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Consumer Valuation of Rice Quality in Colombia

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Consumer Valuation of Rice Quality in Colombia

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Abstract

Rice is a crucial contributor to global food security and is an important staple for over half the world's population. In Colombia, total rice consumption has grown by 25% in the last decade (2011-2021), reaching 1.9 MMT in 2021, yet in 2021 around 15.5 million Colombians were classified as food insecure. Colombia is the third largest rice producer in Latin America, producing 1.8 million metric tons (milled basis) in 2021. Increasing rice consumption coupled with high levels of food insecurity highlights the necessity that rice markets effectively price rice according to consumer preferences. Therefore, the goal of this study focuses on consumer preferences for rice with different broken percentages. Broken rice not only lowers the economic value of the rice crop but also can reduce the rice available for food consumption. A choice experiment and hedonic price model were implemented in Cali and Palmira, Colombia, in April of 2022 to analyze the revealed versus stated preferences for rice quality attributes. The findings of this study highlight potential inefficiencies between what consumers are willing to pay for regarding broken rice versus what is revealed in the market. It gives the rice industry important information about using broken rice for human or non-human consumption. The results also spark a discussion about the importance of knowing the food quality consumers prefer and the potential implications of those choices from an economic and food-security point of view.

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Table of Contents

List of Tables

List of Figures

1. Introduction

Rice is a crucial contributor to global food security and is an important staple for over half the world's population. In Latin America and the Caribbean (LAC), rice supplies more calories than wheat, maize, or other staple crops usually found in the diets of lower income individuals (Calvert et al., 2006). Colombia is the third largest producer in the LAC region behind Brazil and Peru with 1.8 million metric tons (MMT) produced in 2021 (USDA, 2022). Total rice consumption has grown by approximately 25% in the last decade (2011-2021), reaching 1.9 MMT in 2021, given the combination of population growth and an 11% increase in per-capita consumption (Durand-Morat and Bairagi, 2022). Per-capita consumption reached 37.4 kg annually in 2021, accounting for 11% of the average caloric intake (FAOSTAT, 2023). Colombia is a residual importer of rice depending on production performance, with imports varying from 260 thousand MT in 2019 to a low of 60 thousand MT in 2021 (USDA, 2022).

Colombia protects its domestic rice market with a high 80 percent import tariffs on rice coming from all WTO members. Still, it applies preferential rates to Ecuador, Peru, and the US under regional trade agreements (USDA, 2021). Colombia is a growing market for U.S. rice attributed to the preferential access granted under the U.S.-Colombia Trade Promotion Agreement, through which Colombia granted a duty-free tariff-rate quota (TRQ) and a decreasing over-quota import tariff. In 2023, the volume of the TRQ is 128,205 MT of rice (milled equivalent), and the over-quota tariff is at 43%. Under the agreement, rice trade between the U.S. and Colombia will be completely free in 2030 (Organization of American States, 2023).

As the preferential treatment increases, more U.S. rice is expected to be exported into Colombia. This is important to the Colombian rice industry because increased rice imports from the U.S. could create competition for domestic rice producers in Colombia. If the imported rice is cheaper, of higher quality, or both, it could decrease demand for domestic rice, which could result in lower prices and lower profits for domestic rice producers. Rice imports in Colombia can benefit consumers by increasing the variety of rice options in the market and making rice more affordable through a larger supply and lower prices.

Despite Colombia's Peace Accord of 2016 addressing the right to food, food security concerns remain high amidst internal and external conflict, natural disasters, and the impact of the COVID-19 pandemic. According to the World Food Programme (WFP, 2023), around 15.5 million Colombians or 30% of the population are food insecure, 2.1 million of which are severely food insecure. Moreover, around half of the Colombian population is marginally food secure, meaning they are at a high risk of becoming food insecure.

Understanding the urgency of the food security concern linked with the importance of rice as a staple highlights the need to continue improving the rice industry's efficiency to expand the rice options to consumers, including affordable options for the poorest segments of the population. A well-functioning market would price rice in a way that corresponds to the quality of the rice product offered. One of the attributes that define the quality of milled rice is the presence of broken kernels. The general assumption is that the higher the presence of broken kernels, the lower the quality of milled rice. Consequently, a well-functioning market will be one in which everything else constant, the price of milled rice is negatively correlated with the percentage of broken rice.

Broken rice refers to fragments of rice grains that break during any part of the milling process. When paddy rice arrives at the mill, it is first filtered to remove foreign materials and then processed to remove the husk, which results in brown rice. Next, brown rice is milled to remove the bran layer and germ (International Rice Research Institute, 2022). For many reasons, including the genetic characteristics of the rice variety, the growing conditions (e.g., temperature), and both on-farm and post-harvest management practices, a portion of the rice kernels break during milling, which is separated from the whole (head) rice and segregated into different categories of broken. In Colombia, broken rice is classified into four categories: large (between 50% and 75% of the length of the whole kernel), medium (between 25% and 50% of the length of whole kernel), small (less than 25% of the length of a whole kernel, but removed by a 1.4 mm sieve), and fragment (less than 25% of the length of a whole kernel that passes through a 1.4 mm sieve) (ICONTEC, 2007). Broken rice carries a lower value than whole rice. For instance, the 2023 USDA's loan rate is $245.8 per MT for long-grain whole kernels and $148.6 per MT for broken kernels, equivalent to a 39.5% discount (USDA, 2023). Moreover, the average export price for 100% broken long grain rice from India in 2018-2022 averaged $297.9 per MT, compared to $384.6 per MT of long grain milled rice with 5% broken, a 22.5% discount (FAO, 2023).

Milled rice is graded based on several criteria, one of which is the percentage of broken kernels in the total amount of milled rice. Milled rice in Colombia is classified into five grades based on the presence of broken rice, chalky rice, damaged rice kernels, red-rice kernels, and other foreign materials (ICONTEC, 2007). Regarding broken rice, the highest quality (grade 1) allows a maximum of 5% broken, followed by 12% for grade 2, 18% for grade 3, 25% for grade 4, and 35% for grade 5.

Broken rice contains the same nutritional value as a whole grain of rice (Wang et al., 2002). However, in many markets, its inferior appearance results in broken rice leaking out of the food system and into other less valued uses, such as pet food or energy. Using broken rice for non-food purposes lowers the amount of food (rice rations) produced per unit of paddy rice, which has implications for food security and environmental sustainability as more rice area is needed to produce a given number of rice rations. Rice production is the leading agricultural source of CH_4, accounting for 22% of global anthropogenic agricultural emissions (Smartt et al., 2016), and has a global warming potential per metric ton that is 467 and 169 percent higher than wheat and maize, respectively (Linquist et al., 2012). Therefore, increasing the amount of rice that is used for food is crucial in making the rice supply system more sustainable.

1.1. Literature Review: Rice Quality Preferences

Previous studies underline the geographic and cultural heterogeneity of rice preferences and the variation in value placed on various attributes. Rice quality attributes can be classified into intrinsic (taste and texture), extrinsic (packaging and labeling), search (price, appearance, brand, and packaging), experience (ease of cooking, taste, texture), and credence (production, processing, and product content) (Cuevas et al., 2016). Even among low-income households, there is increasing evidence, primarily from Asia and Africa, indicating consumers' awareness of rice quality attributes (Cuevas et al., 2016). Studies examining consumer perception and preference for rice quality have highlighted appearance, taste, aroma, and texture as significant determinants of consumer choices. Calingacion et al. (2014) further emphasizes the global variation in rice grain quality by assessing the major rice quality trait characteristics. Consumers in Southeast Asia prefer long and slender grains, consumers in Indonesia and Bangladesh prefer medium and slender grains, and consumers in North Asia prefer short and bold grains (Calingacion et al., 2014). A rice quality study conducted by Peterson-Wilhelm et al. (2021) in the Democratic Republic of Congo (DRC), Ghana, and Mozambique highlighted rice price is driven by consumer preference for length and length-to-width ratio in the DRC, broken rice percentage in Ghana, and the length-to-width ratio in Mozambique. Furthermore, Saha et al.

(2021) found that rice prices in Bangladesh are driven by broken rice percentages above the threshold of 24.9 percent.

Research has also explored consumer willingness to pay (WTP) for high-quality rice, indicating the economic implications of rice quality preferences. In a WTP for parboiled rice study done in Haiti in 2018, results found that respondents showed inconsistency regarding their WTP for broken grains which led to broken not being a strong attribute in consumers' purchasing decisions (Pavilus, 2018). In addition, a hedonic analysis in the Philippines revealed that greater percentage of broken rice is discounted by middle- and high-income classes (Cuevas et al., 2016). A study conducted in the United States revealed that the appearance of a higher percentage of broken kernels (>20%) affected the consumers' perception of raw milled rice, however, the consumers were not able to differentiate between different samples of broken rice percentages (5%-40%) when measuring the appearance of cooked rice (Richardson et al., 2021).

