

RESEARCH ARTICLE

Hedonic Pricing of Rice Attributes, Market Sorting, and Gains from Quality Improvement in the Beninese Market

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Abstract

Latent class analysis is applied to a hedonic price model to examine the presence of heterogeneity in consumer valuation of quality attributes in the Beninese rice market. Three classes of consumers are found in proportions of 5, 56, and 39 percent. We employ a partial equilibrium model and find modest gains in consumer surplus from an increase in head rice and reduction in chalkiness. The results provide evidence of market sorting, which should be taken into consideration in upgrading rice value chains. Also, it is important to assess potential gains from quality improvement to determine priorities for research and development.

Key words: Benin; hedonic pricing; market/consumer sorting; quality improvement; rice

Introduction

African countries striving to achieve rice self-sufficiency have proposed and implemented several interventions, particularly those aimed at narrowing yield gaps and improving producer welfare. However, little attention has been paid to interventions that would significantly improve consumer welfare. In many parts of Africa, consumers perceive the quality of rice in their local markets to be poor. Therefore, even though an increase in yield would certainly increase supply and consequently reduce prices, the reduction in prices is unlikely to proportionately increase quantity consumed in some countries owing to low price elasticities of demand such as those documented in Tollens (2007), Ulimwengu and Ramadan (2009), Nzuma and Sarker (2010), and Lazaro (2014). Instead, consumers may shift to the consumption of other foods since the market lacks rice of the desired quality. This lack of rice of the desired quality is partly due to the limited information on heterogeneity in consumer preferences that characterizes rice markets. Without this information, upgrading of Africa's rice value chains will remain an uphill task.

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This study applies the hedonic pricing method, a revealed preference method (Loureiro, McCluskey, and Mittelhammer 2003), to determine consumer preferences for rice in Benin, where rice is the second most important cereal after maize. In doing so, it accounts for market (consumer) sorting, failure of which would lead to inconsistent parameter estimates (Gustafson, Lybbert, and Sumner 2016). Market sorting arises from heterogeneity in consumer characteristics and preferences for quality attributes; consumers self-select into searching for certain attributes, which leads to a correlation between consumer characteristics and product attributes (Gustafson, Lybbert, and Sumner 2016). In other words, consumers with similar socio-demographic characteristics, constraints, and, hence, preferences are likely to make similar choices (Kuminoff, Smith, and Timmins 2013). Danneels (1996) refers to this as reverse market segmentation.¹ Therefore, the analysis essentially involves the determination of differential hedonic prices, which can then be used by marketers to build product profiles to more precisely and optimally target consumers and achieve greater market penetration. An exploratory case study by Futakuchi, Manful, and Sakurai (2013) revealed the existence of heterogeneity in consumer preferences for rice attributes in Benin.

Additionally, ensuring that quality meets consumer demand is increasingly becoming an integral part of breeding and crop improvement programs in Africa. As household incomes grow, it is expected that new breeding pipelines that include, for instance, biofortified grain will emerge. Such crop improvement programs often require huge public investments in research and development. But over the last decade, funding for national and international agricultural research has been declining, making priority setting based on rigorous impact assessment more imperative than ever before (Alene et al. 2018). Therefore, this study goes a step further to determine the likely impacts of grain quality improvement on consumer welfare.

Unlike Naseem et al. (2013) who applied a hedonic price model to Beninese consumers' subjective perceptions of rice quality attributes, our study applies a hedonic price model to data obtained from laboratory tests of rice samples collected from different retail markets. The use of laboratory measures of quality, as in Unnevehr (1986), Espinosa and Goodwin (1991), and Cuevas et al. (2016) rather than consumers' and technicians' sensory and semi-quantitative evaluation, provides comparatively reliable information on parameters relevant to the development of food products with sensory attributes desired by consumers (Singham, Birwal, and Yadav 2015; Cuevas et al. 2016). Laboratory tests on rice samples were conducted for physical and chemical characteristics associated with sensory attributes including appearance, aroma, texture, and flavor that are thought to influence consumer acceptance of rice. The attributes were then controlled for in a latent profile model to reveal the nature of hedonic prices of the underlying classes of consumers.

In the next section, we review empirical literature on the application of hedonic pricing to market sorting and to the determination of welfare impacts of quality improvement. Hedonic price functions encompass both supply and demand factors, and therefore, welfare changes accrue to both producers and consumers. However, the review of literature is restricted to consumer welfare, the focus of our study. The third section describes the economic model and the fourth section presents the data.

¹An anonymous reviewer pointed out that the hedonic price model explicitly disallows the analysis of market segmentation, but it is applicable to the analysis of market sorting. They indicated that the crucial difference between the two is that market participants affect equilibrium prices in the case of market segmentation but do not in market sorting.

This is followed by a discussion of the results in the fifth section. The last section summarizes and concludes the article with implications for rice breeding and upgrading of Africa's rice value chains.

Related Literature

Market (Consumer) Sorting

Economists have devoted considerable effort to studying hedonic pricing of extrinsic and intrinsic attributes of several goods such as foods, beverages, and houses. Rosen (1974) intended that an empirical estimation of the hedonic price model involves estimation of the market-clearing implicit (hedonic) price function in the first stage, and the implicit marginal price function in the second stage. However, very rarely have economists been able to move beyond the first-stage estimation of the model because of theoretical and econometric challenges. The implicit marginal price function cannot provide new information without restrictions on its functional form (Brown and Rosen 1982). It suffers from simultaneity in that consumers with a strong preference for a given attribute will buy large quantities of products with this attribute (Bajari and Benkard 2005). As such, heterogeneity in consumer preferences and consumer sorting have been found to be serious problems for conventional hedonic price estimation (Klaiber and Phaneuf 2009; Gustafson, Lybbert, and Sumner 2016), which assumes that consumers manifest homogeneous preferences (Nagler *et al.* 2012). To overcome these problems, a variety of techniques—some of which have been compared with the hedonic model—have been employed in the empirical literature. For instance, Klaiber and Phaneuf (2009) compare estimates of hedonic and sorting models using residential sales and land-use data for east central Minnesota. Their sorting models are essentially random utility model specifications with and without observed heterogeneity and are implemented as in Bayer and Timmins (2007). The models yield similar results for some but not all variables. It is evident that the relatively high-resolution analysis achieved with sorting models comes at a cost of greater complexity in terms of data needs and theoretical assumptions. Gustafson, Lybbert, and Sumner (2016) deal with consumer sorting in the American wine market by integrating consumers' uninfluenced initial choice of wine purchase with their willingness to pay (WTP) for alternate wines in a valuation experiment. They estimate and compare two models: a typical hedonic price model (for all wines in the experiment) and a model in which WTP rather than actual wine price is the dependent variable. The WTP model is estimated in three forms: one with the same wine attributes as the hedonic model but with the addition of a dummy variable for the initially chosen wine; a model with wine attributes, a dummy for initially chosen wine and consumer characteristics; and a model with wine attributes, a dummy for initially chosen wine and a dummy for individual-specific fixed effects to account for sorting and unobserved consumer characteristics. Valuation estimates for wine attributes are found to vary significantly between the two approaches, and the model accounting for sorting and omitted consumer characteristics provides the most precise estimates of aggregate WTP for wine attributes. Bento, Li, and Roth (2012) use the random coefficients multinomial logit model to incorporate consumer heterogeneity and avoid sorting bias in estimating U.S. consumers' marginal WTP for future reductions in fuel costs.

