Fooled by Heteroscedastic Randomness: Local Consistency Breeds Extremity in Price-Based Quality Inferences

BART DE LANGHE
STIJN M. J. VAN OSSELAER
STEFANO PUNTONI
ANN L. MCGILL

In some product categories, low-priced brands are consistently of low quality, but high-priced brands can be anything from terrible to excellent. In other product categories, high-priced brands are consistently of high quality, but quality of low-priced brands varies widely. Three experiments demonstrate that such heteroscedasticity leads to more extreme price-based quality predictions. This finding suggests that quality inferences do not only stem from what consumers have learned about the average level of quality at different price points through exemplar memory or rule abstraction. Instead, quality predictions are also based on learning about the covariation between price and quality. That is, consumers inappropriately conflate the conditional mean of quality with the predictability of quality. We discuss implications for theories of quantitative cue learning and selective information processing, for pricing strategies and luxury branding, and for our understanding of the emergence and persistence of erroneous beliefs and stereotypes beyond the consumer realm.

Consumers frequently need to make a guess about a product's quality before buying, and this guess is often informed by price. Inferences about product quality are informed by consumers' beliefs about the price-quality relationship. Consumers may learn about the price-quality relationship based on direct experience with a product but can also learn from quality ratings provided by experts or other consumers. This article examines the latter situation where consumers learn from description. Although price is not a perfect predictor of quality across the whole price range, it frequently gives a very good indication of quality in one region of the price range. For some product categories, low prices consistently lead to the lowest quality, while higher prices are associated with varying quality. Figure 1*A*, for instance, plots ratings from *Consumer Reports* magazine for laundry detergents (2009–12). The correlation between price and quality is positive (Pearson's $r = .34$) with predictably low quality for low-priced detergents but unpredictable quality for high-priced detergents. For other product categories, high prices consistently lead to the highest quality, while lower prices are associated with varying quality. Figure 1*B*, for instance, plots ratings from *Wine Enthusiast* for Italian sparkling wines (1999–2013). The correlation between price and quality is positive (Pearson's $r = .60$) with predictably high quality for high-priced wines but unpredictable quality

Bart de Langhe (bart.delanghe@colorado.edu) is assistant professor of marketing at the Leeds School of Business, University of Colorado, 995 Regent Drive, Boulder, CO 80309. Stijn M. J. van Osselaer (stijn.vanosselaer@cornell.edu) is professor of marketing at the Samuel Curtis Johnson Graduate School of Management, Cornell University, Ithaca, NY 14853-6201. Stefano Puntoni (spuntoni@rsm.nl) is professor of marketing at the Rotterdam School of Management, Erasmus University, 3062PA Rotterdam, the Netherlands. Ann L. McGill (ann.mcgill@chicagobooth.edu) is professor of marketing at the Booth School of Business, University of Chicago, Chicago, IL 60637. Correspondence: Bart de Langhe. This article is based on the first author's doctoral dissertation. The authors acknowledge the helpful input of the editor, associate editor, and reviewers. In addition, the authors thank participants in seminars and lab groups at the University of Colorado at Boulder, Erasmus University, the University of Chicago, Cornell University, Tilburg University, INSEAD, London Business School, Columbia University, New York University, Johns Hopkins University, Virginia Tech, Hong Kong University of Science and Technology, and the Catholic University of Leuven.

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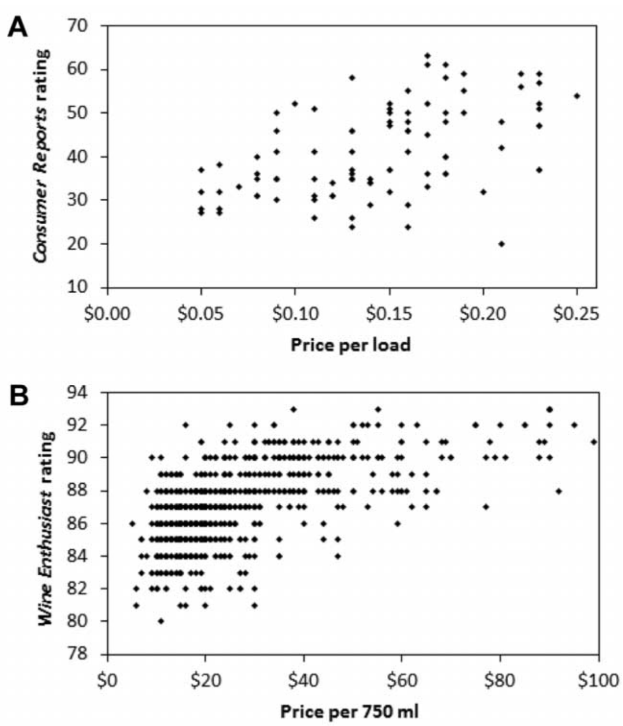
FIGURE 1

PRICES AND QUALITY SCORES FOR LAUNDRY DETERGENT AND SPARKLING WINE



NOTE.—(*A*) Conventional laundry detergents under $0.25 per load rated by *Consumer Reports* between 2009 and 2013. (*B*) Italian sparkling wines under $100 rated by *Wine Enthusiast* between 1999 and 2013.

for low-priced wines. Many other product categories show similar asymmetries in the consistency of quality across the price range (see, e.g., *Consumer Reports* ratings for kitchen knives, toilet paper, digital cameras, etc.).

Prior research in marketing that examined the actual price-quality relationship and consumer beliefs about this relationship has assumed that random variation in quality is constant across the price range. Research on how people learn functional relationships between predictive cues and continuous outcomes in psychology has also not explored whether cue-based outcome inferences may be systematically affected by whether random variation in the outcome is constant across the range of the cue or not—that is, whether randomness is homoscedastic versus heteroscedastic. We find this lack of insight surprising because many cue-outcome relationships that are relevant to people's professional and everyday lives display patterns of randomness that violate the assumption of homoscedasticity. For instance, the relationship between selling price and sales of a product is often negative with unpredictable sales for lower selling prices but consistently low sales for higher selling prices (Simon 1989). The relationship between intelligence and job performance is positive with unpredictable job performance at lower intelligence but consistently high job performance at higher intelligence (Kahneman and Ghiselli 1962). The relationship between income and violent crime rate is negative with highly variable crime rates in low-income communities but consistently low crime rates in high-income communities (Mladenka and Hill 1976).

The current article examines how people form price-based quality inferences when quality is highly consistent in one price region. How does consistently low quality at lower prices affect predicted quality at higher prices? And how does consistently high quality at higher prices affect predicted quality at lower prices? Given that cue-outcome relationships across many different judgment domains are characterized by heteroscedasticity, this research question is not only relevant for consumer decision making but also for understanding managerial, medical, legal, and policy decisions.

THEORETICAL BACKGROUND

Price-Based Quality Predictions

Quality predictions are central to marketing because they drive initial sales, customer satisfaction, repeat sales, and ultimately profit, as well as shareholder value (Aaker and Jacobson 1994; Bolton and Drew 1991; Rust, Zahorik, and Keiningham 1995). Consumers base their quality inferences on variables that are observable and correlated with quality, such as brand name (Keller 1993), advertising intensity (Kirmani and Wright 1989), warranties (Boulding and Kirmani 1993), and country of origin (Hong and Wyer 1989). Price is arguably the most commonly used cue for quality, and therefore the price-quality relationship has taken a central place in the marketing literature.

Some research analyzed the actual relationship between price and quality in the marketplace. The relationship is positive for most product categories, although it is far from perfect, and it varies considerably across product categories (Gerstner 1985; Lichtenstein and Burton 1989; Tellis and Wernerfelt 1987). Other research analyzed consumers' subjective beliefs about the relationship between price and quality. Consumers generally think that price is a good indicator of quality and that a higher price is associated with higher quality (Dawar and Parker 1994; Pechmann and Ratneshwar 1992; Rao and Monroe 1989; Teas and Agarwal 2000). A final stream of research analyzed the correspondence between the actual and the subjective price-quality relationship. Correspondence tends to be modest, and consumers often believe that the price-quality relationship is stronger than it really is (Broniarczyk and Alba 1994; Cronley et al. 2005; Kardes et al. 2004; Lichtenstein and Burton 1989).

Prior research has uncovered some moderators of price-based quality judgments. For example, Broniarczyk and Alba (1994) showed that whereas consumers generally overestimated the quality of higher priced products, this bias was reduced when another cue was present that perfectly predicted quality. Kardes et al. (2004) found that reliance on price for quality predictions was more pronounced when consumers' concern about closure was high, product information was ordered by quality, information about a large number of brands was presented, and that some of these moderators have interactive effects.