While previous studies highlight consumer preference for rice attributes, few analyze the economic valuation placed on rice quality attributes by consumers, especially in LAC. Therefore, an assessment of the economic value of rice quality in Colombia is novel in the literature. This study is unique in that it combines hedonic price analysis and consumer choice experiments to better understand the revealed preference and stated preference for milled rice with different broken percentages. The objective of this study is to analyze consumer preference for broken rice in Colombia. Additionally, this study aims to determine if and by how much consumers discount broken rice which could have important policy implications to aid the economic and environmental sustainability of rice consumption in Colombia. If Colombians do not discount broken rice, then more broken rice can be allocated for human consumption rather than filtering broken rice into the brewing industry, animal feed, or for energy use without price penalties. The findings of this study highlight the importance of evaluating consumer preferences from an economic and food security point of view.

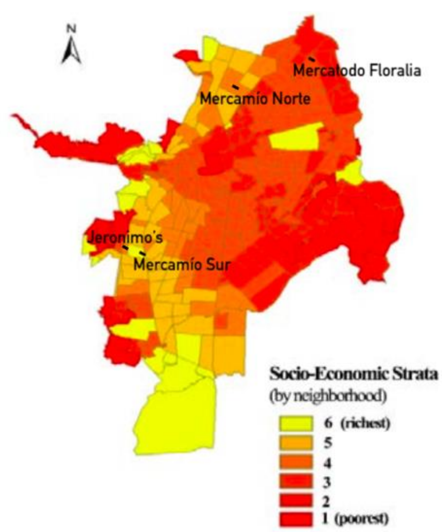
2. Materials and Methodology

A hypothetical choice experiment and a hedonic price model are used to analyze consumers' WTP for broken rice in the market. The advantage of using these two methods is that we can estimate the stated and revealed preferences and better assess whether the rice market is working efficiently in the sense of pricing rice according to consumers' valuation for broken rice. The comparison can provide valuable information to guide the development of marketing and policy strategies that could help bridge any gaps that may exist between what consumers state they prefer and what consumers reveal they prefer, regarding the amount of broken rice in milled rice.

2.1. Data

A total of 400 surveys and 200 rice samples were collected from four major supermarkets and one small outlet store across Cali and Palmira, Colombia in April 2022. One hundred survey responses came from the supermarket Mercamío in the North of Cali, 100 from Mercamío in the South of Cali, 100 from supermarket Cañaveral in Palmira, 26 from Jeronimo's in the South of Cali, and 74 from Mercatodo Floralia in the North of Cali. Figure 1 shows the locations of the four markets in Cali in relation to socioeconomic strata. Colombia uses a system of socioeconomic strata to categorize neighborhoods by labeling houses with one through six, one being the lowest socioeconomic

Figure 1: Poverty Map of Cali in 2010



Scholl and Guerrero (2015)

class and six being the highest socioeconomic class (Arrieta, 2018). While the stratum system is not necessarily based on income, it is highly correlated, and it was primarily designed to assist families who may have difficulty paying their bills. Houses in strata one through three, receive utility subsidies, strata four neither receive subsidies nor pay a premium, and the upper stratum pay a premium for utilities (Arrieta, 2018).

2.2. Choice Experiment

2.2.1. Experimental Design

The survey was available to participants in Spanish and thirty pre-test surveys were conducted at the Center for International Tropical Agriculture (CIAT) for question validation, and the estimated of parameters were employed as priors of Bayesian design. The survey team, composed of eight Colombian natives fluent in Spanish, approached potential participants exiting the respective supermarket locations. If the participants were over 18 and indicated they oversaw household grocery purchasing, including rice, they were invited to participate in the study. If the participant agreed to engage in the study, they were notified that they would be compensated for their time during the choice experiment and subsequent socioeconomic survey. Participants received a supermarket voucher for 30,000 Colombian Pesos (COP) or roughly US$ 8 for completing the choice experiment. Following the choice experiment and socioeconomic questionnaire, the participant was notified of an additional, optional compensation that would be awarded if they agreed to allow a small sample collection of rice they had just purchased from the supermarket; however, purchasing rice from the supermarket was not a prerequisite to participating in the survey. Participants received another voucher for COP 10,000 or roughly US$ 2 for providing a small sample of around 50 grams of rice.

As part of the choice experiment, participants were presented with 5 choice sets of 3 clear-bagged, half-kilo samples of rice with varying levels of price and broken rice and as well as a no-buy option. Then, respondents answered various demographic questions regarding household characteristics and rice consumption habits. In the next section, respondents ranked various attributes of rice that range from most important to least important. Those attributes include price, brand, fortification, whole grain, whiteness, long and thin kernels, cleanliness, presence of broken rice, presence of chalky or opaque rice, fortification, and taste. Finally, if applicable, from those respondents that agreed to it, a small sample of around 50 grams of the rice they bought at the market was collected and the purchase was recorded.

Defining attributes and their respective levels are a crucial part of designing choice experiments for the purpose of revealing consumer preference (Zeleke et al., 2021). In this study, we selected only relevant factors based on the consultation of local rice millers, current market prices of selected supermarkets, and guidance from the Latin American Fund for Irrigated Rice (FLAR) team at CIAT. The market attributes selected were rice price and percentage of broken rice. Prices were derived from the price of 11 brands of long grain white rice across five supermarkets collected a week before the experiment was conducted. Broken percentages were derived using expert opinion from FLAR as well as the five rice grades as defined in the Colombian Technical Standard for Processed Rice published by the Colombian Institute of Technical Standards and Certification: 5%, 12%, 18%, 25% and 35% for Grade 1 through Grade 5, respectively (ICONTEC, 2007). All prices are expressed in the local currency- COP. The rice samples were created in the Rice Quality Laboratory at the CIAT campus. The process of creating the rice samples involved separating the whole and broken rice kernels and then mixing them back at the right proportions by weight. A summary of attributes and attribute levels is outlined in Table 1.

Table 1: Attribute Levels

Attributes	Attribute Levels
Price	2500 COP/kg[1]
	4000 COP/kg
	5500 COP/kg
	7000 COP/kg
	8500 COP/kg
Percentage of Broken Rice	5%
	10%
	15%
	20%
	30%

1. The exchange rate at the time of the survey was $3779.80 COP per $1 USD.

Choice experiments present a series of choice sets to the respondent and each time respondents are to choose the most preferred alternative. In this study, participants were presented three milled rice products with different prices and broken rice levels, and a no-buy option because with a greater number of attributes, the greater the cognitive burden is for the respondent to accurately choose the most preferred alternative (Mangham et al., 2009). An opt-out alternative is important in the experiment design because it more closely emulates a real-world scenario in which the respondent in not required to choose. Figure 2 shows an example of a choice set for the control and the treatment groups. Participants in the treatment group (200 samples) were shown samples with both the explicit broken rice rate presented and the price, whereas the control group (200 samples) received only information about the price of each rice product. The goal of adding the treatment is to ascertain whether consumer decisions are influenced by objective information about the percentage of broken in milled rice versus their perception of quality from assessing the quality of the rice samples without knowing exactly how much broken rice is in each product.

Figure 2: Sample Control and Treatment Choice Set

Control				No-Buy
Treatment				No-Buy

The experimental design for this study consisted of two attributes with five levels and four alternatives, implying a full-factorial design of 625 (=5^4) hypothetical purchasing scenarios. Many scenarios create a cognitive burden for respondents. To mitigate this, a D_b-efficient design was utilized to extract a D-error representing the efficiency with which the experimental design extracts information from the respondent (Szinay et al., 2021). The efficient design requires known prior information about the parameters to be entered into the algorithm, and the specific model used for this study was the Bayesian approach. This approach allows for a probability distribution to describe the unknown certainty of the parameter (Szinay et al., 2021). Following best practices to pilot the study, the results of the D_b-efficient design were used to launch the full discrete choice experiment, which includes 14 different combinations of price and broken percentage, each with a no-buy option.

