a total of 15 $t$ values into biserial correlations and obtained values slightly greater than 1.0 in three cases (1.023, 1.038, and 1.136). We set these values to 1 to calculate the mean effect size and test potential determinants of the observed price–perceived quality effects; however, these three cases do not affect the computed mean effect size because they do not pass the homogeneity test, which we describe subsequently. In Fig. 1, we present the frequency distribution of the observed price–perceived quality effects.

When computing the overall magnitude of the price–perceived quality relationship, we treat multiple measurements as weighted replications to account for the possibility that studies with many measurements may have a greater effect on the meta-analysis results than would studies with fewer measurements; that is, we weigh the effect sizes by the inverse of the number of multiple measures in the study (e.g., Hunter and Schmidt, 1990; Sethuraman, 1995). Furthermore, a correlation based on, say, 200 persons contains more information than one based on 50 persons, because the estimate based on the larger number of observations has smaller sampling error. Therefore, we weigh each correlation by the number of persons in the study to give greater weight to more precise estimates (e.g., Churchill et al., 1985; Hunter and Schmidt, 1990). Hence, the weighted mean effect size is given by:

$$\bar{z} = \frac{\sum_{i=1}^{g}\sum_{j=1}^{h}(n_i - 3)\cdot w_i \cdot z_{ij}}{\sum_{i=1}^{g} n_i}, \qquad (1)$$

where: $\bar{z}$= weighted mean effect size (using Fisher's $z$-coefficients); $n_i$ = sample size of study $i$; $w_i$=1/$h$ = weighting factor for effect sizes in study $i$; $z_{ij}$ = effect size $j$ of study $i$ (converted into Fisher's $z$-coefficient); $i$=1,..., $g$, where $g$ is the number of statistically independent studies; and $j$=1, ..., $h$, where $h$ is the number of dependent effect sizes in study $i$.

Finally, the literature recommends converting correlations to $z$-scores using Fisher's $r$-to-$z$ transformation to account for the skewness of the sampling distribution of correlation coefficients (e.g., Hedges and Olkin, 1985; Silver and Dunlap, 1987). Silver and Dunlap (1987) showed the usefulness of the $r$-to-$z$ transformation using a Monte Carlo simulation; we similarly transform the correlations into Fisher's $z$-coefficients. Subsequently, we average the $z$-coefficients, weigh them by the inverse of the number of multiple measures in the study and the corresponding sample

[4] We convert $t$ values to a point biserial correlation by using $r_{\text{pbis}} = \sqrt{\frac{t^2}{t^2+df}}$, where $t$=$t$ value and $df$ = degrees of freedom (Cohen, 1988, p. 545). Glass et al. (1981) recommended a conversion of this point biserial correlation to a biserial correlation by using $r_{bis} = r_{pbis} \cdot \sqrt{\frac{n_1 \cdot n_2}{\nu \cdot n}}$, where $\nu$ = ordinate of unit normal distribution and $n$ = total sample size. According to this formula, it is possible in practice to obtain values of $r_{\text{bis}}$ greater than 1.00 if the point biserial correlation is larger than approximately 0.8.