Local Consistency and Price-Based Quality Predictions

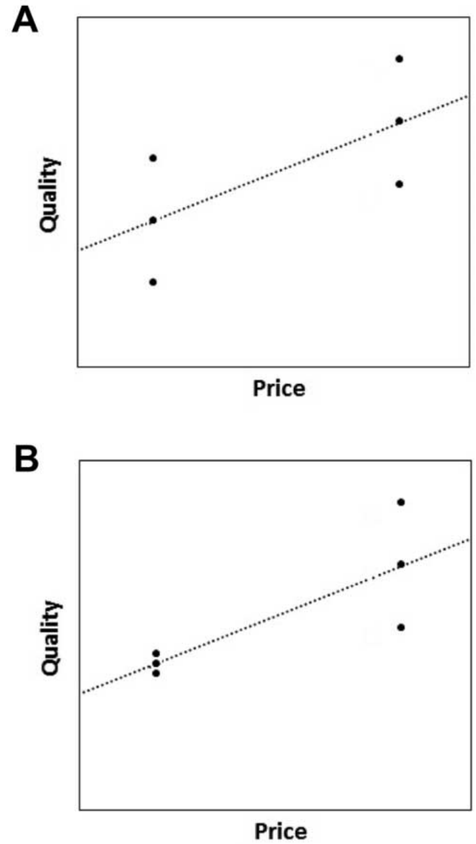
In this article, we investigate a hitherto unexplored moderator of price-based quality judgments: heteroscedasticity in the price-quality relationship. Specifically, we examine how the presence of a price region where quality is locally consistent influences quality predictions in other price regions in which consumers either have no knowledge or have previously seen that quality is hard to predict. We define local consistency as the existence of a price region with no or low unexplained variation in quality. As an example, consider a situation in which a consumer encounters three high-priced products with large variation in quality and three low-priced products with large variation in quality with a positively sloped regression line linking price and quality (see fig. 2*A*). Now suppose we substitute the three low-priced products with large variation in quality with three low-priced products with almost no variation in quality (see fig. 2*B*). Our question is what the presence of a price region in which quality is locally consistent should do to consumers' price-based quality predictions for new products in the high-price region.

Most influential cognitive models propose that people can learn to predict the expected value of an outcome for a specific cue value in one of two ways (Birnbaum 1976; De Langhe, van Osselaer, and Wierenga 2011; Einhorn, Kleinmuntz, and Kleinmuntz 1979; Juslin, Karlsson, and Olsson 2008; Juslin, Olsson, and Olsson 2003; Kelley and Busemeyer 2008; Koh and Meyer 1991). First, according to an exemplar-based process, people store previously seen cue-outcome pairs (i.e., exemplars) in memory. When making a prediction for a new target cue value, these exemplars are activated according to how close their cue values are to the cue value for the new exemplar. Thus, previously seen outcome values associated with similar cue values are weighted more than previously seen outcome values associated with dissimilar cue values. Because the prices for all low-priced products in figure 2*A* and 2*B* are identical, the influence of the quality of these low-priced products on the predicted quality for a new high-priced product should be the same. Thus, as long as the average quality of products at low price remains the same, an exemplar-based process implies the same predicted quality at high price, regardless of whether quality at low price is consistent or not.

Second, according to a cue-abstraction process, people learn a "mental rule" that maps cue values on outcome values. That is, they learn about the intercept and linear slope of the function that relates the outcome to the cue by comparing the value of the outcome at different levels of the cue. When the cue-outcome relationship is less noisy, people should find it easier to abstract the objective function, and outcome predictions lie closer to the least-squares regression line (Brehmer 1973; Brehmer and Lindberg 1970). Because the quality of low-priced products is less noisy in figure 2*B* than in 2*A*, people should find it easier to abstract the objective price-quality function; as a consequence, the predicted quality for a new high-priced product should lie closer to the average quality for high-priced products.

FIGURE 2

VISUAL REPRESENTATIONS OF QUALITY AND PRICE



NOTE.—(*A*) Visual representation of a situation where a consumer encounters noisy quality at high price and noisy quality at low price. (*B*) Visual representation of a situation where a consumer encounters noisy quality at high price and consistent quality at low price.

The Influence of Perceived Covariation on Price-Based Quality Predictions

We hypothesize that price-based quality predictions are also (at least partially) based on the perceived association strength or covariation between price and quality. Because the quality of low-priced products is less noisy in figure 2*B* than in 2*A*, the correlation between price and quality is higher in 2*B*. If price-based quality predictions in the high-price region are based at least partially on perceived covariation, this may increase predicted quality in the high-price region.

It is important to note here that a stronger price-quality correlation should not necessarily imply more extreme predictions of quality given price. If p is linearly related to q, then the relation between p and q can be represented as $q = b_0 + b_1 p + e$, where b_0 is an intercept, b_1 is the slope of the functional relationship, and e is a random variable. The expected value of q given p (i.e., $E[q|p]$) depends on the slope of the function together with the intercept. The association strength between p and q (i.e., the extent to which p is a good predictor of q, or the predictive validity of p) is instead indicated by the Pearson correlation coefficient (r), which is determined by slope but also by error variance (S_e^2) and variance of the cue (S_p^2); to wit, $r^2 = b_1^2 S_p^2 / (b_1^2 S_p^2 + S_e^2)$. This implies that the correlation between p and q can vary independently from the slope of the function relating p and q. For instance, ceteris paribus, an increase in the range of p (i.e., an increase in S_p^2) does not affect slope, but it does increase the correlation between p and q. Similarly, a decrease in error variance (i.e., a decrease in S_e^2) does not affect slope, but it does increase the correlation between p and q. Thus, holding constant intercept and slope, the average predicted quality given price should not depend on the correlation.

To the best of our knowledge, no prior studies in price-quality research or in other research about the prediction of continuous outcomes based on continuous cues have established a conflation between perceived covariation and outcome predictions. However, studies in the probability learning literature can be interpreted as being consistent with such a conflation. In this literature participants learn to predict the presence or absence of a dichotomous outcome based on whether a predictive cue is present or not. Although learning about probabilities seems very different from learning about the level of a continuous variable, and while there is a near-absence of cross-references between these literatures, there are some commonalities at a higher level of abstraction (Broniarczyk and Alba 1994; Juslin, Olsson, and Olsson 2003).

The literature on continuous learning uses (*a*) Pearson's correlation as the normative benchmark for covariation judgments and (*b*) conditional means as the normative benchmark for predictions (conditional means indicate the expected value of a variable given the value of another variable). The probability learning literature instead uses (*a*) the Phi coefficient or Delta-P as the normative benchmark for "contingency judgments" (Φ is a special case of Pearson's correlation that is used when both variables are dichotomous; ΔP is the conditional probability of the outcome given the presence of the cue minus the conditional probability of the outcome given the absence of the cue; see Allan [1980] for a review) and (*b*) conditional probabilities as the normative benchmark for predictions (conditional probabilities indicate the probability or expectation of an event given that another event has occurred; e.g., $P(outcome|cue\ present)$). Thus, Pearson correlation and Φ or ΔP can be seen as analogs because they measure covariation, and conditional mean and conditional probability can be seen as analogs because they measure the expected level of the outcome for a specific cue value.

A notable finding in the literature using dichotomous cues and outcomes is that when people are asked to judge the probability of an outcome being present given that the cue is present, their answers reflect not only the normative representation of conditional probability, $P(outcome|cue\ present)$. The answers are also influenced by the cue-outcome contingency. To give an example, consider a situation where two groups are exposed to the same probability of an outcome in the presence of a cue (say, .50) but different probabilities of the outcome in the absence of the cue (say, .50 vs. .10). There is no contingency between the cue and the outcome for the first group; the cue is not a reliable predictor of the outcome ($\Phi = 0$; $\Delta P = 0$). There is a positive contingency between the cue and the outcome for the second group; the cue is a reliable predictor of the outcome ($\Phi = .44$; $\Delta P = .40$). The conditional probability that the outcome is present given that the cue is present is equal ($P(outcome|cue\ present) = .50$), and thus normatively both groups should provide equal conditional probability judgments of the outcome when presented with the cue. However, the typical finding is that the second group who saw positive cue-outcome contingency judges the conditional probability to be higher than the first group who saw no cue-outcome contingency. Conditional probability judgments are thus more extreme when the cue is perceived to be a better predictor of the outcome. In other words, conditional probability judgments are biased by perceived contingency (Mitchell et al. 2013; Price and Yates 1995; for a review, see Lagnado and Shanks [2002]). In the same vein, predictions for a continuous outcome at a specific cue value (e.g., a prediction of quality at high price) may be biased by perceived covariation (e.g., the extent to which one believes that price is a good predictor of quality).