2.2.2. Empirical Model

The econometric analysis of this choice experiment is focused on random utility modeling based on the Random Utility Theory (McFadden, 1974). According to this theory, given a set of alternatives, individuals choose the alternative that generates the highest level of utility. The utility of an individual i, j alternatives, and t choices can be represented as:

$$U_{ijt} = x_{ijt}\beta_i + \varepsilon_{ijt} \quad (i)$$

where x_{ijt} represents a vector of the variables, β_i represents the vector of parameters that varies across individuals, and ε_{njt} represents the error term. $x_{ijt}\beta_i$ represents the assumed deterministic or observable portion of the individual utility function, while the random error component, ε_{njt}, represents the unobserved portion (Bazzani et al., 2017).

This study uses a random parameter logit (RPL) model is used to estimate the willingness-to-pay space (WTPS) model. WTPS models reparametrize the parameters so that the WTP estimates (rather than the marginal utility) are directly estimated. (Sarrias & Daziano, 2017). The standard logit model assumes that all individuals have the same preferences and that the coefficients on the different attributes of a good or service are fixed across the population. However, RPL models relax this assumption by allowing for individual-specific random parameters to capture heterogeneity in preferences. The RPL model also allows for correlation among the random parameters, which means that some attributes may be more closely related to each other regarding their effect on the choice probabilities. In this study, the utility of each respondent i of choosing alternative j in choice task t can be specified as follows:

$$U_{ijt} = \alpha Price_{ijt} + \beta Broken_{ijt} \quad (ii)$$

where $Price_{ijt}$ represents a continuous variable based on the five experimentally designed price levels and $Broken_{ijt}$ represents a continuous variable based on the five experimentally designed broken percentage levels. The WTPS model is derived from (ii) dividing the attribute coefficient by the price coefficient as represented in the following way (Sarrias and Daziano, 2017):

$$U_{ijt} = \alpha(Price_{ijt} + \frac{\beta}{\alpha} Broken_{ijt}) \quad (iii)$$

where $\frac{\beta}{\alpha}$ is the WTP vector and α is fixed and equal to 1. Furthermore, to analyze the effects of socioeconomic variables on WTP for milled rice with different levels of broken rice, we utilized a function that generates a vector of normally distributed random numbers based on the mean and standard deviation of the broken coefficient in the RPL model results. The vector created represents the WTP for each respondent for the control and treatment group (200 samples each). This is the same sample of consumers used in the WTPS RPL model. An Ordinary Least Squares (OLS) regression using this vector and socioeconomic variables was estimated as follows:

$$WTP = \beta_0 + \beta_1 Edu + \beta_2 MiddleStrata + \beta_3 HighStrata + \varepsilon \qquad (iv)$$

where WTP represents the individual WTP vector for broken extracted from the RPL based on the broken coefficient and broken standard deviation, β_0 represents the regression constant, β_1 represents education level, β_2 and β_3 represent the different socioeconomic strata groups, and ε is the error term.

2.3. Pure Hedonic Price Model

Based on Lancaster's (1966) consumer theory, hedonic price modeling postulates that goods possess attributes that, when combined, provide a price value to the consumer (Chin and Chau, 2003). Lancaster's theory assumes a linear relationship between the characteristics of the goods and the price of the goods, therefore, in this study, the price of rice is a function of its physical characteristics, such that:

$$P_i = aX_i + \varepsilon_i \qquad (v)$$

where P is the price paid by consumer i, X_i is the vector of rice quality attributes, and ε_i is the error term (Saha, 2021). The rice quality attributes included in this study are broken percentage, chalk percentage, average length, average width, and breakdown viscosity. Breakdown viscosity refers to the stickiness of the cooked rice (Balet et al., 2019). The model was estimated with socioeconomic variables, education and strata, and interactions of those variables with the broken percentage attribute to analyze the effect of various socioeconomic variables' perception of broken rice on price per kilogram of rice. The econometric equation is as follows:

$$Price_i = \beta_0 + \beta_1 Broken_i + \beta_2 Chalk_i + \beta_3 AvgLength_i + \beta_4 AvgWidth_i + \beta_5 Breakdown_i + \varepsilon_i \quad (vi)$$

The conceptual foundation for choice experiments is found in hedonic methods where demand for good arise from demand for attributes (Holmes et al., 2017). Choice experiments elicit individuals' stated preference for goods, while hedonic modeling uses data on prices and other characteristics of goods to elicit the revealed preference of those goods. Holmes et al. (2017) found that by combining the information from both approaches, researchers can better understand the trade-offs that individuals make between different attributes and more accurately estimate their values.

2.3.1. Measurement of Physical Attributes of Rice

The rice samples collected were processed for physical analysis at the CIAT facility in Palmira, Colombia. The rice samples were processed using the Vibe QM3 Rice Analyzer and Rapid Viscosity Analyzer (RVA) to determine quality based on brokenness, chalkiness, length, width, and breakdown viscosity. The Vibe QM3 Rice Analyzer accurately measures, counts, and classifies each kernel by size, shape, and color. The key capabilities of the Vibe QM3 include reporting broken percentages with an accuracy of less than 0.5%, size analyses (length and width) with accuracy of less than 50 micron, and abnormal color and damaged kernels analysis using 3,000 color pixels per kernel (Vibe Image Analytics, 2022). The Vibe QM3 was calibrated following the USDA standard by which a whole kernel of rice is at least 7.5/10 the average length of the corresponding whole kernel, and a broken kernel is less than 7.5/10 the average length of the corresponding whole kernel (ICONTEC, 2007). The average size of the samples processed was 50 grams or 400-500 grains of rice.

The broken percentage represents the amount of broken rice in the sample. This is measured as:

$$Broken\ percentage_i = \frac{WB_i}{weight\ of\ working\ sample\ i} * 100 \qquad (vii)$$

where WB_i is the weight of broken rice in sample i (Saha, 2021). The chalkiness of kernels is defined by the USDA (2020) Rice Inspection Handbook as whole or broken kernels of rice that are one-half or chalkier relative to the weight of the sample. Therefore, the chalk percentage is measured as:

$$Chalk\ percentage_i = \frac{WC_i}{weight\ of\ working\ sample\ i} * 100 \qquad (viii)$$

The length and width of the rice are measured in millimeters. The length of the kernel in sample i is the average length across the whole sample n. Similarly, the width of the kernel in sample i is the average width across the entire sample n.

$$Length_i = \sum_{j=1}^{n} \frac{length_{ji}}{n} \qquad (ix)$$

$$Width_i = \sum_{j=1}^{n} \frac{width_{ji}}{n} \qquad (x)$$

The rice samples were also processed to assess their cooking characteristics, specifically, the amylose content, gelatinization temperature, and paste viscosity represented by the breakdown, final viscosity, and setback points. Amylose is one of two starch polymers in rice, and the amylose content is believed to be one of the best indicators of rice texture (Morrison and Azudin, 1987). The amylose content was measured using colorimetry with iodine following Juliano (1971). Based on the amylose content, rice is classified into high amylose (>28%), intermediate (23-28%), and low (<23%). The gelatinization temperature (GT) of rice starch has traditionally been defined as the temperature at which nearly all the starch granules in a sample lose their birefringence or the optical property of rice having a refractive index that depends on the direction of light and polarization (Bhattacharya, 1979). The GT was measured using the differential scanning calorimetry (DSC), which detects changes in thermal behavior and indicates the temperature range where the solid starch structures melt permanently when exposed to water that acts as a plasticizer (Normand and Marshall, 1989). Higher GTs require more water and longer cook times to achieve the same “doneness” as rice samples with lower temperatures (Juliano, 1971). The temperatures can range from low (<70°C) to high (>74°C) (Bhattacharya, 1979).

Paste viscosity, measured using a Rapid Visco-Analyzer (RVA), is another indicator of cooking and eating quality in rice. The RVA imitates the cooking process of a cereal by performing controlled mixing, heating, and cooling processes over a period of time (Xie et al., 2015; Balet et al., 2019). Different parts of the viscosity curve have been associated with GT, apparent amylose content (AAC), and texture. Measured properties of the viscosity curve include pasting temperature (temperature of initial viscosity increase which provides information on minimum temperature to cook rice), peak viscosity (maximum viscosity during heating and holding process), peak time (time to reach the peak), trough (minimum viscosity following peak), final viscosity (viscosity recorded at end of test), breakdown (difference between peak viscosity and lowest viscosity reached during the holding stage), and setback (difference between final viscosity and trough) (Champagne et al., 1999; Balet et al., 2019). When looking at the extent to which RVA predicts textural properties of cooked rice, breakdown explains most of the variance in hardness, and setback explains most of the variance in the cohesiveness of mass, stickiness, and initial starchy coating (Champagne et al., 1999).