While the above studies use the random utility framework to explicitly account for the parameters upon which market sorting is based, our concern is how to analyze market sorting using a hedonic pricing model when there are several unknowns, including

the exact functional form of the model, the number of consumer categories, the consumer characteristics defining those categories, and the full vector of the relevant hedonic attributes. For example, regarding unknown hedonic attributes, Beninese consumers' valuation of rice attributes may partly depend on the type of rice dish (djolof rice, white rice with soup, whatche, porridge, and dough) they desire for a given meal (breakfast, lunch, and dinner), and occasion (religious holidays and social events). This implies that some of the observed rice attributes may simply be proxy indicators of the levels of relevant attributes not directly observed by consumers and perhaps unknown to the analyst. Nagler et al. (2012) demonstrate how a hedonic price model of market sorting can be applied to determine, for different categories of consumers, the gap between marginal WTP for a proxy attribute and marginal WTP for the attribute it represents. The authors observed the levels of the latter attribute from laboratory analysis of the products.

The present study adds to the empirical literature on market sorting by estimating a hedonic price function as a finite mixture linear regression model, which is robust for detecting differential effects when the number of consumer classes and predictors of class membership is not specified *a priori*, when the predictors are unreliable, and when the process that creates classes is complex, such as one involving multiple predictors that interact in multiple ways (Van Horn et al. 2015). A similar approach has been used by Shiroya (2010) to understand household residential sorting patterns in Texas. More recently, Caudill and Mixon (2016) have applied the finite mixture model to a hedonic model of California and Washington wine prices to demonstrate its superiority over the Local Polynomial Regression Clustering (LPRC) procedure introduced by Costanigro, Mittelhammer, and McCluskey (2009). They find it to have better aggregate out-of-sample performance than the LPRC model.

Welfare Measurement

Conceptually, the measure of change in consumer welfare due to a change in a quality attribute is a measure of change in the consumer's utility. However, because utility is unobservable, a change in consumer welfare is often measured by a monetary measure of the consumer's own valuation of the change in their welfare. An example is the Hicksian compensating measure in the form of the maximum amount of money that the consumer is willing to pay to achieve the change, in the case of an improvement in quality, or the minimum amount that they are willing to accept to endure the change, in the case of a decline in quality (Day 2001).

Measurement of welfare effects due to changes in quality characteristics remains scarce in the empirical hedonic pricing literature. Palmquist (1988) attributes the scarcity to the complexity of analyzing welfare when hedonic price schedules are nonlinear. He proposes a technique for deriving exact measures of consumer welfare in a way that accounts for the nonparametric nature of prices. Still, the practice seems to have remained that of using implicit marginal prices as direct measures of welfare benefits since they represent the WTP for a marginal change in an attribute (see, for instance, Kim, Phipps, and Anselin 2003). Harrison and Rubinfeld (1978) and Chattopadhyay (2002) use implicit marginal price functions (employed in the second-stage regression of Rosen's (1974) procedure) to obtain estimates of household benefits from nonmarginal improvement in quality attributes in the housing market.

Hedonic estimates of marginal WTP can be used to derive partial equilibrium welfare effects (Kuminoff and Pope 2009) as demonstrated by Unnevehr (1986) and Voon

wand Edwards (1991). Unnevehr (1986) estimates hedonic prices and calculates changes in consumer surplus (CS) due to an improvement in rice grain quality in three Asian countries. The method is intuitive and, hence, provides an appropriate framework for the current study. On the contrary, Voon and Edwards (1991) apply a hedonic price estimate obtained from the literature to determine the economic benefits to producers, input suppliers, marketers, and consumers of reducing backfat depth in Australian pork.

Economic Model

The hedonic price regression can be traced back to at least Court (1938). Unlike the traditional theory of consumer demand in which goods are the direct objects of utility, the theory of hedonic pricing is based on the notion that utility is, in fact, derived, not from goods *per se* but from their hedonic attributes. Rosen (1974) derives a model of product differentiation in a competitive market and provides an interpretation of the estimated hedonic (implicit) prices. Assume a market of differentiated products that are characterized by n attributes, z_1, \dots, z_n . It is assumed that consumers have the same perception of the quantity of attributes in each product. Each product has an observed market price such that $\mathbf{p}(\mathbf{z}) = p(z_1, \dots, z_n)$. Rosen then derives consumption and production decisions and shows that in equilibrium, the implicit price function $\mathbf{p}(\mathbf{z})$ represents a joint envelope of a buyer's value function and seller's offer function.