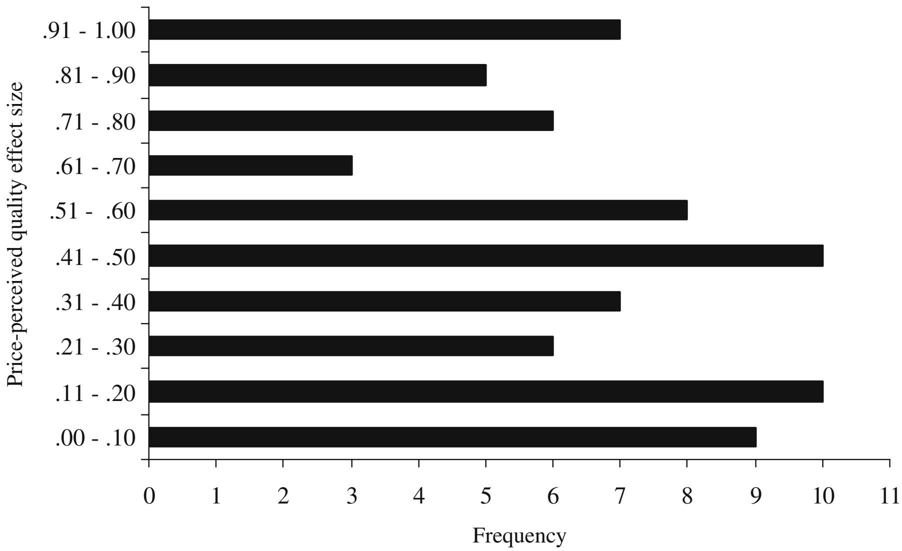


**Fig. 1** Frequency distribution of observed price–perceived quality effects ($n$=71)

size (see Eq. 1), and reconvert them into correlation coefficients (Hedges and Olkin, 1985; Hunter and Schmidt, 1990; Sethuraman, 1995). Such a procedure is commonly used in meta-analyses to calculate the mean effect size. However, because Rao and Monroe (1989) did not use Fisher's $z$-coefficients, we calculate the mean effect size both with and without Fisher's $r$-to-$z$ transformation.

Before integrating the effect sizes, we investigated whether the studies produced effect sizes of the same underlying population according to a chi-square homogeneity of effect size test (e.g., Hedges and Olkin, 1985; Rao and Monroe, 1989). If the test fails to accept the null hypothesis of no significant differences, the variation in results across studies cannot be explained simply by sampling error, and variability in effect sizes may be caused by moderating variables (see "Determinants of observed price–perceived quality effects" section). Acceptance of the null hypothesis offers evidence of homogeneity, and the effect sizes can be integrated. The homogeneity test shows that the data are not homogeneous ($p<0.01$), so we identify and exclude those data points that contributed most to the nonhomogeneity of effect sizes according to the chi-square statistic (Hedges and Olkin, 1985). This stepwise procedure resulted in a set of 32 homogenous effect sizes to be integrated.[5]

The weighted mean effect size is 0.286±0.032 with a 95% confidence interval. Because Rao and Monroe (1989) did not use Fisher's $z$-coefficients, we calculate the mean effect size without Fisher's $r$-to-$z$ transformation, which produced a weighted mean $\bar{r}$ of 0.273, lower than the mean effect size ($\bar{r} = 0.341$; $\bar{\eta}^2 = 0.116$) of Rao and Monroe (1989). Thus, both with and without Fisher's $r$-to-$z$ transformation, the effect of price on perceived quality seems to be, on average, smaller than the mean

[5] Rao and Monroe (1989) used a reduced set of 33 price–perceived quality data points in their analyses.

effect size found by Rao and Monroe (1989). However, we also find a moderately strong (for a benchmark, see Cohen, 1988) and highly significant ($p<0.001$ [$z=18.970$]) relationship between price and perceived quality that indicates consumers still use price as an important indicator of quality.

Finally, we address the issue of publication bias, or the greater likelihood that research containing statistically significant results will be reported compared with research indicating null or nonsignificant results. We compute the availability bias number, or the number of unpublished studies with a null result, that are needed to reduce the cumulative effect across studies to nonsignificance (Lipsey and Wilson, 2001). We find that an additional 1,731 reported effects with an average zero effect size would be needed to reduce the statistical significance of the price–perceived quality relationship below the 0.05 level. This high number indicates that new or unpublished studies not included in the meta-analysis do not represent serious threats to the validity of the overall magnitude of the price–perceived quality relationship. In addition, 1,731 effects are far more than the commonly used critical value for availability bias, which in this case would be 170 (i.e., number of effect sizes × 5+10; Rosenthal, 1993).

## 3 Determinants of observed price–perceived quality effects

The statistically significant chi-square value ($p<0.01$) of the homogeneity test reveals variability across effect sizes and suggests the need to examine theoretically relevant substantive moderators and methodological characteristics to explain this variance (Hunter and Schmidt, 1990). In the following discussion, we present hypotheses to guide the moderator analysis. The analysis of potential moderating variables is particularly interesting for designing and interpreting future studies on the price–perceived quality link because it creates generalizations and seeks the limits and modifiers of those generalizations. If certain moderating variables explain the heterogeneity of the results, researchers should consider them when designing their studies and developing their conclusions. Furthermore, moderator analyses offer a means to make credible estimates of specific unstudied combinations of situations, methods, and research designs (e.g., Farley et al. 1995).