Returning to the scenario in figure 2, if consumers base their predictions of quality given price on perceived covariation, the presence of a price region where quality is locally consistent (see fig. 2*B*) should increase predicted quality at high price. This would be the case because greater consistency in quality increases the Pearson correlation between price and quality, leading to an increase in the perceived covariation between price and quality that in turn drives price-based quality predictions. Of course, judgments of covariation do not conform perfectly to objective differences in Pearson correlation (Crocker 1981; Lane, Anderson, and Kellam 1985). Price-based quality predictions should thus be traced to differences in perceived covariation and not differences in objective correlation. In other words, a configuration of price-quality pairs that is characterized

TABLE 1

PRICE-QUALITY PAIRS USED IN STUDY 1

	Condition 1		Condition 2		Condition 3			Condition 4		
Local consistency:	Yes		No		Yes			No		
Cue competition:	No		No		Yes			Yes		
	Price	Rating	Price	Rating	Price	Cuisine	Rating	Price	Cuisine	Rating
	$$$	**	$$$	**	$$$	Chinese	**	$$$	Chinese	**
	$$$	***	$$$	***	$$$	Chinese	***	$$$	Chinese	***
	$$$	****	$$$	****	$$$	Chinese	****	$$$	Chinese	****
	$$$$	****	$$$$	***	$$$$	Italian	****	$$$$	Italian	***
	$$$$	****	$$$$	****	$$$$	Italian	****	$$$$	Italian	****
	$$$$	****	$$$$	*****	$$$$	Italian	****	$$$$	Italian	*****

by local consistency may lead to more extreme price-based quality predictions relative to a configuration of price-quality pairs that is not characterized by local consistency, even if both configurations have the same objective correlation. In sum, we hypothesize that consumers will be fooled by local consistency: Ceteris paribus, experiencing consistently low (high) quality products at lower (higher) prices should lead to more extreme price-based quality predictions at higher (lower) prices.

OVERVIEW OF STUDIES

In study 1, we examine whether quality predictions in a price region that participants have no direct quality information about are more extreme when quality is locally consistent in another price region (and the price-quality correlation is higher) compared to when quality is not consistent in any price region (and the price-quality correlation is lower). We also test whether the biasing effect of local consistency generalizes to situations in which products are described on more than one cue, not just price. In study 2, we manipulate heteroscedasticity in the relationship between price and quality while keeping the objective price-quality correlation constant. Participants in this study make predictions in a price region where they have previously seen that quality is noisy (as opposed to a price region of which participants have no prior knowledge). In study 3, we examine the effect of local consistency in a situation in which objective correlation is undefined. Participants learn about quality at one price point only. Quality at this price point is either locally consistent or inconsistent and based on that knowledge participants predict quality in another price region.

The experiments address two major ways in which consumers may learn about the price-quality relationship. Sometimes consumers learn about the price-quality relationship through list-based information that presents price and quality information simultaneously for many products. For example, consumers may visit websites such as Yelp.com or Urbanspoon.com to decide which restaurant to go to. On these websites, several restaurants are listed based on few attributes, primarily price and an overall quality rating (often provided by other users), all presented at the same time. To structurally mimic such a simultaneous learning process in an experimental setting, studies 1 and 3 adopt a learning paradigm in which participants are exposed to a number of restaurants with varying prices and quality ratings in tabular format. At other times, consumers learn about one product at a time (i.e., the information is not available all at once). For instance, a consumer may learn about the price and quality rating for a wine on one day and about the price and quality rating for another wine a few days later. To approximate such a sequential learning process in a lab setting, study 2 adopts a learning paradigm in which participants are exposed to products with varying prices and quality scores one by one. Following prior work on consumer learning, we use wines as the target product category (van Osselaer, Janiszewski, and Cunha 2004).

STUDY 1

Study 1 had four conditions. Participants in the first condition were exposed to three restaurants of varying quality at intermediate prices, together with three restaurants of consistently high quality at high prices (see table 1, condition 1). Participants in the second condition were exposed to three restaurants of varying quality at intermediate prices, together with three restaurants of varying quality at high prices (see table 1, condition 2). The average quality given price was the same in both conditions. After this learning phase, all participants judged the relationship strength between price and quality and, more importantly, predicted the average quality for restaurants in the low-price region. We are interested in the extremity of quality predictions: are they equally, less, or more extreme when quality is consistent in another price region? Our hypothesis is that the perceived covariation between price and quality is higher when quality is consistent in one price region (condition 1) than when it is not (condition 2) and that consumers use their perception of high covariation as a basis for their quality predictions. This should lead to lower quality predictions in the low-price region.

Consumers often see and use more than one cue for quality, and these cues are oftentimes correlated. Correlated cues lead to cue competition, which may reduce the effect of price on quality predictions (Pavlov 1927; van Osselaer and Alba 2003). Thus, the presence of another cue in addition to price may reduce any effect involving price. We therefore added two more conditions that are identical to the first two conditions except that in these conditions participants saw a second cue that is perfectly correlated with price (see table 1, conditions 3 and 4). We added this manipulation for generalizability and robustness.

Method

Participants and Design. One hundred and thirty-nine undergraduate students at the University of Colorado Leeds School of Business participated for course credit (70 females; $M_{age} = 20.20$, SD $= 2.19$). The study used a 2 (locally consistent information: no vs. yes) × 2 (cue competition: no vs. yes) full factorial experimental design. Participants were randomly assigned to conditions. The local consistency factor indicates whether quality was consistently high or variable with the same high mean when price was high. The cue competition factor indicates whether or not the table presented a second cue—cuisine (Chinese vs. Italian)—that correlated perfectly with price.

Procedure. Participants were instructed that they would receive information about restaurants and were asked to carefully examine the price and corresponding consumer ratings for the restaurants. The instructions indicated that the price of the restaurants could be very low ($), low ($$), medium ($$$), high ($$$$), or very high ($$$$$) and that the consumer rating of the restaurants could be very low (*), low (**), medium (***), high (****), or very high (*****). Next, participants saw a table with information on the price and average consumer rating for six restaurants. The restaurants were ordered in increasing price order. Three of the restaurants were medium priced ($$$) and had quality levels of low (**), medium (***), and high quality (****), respectively. The three other restaurants were high priced ($$$$). In the condition with locally consistent information, all three high-priced restaurants were of high quality (****). In the condition without locally consistent information, the three high-priced restaurants were of medium (***), high (****), and very high quality (*****), respectively. Thus, the tables were identical except for the consistency of the quality rating for high-priced restaurants. The tables in the cue competition and no cue competition conditions were identical except for the presence of a cuisine cue that was perfectly correlated with price (i.e., all medium-priced restaurants were Chinese, whereas all high-priced restaurants were Italian). Table 1 presents the four tables that were presented to participants across conditions.

On the following page, we asked participants to rate three statements on a scale from 1 (completely disagree) to 7 (completely agree): "Generally speaking, the higher the price of the restaurant, the higher the consumer rating"; "Generally speaking, the lower the price of the restaurant, the lower the consumer rating"; and "The price of a restaurant is a good indicator of its consumer rating." We averaged participants' ratings across these items to obtain an index of the perceived covariation between price and quality (Cronbach's $\alpha = 0.64$). We then asked all participants to predict the average consumer rating for a restaurant with a low price ($$), which was below the price range of restaurants presented in the table and was the dependent variable in this study. To allow estimating the slope of the subjective price-quality function, we also asked participants to rate the quality of a restaurant with a high price ($$$$). Participants received no information about cuisine at this stage.

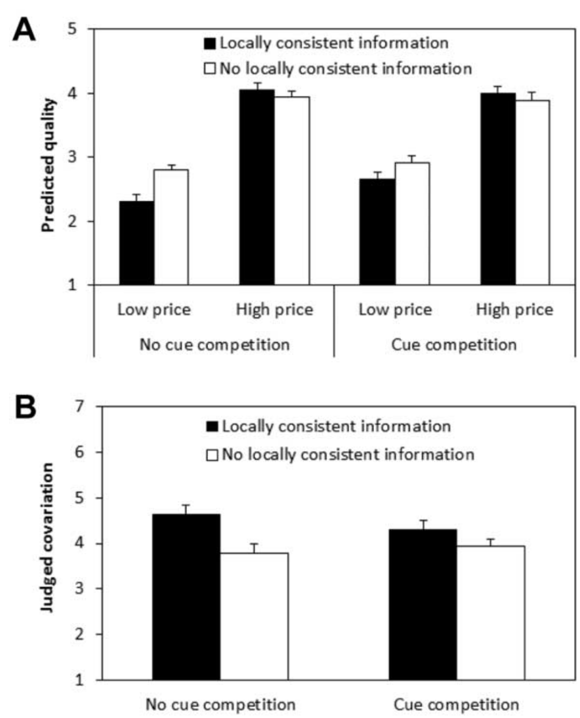
Results

Predicted Quality. Figure 3*A* plots predicted quality for the new restaurants by condition. We analyzed predictions with a repeated-measures ANOVA in which we entered price of the new restaurant (low price vs. high price) as a within-participant factor, and we entered local consistency (no vs. yes) and cue competition (no vs. yes) as between-participant factors. Not surprisingly given the positive relationship between price and quality scores presented in the tables, this analysis revealed a main effect for the price of the new restaurant ($F(1, 135) = 302.94$, $p < .001$). Participants predicted lower quality for the low-priced restaurant ($M = 2.67$) than for the high-priced restaurant ($M = 3.97$). This effect was qualified by two two-way interactions.