2.3.2. Piecewise Analysis

A piecewise, or segmented, regression analysis estimates linear models with one or more relationship segments in the predictor model (Muggeo, 2023). This is used to understand how independent variables affect the dependent variable over certain thresholds. In relation to this study, understanding these thresholds are important because the price might not be sensitive to broken percentages above or below a specific rate. This analysis was performed using the NL command in Stata®. Segmented regression analysis in Stata involves fitting a series of linear models to different data segments, and the number of breakpoints was identified through visual inspection of the data. The function fits a segmented linear relationship regression model with one breakpoint based on the specified predictor variable, broken percentage.

3. Results

3.1. Descriptive Statistics

Table 3 outlines the socioeconomic characteristics of the choice experiment sample and population. Almost 80% of the respondents in the sample were female, compared to 53.9% in the population at large, as observed in 2020 by the Administrative Department of Planning in Cali, Colombia, as well as the Ministry of Education Municipality of Santiago de Cali (Morales, 2021; Rodríguez et al., 2016). The larger share of females in the sample was expected, given that women are primarily in charge of food purchases, a pre-requisite for participation in the survey. Around 20% of our sample has at most completed primary school, 45.8% reported to have completed secondary school, 29% have a university degree, and 5.3% have a postgraduate degree. The population data for education for Cali was not available, therefore, the population proportion reflects the distribution of the workforce by education level for all of Colombia (DANE, 2022). We conclude that our sample is overeducated compared to the population. While monthly income data was collected, strata were used in this study because it is significantly and positively correlated with income and Colombians know the strata their household belongs to. The sample collected shows 48.75% of respondents in strata 1 or 2 (low strata), 39.25% in 3 or 4 (middle strata), and 11.55% in 5 or 6 (high strata). In 2020, the frequency distribution of the population across strata was 15.46% and 20.18% for low strata, 24.71% and 16.6% for middle strata, and 15.80% and 7.24% for high strata. While our sample is biased toward the low strata, we believe that could result from the COVID-19 pandemic, which could have shifted the population to lower strata levels.

Table 2: Sociodemographic Characteristics of the Sample

Characteristic	Sample (%, n = 400)	Population
Gender		
Female	79.5	53.9
Male	20.5	46.1
Education		
Primary or less	20	30.8
Secondary	45.8	40.8
University	29	23.7
Postgraduate	5.3	4.0
Strata		
1	14.5	15.5
2	34.3	20.2
3	23.5	24.7
4	15.8	16.6
5	11.5	15.8
6	0.1	7.2

The socioeconomic characteristics of the hedonic modeling sample population reported similar proportions. A Welch two-sample t-test revealed that the distribution of the sub-sample of 200 consumers that provided rice samples was not statistically different ($p>0.05$) from the original sample of 400 consumers for both socioeconomic strata and education.

3.2. Estimates from Choice Experiment

The results of the RPL model are presented in Table 3. Model 1 estimates an RPL model where broken enters as a continuous and sole explanatory variable for control and treatment groups. The scale represents the average heterogeneity. No-buy can be described as the utility expressed in COP that consumers are losing by not purchasing rice. The standard deviation represents the distribution of the broken coefficient among individuals. The tau estimates represent the variance of the random effect parameter in the RPL model and are negative and statistically significant in both models, indicating that there is heterogeneity in the preferences for broken rice among individuals.

Table 3: WTP for Broken Estimates from RPL Model

	Model 1	
	Control	Treatment
Scale	-4.14***	-5.08***
No-Buy	-556.98	-1322.87
Broken	-2.45***	-6.24***
SD Broken	0.43	0.24
Tau	-1.15**	-1.13**
Log-Likelihood	-1164.60	-1157.20
N	1000	1000

***, **, *, indicate significance at 1%, 5%, and 10% level, respectively.

For Model 1, the negative sign of the coefficient on *Broken* suggests that consumers are willing to pay COP 2.45/kg less for each point increase in the percentage of broken when they do not know for certain the percentage of broken present in the milled rice, but their WTP decreases to COP 6.24/kg when they know precisely how much broken rice is in the milled rice. Considering the range of broken percentage values used in this study and the estimated economic value based on the stated preferences of consumers, we estimate that the price of milled rice can vary by COP 61.25/kg between milled rice with 5-percent and 30-percent broken (the latter having a lower price) for the control group, and up to COP 156.00/kg for the treatment group. Considering that the average market price of rice used in the experiment was COP 5,500/kg, the relative impact of broken percentage on the price of rice is small (maximum of 1.1 percent and

2.8 percent for control and treatment, respectively). Additionally, the treatment group discounts broken rice at a higher rate than the control group, which did not receive information regarding the percentage of broken within the samples. The likelihood ratio test (control coefficient: -1164.6; treatment coefficient: -1157.2; p-value: 2.2e-16) confirmed that the results for broken in the control and treatment groups are statistically and significantly different.

Table 4 presents Model 2, which estimates a linear regression to explain the WTP for rice with different broken percentages (estimated from the RPL model results) using the selected socioeconomic variables of education and strata. The method of evaluating WTP for broken based on socioeconomic variables conducted is done using an OLS regression because the socioeconomic variables are case-specific variables. Case-specific variables refer to factors unique to each individual in the dataset, including demographics or socioeconomic status, for example. Case-specific variables cannot be used in this type of model is because the random parameter logit model assumes that the preference heterogeneity among individuals is captured solely by the random parameters. The model assumes that the preference variations can be explained by the distribution of random parameters, which are estimated from the observed choices in the choice experiment. Including case-specific variables would violate the model's assumptions and could lead to biased estimates. Socioeconomic strata are used to construct two binary variables: high strata (equals to one if strata 5 and 6, zero otherwise) and middle strata (equals to 1 if strata 3 and 4, zero otherwise). Education is coded as a binary variable equal to 1 if university or postgraduate degree is completed, and zero otherwise.

Table 4: OLS Regression WTP for Broken on Socioeconomic Variables

	Model 2	
	Control	Treatment
Intercept	-2.41***	-6.30***
High Education	-0.08	0.13***
High Strata	0.02	-0.04
Middle Strata	0.006	0.02
Multiple R^2	0.006	0.058
Adjusted R^2	-0.009	0.043

***, **, *, indicate significance at 1%, 5%, and 10% level, respectively.

The intercept indicates that all else equal, the low strata and low education consumers are willing to pay COP 2.41/kg less for a one percentage point increase in broken when they do not know the percentage of broken present in the milled rice. However, when those consumers know how much broken rice is in the milled rice, their WTP decreases to COP 6.30/kg. Consumers with a higher level of education indicate negative but not significant (p>0.1) WTP values when they do not know the percentage of broken presented in milled rice; however, when they do know how much is present, their WTP increases to COP 0.13/kg for a one percentage point increase in broken. This finding is counterintuitive as we would expect more educated people could value rice quality (as represented by the percentage of broken rice) more than less educated respondents. Nevertheless, the value is so small that it has a negligent impact on rice pricing. Interactions between strata and broken were initially included to capture WTP for broken by income level, however, these results were dropped due to collinearity issues.

To ascertain whether the marginal value of broken percentage changes with the levels of broken percentage in the milled rice, we estimated an RPL model with broken rice entered as a set of binary variables rather than continuous variables. Four binary variables were created, one for each of the following four levels of broken percentage: 5%, 10%, 15%, and 20%. The bootstrap method, a resampling technique used to estimate the sampling distribution of a statistic and obtain confidence intervals, was instrumentalized by simulating 10,000 parameters (Efron, 1979). We tested the statistical difference between coefficients using the Poe test (Poe et al., 2005). Figure 3 and 4 provides the estimates of the average perceived marginal value for each broken level relative to rice with 30% broken, which serves as the benchmark, for both control and treatment groups.