### 3.1 Hypothesized effects

#### *3.1.1 Number of cues*

Empirical research in the price–perceived quality area can be divided into single cue (i.e., price only) versus multicue studies. Single cue studies examine the influence of price on quality judgments in isolation; in the absence of any other information, respondents should exhibit a positive price-quality effect (e.g., Johnson and Kellaris, 1988). However, price is rarely the only information available about a product, and the impact of a single cue falls as other diagnostic cues become available.

*H1* The price–perceived quality effect size is greater for single-cue studies than for multicue studies.

*3.1.2 Experimental design*

The use of within-subjects designs has been considered somewhat artifactual because respondents who answer repeated measures across several prices may guess the true intent of the research and respond accordingly (e.g., Sawyer, 1975). In addition, within-subjects designs likely produce larger effects than between-subjects designs because the former control for individual difference, which reduces error variance.

*H2* The price-perceived quality effect size is greater for within-subjects designs than for between-subjects designs.

*3.1.3 Price manipulation*

The strength of the independent variable manipulation generally influences whether statistically significant differences occur in the dependent variable. That is, greater differences between the prices used as levels of an independent variable should produce larger effects (Rao and Monroe, 1989). Furthermore, empirical evidence indicates that a consumer's tendency to associate price and quality increases with greater price variation within the product category (Johnson and Kellaris, 1988; Zeithaml, 1988).

*H3* The price–perceived quality effect size varies positively with the strength of the price manipulation.

*3.1.4 Price level*

Price reliance may be more likely for products that are relatively expensive and purchased infrequently (e.g., Smith and Natesan, 1999). As the price level increases, the risk associated with an incorrect quality assessment increases, and consumers may rely on their belief in a price–quality correlation as a perceived risk reduction strategy.

*H4* The price–perceived quality effect size varies positively with the price level of the test products.

*3.1.5 Sample (student versus nonstudent)*

Most price–perceived quality studies use students as subjects. The issue of whether students are appropriate research surrogates for consumers other than students has been debated heatedly in a variety of disciplines for more than five decades (e.g., Peterson, 2001; Winer, 1999). Some conceptual and empirical work suggests that the results obtained from student samples should generalize to nonstudent samples (e.g., Kardes, 1996; Petty and Cacioppo, 1996). In contrast, in a general social science meta-analysis, Peterson (2001) found that the effect sizes derived from students frequently differ from those of nonstudents. However, no strong theoretical basis exists for an a priori hypothesis about the direction of the difference. Peterson (2001) also emphasized that whether conclusions in social science research based on student subjects are generalizable to nonstudent populations remains an empirical question.

We therefore test whether the price–perceived quality effect size differs between student and nonstudent samples. The result should be particularly important for designing future studies on the positive role of price and interpreting future studies' results. If no significant difference is found, the use of students seems appropriate. In case of a significant difference, caution must be exercised when attempting to extend any price–perceived quality relationships found using student subjects to a non-student population.

*H5* The price–perceived quality effect size differs for student samples and non-student samples.

### *3.1.6 Familiarity with the product category*

Previous research suggests a moderating influence of familiarity with a product (e.g., Gardner, 1970; Johnson and Kellaris, 1988; Rao and Monroe, 1988), such that when consumers lack familiarity and consequently the expertise or ability to assess quality, they tend to rely more on price as an indicator to form their personal evaluations.

Rao and Monroe (1988) showed that price reliance declines but then increases with familiarity in certain circumstances. If a product is known to exhibit a positive price–quality association in the marketplace, highly familiar consumers are aware of such an association and confident that prices are reliable predictors of quality. In other words, if a consumer's past experience is consistent with a positive price–quality relationship, his or her price reliance should increase with familiarity, which represents an interaction effect between familiarity and the consumer's past price–quality experiences.

Hence, the direction of the effect is unclear, and we simply state that the price–perceived quality effect size differs between familiar respondents and unfamiliar respondents.

*H6* The price–perceived quality effect size differs according to respondent's familiarity with the test products.

### *3.1.7 Product category*

The type of product category is one of the variables most commonly investigated in meta-analyses in marketing (e.g., Bijmolt et al., 2005, Tellis, 1988). Moderating effects of the type of product category are particularly interesting for interpreting research on the price–perceived quality link because, as with most empirical studies in marketing, these studies likely vary with regard to the type of product investigated. Furthermore, Rao and Monroe (1989) explicitly note that research is necessary to establish whether the price–perceived quality relationship differs according to the general nature of the product.