First, there was an interaction effect with cue competition ($F(1, 135) = 3.82$, $p = .05$). Quality predictions were less

FIGURE 3

RESULTS FOR STUDY 1



sensitive to price when the table presented information about cuisine than when the table did not present information about cuisine. That is, the difference between predicted quality for low-priced and high-priced restaurants was greater in the condition with no cue competition ($M = 1.44$) than in the condition with cue competition ($M = 1.15$). This is consistent with existing demonstrations of cue competition effects showing that the effect of one cue on quality judgments (i.e., price) is reduced when another, equally predictive cue (i.e., cuisine) is presented (van Osselaer and Alba 2003).

Second, and more important, there was an interaction effect with local consistency ($F(1, 135) = 10.81$, $p < .01$). Predictions for the low-priced restaurant were more extreme (i.e., lower) when quality for high-priced restaurants was consistently high (always ****, $M = 2.49$) rather than variable with the same mean (one ***, one ****, and one *****; $M = 2.86$; $t(135) = -3.77$, $p < .001$). Thus, the data confirm our hypothesis that locally consistent quality in one price region (i.e., the high-price region) leads to more extreme price-based quality predictions in another price region (i.e., the low-price region). The tabular format with a limited number of restaurants made it very easy to recall the average quality of the three high-priced restaurants when judging the quality of a new restaurant at exactly the same price. Therefore, we expected predicted quality for the high-priced ($$$$) restaurant to be close to the conditional mean (i.e., four indicating ****) regardless of consistency. This was indeed the case. Predicted quality for the high-priced restaurant did not depend on consistency ($M_{\text{yes}} = 4.03$ vs. $M_{\text{no}} = 3.92$; $p = .27$) and was very close to four stars. As a result, the difference between predicted quality for the low-priced restaurant and predicted quality for the high-priced restaurant was greater in the condition with locally consistent information ($M = 1.54$) than in the condition without locally consistent information ($M = 1.06$; $t(135) = -3.29$, $p < .01$). Quality predictions were thus more strongly dependent on price in the condition where quality for high-priced restaurants was consistently high than in the condition where quality for high-priced restaurants was high but not consistently so. No other effects in the model were statistically significant. Specifically, the three-way interaction effect between the price of the new restaurant, local consistency, and cue competition was not significant ($p = .42$). This indicates that the effect of local consistency on prediction extremity does not significantly depend on cue competition. That is, regardless of whether quality predictions depend on price more (i.e., in the no cue competition condition) or less (i.e., in the cue competition condition), consistently high quality at high price increased the extremity of predicted quality in the low-price region.

Judged Covariation. Figure 3*B* plots covariation judgments by condition. We analyzed judgments with a two-way ANOVA in which we entered local consistency (no vs. yes) and presence of a competing cue (no vs. yes) as between-participant factors. Unsurprisingly, given the fact that objectively the price-quality correlation is higher in the conditions with locally consistent information, this analysis revealed a main effect of local consistency ($F(1, 135) = 9.99$, $p < .001$). Participants judged the relationship between price and quality as stronger when quality for high-priced restaurants was consistently high ($M_{\text{yes}} = 4.46$ vs. $M_{\text{no}} = 3.86$). There was no main effect of cuisine ($p = .63$) and no interaction effect between local consistency and cuisine ($p = .24$).

We hypothesized that consumers inappropriately use their perception of price-quality covariation to make quality predictions. To examine whether there is a significant indirect effect of consistency on predicted quality through perceived covariation, we used the bootstrapping procedure by Preacher and Hayes (2004; see Zhao, Lynch, and Chen [2010], for why it is preferable to use this method over the Sobel test). This procedure generates a 95% confidence interval (CI) around the indirect effect and mediation is significant if zero falls outside that confidence interval. The indirect effect involving perceived covariation was significant (95% CI $= -.09$ to $-.02$) indicating significant mediation through this path.

Discussion

Study 1 shows that predicted quality at low price is lower when quality at high price is consistently high than when quality at high price is high but not consistently so. This effect holds also in the presence of a competing cue. This pattern of results is inconsistent with an exemplar-based process according to which predicted quality depends on the average quality encountered at different prices, not the consistency of quality. The pattern of results could be consistent with a cue-abstraction process according to which people learn about the intercept and slope of the function relating quality to price. Indeed, when quality is consistent at high price, predicted quality at low price lies closer to the level of quality implied by the objective least-squares regression line (i.e., closer to 2). However, when people make predictions in a price region about which they have no prior knowledge, quality predictions may be more regressive in general. Given that participants made predictions outside of the range of prices used in the training phase, we cannot compare predicted quality with the actual average quality at low price, and thus we cannot rule out a cue-abstraction process purely based on quality predictions in this study. Although our mediation analysis supports our hypothesis that perceived association strength between price and quality feeds into consumers' price-based quality predictions, we address this issue more conclusively in the next study where participants make predictions within the range of prices used in the training phase.

STUDY 2

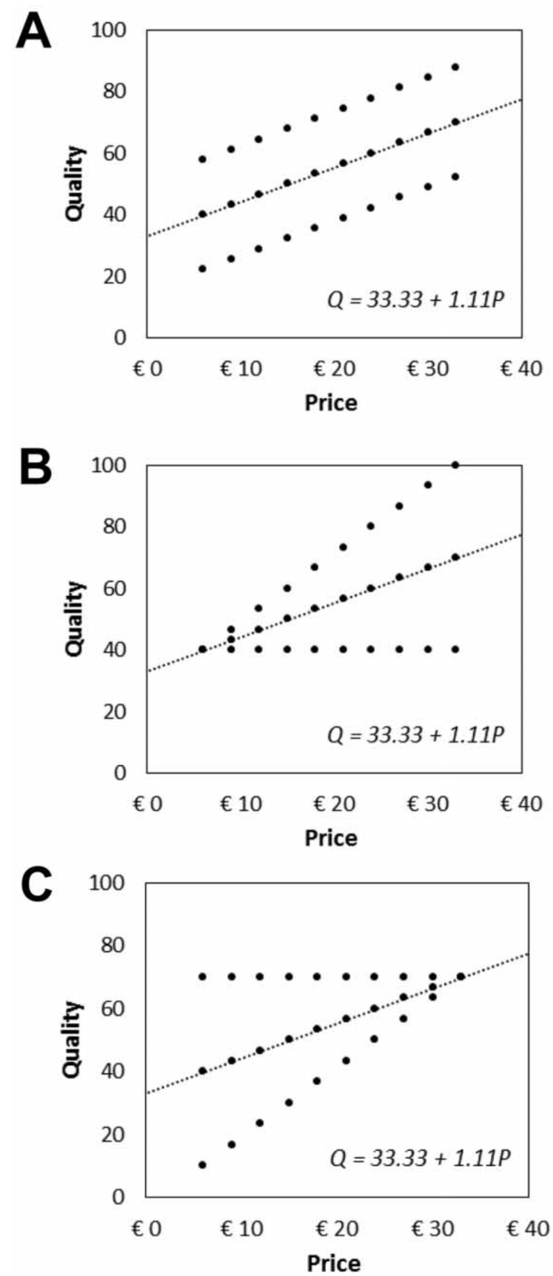
In the previous study, actual covariation between price and quality as expressed by the Pearson correlation coefficient was higher in the conditions with locally consistent information (0.65 vs. 0.52). Thus, it is possible that our core effect is driven by the objective correlation between price and quality instead of local consistency in itself. In study 2, we examine whether the effect of local consistency on prediction extremity occurs even when there is no difference in objective correlation. Specifically, we explore whether a heteroscedastic price-quality relationship in which quality is highly consistent in one price region would yield overly extreme quality predictions in other price regions even when not just the average quality given price but also the overall correlation between price and quality is kept constant. To do this, we developed three sets of price-quality pairs that had the same slope (i.e., the same average quality given price) and the same correlation between price and quality. The three sets only differed in terms of how randomness was distributed across the price range. Randomness was homoscedastic in the first condition: quality was moderately inconsistent across the price range (see fig. 4*A*). Randomness was heteroscedastic and increasing in the second condition: quality was consistently low for low prices but highly inconsistent for high prices (i.e., as in the laundry detergent category; see fig. 4*B*). Randomness was heteroscedastic and decreasing in the third condition: quality was consistently high for high prices but highly inconsistent for low prices (i.e., as in the Italian sparkling wines category; see fig. 4*C*).