Later, Ladd and Suvannunt (1976) derive the consumer goods characteristics model based on assumptions that specifically define the behavior of individual consumers. In this model, a product's observed market price is a weighted linear combination of the product's attributes, where each weight is the marginal implicit price of an attribute. Suppose Z_{0j} is the total quantity of attribute j provided by all products consumed, Z_{ij} is the quantity of attribute j provided by one unit of product i , Z_{0m+i} is the quantity of unique attribute m provided by product i , q_i is the quantity consumed of product i , and I is income. Therefore,

$$Z_{0j} = f_j(q_1, \dots, q_n; Z_{1j}, \dots, Z_{nj}) \text{ and } Z_{0m+i} = f_{m+i}(q_i; Z_{im+i}) \quad (1)$$

The consumer maximizes

$$U = U(Z_{01}, \dots, Z_{0m}; Z_{0m+1}, \dots, Z_{0m+n}) \quad (2)$$

subject to

$$\sum_i p_i q_i \leq I \quad (3)$$

Hence,

$$p_i = \sum_j (\partial Z_{0j} / \partial q_i) [(\partial U / \partial Z_{0j}) / (\partial U / \partial I)] + (\partial Z_{0m+i} / \partial q_i) [(\partial U / \partial Z_{0m+i}) / (\partial U / \partial I)] \quad (4)$$

The term in the first square brackets is the marginal rate of substitution between income (or expenditure according to equation 3) and attribute j . It is the marginal (implicit) price of attribute j . Notice that

$$\frac{(\partial U / \partial Z_{0j})}{(\partial U / \partial I)} = \frac{\partial I}{\partial Z_{0j}} = \frac{\partial E}{\partial Z_{0j}} \quad (5)$$

where E is the total expenditure on all products and $(\delta Z_{0j}/\delta q_i)$ is the marginal yield of attribute j by product i . Thus, equation 4 implies that the observed market price of a product is equal to the sum of the marginal values of the attributes, where each attribute's marginal value is the quantity of the attribute per marginal unit of the product (i.e., yield) multiplied by the attribute's hedonic price. Equation 4 is the implicit (hedonic) price equation and can be rewritten as follows:

$$p_i = \sum_{j=1}^m p_{ij}Z_{ij} + u \tag{6}$$

where the coefficients p_{ij} are the hedonic or implicit marginal prices of attributes, which can be interpreted as the marginal WTP for a change in the attributes since they encapsulate consumers' preferences (Nerlove 1995; Costanigro, McCluskey, and Mittelhammer 2007), and u is the random error term. If an additive intercept is added to equation 6, the coefficients can be interpreted as premiums or discounts over a base price defined by the intercept.

To analyze market sorting, we apply latent class (LC) analysis to equation 5. LC analysis is a set of techniques used to model situations in which the observed data are comprised of a finite number of distinct classes (subgroups), but class membership is not directly observed (Canette 2018). LC models permit disaggregation of a sample into existing latent classes using one or more observed dependent variables, which may be categorical or continuous.² In this study, we apply a finite mixture linear regression model,³ a type of LC maximum-likelihood-based model derived from a mixture of underlying distributions, and use one dependent variable (Greene 2008, p. 558; Costanigro, Mittelhammer, and McCluskey 2009; Canette 2018).

Following Greene (2008, p. 559), if a population consists of a mixture of two underlying normal distributions,⁴ the contribution to the likelihood function for individuals or products in classes 1 and 2 is, respectively,

$$f(y_i | \text{class}_i = 1) = N[\mu_1, \sigma_1^2] \tag{7}$$

$$f(y_i | \text{class}_i = 2) = N[\mu_2, \sigma_2^2] \tag{8}$$

where y_i is the outcome variable for individual or product i . Assuming that the proportion of individuals or products in class 1 is $\text{Prob}(\text{class}_i = 1)$ and those in class 2 is

²When the observed variable is continuous, the model is referred to as a latent profile model.

³In the context of this study, an anonymous reviewer pointed out that this model can be better viewed as functional approximation consistent on a single hedonic model under market sorting. Since the probability of belonging to any class is totally random (does not depend on any consumer characteristic), this does not violate the hedonic model assumptions because consumers will in this case not affect equilibrium prices. After estimation, one may relate the class prices to consumer characteristics such as income if needed to ascertain why and how they sort themselves. For this study, however, we did not collect data on consumer characteristics.

⁴The model is applicable to cases where dependent variables might follow other types of distributions such as the log-normal distribution in the case of prices (since prices take on only positive real values). However, the logarithm of a log-normally distributed variable is normally distributed.

$(1 - \text{Prob}(\text{class}_i = 1))$, and \mathbf{z}_i is the vector of variables (attributes) that might explain class probabilities, then the conditional density for product i is

$$f(y_i|z_i) = \frac{\text{Prob}(\text{class} = 1|z_i)\exp[-(1/2)(y_i - \mu_1)^2/\sigma_1^2]}{\sigma_1\sqrt{2\pi}} + \frac{[1 - \text{Prob}(\text{class} = 1|z_i)]\exp[-(1/2)(y_i - \mu_2)^2/\sigma_2^2]}{\sigma_2\sqrt{2\pi}} \quad (9)$$

The usual logit model can be used to parameterize the probabilities. The log-likelihood, in this case, features two random variables; the outcome variable y_i and class_i . For the more general case of K classes, the finite mixture model for variable y_i can be specified as

$$f(y_i|\text{class}_i = k, z_i) = h_k(y_i, z_i, \gamma_k) \quad (10)$$

where h_k is the density conditioned on class k , z_i is a vector of covariates, and γ_k is the k th parameter vector. However, even if it is impossible to conjecture the classes present in the sample, as is the case in this study, the model remains amenable to estimation as illustrated by Canette (2018).