Figure 3: Treatment Group Mean Price Difference for Milled Rice with 5%, 10%, 15%, and 20% Broken Rice Relative to 30% Broken Rice (Bars represent 95% confidence intervals)

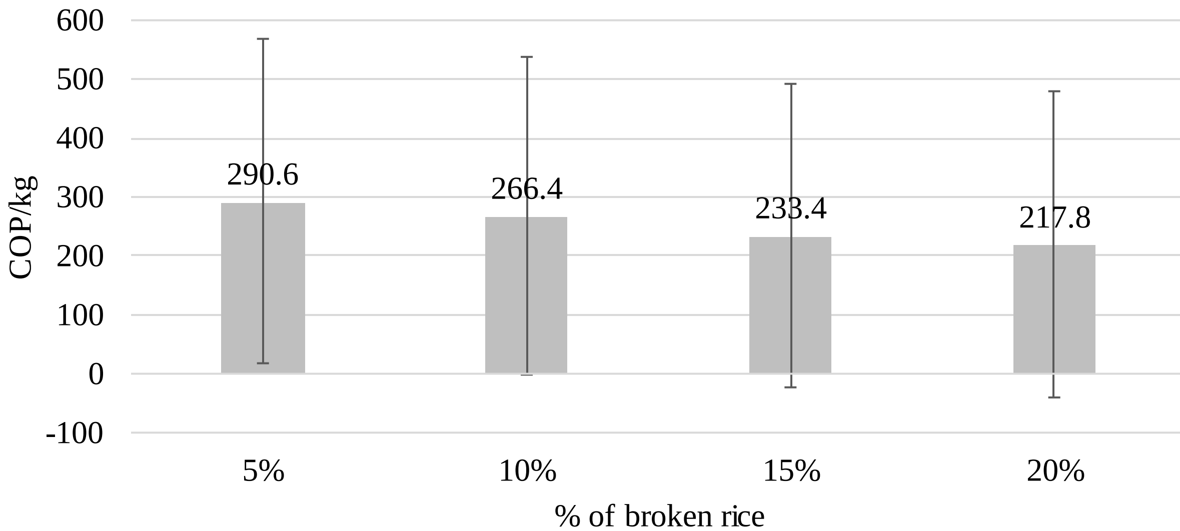
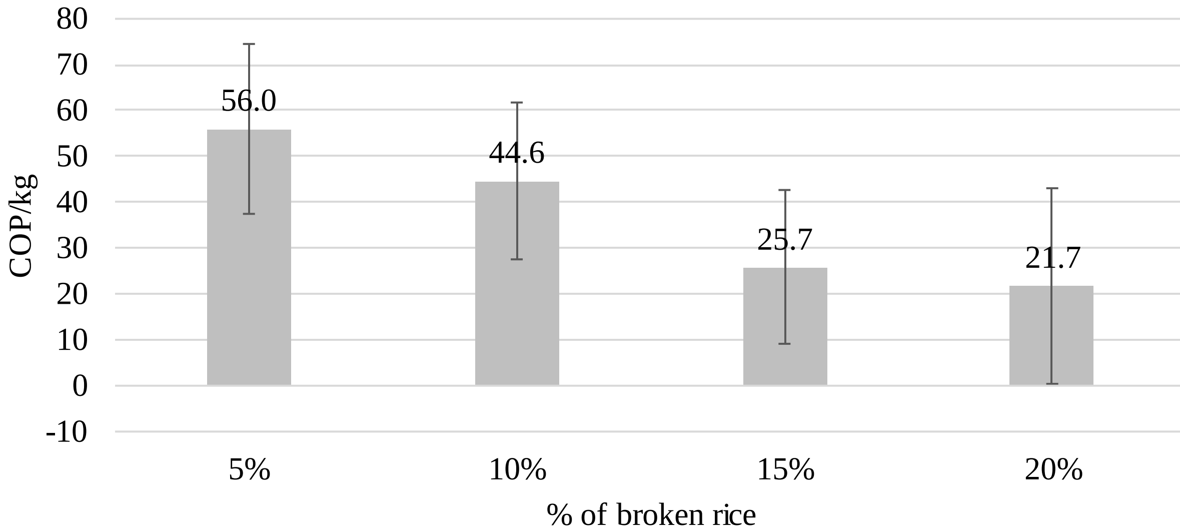


Figure 4: Control Group Mean Price Difference for Milled Rice with 5%, 10%, 15%, and 20% Broken Rice Relative to 30% Broken Rice (Bars represent 95% confidence intervals)



First, it is important to notice that the results are consistent with the expected signs and magnitudes. The coefficients, understood as price premiums relative to milled rice with 30% broken rice, are positive and negatively correlated with the percentage of broken rice, and they are larger for the information treatment than the control. For the treatment group (Figure 3), the premium for milled rice with 5% broken (p>0.05), 10% broken (p>0.10) and 15% broken (p>0.10) are significantly different from zero. The Poe test results (not shown) suggest that there are no significant differences in the price premiums between the 5%, 10%, 15%, and 20% broken percentage.

For the control group (Figure 4), the results show that the price premiums for rice with 5% (p>0.01), 10% broken (p>0.01), 15% broken (p>0.01), and 20% broken (p>0.10) are statistically different than zero, which means consumers are willing to pay a premium for these qualities relative to milled rice with 30% broken. The Poe test results (not shown) show that the there is no statistical difference in price premiums between 5% and 10% broken, but that the premium for 5% broken is significantly (p>0.01) higher than that of 15% and 20% broken. Similarly, the premium for 10% broken is statistically ($p>0.05$) higher than that for 15% and 20% broken, and there are no statistical differences between the premiums for 15% and 20% broken.

The control group most accurately reflects how consumers receive information, or lack thereof, regarding broken rice in the market since rice packaging regulations in Colombia do not require manufacturers to state the percentage of broken rice in milled rice. These findings suggest consumers may be more inclined to pay a premium for rice with lower levels of broken grains (<10% broken) and consider it to be of higher quality. On the other hand, producers should be aware of the consumer preference for rice with lower broken levels and may need to adjust their pricing strategies accordingly.

3.3. Estimates from the Pure Hedonic Price Model

Table 5 reports the retail price of rice and rice quality attributes for the attribute selected. The average price was roughly 3670 COP/kg (0.8 US$/kg), with ranges from 1327 to 9800 COP/kg (0.29 to 2.12 US$/kg). The average broken percentage rate was 17.5%, ranging from 1.5% to 46.3%. By U.S. rice milling standards this is considered reasonably well-milled. For context, the average of broken from the samples collected in this study is classified by the USDA (2020) as between US No. 3 and US No. 4 grade, or 15-25% broken (Hardke & Siebenmorgen, 2009). Six observations were dropped from the initial sample collection of 200 due to misreporting or missing price per kilogram of rice purchased.

Table 5: Retail Price of Rice and Rice Quality Attributes for Sample (n=194)

Variable	Mean	Std. Dev.	Min	Max
Price (COP per kg)	3699.9	1148.3	1327	9800
Broken (%)	17.5	7.7	1.5	46.3
Chalk (%)	20	6.1	3.8	35.4
Length (mm)	6.9	0.2	6.5	7.5
Width (mm)	2.1	0.0	2	2.2
Amylose	31	1.5	27.1	33
Gelatinization Temperature	68.2	1.1	65.6	70.7
Final Viscosity	4164.6	528.6	3114	5655
Setback	1295.1	340.8	317	2571
Breakdown	1017.2	243.4	344	1667

Out of the cooking characteristics measured (amylose content, gelatinization temperature, and paste viscosity), breakdown was the only variable that exhibited significant variability. All but one sample were classified as high amylose (>28%); therefore, the model did not include amylose. According to the range, low (<70°C) to high (>74°C), as stated in Bhattacharya (1979) for gelatinization temperatures, there are no measurements in our sample in the high range one sample in the intermediate range, and 193 samples in the low range, therefore, it is not included in the model. Final viscosity is correlated with both setback and breakdown, however, within the setback measurements, all but one sample falls in the low range (<750). Therefore, breakdown was instrumentalized as a dummy variable, with 1 indicating samples with breakdown scores less than 1,000 and zero otherwise.

While the estimates from the consumer choice experiment represent the stated WTP for broken rice, the results from the hedonic price model represent the revealed preferences for broken rice and the other selected physical attributes (chalk percentage, length, width, etc.). Table 6 presents the results of the pure hedonic price model based on rice samples collected from the markets. Strata and education were grouped similarly to the choice experiment variables to facilitate comparability between models.

Table 6: Estimates from Pure Hedonic Price Model

Variables	Model 1	Model 2
Intercept	-7612.82	-8700.78
Broken	-29.62**	-27.70**
Chalk	-20.57	-13.22
Avg Length	999.32**	996.40**
Avg Width	2553.86	2856.62
Breakdown	-231.99	-237.91
Education		-21.88
High Strata		611.81**
Middle Strata		562.01***
R^2	0.096	0.154
Adjusted R^2	0.071	0.118
N	194	194

***, **, *, indicate significance at 1%, 5%, and 10% level, respectively.
The Breusch-Pagan test for heteroskedasticity rejects the null hypothesis (homoskedasticity) in the two models. Consequently, significance is estimated based on robust standard errors.