We expected that, although the price-quality correlation was identical across conditions, participants would make more extreme predictions in the conditions with heteroscedastic randomness. This is because in these conditions, there was one price region in which quality was highly accordant with the hypothesis of a strong relationship (i.e., strong perceived covariation), which in turn provides the basis for extreme quality predictions. Low-priced products were consistently of low quality in condition 2, and high-priced products were consistently of high quality in condition 3; moderate levels of error were present across the price range in the homoscedastic condition 1.

Three additional differences with the previous studies are worth mentioning. First, participants in study 2 encountered prices and quality scores across the whole price range in the training phase, and they also made quality predictions across the whole price range in the test phase. This feature of the design allows us to examine the slope of participants' price-based quality predictions (i.e., the sensitivity of participants' quality predictions to price), as well as compare participants' quality predictions with the actual average quality encountered in different price regions in the training phase (i.e., the deviation between participants' predicted quality at a price point and the actual average quality at that price point). Second, eliciting quality predictions in the absence of a measure of covariation rules out the possibility that the presence of a measure of covariation is required to observe an effect of local consistency on prediction extremity. Third, in study 2 we test our hypothesis using a sequential format where participants encounter products one by one instead of the tabular format used in study 1.

FIGURE 4

GRAPHICAL REPRESENTATION OF PRICE-QUALITY DATA PRESENTED TO PARTICIPANTS DURING THE TRAINING PHASE OF STUDY 2



NOTE.—These price-quality configurations were presented to participants with a small random component added to both price and quality. (*A*) Quality is never consistent; (*B*) quality is consistently low for low price; (*C*) quality is consistently high for high price.

Method

Participants and Design. One hundred and fourteen undergraduate students at Erasmus University Rotterdam School of Management took part in this study in exchange for course credit (54 females; $M_{age} = 19.96$, SD $= 2.05$). The study used a three-group design in which we manipulated between participants the presence and location of a price region with consistent quality. In the first condition, quality was never consistent. In the second condition, quality was consistently low at low price. In the third condition, quality was consistently high at high price.

Procedure. The study consisted of two phases. The first phase was a training phase in which we presented participants with the prices and quality scores for several Chilean wine brands. In this phase, we manipulated the local consistency of quality. The second phase was a test phase in which we asked participants to estimate wine quality for several new wine brands sampled across the price range.

In the first phase, we presented participants sequentially with 30 different Chilean wine brands and their respective selling prices. We asked participants to estimate the quality of each brand. Each time, after having made a quality prediction, participants received feedback about the actual quality of the brand. Quality was expressed as a score ranging from 0 to 100. We instructed participants to observe the price (p) and quality (q) for each brand carefully and told them that the actual quality was determined by a panel of wine experts in a blind taste test. Unknown to participants, the quality of the wine was predetermined according to the following formula:

$$q = 33.33 + 1.11p + \varepsilon.$$

Selling prices ranged from €5 to €34. We divided the price range in 10 blocks of three different prices (i.e., block 1 ranged from €5 to €7, block 2 ranged from €8 to €10 . . . and block 10 ranged from €32 to €34), and we randomly sampled three prices with replacement from each block. For each triplet of prices drawn from each of the 10 price blocks, we added a positive error component to the quality score of the first price, a negative error component (equal in absolute value to the positive error component) to the quality score of the second price, and no error component to the quality score of the third price. In the condition with consistently low quality for low prices, the error component was 0 in block 1 and increased with 3.33 with every price block. We reversed this procedure to obtain the error terms for the condition with consistently high quality for high prices. In the condition where quality was never consistent, the error component was instead set to 17.80 in all 10 price blocks. This procedure ensured that the slope of the price-quality function and the correlation between price and quality were the same across conditions ($b_1 = 1.11$ and Pearson's $r = 0.55$). Figure 4 graphically represents the price-quality pairs presented in the condition where quality was never consistent (fig. 4*A*), the condition with consistently low quality in the low-price region (fig. 4*B*), and the condition with consistently high quality in the high-price region (fig. 4*C*).

In the second phase, we presented participants with 10 new Chilean wine brands and their prices (one price from each of the 10 price blocks). For each brand, we asked participants to estimate quality on a scale from 0 to 100.

Results

We examined the effect of local consistency on prediction extremity by fitting a mixed general linear model to participants' quality estimates:

$$y_{ij} = \beta_0 + \delta_{0A}D_A + \delta_{0B}D_B + (\beta_1 + \delta_{1A}D_A + \delta_{1B}D_B)(p_{ij}) + (u_{0i} + u_{1i}p_{ij} + \varepsilon_{ij}),$$

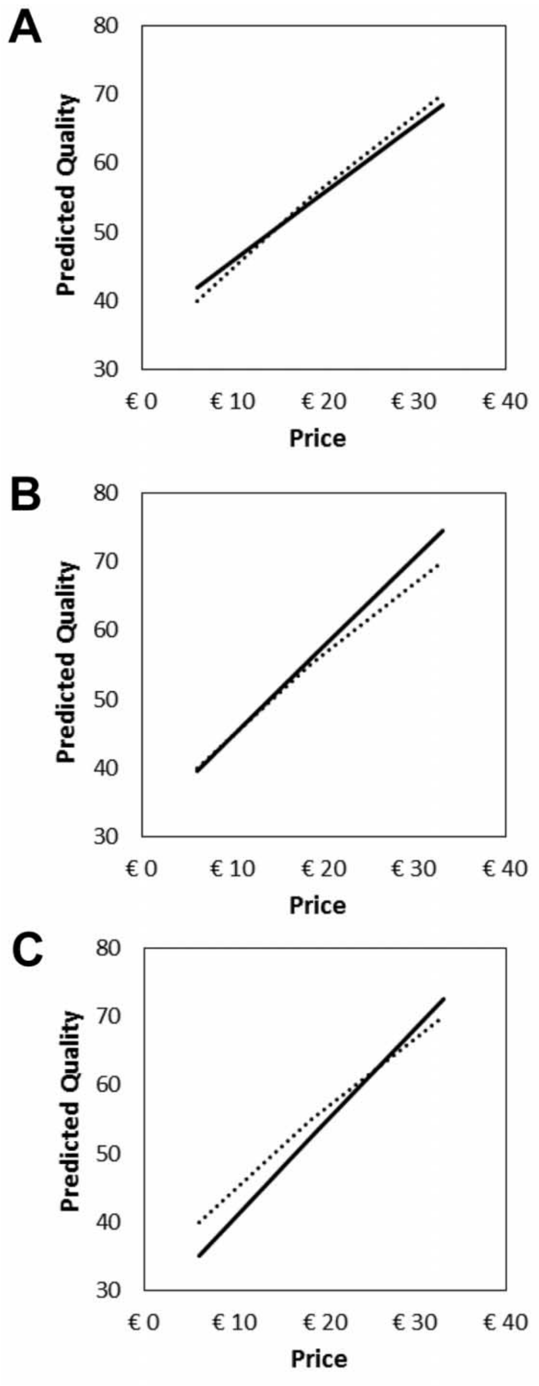
where y_{ij} is the predicted quality by participant i on trial j, D_A is a dummy variable taking a value of 1 for observations in the condition with consistently low quality at low price and 0 otherwise, D_B is a dummy variable taking a value of 1 for observations in the condition with consistently high quality at high price and 0 otherwise, β_0 is the regression intercept in the condition where quality is never consistent, δ_{0A} and δ_{0B} are fixed effects indicating deviations from the regression intercept in the condition where quality is never consistent, β_1 is the regression slope of price in the condition where quality is never consistent, δ_{1A} and δ_{1B} are fixed effects indicating deviations from the regression slope in the condition where quality is never consistent, p_{ij} is the selling price (mean-centered) of the brand that is presented to participant i on trial j, u_{0i} is a random effect indicating the participant-specific deviation from the regression intercept, u_{1i} is a random effect indicating the participant-specific deviation from the regression slope, and ε_{ij} is a random error component. Figure 5 plots the least-squares mean quality estimates across the price range for each of the three conditions relative to the actual encountered quality in the training phase.

The parameters of interest are the fixed effects in the model (see table 2). The regression slope for price in the condition where quality is never consistent (β_1) is significantly greater than 0. This indicates that participants in this condition provide higher quality estimates for higher priced wines than for lower priced wines. This is of course in line with the price-quality data that participants encountered in the training phase. Crucially, δ_{1A} and δ_{1B} are also significantly greater than 0. This implies that, relative to the condition where quality is never consistent, the regression slope for price is steeper in both conditions where quality is locally consistent. Specifically, for the same unit increase in price participants who consistently encountered low quality at low price expect a 33% (δ_{1A}/β_1) greater increase in quality than participants who never encountered consistent quality. Similarly, for the same unit increase in price participants who consistently encountered high quality at high price expect a 41% (δ_{1B}/β_1) greater increase in quality than participants who never encountered consistent quality.