Estimated hedonic prices can be used to calculate the change in CS due to a non-marginal improvement in attributes. As in Unnevehr (1986), we use a partial equilibrium model to this end. Improvement in a quality attribute causes a rightward shift in demand, and the gain, G , in CS per unit of the product consumed by a given class of consumers can be calculated as follows:

$$G = \sum_{j=1}^m (Z_{ij}^* - Z_{ij})p_{ij} \quad (11)$$

where Z_{ij}^* is the new value of attribute j per unit of the product and p_{ij} is the estimated hedonic price for a given class of consumers. At the aggregate level, assuming the infinitely elastic supply of the improved product and constant production costs, the level of demand for the product after quality improvement, q_i^* , is

$$q_i^* = q_i(1 + \varepsilon_{ij}^q) \quad (12)$$

where

$$\varepsilon_{ij}^q = -\frac{p_{ij}Z_{ij}}{p_i}\varepsilon^* \quad (13)$$

is the elasticity of quantity consumed of the product with respect to the quantity of attribute j , and ε^* is the own-price elasticity of demand for product i . These assumptions do not permit gain in producer surplus. The total gain in CS is

$$\text{CS} = q_iG + \frac{1}{2}(q_i^* - q_i)G \quad (14)$$

Unlike in Unnevehr (1986), our study requires an estimate of ϵ^* for each class of consumers. However, we do not have the necessary data to empirically obtain estimates of it, and turning to the literature, we find a paucity of empirical studies that have estimated ϵ^* for rice in Benin. For all we know, the recent study by Codjo (2019) has been the only attempt to estimate the parameter; he estimates ϵ^* for three income groups (low, middle, and high) and three levels of rice quality and finds it to range between -0.91 and -2.69 . Therefore, we use the average of Codjo's (2019) estimates, and we conduct a sensitivity analysis for the relevant consumer classes in order to ascertain the robustness of our model's results.

Data and Estimation

In a study like this that aims to generate aggregate demand and CS based on sample data, ensuring that the sample is representative of the population is imperative. At the time of this study, a list of all rice retailers in the country and the types or brands of rice they sell was unavailable. Moreover, the cost of obtaining it and collecting samples from retailers who are dispersed throughout the country would have been prohibitive. Nonetheless, we were able to obtain rice samples representative of the rice consumed in the country's four official geopolitical and cultural regions, namely Northeast, Northwest, Central, and South. For each region, a list of all food markets was obtained, from which a random sample of markets was drawn. The number of markets randomly selected from each region was proportional to the region's share of markets in the country. Thus, a total of 33 markets were randomly selected: South (20), Central (4), Northwest (6), and Northeast (3). In each market, rice retailers and the type(s) of rice they sell were identified, and rice samples randomly collected. Only one sample per rice type or brand was obtained from each selected retailer. A total of 316 rice samples, which is adequate for our finite mixture model (Van Horn et al. 2015), was obtained: South (176), Central (35), Northwest (64), and Northeast (41).

The distance of each market (in km) from the Cotonou port was recorded. The Northeast and Northwest of Benin are about 800–1,000 km from Cotonou port, and the populations there have a history of rice cultivation. The Northeast is the most important rice-producing region in Benin and harbors one of the country's rice sector development hubs⁵—Malanville. The Central region is about 300–500 km from Cotonou port and harbors the other rice hub, Glazoue. Unlike Malanville, which is irrigated, the Glazoue hub is rainfed. The South is close (<300 km) to Cotonou port and is home to Cotonou city, the largest city in Benin, and to Porto-Novo, the country's political capital. Most of the inhabitants of this region do not have a rice cultivation history.

A detailed description of the grain quality analysis that produced data on the attributes used in the hedonic pricing model is available from the authors on request, and summary statistics of the physical (extrinsic) and chemical (cooking) attributes used in the model are presented in Table 1. Extrinsic attributes include moisture content, head rice (proportion of intact grains), length–width ratio (grain shape), chalkiness (white belly/opaque portion of a rice grain), lightness/whiteness, distance (km) of a market from Cotonou port, market type (1 = rural, 0 = urban), rice type (1 = parboiled, 0 = non-parboiled), and origin (1 = imported, 0 = local). A high moisture content of above 14

⁵Rice hubs are zones selected by the country's rice value chain stakeholders and represent key rice-growing environments where research outputs are integrated along the value chain to produce maximum impact (Africa Rice Center 2011).

Table 1. Summary Statistics of Variables Used in the Analysis ($n = 316$)

Variable	Mean	St. Dev.	Minimum	Maximum
Price (USD/kg)	0.99	0.30	0.60	2.40
Moisture content (%)	13.25	0.86	10.90	16.80
Head rice (%)	84.35	13.45	20.43	100.00
Length–width ratio	3.10	0.36	2.26	4.36
Chalkiness (%)	14.61	10.51	2.54	43.69
Lightness (%)	59.73	7.52	41.55	73.58
ASV (index)	6.11	0.87	2.67	7.00
Setback viscosity (centipoise)	813.89	578.10	19.33	2,670.00
Amylose content (%)	26.47	3.97	13.18	37.36
Distance from port (km)	248.33	238.33	7.10	739.00
Market type (1 = rural, 0 = urban)	0.59	0.49	0	1
Rice type (1 = parboiled, 0 = white)	0.53	0.50	0	1
Origin (1 = imported, 0 = local)	0.73	0.45	0	1

percent is undesirable as it leads to a deterioration of grain during storage (Tang *et al.* 2019). The distance of a market from the port, type of market, and origin of rice are informational cues that may influence consumers' perception of the quality of rice. For instance, the type of market may account for ease of access to market and quality information about the product, while the origin of a product may influence consumers' perception of its quality (Elliott and Cameron 1994), in addition to capturing consumers' ethnocentric attitudes.

Chemical attributes include amylose content, setback viscosity, and alkali spreading value (ASV). Amylose content determines the texture of cooked rice, whereby the greater the amylose content, the drier, the less sticky, and less tender the rice is. Setback viscosity, an indicator of the pasting quality of rice, determines the firmness of cooked rice, with higher values indicating greater firmness after cooling. The ASV is used to measure gelatinization temperature and, hence, cooking time. The higher the ASV, the lower the gelatinization temperature and, hence, the shorter the cooking time.

Results

The hedonic price finite mixture regression model was estimated in the form of a log-linear (double-log) model,⁶ and Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were used to determine the number of distinct consumer classes present in the data. Both criteria found three classes, as shown in Table 2. We find that about 5 percent of the observations are in class 1 that pays an average rice price of \$1.32/kg, while 56 percent are in class 2 with an average price of \$0.89/kg, and 39

⁶The double-log form provided the best fit to the data. Note that because of some dummy variables in the model, it is not a completely double-log specification.