Previous research provides some evidence that consumers might expect a stronger price–perceived quality relationship for durable than for nondurable goods (e.g., Lichtenstein and Burton, 1989). This expectation may reflect consumers' lesser knowledge about durable goods because of the infrequency of purchases in most durable goods categories. Durable goods also may be viewed as complex products whose quality assessments consumers find more difficult. The same arguments might hold for services. Services are generally low in search qualities (i.e., attributes that a consumer can determine before purchase) and high in experience and credence qualities, which increases perceived risk and thus consumers' reliance on price as a quality indicator. However, Bijmolt et al. (2005) established that consumers' price sensitivity is higher for durables than for nondurable goods. Hence, the direction of the difference is unclear, and we simply state that effect sizes differ by the general nature of the product.

*H7* The price–perceived quality effect size differs according to the general nature of the product (i.e., durable goods, services, fast moving consumer goods).

#### 3.1.8 Country

Finally, for empirical generalizations, it is important to know whether the empirical results for the price–perceived quality relationship reported in the literature are specific to the country in which the studies were conducted. Hofstede (2003) empirically demonstrated international variations among factors that could contribute to price reliance, such as risk aversion. We therefore test whether the price–perceived quality effect size differs between countries. We define country clusters along the following lines: (1) North American countries (United States and Canada), (2) European countries, and (3) others. The "other" category generally represents economically less developed countries (e.g., India, China).

*H8* The price–perceived quality effect size differs by country (i.e., North American, European, and other countries).

### 3.2 Regression analysis

We test the hypotheses using a weighted least squares regression analysis, which enables us to account for multiple measures and varying sample sizes (Kmenta, 1986). We weigh the effect sizes by the inverse of the number of multiple measures in the study and the number of persons in the study. We code the study design (between or within) and number of cues (multiple or single) as 0, 1 dummy variables, such that we expect a positive coefficient for experimental design and number of cues. We follow Rao and Monroe (1989) in determining the strength of the price manipulation by computing a proportional variation between the highest and lowest price for each product studied [(high–low)/high)]. To determine the price level, we calculate the mean of the highest and lowest price in each study [(high + low)/2]. We code the sample (nonstudent or student) as 0, 1 dummy variable. Furthermore, we included a 0, 1 dummy variable for respondents' familiarity with the test products and code those studies that only interviewed respondents who were familiar with the test products as 1. Specifically, we code a study as 1 if (a) the familiarity with the product was explicitly measured and respondents with poor familiarity were excluded from the analysis, or (b) a pretest established a high familiarity with the product and the authors ensured that the main study's sample was comparable with the pretest sample in terms of demographic characteristics. We also include dummy variables for the product category (fast moving consumer goods as the base). Finally, we use dummy variables for the country clusters for which the North American region is the base.

In Table 2, we provide summary statistics of the data set. The regression analysis is based on the total set of 71 effect sizes, because the objective of a moderator analysis is to explain heterogeneity in the effect sizes. We also provide estimates of the mean effect size for each level of the moderator variables with nominal scale in Table 2, which gives an intuitive understanding of the influence of each moderator variable on the price–perceived quality link.

We examine the data set for outliers and influential data points (e.g., Chatterjee and Hadi, 1986), but do not classify any data points as outliers or influential. The regression analysis results, which we summarize in Table 3, demonstrate that the proposed model is significant ($F$=6.782, $p$<0.0001) and that the hypothesized moderators account for 45.2% of the variance in the observed price–perceived quality relationships. Moreover, the regression model seems free of multicollinearity (maximum variance inflation factor = 2.3; Hair et al. 1998) after we exclude the