In Model 1, the broken coefficient indicates a price reduction of rice by COP 29.62/kg for each point increase in broken percentage, holding all other variables constant. This negative and significant estimate is consistent with the findings from the RPL models. Additionally, the average length is positive and significant ($p<0.05$), indicating that an increase in average length leads to a higher price per kilogram by roughly COP 1,000 per millimeter in length. This large value could be due to the low variability in the average length of samples. The effects of broken percentage on the price of milled rice are larger than the estimate in the choice experiment. Holding all other attributes constant, we estimate a variability in the price of COP 1,327/kg based solely on the differences in broken percentage across samples (minimum broken percentage of 1.5% and maximum of 46.3%, Table 5) and the discount per point change in broken percentage (Table 6). The price variability implied by the discount per point change in broken percentage and the range of broken percentage in the sample is relevant considering the average price of rice per kilogram is COP 3,700/kg.

Model 2 reports the price impacts when including the socioeconomic variables of education and socioeconomic strata. The sign and magnitude of the parameter for broken and average length are similar to those estimated in Model 1. All else constant, socioeconomic strata reveal a price increase of COP 612/kg and COP 562/kg for middle and high strata, respectively. This could indicate that the more income an individual has, the more they are willing to pay for rice regardless of quality. These models suggest that broken percentage and the average length of kernels are important attributes explaining the price consumers pay for rice.

3.4. Piecewise Regression Analysis

Table 7 reports the results of a segmented regression analysis that models the relationship between broken percentage and price. The segmented regression analysis divides the range of the independent variable into two or more segments and estimates a separate regression line for each segment.

Table 7: Results of Segmented Regression Analysis

	Coefficient	Std. Err.	P-value	95% Confidence Interval	
Intercept 1	5286.34	439.41	0.00	4419.61	6153.06
Slope 1	-170.91	60.34	0.01	-289.92	-51.89
Intercept 2	10.72	1.97	0.00	6.83	14.60
Slope 2	9.85	16.39	0.55	-22.47	42.17

***, **, *, indicate significance at 1%, 5%, and 10% level, respectively.

The analysis suggests that there is an inflection point at 10.72 in the broken percentage, which means that there is a significant change in the slope of the relationship between price and broken percentage at this point. The first segment from 0 to 10.72 broken percentage with a slope of -170.91 ($p<0.01$) means that the rice price decreases by COP 170.91/kg for every percentage increase in the broken percentage. The second segment shows a slightly positive slope that is not significantly different from zero (p>0.10), therefore, the consumers appear indifferent to broken percentage beyond the threshold of 10.72 percent broken.

Figure 5: Segmented Regression Estimate Plot

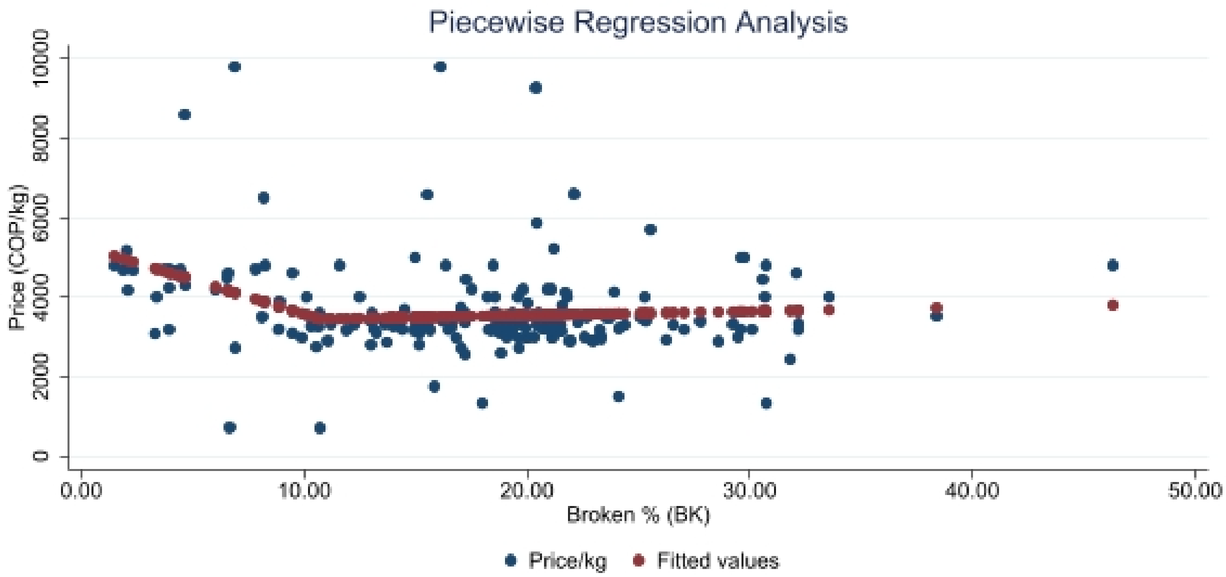


Figure 5 displays the relationship between the independent variable broken percentage and the dependent variable price per kilogram as expressed in COP. This figure highlights the significant change in the slope occurring at the estimated breakpoint of 10.72. Beyond this point, while there is a positive slope, it is insignificant, indicating consumers are indifferent to broken percentage beyond this threshold.

4. Discussion & Conclusion

Rice is an important staple food globally and is increasingly important across LAC. Functioning markets and pricing efficiency are key tools for promoting food security for the vulnerable populations of Colombia. Our study highlights that both the consumer choice experiment and the hedonic price model methods point to similar behaviors but also important differences that can highlight potential market inefficiencies. The choice experiment demonstrates a negative impact on WTP as the percentage of broken changes. Additionally, information treatment had a greater impact when consumers knew precisely how much broken percentage was in the milled rice. This suggests that consumers perceive broken grains as a quality defect or an undesirable attribute of the rice product. The hedonic choice model demonstrates similar results- there is a negative impact on price as the percentage of broken increases. The piecewise regression analysis indicates that consumers discount broken rice up to 10.72% but are indifferent to the percent of broken beyond that point. This suggests that consumers have a threshold beyond which the negative impact of the broken percentage of their WTP may become less significant or less easily discernable.

The stated preference of consumers when they are not certain of the percentage of broken in the milled rice samples to compared to their revealed preferences through the hedonic price model samples shows inconsistencies in what consumers state they prefer versus what is revealed in the market. These models find that the choice experiment reveals there is no difference in consumers' WTP between the 5% and 10% broken levels. When consumers can state their preference within the choice experiment, the WTP is the same for 5-10%, and they discount higher levels (>10%) of broken rice, specifically for the control group. However, when the broken percentage and price are plotted against each other using the hedonic pricing data, there indicates a significant and negative slope up to 10.72% broken. When consumers cannot state their preference within the hedonic price model, they are not indifferent to discounting higher levels of broken rice.

When consumers can express their preferences in the choice experiment, they are willing to discount higher levels of broken rice. This suggests that they are aware of the quality difference associated with higher levels of breakage and adjust their WTP accordingly. On the other hand, where consumers cannot explicitly state their preferences within the hedonic pricing data, there is a lack of willingness to discount higher levels of broken rice. This could be attributed to factors such as incomplete information or other market dynamics influencing consumer decision-making. This could also indicate that the consumers are experiencing a loss of utility due to not being served according to their preferences. Consumers will discount broken rice, but the market will not. As a result, producers who cannot effectively communicate their products' quality attributes to consumers may struggle to capture the full value of their rice, even if it has lower levels of breakage.

The current pricing system, as revealed, appears to disregard the consumers' preferences when it comes to the willingness to pay for milled rice with different levels of broken rice. It seems there is an effort to differentiate the price of premium rice (with less than 10% broken). This demonstrates that the industry is capturing welfare gains for low levels of broken rice and benefitting from charging more for low levels of broken rice. In this situation, the industry emerges as the winner, as it can extract higher prices for certain rice products. However, the losers in this scenario are the consumers themselves. Despite their willingness to pay less for higher levels of broken rice, the market fails to recognize this preference, leading to a loss of utility for the consumers.

The disconnect between consumer preference and market pricing results in a consumer not obtaining the maximum value from their purchases. When the market fails to recognize and accommodate consumer preferences, it can lead to a situation where essential food items, such as rice, become less affordable for those who need them the most. This can exacerbate food insecurity, particularly for low-income individuals or communities. Adjusting the price of rice with a high broken percentage as stated by consumers could help low-income households afford more rice with the same budget, thus potentially improving their food security. If the pricing system prioritizes profit over meeting the affordability needs of consumers, it may result in reduced access to an important staple food like rice. Additionally, by not aligning prices with consumer demands, the market may miss out on opportunities to cater to specific population segments and develop products that better meet their needs. This lack of responsiveness can hinder the overall growth and development of the rice industry.