As can be seen from figure 5, participants' quality esti-

FIGURE 5

LEAST-SQUARES REGRESSION LINES FOR PREDICTED QUALITY DURING THE TEST PHASE



NOTE.—Least-squares regression lines for predicted quality during the test phase (*solid lines*) relative to regression lines for actual quality encountered during the training phase (*dotted lines*) in study 2. (*A*) When quality is never consistent; (*B*) when quality is consistently low for low price; (*C*) when quality is consistently high for high price.

mates in the condition where quality is never consistent lie close to the actual average quality encountered by participants at different price points. In the conditions where quality is locally consistent, participants' quality estimates are less accurate. However, participants in the locally consistent conditions do not over- or underestimate quality uniformly across the price range. As expected, the inaccuracy is concentrated in the price regions where quality is more variable (i.e., in the high price region when quality is consistently low at low price and in the low price region when quality is consistently high at high price).

To examine prediction accuracy in the condition where quality is never consistent, we again used the mixed general linear model specified above but now fitted it to the deviation of participants' quality estimates from the actual encountered average quality at any given price. That is, for each price, we subtracted the average quality encountered during the training phase from participants' quality predictions in the test phase. Thus, difference scores below zero reflect quality estimates that are lower than the average quality encountered for that price in the training phase. Difference scores above zero reflect quality estimates that are higher than the average quality encountered for that price in the training phase. In this model, β_0 is the regression intercept in the condition where quality is never consistent. When price is mean-centered, it indicates how participants' quality estimates for the average price in the condition where quality is never consistent deviate from the actual average quality encountered for average-priced wines in the training phase. We are interested in the accuracy of participants' quality estimates in the high and the low price regions. For both high-priced wines (i.e., spotlight analysis with price centered at €34; $\beta_0 = -1.68$, SE $= 1.56$, $p > .28$) and low-priced wines (i.e., spotlight analysis with price centered at €5; $\beta_0 = 2.12$, SE $= 1.56$, $p > .17$), participants' quality estimates in the homoscedastic control condition where quality is never consistent do not deviate significantly from the average quality encountered for high-priced and low-priced wines in the training phase.

To examine prediction accuracy in the condition with consistently low quality at low price, we estimated the same mixed general linear model after changing the dummy-coding. We now specified D_A as a dummy variable (taking a value of 1 for observations in the condition where quality is never consistent and 0 otherwise) and D_B as a dummy variable (taking a value of 1 for observations in the condition with consistently high quality at high price and 0 otherwise). In this model, β_0 is the regression intercept in the condition with consistently low quality at low price. When price is mean-centered, it indicates how participants' quality estimates for the average price in the condition with consistently low quality at low price deviate from the actual average quality encountered for average-priced wines in the training phase. We are interested in the accuracy of participants' quality estimates in the high- and the low-price regions. For high-priced wines (i.e., spotlight analysis with price centered at €34; $\beta_0 = 4.69$, SE $= 1.60$, $p < .01$), participants' quality

TABLE 2

PARAMETER ESTIMATES FOR FIXED EFFECTS, STANDARD ERRORS, AND CORRESPONDING *P*-VALUES FOR THE MIXED GENERAL LINEAR MODEL ESTIMATES IN STUDY 2

Parameter	Estimate	Standard error	*P*
β_0, the mean predicted quality in the homoscedastic condition	55.22	1.22	<.001
δ_{0A}, deviation of the mean predicted quality in the heteroscedastic increasing condition from the mean predicted quality in the homoscedastic condition	1.79	1.75	>.30
δ_{0B}, deviation of the mean predicted quality in the heteroscedastic decreasing condition deviates from the mean predicted quality in the homoscedastic condition	−1.43	1.74	>.41
β_1, deviation of the slope of the subjective price-quality function in the homoscedastic condition	.98	.11	<.001
δ_{1A}, deviation of the slope of the subjective price-quality function in the heteroscedastic increasing condition deviates from the slope in the homoscedastic condition	.32	.15	<.05
δ_{1B}, deviation of the slope of the subjective price-quality function in the heteroscedastic decreasing condition deviates from the slope in the homoscedastic condition	.40	.15	<.01

estimates in the condition with consistently low quality at low price are significantly higher than the average quality encountered for high-priced wines in the training phase. For low-priced wines (i.e., spotlight analysis with price centered at €5; $\beta_0 = -0.67$, SE $= 1.60$, $p > .67$), participants' quality estimates in the condition with consistently low quality at low price do not deviate significantly from the average quality encountered for low-priced wines in the training phase.

To examine prediction accuracy in the condition with consistently high quality at high price, we estimated the same mixed general linear model after changing the dummy coding. We now specified D_A as a dummy variable (taking a value of 1 for observations in the condition where quality is never consistent and 0 otherwise) and D_B as a dummy variable (taking a value of 1 for observations in the condition where quality is consistently low at low price and 0 otherwise). In this model, β_0 is the regression intercept in the condition with consistently high quality at high price. When price is mean-centered, it indicates how participants' quality estimates for the average price in the condition with consistently high quality at high price deviate from the actual average quality encountered for average-priced wines in the training phase. We are interested in the accuracy of participants' quality estimates in the high- and the low-price regions. For high-priced wines (i.e., spotlight analysis with price centered at €34; $\beta_0 = 2.76$, SE $= 1.58$, $p > .08$), participants' quality estimates in the condition with consistently high quality at high price do not deviate significantly from the average quality encountered for high-priced wines in the training phase. For low-priced wines (i.e., spotlight analysis with price centered at €5; $\beta_0 = -5.18$, SE $= 1.58$, $p < .01$), participants' quality estimates in the condition with consistently high quality at high price are significantly lower than the average quality encountered for low-priced wines in the training phase.

Discussion

Study 2 supports the conclusion that local consistency breeds prediction extremity. Even when the Pearson correlation between price and quality was kept constant, the existence of a locally consistent price region led to more extreme quality predictions in other price regions. The existence of one region that is clearly accordant with the existence of a strong price-quality relationship is enough to create the perception of a strong relationship and this perception drives the extremity of quality predictions. Because participants in study 2 made predictions within the range of prices encountered in the training phase, we could also examine the accuracy of quality predictions. We find that if low-priced wine is consistently of low quality, consumers overestimate the quality of high-priced wine. Similarly, if high-priced wine is consistently of high quality, consumers underestimate the quality of low-priced wine. Our results are inconsistent with a cue-abstraction process. Relative to the control condition where quality is never consistent, it should be easier to abstract the function relating quality to price when quality is highly consistent in one price region. As a consequence, predictions should lie closer to the average level of quality given the price encountered in the training phase (i.e., the objective least-squares regression line). We find the opposite pattern: local consistency reduces accuracy.

STUDY 3

In study 3, we manipulated whether participants were exposed to the quality of restaurants at two prices versus at one price only. When participants are exposed to one price only, the correlation between price and quality is not defined (because there is no variation in price), and thus we can manipulate local consistency independent of correlation. For

TABLE 3

PRICE-QUALITY PAIRS USED IN STUDY 3

	Condition 1		Condition 2		Condition 3		Condition 4	
Prediction region:	Low price ($$)		Low price ($$)		High price ($$$$)		High price ($$$$)	
Local consistency:	Yes		No		Yes		No	
Training:	Two prices		Two prices		Two prices		Two prices	
	Price	Rating	Price	Rating	Price	Rating	Price	Rating
	$$$	**	$$$	**	$$	**	$$	*
	$$$	***	$$$	***	$$	**	$$	**
	$$$	****	$$$	****	$$	**	$$	***
	$$$$	****	$$$$	***	$$$	**	$$$	**
	$$$$	****	$$$$	****	$$$	***	$$$	***
	$$$$	****	$$$$	*****	$$$	****	$$$	****
	Condition 5		Condition 6		Condition 7		Condition 8	
Prediction region:	Low price ($$)		Low price ($$)		High price ($$$$)		High price ($$$$)	
Local consistency:	Yes		No		Yes		No	
Training:	One price		One price		One price		One price	
	Price	Rating	Price	Rating	Price	Rating	Price	Rating
	$$$$	****	$$$$	***	$$	**	$$	*
	$$$$	****	$$$$	****	$$	**	$$	**
	$$$$	****	$$$$	*****	$$	**	$$	***

instance, participants in a high-consistency condition could be exposed to three restaurants with the same low price and low quality, while participants in the low-consistency condition could be exposed to three restaurants with the same low price and same low average quality but with high variation in quality. If participants in the conditions where local consistency is high still make more extreme predictions in the high-price region, we can be sure that local consistency is enough to breed extremity (i.e., the extreme prediction effect does not necessitate differences in objective correlation).