**Table 2** Summary statistics

| Variable | Levels | Number of effect sizes | Variable mean (standard deviation) | Mean effect size (standard deviation) |
|---|---|---|---|---|
| Number of cues | Multiple cues | 59 | Nominal scale | 0.49 (0.30) |
| | Single cue | 12 | | 0.31 (0.29) |
| Experimental design | Between-subjects | 50 | Nominal scale | 0.42 (0.26) |
| | Within-subjects | 21 | | 0.54 (0.40) |
| Price manipulation | Linear effect | 71 | 0.51 (0.31) | 0.46 (0.31) |
| Price level | Linear effect | 71 | 53.93 (100.58) | 0.46 (0.31) |
| Sample | Nonstudent | 16 | Nominal scale | 0.55 (0.35) |
| | Student | 55 | | 0.43 (0.29) |
| Familiarity | Low familiarity | 45 | Nominal scale | 0.53 (0.31) |
| | High familiarity | 26 | | 0.33 (0.26) |
| Product category | Fast-moving consumer goods | 26 | Nominal scale | 0.52 (0.34) |
| | Services | 7 | | 0.35 (0.27) |
| | Durable goods | 38 | | 0.45 (0.29) |
| Country | North American countries (US/Canada) | 47 | Nominal scale | 0.41 (0.26) |
| | European countries | 16 | | 0.45 (0.29) |
| | Other (India and China) | 8 | | 0.75 (0.32) |

durable goods variable (strong positive correlation with price level) and the "other" countries variable (strong negative correlation with design).

As we show in Table 3, within-subjects designs generate greater effects than do between-subjects designs, in support of H2 and coincident with Rao and Monroe's (1989) results. However, this finding does not necessarily mean that the use of such designs is incorrect or a source of demand artifacts; rather, researchers must simply be aware that within-subjects designs generally are more powerful and should consider this point when designing their studies and developing their conclusions. Furthermore, when consumers evaluate alternative products in a store, they may be confronted with a within-subjects evaluation decision environment. For example, when walking down an aisle in a store, consumers typically view different prices. However, if a researcher is interested in, for example, the marginal impact of price information, a between-subjects design seems more appropriate (e.g., Monroe and Dodds, 1988). In other words, the choice of the design depends on, among other things, the particular research question.

Price level is significantly and positively related to effect size, in support of H4. Whereas Rao and Monroe (1989) did not find a significant association between price level and size of effect, probably because they do not include studies of relatively higher priced products, we have sufficient variance in our data to establish that the price–perceived quality relationship differs by relative price level. The significantly

**Table 3** Effects of determinants on price–perceived quality effect size (nonhomogenous data set)

| Determinant[a] | Levels | Parameter estimate (standardized) | Hypothesis |
|---|---|---|---|
| Number of cues | Multiple cues | | |
| | Single cues | −0.001ns | + |
| Experimental design | Between-subjects | | |
| | Within-subjects | +0.425*** | + |
| Price manipulation | Linear effect | +0.094ns | + |
| Price level | Linear effect | +0.212** | + |
| Sample | Nonstudent | | |
| | Student | +0.131ns | No direction |
| Familiarity | Low familiarity | | |
| | High familiarity | −0.528*** | No direction |
| Product category[b] | Fast moving consumer goods | | |
| | Services | −0.244* | No direction |
| | Durable goods | – | |
| Country[b] | North American countries (US/Canada) | | |
| | European countries | +0.264* | No direction |
| | Other (India and China) | – | |

ns=not significant.
Intercept term: unstandardized estimate=0.303.
* $p<.10$ (two-sided test).
** $p<.05$ (two-sided test).
*** $p<.01$ (two-sided test).
[a] Each categorical variable uses dummy variables; the first category is the base.
[b] Durable goods and "other" countries had to be excluded from the multivariate regression analysis because of multicollinearity.

positive effect of price level on effect size indicates that people are more likely to use simple learned heuristics based on folk wisdom, such as "you get what you pay for," for relatively expensive products.

With regard to the new determinants, familiarity with the test product (H6) is associated significantly and negatively with effect size. This finding reinforces the notion that the inferences consumers draw from a given cue are sensitive to the amount and type of other information available. As consumers gain more experience and become more familiar with a product through repeated purchase and usage, their tendency to infer product quality from readily available cues such as price decreases, which implies price is a relatively more important quality cue for new brands and products.

Furthermore, we find that the price–perceived quality relationship is lower for services than for fast-moving consumer goods, which is consistent with Bijmolt et al. (2005). A possible explanation for this result is that consumers tend to be less motivated to engage in extensive decision making for fast-moving consumer goods than for services. Consequently, they will be more apt to use easily recognizable cues such as price to facilitate their shopping. Relying on the price cue saves time and provides convenience by simplifying the decision-making process. However, our results also show that this effect declines as consumers become more familiar with the product; we find a significantly ($p<0.01$) negative interaction effect between familiarity and the dummy variable for fast-moving consumer goods.