In conclusion, these differences between the choice experiment and the hedonic price model emphasize the importance of considering consumer preferences and market outcomes when assessing market efficiency. By integrating insights from both approaches, policymakers and market participants can better understand the factors influencing consumer choices and market prices. The discrepancy between consumer preferences and market behavior about broken rice suggests that producers need to be proactive in understanding and meeting consumer expectations. This knowledge can help identify potential areas for improvement, such as addressing information asymmetry or implementing quality standards to enhance market efficiency and consumer welfare.

5. References

Arrieta, R. (2018). Living in Bogotá: How the strata system in Colombia works. *Colture*. https://www.colture.co/bogota/tips/to-live/strata-system-in-colombia/

Balet, S., Guelpa, A., Fox, G., & Manley, M. (2016). Rapid Visco Analyser (RVA) as a Tool for Measuring Starch-Related Physiochemical Properties in Cereals: A Review. *Food Analytical Methods*, *12*, 2344–2360.

Bazzani, C., Caputo, V., Nayga, R., & Canavari, M. (2017). Revisiting consumers' valuation for local versus organic food using a nonhypothetical choice experiment: Does personality matter? *Food Quality and Preference*, *62*, 144–154.

Bhattacharya, K. R. (1979). Gelatinization temperature of rice starch and its determination. *Proceedings of the Workshop on Chemical Aspects of Rice Grain Quality*, *24*(2), 116–118.

Calingacion, M., Laborte, A., Nelson, A., Resurreccion, A., Concepcion, J. C., & Daygon, V. D. (2014). Diversity of Global Rice Markets and the Science Required for Consumer-Targeted Rice Breeding. *PLoS ONE*, *9*(1). https://doi.org/10.1371/journal.pone.0085106

Calvert, L., Sanint, L. R., Châtel, M., & Izquierdo, J. (2006). Rice production in Latin America at critical crossroads. *International Rice Commission Newsletter*, *55*, 66–73.

Champagne, E. T., Bett, K. L., Vinyard, B. T., McClung, A. M., Barton II, F. E., Moldenhauer, K., Linscombe, S., & McKenzie, K. (1999). Correlation Between Cooked Rice Texture and Rapid Visco Analyser Measurements. *Cereal Chemistry*, *76*(5), 764–771.

Chin, T.-L., & Chau, K. (2003). A Critical Review of Literature on the Hedonic Price Model. *International Journal for Housing Science and Its Applications*, *27*(2), 145–165.

Cuevas, R. P., Pede, V. O., McKinley, J., & Velarde Orlee. (2016). Rice Grain Quality and Consumer Preferences: A Case Study of Two Rural Towns in the Philippines. *PLoS ONE*, *11*(3). https://doi.org/10.1371/journal.pone.0150345

DANE. (2022). *Fuerza laboral y educación* [Boletín Técnico Gran Encuesta Integrada de Hogares (GEIH)]. https://www.dane.gov.co/files/investigaciones/boletines/especiales/educacion/Bol_edu_2021.pdf

Durand-Morat, A., & Bairagi, S. (2022). *International Rice Outlook: International Rice Baseline Projections 2021–2031* (Research Reports and Research Bulletins). University of Arkansas. https://scholarworks.uark.edu/cgi/viewcontent.cgi?article=1052&context=aaesrb

Efron, B. (1979). Bootstrap Methods: Another Look at the Jackknife. *The Annals of Statistics*, *7*(1), 1–26. https://doi.org/10.1214/aos/1176344552

FAOSTAT. (2023). *Suite of Food Security Indicators*. https://www.fao.org/faostat/en/#country/44

Food and Agriculture Organization of the United Nations (FAO). (2023). *FAO Rice Price Update* [Markets and Trade]. https://www.fao.org/markets-and-trade/commodities/rice/fao-rice-price-update/en/

Hardke, J., & Siebenmorgen, T. (2009). Chapter 13: Rice Grades. In *Arkansas Rice Production Handbook MP192* (pp. 165–167). https://www.uaex.uada.edu/publications/pdf/mp192/chapter-13.pdf

Holmes, T., Adamowicz, W., & Carlsson, F. (2017). Choice Experiments. In *A Primer on Nonmarket Valuation* (pp. 133–186).

ICONTEC. (2007). *Norma Técnica Colombiana* (No. 671; ARROZ ELABORADO (BLANCO) PARA CONSUMO). Instituto Colombiano de Normas Técnicas y Certificación.

International Rice Research Institute (IRRI). (2022). Modern rice milling. *Rice Knowledge Bank*. http://www.knowledgebank.irri.org/training/fact-sheets/postharvest-management/item/modern-rice-milling-fact-sheet

Juliano, B. O. (1971). A Simplified Assay for Milled-Rice Amylose. *Cereal Science Today*, *16*(11). https://www.researchgate.net/profile/Bienvenido-Juliano/publication/275886661_A_Simplified_Assay_for_Milled-Rice_Amylose/links/576b5b3c08ae6e772780bb1f/A-Simplified-Assay-for-Milled-Rice-Amylose.pdf

Linquist, B., van Groenigen, K. J., Adviento-Borbe, M. A., Pittelkow, C., & van Kessel, C. (2012). An agronomic assessment of greenhouse gas emissions from major cereal crops. *Global Change Biology*, *18*, 194–209. https://doi.org/10.1111/j.1365-2486.2011.02502.x

Mangham, L. J., Hanson, K., & Barbara, M. (2009). How to do (or not to do) … Designing a discrete choice experiment for application in a low-income country. *Health and Policy Planning*, *24*(2), 151–158.

McFadden, D. (1973). Conditional logit analysis of qualitative choice behavior. In *Frontiers in Econometrics* (pp. 105–142). University of California at Berkley.

Morales, G. E. (2021). *Cali en Cifras 2021* (Cali En Cifras). Alcaldía de Santiago de Cali Departamento Administrativo de Planeación. https://www.cali.gov.co/planeacion/publicaciones/137803/documentos-cali-en-cifras/

Morrison, W., & Azudin, M. N. (1987). Variation in the amylose and lipid contents and some physical properties of rice starches. *Journal of Cereal Science*, *5*(1), 35–44.

Muggeo, V. M. (2023). *Package 'segmented.'* Cran R-Project. https://cran.r-project.org/web/packages/segmented/segmented.pdf

Normand, F. L., & Marshall, W. E. (1989). Differential Scanning Calorimetry of Whole Grain Milled Rice and Milled Rice Flour1. *Cereal Chemistry*, *66*(4). https://www.cerealsgrains.org/publications/cc/backissues/1989/Documents/66_317.pdf

Organization of American States. (2023). *Foreign Trade Information System* [Colombia - United States Trade Promotion Agreement]. http://www.sice.oas.org/Trade/COL_USA_TPA_e/Index_e.asp

Pavilus, C. (2018). *Assessing Rice Consumers' Preferences and Willingness to Pay in Haiti* [University of Arkansas]. https://scholarworks.uark.edu/etd/3104/

Peterson-Wilhelm, B., Nalley, L., Durand-Morat, A., Shew, A., Tsiboe, F., & Mulimbi, W. (2023). Quality determinates of rice price in open bag markets in Sub-Saharan Africa. *Journal of Agribusiness in Developing and Emerging Economies*, *13*(3), 361–378. https://doi.org/10.1108/JADEE-02-2021-0038

Poe, G. L., Giraud, K. L., & Loomis, J. B. (2005). Computational methods for measuring the difference of empirical distributions. American Journal of Agricultural Economics, 87, 353–365. https://doi.org/10.1111/j.1467-8276.2005.00727.x

Richardson, M., Crandall, P., Seo, H.-S., & O'Bryan, C. (2021). US Consumers' Perceptions of Raw and Cooked Broken Rice. *Foods*, *10*(2899). https://doi.org/10.3390/ foods10122899

Rodriguez, J. C., Mosquera, W. C., & Grijalba, D. S. D. (2016). *Anuario Educativo del Municipio de Santiago de Cali*. https://www.cali.gov.co/loader.php?lServicio=Tools2&lTipo=descargas&lFuncion=descargar&idFile=20449

Saha, I., Durand-Morat, A., Lanier Nalley, L., Jahangir Alam, M., & Nayga, R. (2021). Rice quality and its impacts on food security and sustainability in Bangladesh. *PLoS ONE*, *16*(12). https://doi.org/10.1371/journal.pone.0261118

Sarrias, M., & Daziano, R. (2017). Multinomial Logit Models with Continuous and Discrete Individual Heterogeneity in R: The gmnl Package. *Journal of Statistical Software*, *79*(2), 1–46.