Method

Participants and Design. We paid 184 respondents from Amazon Mechanical Turk a small amount to participate (59 females; M_{age} = 28.04, SD = 8.87). The study used a 2 (prediction region: low price vs. high price) × 2 (local consistency: no vs. yes) × 2 (training: one price vs. two prices) full factorial experimental design. Participants were randomly allocated to conditions. The "prediction region" factor indicates whether participants were trained in the higher price region and predicted quality at low price versus participants who were trained in the lower price region and predicted quality at high price. This factor is included for generalization to ascertain that our effect occurs with quality predictions of both high- and low-priced products. The "local consistency" factor indicates whether participants saw that quality was consistent versus not at least at one price level. This is the main independent variable driving our core effect of consistent price-quality information in one price region on quality predictions in other price regions. The "training" factor indicates whether participants obtained information about quality at one or two levels of price. Contrasting the effect of consistency on quality predictions when participants have encountered products in just one region versus in two regions allows us to assess whether the effect of local consistency requires differences in objective correlation versus only requires the presence or absence of consistent price-quality information in one price region.

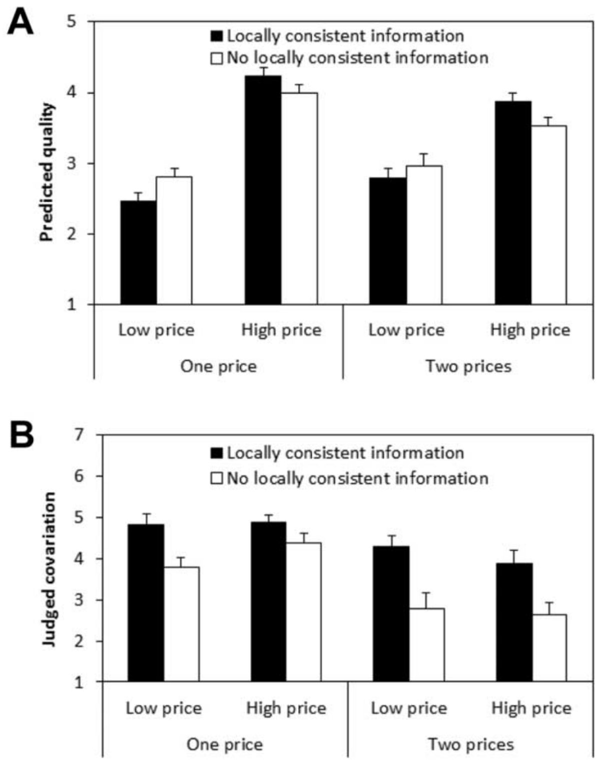
Procedure. As in study 1, participants saw a table with information on the price and consumer rating for several restaurants (three restaurants in the one price training condition and six restaurants in the two prices training condition). Table 3 presents the eight tables that were presented to participants across conditions. On the following page, we asked participants to rate the three statements we used in study 1 to assess perceived covariation between price and quality (Cronbach's α = 0.89). We then asked participants to predict the average consumer rating for a restaurant with a price outside the price region presented in the table. Specifically, participants trained in the higher price region predicted the quality of a low-priced restaurant ($$), and participants trained in the lower price region predicted the quality of a high-priced restaurant ($$$$).

Results

Predicted Quality. Figure 6*A* plots predicted quality for the new restaurant by condition. We analyzed predictions with a three-way ANOVA in which we entered prediction region (low price vs. high price), local consistency (no vs. yes), and training (one price vs. two prices) as between-participant factors. As in the previous studies, this analysis revealed the obvious main effect of prediction region (F(1, 176) = 156.68, p < .001). The predicted quality rating was lower when the prediction was for a low-priced restaurant

FIGURE 6

RESULTS STUDY 3



(M = 2.75) than when the prediction was for a high-priced restaurant (M = 3.91). Critically, this effect was qualified by an interaction effect with local consistency ($F(1, 176) = 9.23$, $p < .01$). This replicates the core finding in the previous studies. Predictions for the low-priced restaurant were more extreme (i.e., lower) when quality was consistently high for high-priced restaurants ($M_{yes} = 2.62$ vs. $M_{no} = 2.89$; $t(176) = -1.99$, $p < .05$). Similarly, predictions for the high-priced restaurant were more extreme (i.e., higher) when quality was consistently low for low-priced restaurants ($M_{yes} = 4.06$ vs. $M_{no} = 3.74$; $t(176) = 2.31$, $p < .05$). This two-way interaction was not qualified by a three-way interaction with training ($p = .86$). This indicates that the effect of local consistency on extremity does not depend on whether the objective correlation between price and quality was defined or not. That is, confirming our core hypothesis, we found that regardless of whether participants observed quality at one price or at two prices, quality predictions were more extreme when local consistency was high than when local consistency was low. Collapsing over local consistency, the analysis also revealed an interaction effect between price region and training ($F(1, 176) = 12.73$, $p < .001$). Predictions for the low-priced restaurant were marginally more extreme (i.e., lower) when participants were trained at one price point only (M = 2.63) than when they were trained at two price points (M = 2.87; $t(176) = 1.79$, $p < .10$). Similarly, predictions for the high-priced restaurant were more extreme (i.e., higher) when participants were trained at one price point only (M = 4.13) than when they were trained at two price points (M = 3.69; $t(176) = -3.28$, $p < .01$).

Judged Covariation. Figure 6*B* plots covariation judgments by condition. We analyzed judgments with the same three-way ANOVA. This analysis revealed the core expected main effect of local consistency ($F(1, 176) = 26.94$, $p < .001$). Participants judged the relationship between price and quality as stronger when quality was highly consistent at least for one price level ($M_{yes} = 4.45$ vs. $M_{no} = 3.34$). Mirroring the effect of training on extremeness of quality predictions, this analysis also revealed a main effect of training ($F(1, 176) = 27.51$, $p < .001$). Participants judged the price-quality relationship as stronger when they only observed consistent quality at one price (M = 4.48) than when they also observed inconsistent quality at another price (M = 3.38). No other effects in the model were significant (all $p > .13$). Thus far, we have shown that highly consistent quality at low price as well as highly consistent quality at high price (1) respectively increases predicted quality at high price and decreases predicted quality at low price and (2) increases judgments of covariation. To examine whether there is a significant indirect effect of consistency on predicted quality through perceived covariation, we again used the bootstrapping procedure by Preacher and Hayes (2004). Before estimating the indirect effect we reversed the coding for quality predictions at low price (i.e., reverse-coded prediction = 6 − prediction), while we left the coding for quality predictions at high price unchanged. As a consequence of this recoding, higher values now indicate more extreme predictions at both low price and high price. The indirect effect involving perceived covariation was significant (95% CI = .04 to .13), indicating significant mediation through this path.

Discussion

Results in study 3 further confirm that the effect of consistent price-quality information in one price region on extremity of quality predictions in another price region is not driven solely by differences in the objective correlation between price and quality. We presented participants with restaurants at only one price point (which leaves the correlation, as well as slope, between price and quality undefined) before asking them to predict quality in another price region. We find our core effect and find that it is not smaller than when participants saw restaurants at more than one price point. Thus, having consistent quality information in one region is sufficient for the effect to occur—local consistency is enough to breed extremity. This study also provides additional evidence against a cue-abstraction process. Abstracting the linear slope that relates quality to price requires comparing quality at two different prices (Juslin et al. 2008).

In conditions 5–8, participants experienced quality at one price only, preventing a cue-abstraction process.

GENERAL DISCUSSION

When consumers make purchasing decisions, they often have to predict the quality of the products they are considering on the basis of other cues, such as price. The relationship between price and quality is rarely perfect. The price-quality relationship is characterized by random error around the regression line. Often, this error is not constant across the price range. That is, the price-quality relationship is heteroscedastic. The main question we addressed in this article is what happens to quality predictions when the price-quality relationship is heteroscedastic. We find that when low-priced products are consistently of low quality, consumers overestimate the quality of high-priced products. When high-priced products are consistently of high quality, consumers underestimate the quality of low-priced products. Thus, we find that heteroscedasticity breeds extremity in consumer predictions of product quality. Our studies show that this effect on prediction extremity is robust to cue competition (study 1) and occurs both when learning is simultaneous (studies 1 and 3) and sequential (study 2). Our results, furthermore, show that the effect of local consistency does not require differences in objective price-quality correlation (studies 2 and 3) and that it is mediated by perceived covariation (studies 1 and 3).

Implications

The Psychology of Prediction. Our findings suggest that outcome predictions cannot only be based on learning about the average level of the outcome given the cue; they are based also on the perceived covariation between cue and outcome. In other words, in continuous cue-continuous outcome learning people conflate conditional means with covariation. Moreover, our results show how perceived covariation deviates from objective correlation. We find that low-error cue-outcome information in one cue region that is accordant with the existence of a strong relationship is sufficient for consumers to perceive a strong relationship. That is, we found that local consistency made consumers perceive a strong relationship and/or made more extreme outcome predictions even when there was no correlation (study 3, conditions 5–8) or when local consistency was manipulated while keeping correlation constant (study 2).