Table 2. Results of Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) for Model Selection

Number of classes	Log-likelihood	Degrees of freedom	AIC	BIC
1	134.40	14	-240.80	-188.22
2	205.51	29	-353.02	-244.10
3	254.39	44	-420.78	-255.53
4	258.57	53	-411.14	-212.09

percent are in class 3 with an average price of \$1.00/kg. Table 3 summarizes the results of the three-class model. In a log-linear model, coefficients on continuous regressors are elasticities, while those on discrete ones show the discontinuous effect on the regressand. Therefore, we calculate and report hedonic prices of the statistically significant attributes. The hedonic price of each continuous attribute is calculated as the product of the attribute's coefficient and the average price of rice divided by the average value of the attribute, and it reflects the change in the market price of rice for a one-unit change in the attribute. For a discrete attribute, however, the hedonic price is the effect on the price of rice of one category relative to another. It is calculated as $(e^{\beta} - 1)$, and the percentage effect is $100(e^{\beta} - 1)$, where β denotes the coefficient (Halvorsen and Palmquist 1980).

The smallest class (class 1) exhibits several unique characteristics: it is sensitive to all but one attribute—moisture content—and it is willing to pay price premiums for the relatively expensive imported rice and rice with chalkier grains, while discounting rice with a relatively high proportion of intact grains (head rice), lighter grains (lightness), rice that becomes firm on cooling after cooking (setback viscosity), and rice sold in markets far from the port of Cotonou. The other characteristics of this class, although not unique to it, are that it likes rice with slender grains, nonsticky rice when cooked, and shorter cooking time, and it discounts parboiled rice and rice sold in rural markets. Taken together, these characteristics point to a category of consumers that is likely to be comprised of relatively high-income consumers including foreign nationals in and around major urban centers such as Cotonou city.

Classes 2 and 3 do not care for the origin of the rice they consume, a finding that is contrary to that of Naseem et al. (2013), who concluded that rice consumers in Benin prefer imported to local rice. Consumers in the largest class (class 2) are sensitive to only five of the 12 attributes. They discount parboiled rice, rice sold in rural markets, and rice with chalky grains, but are willing to pay price premiums for head rice and amylose content. When comparing the hedonic prices in this class with those paid by consumers in the other two classes, it is quite clear that consumers in class 2 exhibit relatively weak preferences. For instance, they discount chalkiness by \$0.006/kg, which is only 30 percent of the discount paid by consumers in class 3, and parboiled rice by 32 percent (\$0.21/kg) of the discount paid by consumers in class 1. For class 2, gain in consumer welfare would likely come from a reduction in chalkiness, an increase in head rice, and an increase in amylose content.

Consumers in class 3 are sensitive to half of the attributes. They are willing to pay the same price premium for rice with a relatively high proportion of intact grains as consumers in class 2. They like slender grains, lighter grains, and rice that cooks fast. However, they discount rice with chalky grains and are the only class that discounts

Table 3. Estimated Regression Results of the Finite Mixture Model

Variable	Class 1				Class 2				Class 3			
	Coefficient	z-Statistic	p-Value	Hedonic price	Coefficient	z-Statistic	p-Value	Hedonic price	Coefficient	z-Statistic	p-Value	Hedonic price
Moisture content	0.002 (0.003)	0.59	0.553		-0.203 (0.244)	-0.83	0.406		0.229 (0.199)	1.15	0.249	
Head rice	-0.158 (0.0004)	-421.53	0.000	-0.002	0.318 (0.107)	2.97	0.003	0.004	0.304 (0.053)	5.76	0.000	0.004
Length-width ratio	0.051 (0.001)	49.37	0.000	0.02	0.073 (0.157)	0.47	0.641		1.272 (0.241)	5.27	0.000	0.41
Chalkiness	0.080 (0.0004)	180.29	0.000	0.005	-0.091 (0.042)	-2.16	0.031	-0.006	-0.227 (0.044)	-5.16	0.000	-0.02
Lightness	-0.741 (0.001)	-524.21	0.000	-0.01	-0.205 (0.311)	-0.66	0.509		1.552 (0.386)	4.02	0.000	0.03
Alkali spreading value	0.173 (0.0008)	225.82	0.000	0.03	0.045 (0.570)	0.80	0.425		0.435 (0.096)	4.52	0.000	0.07
Setback viscosity	-0.037 (0.0001)	-463.16	0.000	-0.00005	-0.011 (0.014)	-0.77	0.442		0.011 (0.014)	0.78	0.435	
Amylose content	0.108 (0.0005)	216.38	0.000	0.004	0.153 (0.085)	1.80	0.071	0.006	-0.420 (0.063)	-6.69	0.000	-0.02
Distance from port	-0.034 (0.0002)	-156.01	0.000	-0.0001	0.016 (0.010)	1.61	0.107		0.009 (0.019)	0.45	0.653	
Market type (0 = urban)	-0.071 (0.0002)	-407.12	0.000	-0.07	-0.036 (0.020)	-1.79	0.073	-0.04	0.017 (0.036)	0.47	0.639	
Rice type (0 = white)	-1.061 (0.0004)	-2,393.67	0.000	-0.65	-0.236 (0.059)	-4.03	0.000	-0.21	-0.068 (0.054)	-1.26	0.209	
Origin (0 = local)	0.104 (0.006)	163.70	0.000	0.11	0.031 (0.040)	0.78	0.433		0.067 (0.045)	1.49	0.137	
Constant	4.013 (0.014)	274.70	0.000		-0.492 (1.659)	-0.30	0.767		-8.707 (1.217)	-7.16	0.000	

Dependent variable is the natural log of rice prices. Figures in parentheses are robust standard errors.

Table 4. Parameters Used in the Partial Equilibrium Model of Quality Improvement

Parameter	Value
Current level of aggregate demand for rice by class 2	99,680 ^a MT
Current level of aggregate demand for rice by class 3	69,420 ^a MT
Current average price of rice	\$1.00/kg
Own-price elasticity of demand for rice	-1.64 ^b
Current level of head rice per unit of rice	84.35
Current level of chalkiness per unit of rice	14.61
New level of head rice per unit of rice after quality improvement	109.66
New level of chalkiness per unit of rice after quality improvement	10.23
Estimated hedonic price of head rice for class 2	\$0.004/kg
Estimated hedonic price of head rice for class 3	\$0.004/kg
Estimated hedonic price of chalkiness for class 2	-\$0.006/kg
Estimated hedonic price of chalkiness for class 3	-\$0.02/kg
Elasticity of quantity consumed of rice with respect to the quantity of head rice for class 2	0.55
Elasticity of quantity consumed of rice with respect to the quantity of head rice for class 3	0.55
Elasticity of quantity consumed of rice with respect to the quantity of chalkiness for class 2	-0.14
Elasticity of quantity consumed of rice with respect to the quantity of chalkiness for class 3	-0.48

^aAggregate demand for rice in Benin was projected to reach 178,000 MT in 2018 (Republic of Benin 2011). We assume demand by a consumer class to be proportional to the share of the class in the sample.