To test the influence of durable goods, we perform a univariate regression analysis and find that studies using durable goods produce significantly lower price–perceived quality links (standardized parameter estimate = −0.288, $p<0.05$) than studies using fast-moving consumer goods. In line with our finding for services, this result seems to imply that consumers' motivation to simplify cognitive tasks is stronger for fast-moving consumer goods than for durables or services. However, this effect declines with decreasing familiarity. That is, we find a significantly ($p<0.01$) positive interaction effect between the dummy variable for durable goods and the reverse coded familiarity variable (i.e., 1 = low familiarity, 0 = high familiarity), which further supports our finding regarding familiarity. Taken together, our results pertaining to product category offer strong support for the notion that the price–perceived quality relationship differs according to the general nature of the product.

Finally, studies with respondents from European countries generate greater effects than those conducted in North American countries. One possible explanation for this finding is that price reliance may be positively correlated with a culture's level of risk aversion. Hofstede (2003) demonstrated that European countries tend to score higher on the cultural dimension of uncertainty avoidance than do North American countries. High uncertainty avoidance increases consumers' tendency to use price as an insurance policy against a bad purchase, possibly because of the higher risk aversion of members of high-uncertainty avoidance cultures. By performing a univariate regression analysis, we also find that studies conducted in other countries (e.g., economically less developed countries such as India and China) also produce significantly higher price–perceived quality links than studies conducted in North American countries ($p<0.01$).

A striking null result we find is that the number of cues does not affect the price–perceived quality relationship significantly. We additionally allow a continuous range of the number of cues, but again find no significant effect. Even different classifications involving the type of cues used in the studies reveal no significant effects (the most common additional cue was brand name, but some studies use information about the store name, the country of origin, advertisements, or other product features). Taken together with the null result indicated by Rao and Monroe (1989), this finding strongly supports the notion that multicue studies do not necessarily produce smaller price-quality effects than do single cue studies. Furthermore, the null sample result (student versus nonstudent) indicates that it is appropriate to use college students when examining the effect size and significance of price–perceived quality relationships—a particularly important result given the predominant use of college students as subjects in previous studies.

We find no significant effect of the strength of the price manipulation on the observed price–perceived quality relationship. One possible explanation for this nonsignificant effect is the so-called "range effect" that occurs in measures of attribute importance and is known from the practice of measuring consumers' preferences within the framework of multi-attribute decision making. When measuring attribute importance weights, the weights should depend on the attribute range, but empirical studies using different ranges suggest that decision makers adjust their attribute weights to a lesser degree than theoretically required (Gedenk and Sattler, 2006).

## 4 Conclusions

We present the results of a meta-analysis on the price–perceived quality link that integrates research from 1989 to 2006 and extend the range of potential determinants from Rao and Monroe's (1989) landmark study. Our meta-analysis finds an average effect size of 0.273, which means that the effect of price on perceived quality has decreased. Nevertheless, the moderately strong and highly significant average effect size indicates that consumers still use price as an important indicator of quality. Furthermore, we find that the size of the price–perceived quality relationship varies and uncover strong and statistically significant effects for several methodological and substantive determinants of the observed link between price and perceived quality.

Managers must be aware that price–quality inferences remain important aspects of consumers' behavior and consider them when setting prices. For example, setting a low selling price or lowering a price with a discount not only lowers consumer costs but also threatens to lower their perceptions of product quality through negative signaling effects. Managers should therefore be cautious when using discounts or pure penetration pricing to induce consumers to try new products or switch to less familiar brands and retailers. In these cases, consumers likely make negative price–quality inferences and begin to doubt the quality of the promoted product.

Further research might measure the dual role of price (i.e., indicator of both monetary sacrifice and product quality). Prior work has focused mainly on one price effect and rarely on both in the same study. For example, the economic theory of consumer behavior (e.g., Nagle, 1984) and research on hedonic prices (e.g., Rosen, 1974) both focus on the negative role of price, whereas marketing research tends to concentrate on the positive role of price. These two roles are conceptually distinct, yet their measurement may be confounded by the difficulty of empirically isolating their effects. Völckner and Sattler (2005) present a methodology for separating the negative and positive effects of price using a choice-based conjoint analysis approach. Because meta-analytic approaches have summarized research findings on either the negative or the positive role of price, further research should investigate how to separate and integrate findings on its dual role using meta-analytic procedures.

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