Our work builds on demonstrations in consumer research and psychology of selective information processing (Hoch and Deighton 1989; Russo, Medvec, and Meloy 1996; Sanbonmatsu et al. 1998) and it supports the central role of confirmatory processing in learning about price and quality (Kardes et al. 2004; Cronley et al. 2005). It contributes to this literature by highlighting the special status of local consistency and specifically of having a cue region that is unambiguously accordant with the hypothesis of a strong relationship. The effect of local consistency on prediction extremity was not necessarily anticipated by existing accounts of selective information processing. For instance, consider the tables presented to participants in conditions 1 and 2 of study 1. Four out of six observations are identical. The average quality at medium price and at high price is identical. The only difference is the consistency of quality at high price. Because quality is consistently high when price is high in condition 1, there is no latitude for biased information processing at that price level. In condition 2, standard selective information processing would lead to the observation with high price and very high quality receiving more weight than the observation with high price and medium quality. Thus, if selective information processing implies that "consumers who believe that a strong positive relationship exists between price and quality are likely to focus on high price/high quality products and on low price/low quality products" (Kardes et al. 2004, 368), we would expect more extreme price-based quality inferences in condition 2. We find the opposite. Thus, our results suggest that the locally consistent information in the low-error region of the cue in continuous cue–continuous outcome learning is special.

Product Evaluation and Consumer Welfare. Our findings have several implications for product evaluation and consumer welfare. First, the results of study 2 suggest that heteroscedasticity leads consumers to overestimate the quality of high-priced products or underestimate quality of low-priced products when making initial purchasing decisions. This may lead consumers to overspend and choose more expensive products (Lichtenstein, Bloch, and Black 1988; Ofir 2004).

Second, local consistency may lead to dissatisfaction after quality is revealed because of expectancy-disconfirmation (Gotlieb, Grewal, and Brown 1994; Oliver 1980). Due to the overexpectation of quality at high price levels, revealed quality of high-priced products would be lower than expected given the price. This disappointment should lead consumers to feel that the product was not as good value for money as they expected. To empirically test this implication, we had 57 participants (27 females; $M_{age} = 20.28$) go through a training phase similar to the homoscedastic condition of study 2 and the increasing heteroscedastic condition where quality was consistently low for low price products but highly variable for high price products. Instead of predicting quality based on price in the test phase, participants judged the value for money of a high-priced brand with a quality level equal to the actual encountered conditional mean of quality at that price point, on a scale from 1 (bad value for money) to 7 (good value for money). Participants perceived the product to be of worse value for money in the heteroscedastic condition ($M = 2.72$) than in the homoscedastic condition ($M = 3.29$; $F(1, 55) = 5.20$, $p < .05$) . Thus, heteroscedasticity can lead consumers to feel that they received bad value for money after buying high-priced products. Likewise, we would expect that in heteroscedastic decreasing scenarios (where high-price products are consistently of high quality whereas low-priced products show high variability), low-priced products will tend to exceed expectations, leading to customer delight and perceptions of high value for money.

Third, our findings show how quality perceptions of products in one price region are affected by products in very different price regions and not just by close competitors. Specifically, our studies may have implications for low-cost competition and luxury branding. Managers of high-priced brands typically see low-cost market entries as either irrelevant because they are so different or as a threat because they increase price competition and reduce margins (Kumar 2006; Ritson 2009). Our studies suggest that low-cost rivals can actually be beneficial for the perceived quality of higher priced brands if the quality of those low-cost rivals is consistently low. In fact, low-cost competition providing consistently low quality may increase the effectiveness of price signaling strategies that lie at the heart of luxury branding. Price signaling refers to the strategic use of price to signal product quality and therefore entails setting relatively high prices (Tellis 1986). This strategy should be more effective to the extent that price-based quality inferences are more extreme (because consumers expect a greater increase in quality for the same price increase). Our studies suggest that price-based quality inferences are more extreme when randomness is either increasing (e.g., 33% more extreme in study 2) or decreasing (e.g., 41% more extreme in study 2) than when randomness is constant. Price signaling should thus be a more effective strategy in markets characterized by randomness that is increasing or decreasing across the price range. On the other side of the price spectrum, should managers of low-cost brands be worried about higher priced rivals entering the market? Our studies suggest that higher priced brands can be detrimental for the perceived quality of lower priced brands if the quality of those high-priced rivals is consistently high.

Broader Implications. Although we specifically examined price-quality learning, our findings should generalize outside the price-quality domain. As we noted in our introduction, many cue-outcome relationships beyond the consumer realm violate the assumption of constant randomness. Besides its relevance for consumer decision making, the biasing effect of local consistency on prediction extremity may therefore be important in many other contexts. For instance, the relationship between selling price and sales of a product is often negative with unpredictable sales for lower selling prices but consistently low sales for higher selling prices (Simon 1989). If heteroscedasticity breeds extremity in the high-error region of the cue range, this should lead marketing managers to overestimate sales of lower priced products, basically overestimating customer price sensitivity and making them set prices that are too low. The relationship between intelligence and job performance is reported to be positive with unpredictable job performance at lower intelligence but consistently high job performance at higher intelligence (Kahneman and Ghiselli 1962). This should lead managers to underestimate the performance of workers with lower intelligence, biasing those managers against hiring workers with lower IQs. Mladenka and Hill (1976) find that the rate of violent crime is unpredictable in low-income communities but consistently low in high-income communities. Our findings suggest that experiencing consistently low crime rates in high-income communities may increase expectations of crime rates in low-income communities. This might reduce poor people's chances of being hired, might lead juries and judges to overestimate their probability of recidivism, or might lead law enforcement personnel and others to overestimate the physical threat poor people represent, potentially leading them to take a more aggressive stance. The key takeaway is that heteroscedasticity is likely to be an important factor explaining why and how erroneous beliefs and stereotypes in many judgment domains come into being and persist over time. Future research should address the role of heteroscedasticity in each of these domains specifically.

Limitations

With the exception of study 1 our studies involve single-cue, linear situations. Although this may appear to be an oversimplified representation of the data patterns that consumers encounter in real life, single-cue linear task structures have taken a prominent place in the learning literature. There are two theoretically sound reasons for this. First, judgments in multiple-cue settings are mostly determined by the cue that is in the focus of attention (for a review, see Fiedler, Walther, and Nickel [1999]). In a marketing context, price is arguably the most observable and most salient extrinsic cue for quality (see also Broniarczyk and Alba 1994). Second, people tend to impose a cognitive linear structure on nonlinear functions (DeLosh et al. 1997). The relationship between price and quality for sparkling wines for instance is not perfectly linear, it is slightly concave (see fig. 1*B*). In fact, the actual function relating price to quality and price to online consumer ratings is mostly concave (De Langhe, Fernbach, and Lichtenstein 2013). If people mentally linearize nonlinearity, the concavity in the price-quality function might in fact exacerbate the perception that randomness is decreasing. This may further inflate the effect of consistency on extremity. We leave the extension of our findings to multiple-cue, nonlinear situations for future research.

Participants in our studies did not learn about the price-quality relationship from direct experience with a product but instead learned from descriptive information. We believe that expert and consumer ratings of quality are an important source of consumer learning about the price-relationship. Moreover, the use of quality descriptions allowed us to objectively manipulate heteroscedasticity in the price-quality relationship. Quality experiences instead are known to be ambiguous and influenced by marketing variables. For instance, Plassmann et al. (2008) demonstrated that wine prices modulate activation in the brain's reward center (i.e., the orbitofrontal cortex), and Shiv, Carmon, and Ariely (2005) demonstrated that price alters the actual efficacy of energy drinks (as measured by participants' ability to solve puzzles). Future research should examine whether our findings generalize to situations where quality is actually experienced.

Conclusion

In this article, we demonstrated a bias that we believe to be of fundamental importance in many domains in which people judge an outcome based on information about a cue. Our results suggest that when cue-outcome relationships violate the assumption of constant randomness, showing low error variance at one end of the cue range and much higher variance at the other end, people will make outcome predictions that are overly extreme. Our results in the context of price and quality suggest that people are fooled by such heteroscedasticity because locally consistent information breeds inferences of strong covariation which in turn increase the extremity of price-based quality inferences.

DATA COLLECTION INFORMATION

For study 1, the first author supervised the collection of data by research assistants at the Leeds School of Business' Behavioral Lab in the spring of 2013. For study 2, the first author supervised the collection of data by research assistants at the Rotterdam School of Management's Behavioral Lab in the fall of 2009. For study 3, the first author supervised the collection of data by research assistants from Amazon Mechanical Turk in the spring of 2013. The data for the first and third studies were analyzed by the first author. The data for the second study was analyzed by the first and third author.

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