^bSource: Authors' calculation based on Codjo's (2019) estimates.

rice that does not stick together when cooked. Also notable about this class is that it is the only one that is indifferent about the type of market in which rice is sold. Based on these characteristics, this category of consumers is likely comprised of periurban and rural consumers, and it would gain from an increase in head rice and reduction in chalkiness, among other things.

To determine the consumer welfare implications of grain quality improvement, we consider improvement in two attributes whose coefficients are statistically significant and of the same sign in classes 2 and 3. The two classes together comprise 95 percent of the observations. We consider an increase in head rice by 30 percent and an equivalent reduction in chalkiness. Both attributes can be improved upon through breeding and better postharvest handling and processing. Parameters used in the partial equilibrium model of quality improvement and the results obtained are summarized in Tables 4 and 5, respectively.

We find that better head rice increases the demand for rice to 154,837 and 107,833 MT for classes 2 and 3, respectively. This represents a 55 percent increase in demand by each class. A reduction in chalkiness causes demand to increase by 14 and 48 percent, in classes 2 and 3, respectively. The combined annual gains in CS

Table 5. Results of the Partial Equilibrium Model of Quality Improvement

	Class 2	Class 3
Gain in CS per unit of rice consumed after improvement in head rice (\$)	0.10	0.10
Gain in CS per unit of rice consumed after improvement in chalkiness (\$)	0.03	0.09
Level of aggregate demand for rice after improvement in head rice (MT)	154,836.53	107,832.59
Level of aggregate demand for rice after improvement in chalkiness (MT)	114,010.24	102,686.62
Total annual gain in CS after improvement in head rice (\$)	12,881.08	8,970.75
Total annual gain in CS after improvement in chalkiness (\$)	2,809.81	7,543.43

for the two classes are \$21,852 for head rice and \$10,353 for chalkiness. Since this study addresses a practical matter concerning upgrading rice value chains, it is important to consider not only the direction of change in CS but also the magnitude of the change. The gains in CS appear to be modest. A benefit–cost analysis would be informative in assessing the feasibility of investment in quality improvement. However, an attempt to determine the costs for Benin alone was met with difficulty. As has been observed in the literature (see, for instance, Pardey *et al.* 2002), the matching of research benefits to costs is a rampant problem, especially where collaborative research is involved and information on costs is not clearly documented. Rice varietal improvement programs in Africa have been led by the Africa Rice Center and the International Rice Research Institute in collaboration with National Agricultural Research Institutes such as the National Institute of Agricultural Research of Benin. The programs and their associated costs are typically spread across several regions and countries. Because of the lack of information, we were unable to calculate the relevant costs, let alone apportion them to the different activities and countries. This is an area for further research. But going by the observed internal rates of return to rice genetic improvement that range from 18 to 182 percent in West and Central Africa (Tollens *et al.* 2013), it is plausible that even in the case of Benin, the present value of benefits from grain quality improvement is highly relative to the present value of costs. Nonetheless, we are careful not to make broad-stroke recommendations for quality improvement based on the relatively small welfare impacts obtained in this study.

To examine the robustness of our results, we undertake a sensitivity analysis by varying the price elasticity of demand for rice, while holding other parameters constant. We consider 10, 20, and 30 percent increases and reductions in the price elasticity and observe corresponding changes in CS. The results are presented in Table 6. Generally, our model results are not very sensitive to changes in the price elasticity of demand. For instance, a 10 percent increase in the price elasticity increases the annual gain in CS from improvement in head rice by 2.16 percent for class 2, while a 30 percent increase would improve CS by 6.50 percent. Likewise, with respect to improvement in chalkiness for class 3, a 10 percent reduction in elasticity would reduce annual gains in CS by 1.93 percent, while a 30 percent reduction would cut gains in CS by 5.80 percent.

Table 6. Gain in Consumer Surplus (USD) for Different Price Elasticities of Demand

Elasticity	Improvement in head rice		Improvement in chalkiness	
	Class 2	Class 3	Class 2	Class 3
-1.804	13,160.23	9,165.16	2,828.66	7,689.24
-1.968	13,439.38	9,359.57	2,847.50	7,835.05
-2.132	13,718.52	9,553.97	2,866.34	7,980.86
-1.476	12,601.93	8,776.35	2,790.97	7,397.63
-1.312	12,322.79	8,581.94	2,772.13	7,251.82
-1.148	12,043.64	8,387.54	2,753.28	7,106.01

Summary and Conclusions

This study uses a hedonic price model to examine market sorting in the Beninese rice market and examines the effect of grain quality improvement on CS. It applies data obtained from laboratory tests of grain quality traits. Controlling for, among other things, two attributes, namely the origin and type of rice that are commonly used to characterize the country's consumer categories, the study has established that there are at least three classes of consumers in the Beninese rice market, manifesting in proportions of 5, 56, and 39 percent. Of the three classes, the smallest class pays the highest price, significantly discounts parboiled rice, and prefers imported to local rice. The second class also discounts parboiled rice but does not place a significant value on the origin of rice, whereas the third category values neither the origin nor the type of rice. Similarly, preferences for other quality attributes vary from one class to another.

Hedonic prices obtained for head rice and chalkiness are applied to a partial equilibrium model to determine the welfare implications of quality improvement for categories 2 and 3. The first important outcome from this exercise is the computed elasticities of demand for rice with respect to the quantities of the two attributes. This is especially informative because these elasticities enable breeders and private seed companies to quickly understand how consumers will respond to grain quality improvement. We then find that an increase in head rice and a reduction in chalkiness autonomously lead to modest gains in consumer welfare.