Scholl, L., & Guerrero, A. (2015). Comparative Case Studies of Three IDB-supported Urban Transport Projects: Cali Case Study Annex. *Inter-American Development Bank*. https://publications.iadb.org/en/comparative-case-studies-three-idb-supported-urban-transport-projects-cali-case-study-annex

Smartt, A. D., Brye, K. R., Rogers, C. W., Norman, R. J., Gbur, E. E., Hardke, J. T., & Roberts, T. L. (2016). Previous Crop and Cultivar Effects on Methane Emissions from Drill-Seeded, Delayed-Flood Rice Grown on a Clay Soil. *Applied and Environmental Soil Science*. http://dx.doi.org/10.1155/2016/9542361

Szinay, D., Cameron, R., Naughton, F., Whitty, J. A., Brown, J., & Jones, A. (2021). Understanding Uptake of Digital Health Products: Methodology Tutorial for a Discrete

Choice Experiment Using the Bayesian Efficient Design. *Journal of Medical Internet Research*, *23*(10). https://doi.org/10.2196/32365

USDA. (2020). *Rice Inspection Handbook*. United States Department of Agriculture. https://www.ams.usda.gov/sites/default/files/media/RiceHB.pdf

USDA. (2021). *Colombia Rice TRQ Unfilled for the First Time*. USDA FAS. https://www.fas.usda.gov/data/colombia-rice-trq-unfilled-first-time

USDA. (2022). *Grain and Feed Annual* (No. CO2022-0002). USDA FAS & GAIN. https://apps.fas.usda.gov/newgainapi/api/Report/DownloadReportByFileName?fileName=Grain%20and%20Feed%20Annual_Bogota_Colombia_CO2022-0002.pdf

USDA. (2023). *USDA Announces 2023 Marketing Assistance Loan Rates for Wheat, Feed Grains, Oilseeds, Rice and Pulse Crops*. Farm Service Agency. https://www.fsa.usda.gov/news-room/news-releases/2023/usda-announces-2023-marketing-assistance-loan-rates-for-wheat-feed-grains-oilseeds-rice-and-pulse-crops#:~:text=Medium%2FShort%20Grain%20Rice&text=The%20loan%20rate%20for%20long,classes)%2C%20%246.74%20per%20cwt

Vibe Image Analytics. (2022). *Vibe QM3i Rice Analyzer*. https://www.vibeia.com/qm3i-rice-analyzer

Wang, Y.-J., Wang, L., Stephard, D., & Wang, F. (2002). Properties and Structures of Flours and Starches from Whole, Broken, and Yellowed Rice Kernels in a Model Study. *Cereal Chemistry*, *79*(3). https://doi.org/10.1094/CCHEM.2002.79.3.383

World Food Programme (WFP). (2023). *2023—Food Security Assessment of Colombian Population—Executive Summary*. https://www.wfp.org/publications/2023-food-security-assessment-colombian-population-executive-summary#:~:text=Of%20the%2015.5%20million%20Colombians,million%20are%20moderately%20food%20insecure

Xie, L., He, X., Duan, B., Tang, S., & Luo Ju. (2015). Optimization of Near-Infrared Reflectance Model in Measuring Gelatinization Characteristics of Rice Flour with a Rapid Viscosity Analyzer (RVA) and Differential Scanning Calorimeter (DSC). *Cereal Chemistry*, *92*(5), 522–528. https://doi.org/10.1094/CCHEM-08-14-0171-R

Zeleke, F., Kassie, G. T., Haji, J., & Legesse, B. (2021). Preference and Willingness to Pay for Small Ruminant Market Facilities in the Central Highlands of Ethiopia. *Journal of International Food and Agribusiness Marketing*, *33*(5). https://doi.org/10.1080/08974438.2020.1838385

6. Appendix A. IRB Approval

UNIVERSITY OF ARKANSAS

To:	Alvaro Durand-Morat
From:	Douglas J AdamsJustin R Chimka, Chair IRB Expedited Review
Date:	04/27/2022
Action:	**Exemption Granted**
Action Date:	04/27/2022
Protocol #:	2202388196
Study Title:	Consumer preferences for rice quality in Colombia

The above-referenced protocol has been determined to be exempt.

If you wish to make any modifications in the approved protocol that may affect the level of risk to your participants, you must seek approval prior to implementing those changes. All modifications must provide sufficient detail to assess the impact of the change.

If you have any questions or need any assistance from the IRB, please contact the IRB Coordinator at 109 MLKG Building, 5-2208, or irb@uark.edu.

cc: Lawton L Nalley, Investigator
Wei Yang, Investigator
Juliann E Phillips, Investigator

7. Appendix B. Example Survey (Translated)

Date: ________ Surveyor (initials): ________ Market:_______ Questionnaire #:__________

☐ **Mark the box if treatment "broken" (**labels indicate (1) the price and (2) the % of broken**)**

Mark the selected option in each row for each question

Question	Alt 1	Alt 2	Alt 3	Alt 4
2	L	B	G	No buy
3	C	H	M	No buy
4	D	I	A	No buy
5	N	E	J	No buy
1	F	K	A	No buy

Rand: 46

Socioeconomic Questionnaire

1. **Gender**
   ☐**1.** Male ☐ **2.** Female

2. **Age**
   ☐ **1.** 30 years or less ☐ **2.** 31-40 years ☐ **3.** 41-50 years ☐ **4.** 51 years or more

3. **What is your household size? _______**

4. **Level of education completed**
   ☐ **1.** Primary or less ☐ **2.** Secondary ☐ **3.** University or equivalent ☐ **4.** Postgraduate

5. **Total monthly income for your household**
   ☐ **1.** Less than C$ 700,000 ☐ **2.** C$ 700,000 – C$ 1,400,000
   ☐ **3.** C$ 1,400,000 – C$ 2,100,000 ☐ **4.** C$ 2,100,000 – C$ 2,800,000
   ☐ **5.** C$ 2,800,000 – C$ 3,500,000 ☐ **6.** More than C$ 3,500,000

6. **Which strata do you belong to?**
   ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6

7. **What portion of your income do you spend on food?**

☐ **1.** Less than 20% ☐ **2.** 20%- 40% ☐ **3.** 41% - 60% ☐ **4.** 61%-80%

☐ **5.** More than 80%

8. Which type of store do you usually buy rice? *(single response)*
☐ **1.** Supermarket ☐ **2.** Neighborhood markets ☐ **3.** Farmers markets ☐ **4.** Other:___

9. How much rice does your household consume in a week?
☐ **1.** Less than ½ kilo ☐ **2.** ½–1.0 kilo ☐ **3.** 1.0–1.5 kilo ☐ **4.** 1.5–2.0 kilos

☐ **5.** More than 2 kilos

10. Is it customary for you to wash and clean the rice before consuming it?
☐ **1.** Si ☐ **2.** No

11. If you responded "yes" to (10), why do you do this? *(multiple response)*
☐ **1.** Because it reduces cooking time ☐ **2.** To eliminate damaged or odd grains
☐ **3.** For tradition ☐ **4.** To eliminate impurities

☐ **5.** Because it improves the taste of the rice

☐ **6**. Other: ________________

12. If you could choose, do you prefer national or imported rice?
☐ **1.** National ☐ **2.** Imported ☐ **3.** Indifferent

13. Number the most important characteristics that determine the rice that you buy.

	1. Very important	**2.** Important	**3.** Somewhat important	**4.** A little important	**5.** Not important
A. Price	☐	☐	☐	☐	☐
B. Brand	☐	☐	☐	☐	☐
C. Uniform Grain	☐	☐	☐	☐	☐
D. Whiteness	☐	☐	☐	☐	☐
E. Long and thin grains	☐	☐	☐	☐	☐
F. Cleanliness	☐	☐	☐	☐	☐
G. Prescence of broken rice	☐	☐	☐	☐	☐
H. Prescence of chalky or dull rice	☐	☐	☐	☐	☐
I. Fortified	☐	☐	☐	☐	☐
J. Taste	☐	☐	☐	☐	☐

14. Due to the COVID-19 pandemic, have you change the quantity of rice consumed in your household?

☐ **1.** Yes ☐ **2.** No

15. **If you responded "Yes" in (14), have you bought more or less rice as a result?**

☐ **1.** More **1.1.** In what percentage (%)_____ ☐ **2.** Less **2.1** In what percentage(%)____

Did they provide a sample of rice to analyze? ☐ **1.** Yes ☐ **2.** No

If they provide a sample:

16. ¿How much did you pay for the rice? (make sure to put the price and the unit, for example, ½ kilo, 1 kilo, 5 kilos, etc.) **Value C$** _______ **Amount (in grams)__________**

17. Sample ID (*day, surveyor intial, market, questionnaire number*): ____________________

Write the sample ID on the bag.