These results have two important implications for upgrading rice value chains in Benin and other African countries. First and foremost, any upgrading strategy ought to begin by recognizing potential heterogeneity in consumer preferences for rice quality attributes and that existing product categories may not fully capture the heterogeneity. As demonstrated in this study, each class of consumers has a unique hedonic price function and almost all quality attributes—head rice, grain shape, chalkiness, lightness, cooking time, and amylose content—can be targeted for product upgrading. Therefore, upgrading rice value chains requires information on the nature of demand or hedonic price function of the different categories of consumers.

Second, knowledge of the impacts of quality improvement on consumer welfare is informative for setting priorities for spending on research and development. For instance, although our estimates are generally small on economic impact, we see that an improvement in head rice leads to far greater benefits for consumers than an improvement in chalkiness. Our analysis, therefore, demonstrates a straightforward

application of hedonic pricing and partial equilibrium methods to evaluating priorities for crop improvement and value chain upgrading. Currently, there are ongoing efforts by the CGIAR Consortium to develop product profiles of mega rice varieties in Africa in order to achieve certain development outcomes. The analysis used in this study can be integrated in the proposed three-stage approach to product profiling. Of course, it would be even more enlightening to consider net welfare changes by accounting for impacts on producers.

Data Availability Statement. Data used in this study are available from the corresponding author upon request.

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Conflicts of Interest. None.

References

- Africa Rice Center.** 2011. *Boosting Africa's Rice Sector: A Research for Development Strategy 2011–2020*. Cotonou: Africa Rice Center.
- Alene, A.D., T. Abdoulaye, J. Rusike, R. Labarta, B. Creamer, M. del Rio, H. Ceballos, and L.A. Becerra.** 2018. "Identifying Crop Research Priorities Based on Potential Economic and Poverty Reduction Impacts: The Case of Cassava in Africa, Asia and Latin America." *PLoS ONE* 13(8): e0201803.
- Bajari, P., and C.L. Benkard.** 2005. "Demand Estimation with Heterogeneous Consumers and Unobserved Product Characteristics: A Hedonic Approach." *Journal of Political Economy* 113(6): 1239–1276.
- Bayer, P., and C. Timmins.** 2007. "Estimating Equilibrium Models of Sorting Across Locations." *Economic Journal* 117(518): 353–374.
- Bento, A.M., S. Li, and K. Roth.** 2012. "Is There an Energy Paradox in Fuel Economy? A Note on the Role of Consumer Heterogeneity and Sorting Bias." *Economics Letters* 115(1): 44–48.
- Brown, J.N., and H.S. Rosen.** 1982. "On the Estimation of Structural Hedonic Price Models." *Econometrica* 50(3): 765–768.
- Canette, I.** 2018. "Latent Class Analysis with Stata." In *2018 Mexican Stata Users Group Meeting*, August 16–17, Tlaxcala, Mexico. Available at: https://www.stata.com/meeting/mexico18/slides/5_Mexico18_Canette.pdf (accessed August 2019).
- Caudill, S.B., and F.G. Mixon Jr.** 2016. "Estimating Class-Specific Parametric Models Using Finite Mixtures: An Application to a Hedonic Model of Wine Prices." *Journal of Applied Statistics* 43(7): 1253–1261.
- Chattopadhyay, S.** 2002. "Divergence in Alternative Hicksian Welfare Measures: The Case of Revealed Preference for Public Amenities." *Journal of Applied Econometrics* 17(6): 641–666.
- Codjo, O.S.** 2019. "Estimating Demand Elasticities for Rice in Benin." M.S. thesis, University of Arkansas, Fayetteville. Available at: <https://scholarworks.uark.edu/etd/3394> (accessed April 2020).
- Costanigro, M., J.J. McCluskey, and R.C. Mittelhammer.** 2007. "Segmenting the Wine Market Based on Price: Hedonic Regression When Different Prices Mean Different Products." *Journal of Agricultural Economics* 58(3): 454–466.
- Costanigro, M., R.C. Mittelhammer, and J.J. McCluskey.** 2009. "Estimating Class-Specific Parametric Models under Class Uncertainty: Local Polynomial Regression Clustering in an Hedonic Analysis of Wine Markets." *Journal of Applied Econometrics* 24(7): 1117–1135.
- Court, A.T.** 1938. "Hedonic Price Indexes with Automotive Examples." Paper Presented at a Joint Meeting of the American Statistical Association and the Econometric Society, Detroit, Michigan, December 27, 1938.
- Cuevas, R.P., V.O. Pede, J. McKinley, O. Valarde, and M. Demont.** 2016. "Rice Grain Quality and Consumer Preferences: A Case Study of Two Rural Towns in the Philippines." *PLoS ONE* 11(3): e0150345.

- Danneels, E.** 1996. "Market Segmentation: Normative Model Versus Business Reality." *European Journal of Marketing* 30(6): 36–51.
- Day, B.** 2001. *The Theory of Hedonic Markets: Obtaining Welfare Measures for Changes in Environmental Quality Using Hedonic Market Data*. Economics for the Environment Consultancy. Available at: https://pdfs.semanticscholar.org/0c4a/6ac6e14fa2600a75f329fb0f66dac2ee9e5b.pdf?_ga=2.3570736.1874833831.1587044089-268085870.1580825549 (accessed March 2020).
- Elliott, G.R., and R.C. Cameron.** 1994. "Consumer Perception of Product Quality and the Country-of-Origin Effect." *Journal of International Marketing* 2(2): 49–62.
- Espinosa, J.A., and B.K. Goodwin.** 1991. "Hedonic Price Estimation for Kansas Wheat Characteristics." *Western Journal of Agricultural Economics* 16(1): 72–85.
- Futakuchi, K., J. Manful, and T. Sakurai.** 2013. "Improving Grain Quality of Locally Produced Rice in Africa." In M.C.S. Wopereis, D.E. Johnson, N. Ahmadi, E. Tollens, and A. Jalloh (eds.), *Realizing Africa's Rice Promise*. Wallingford, Oxfordshire and Boston, MA: CAB International.
- Greene, W.H.** 2008. *Econometric Analysis*. 6th Ed. Upper Saddle River, NJ: Pearson Prentice Hall.
- Gustafson, G.R., T.J. Lybbert, and D.A. Sumner.** 2016. "Consumer Sorting and Hedonic Valuation of Wine Attributes: Exploiting Data from a Field Experiment." *Agricultural Economics* 47(1): 91–103.
- Halvorsen, R., and R. Palmquist.** 1980. "The Interpretation of Dummy Variables in Semilogarithmic Equations." *American Economic Review* 70(3): 474–475.
- Harrison Jr., D., and D.L. Rubinfeld.** 1978. "Hedonic Housing Prices and the Demand for Clean Air." *Journal of Environmental Economics and Management* 5: 81–102.
- Kim, C.W., T.T. Phipps, and L. Anselin.** 2003. "Measuring the Benefits of Air Quality Improvement: A Spatial Hedonic Approach." *Journal of Environmental Economics and Management* 45(1): 24–39.
- Klaiber, H.A., and D.J. Phaneuf.** 2009. "Do Sorting and Heterogeneity Matter for Open Space Policy Analysis? An Empirical Comparison of Hedonic and Sorting Models." *American Journal of Agricultural Economics* 91(5): 1312–1318.
- Kuminoff, N.V., and J.C. Pope.** 2009. "Capitalization and Welfare Measurement in the Hedonic Model." Working Paper No. 2009-1, Department of Agricultural and Applied Economics, Virginia Tech.
- Kuminoff, N.V., V.K. Smith, and C. Timmins.** 2013. "The New Economics of Equilibrium Sorting and Policy Evaluation Using Housing Markets." *Journal of Economic Literature* 51(4): 1007–1062.
- Ladd, G.W., and V. Suvannunt.** 1976. "A Model of Consumer Goods Characteristics." *American Journal of Agricultural Economics* 58(3): 504–510.
- Lazaro, E.E.** 2014. *An Empirical Analysis of Rice Demand in Tanzania*. M.S. thesis, Department of Agricultural, Environmental and Development Economics, Ohio State University.
- Loureiro, M.L., J.J. McCluskey, and R.C. Mittelhammer.** 2003. "Are Stated Preferences Good Predictors of Market Behavior?." *Land Economics* 79(1): 44–55.
- Nagler, M.G., F. Kronenberg, E.J. Kennelly, B. Jiang, and C. Ma.** 2012. "The Use of Indicators for Unobservable Product Qualities: Inferences Based on Consumer Sorting." *International Journal of Marketing Studies* 4(6): 19–34.
- Naseem, A., S. Mhlanga, A. Diagne, P.Y. Adegbola, and G.S.-K. Midingoyi.** 2013. "Economic Analysis of Consumer Choices Based on Rice Attributes in the Food Markets of West Africa – The Case of Benin." *Food Security* 5(4): 575–589.
- Nerlove, M.** 1995. "Hedonic Price Functions and the Measurement of Preferences: The Case of Swedish Wine Consumers." *European Economic Review* 39(9): 1697–1716.
- Nzuma, J.M., and R. Sarker.** 2010. "An Error Corrected Almost Ideal Demand System for Major Cereals in Kenya." *Agricultural Economics* 41(1): 43–50.
- Palmquist, R.B.** 1988. "Welfare Measurement for Environmental Improvements Using the Hedonic Model: The Case of Nonparametric Marginal Prices." *Journal of Environmental Economics and Management* 15(3): 297–312.
- Pardey, P.G., J.M. Alston, C. Chan-Kang, E.C. Magalhaes, and S.A. Vosti.** 2002. "Assessing and Attributing the Benefits from Varietal Improvement Research: Evidence from Embrapa, Brazil." EPTD Discussion Paper No. 95, International Food Policy Research Institute, Washington, DC.
- Republic of Benin.** 2011. *National Rice Development Strategy for Benin*. Available at: https://riceforafrica.net/downloads/NRDS/benin_en.pdf (accessed July 2019).
- Rosen, S.** 1974. "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition." *Journal of Political Economy* 82(1): 34–55.

- Shiroya, M.** 2010. *A Finite Mixture Approach for Household Residential Choices*. M.S. thesis, Department of Agricultural and Applied Economics, Texas Tech University.
- Singham, P., P. Birwal, and B.K. Yadav.** 2015. "Importance of Objective and Subjective Measurement of Food Quality and Their Interrelationship." *Journal of Food Processing and Technology* 6(9): 1–7.
- Tang, E.N., S.A. Ndindeng, J. Bigoga, K. Traore, D. Silue, and K. Futakuchi.** 2019. "Mycotoxin Concentrations in Rice from Three Climatic Locations in Africa as Affected by Grain Quality, Production Site, and Storage Duration." *Food Science and Nutrition* 7(4): 1274–1287.
- Tollens, E.** 2007. "Markets and Institutions for Promoting Rice for Food Security and Poverty Reduction in Sub-Saharan Africa." *African Crop Science Journal* 15(4): 237–242.
- Tollens, E., M. Demont, M. Sie, A. Diagne, K. Saito, and M.C.S. Wopereis.** 2013. "From WARDA to Africa Rice: An Overview of Rice Research for Development Activities Conducted in Partnership in Africa." In M.C.S. Wopereis, D.E. Johnson, N. Ahmadi, E. Tollens, and A. Jalloh (eds.), *Realizing Africa's Rice Promise*. Wallingford, Oxfordshire and Boston, MA: CAB International.
- Ulimwengu, J.M., and R. Ramadan.** 2009. "How Does Food Price Increase Affect Ugandan Households? An Augmented Multimarket Approach." Discussion Paper No. 00884, International Food Policy Research Institute, Washington, DC.
- Unnevehr, L.J.** 1986. "Consumer Demand for Rice Grain Quality and Returns to Research for Quality Improvement in South East Asia." *American Journal of Agricultural Economics* 68(3): 634–641.
- Van Horn, M.L., T. Jaki, K. Masyn, G. Howe, D.J. Feaster, A.E. Lamont, M.R.W. George, and M. Kim.** 2015. "Evaluating Differential Effects Using Regression Interactions and Regression Mixture Models." *Educational and Psychological Measurement* 75(4): 677–714.
- Voon, J.P., and G.W. Edwards.** 1991. "Research Payoff from Quality Improvement: The Case of Backfat Depth in Pigs." *Journal of Agricultural Economics* 42(1): 66–76.