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Understanding demand for broken rice and its potential food security implications 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. Irrigated paddy rice is a water-intensive crop, and an important contributor to greenhouse gas emissions. Thus, improving the efficiency of using rice as food rather than non-food uses is paramount to sustainably feeding a growing global population. One source of inefficiency in the rice market is using broken rice for non-food purposes. This study focuses on consumer preferences for rice with different broken percentages in Colombia. We used a mixed-method approach to ascertain the stated (experimental setting) and revealed (using samples that consumers independently purchased in a market) willingness to pay for broken rice to assess whether the rice market in Colombia efficiently prices rice quality. The findings highlight that consumers are aware of quality differences and are willing to pay a premium for rice with a low broken percentage, but also point to potential inefficiencies given that the willingness to pay estimates from both the two methods are statistically different. We find that the discount revealed in the market is significantly higher than that stated experimentally, which can have implications for pricing rice based on quality. Both methods found consumers were willing to pay a premium for rice under 10% broken, but beyond that threshold, there were no differences in willingness to pay. The Colombian rice industry and policymakers can use these findings to make the domestic rice market more responsive to the revealed preferences of consumers, which could have significant consequences for food security and sustainability.

1. Introduction

Rice is an essential staple for over half the world's population and crucial for global food security. In 2020, rice provided 16.7% of the average caloric intake worldwide, second only to wheat (17.0%) and as much as 41.8% in Southeast Asia [1]. In Latin America and the Caribbean (LAC), rice supplied 9.7% of the caloric intake in 2020. With the global population reaching 8 billion in 2022 and projected to grow to 9.7 billion by 2050 [2], improving the efficiency in using production resources to maximize agricultural production, particularly for rice and its large water footprint is imperative. Irrigated paddy rice is water-intensive, accounting for approximately 25 percent of global annual freshwater usage [3] and 34 to 43 percent of global irrigation use [4]. Given that two-thirds of the global population is now confronting water scarcity [5] and the fact that rice uses such large amounts of water for sustainability reasons, it is becoming increasingly important that all rice goes to human consumption and not to an alternative use because of poor quality. Efficiency in both rice production and consumption is important as rice production is the leading agricultural source of methane, accounting for 22% of global anthropogenic agricultural emissions [6] and has a global warming potential per metric ton that is 467 and 169 percent higher than wheat and maize, respectively [7]. Rice cultivation alone contributes about 30% of the total global agricultural methane emissions [8], and around 30% and 11% of the global agricultural methane and nitrous oxide emissions come from rice fields [9]. Therefore, increasing the amount of rice used for human consumption instead of by-products because of poor perceived quality is pivotal in making the rice supply system more sustainable.

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One way to improve the proportion of the amount of rice production consumed as food is to develop food supply channels responsive to consumers' preferences. More specifically, it is important to know what drives consumers to choose the rice they eat. Relative to other staples, rice undergoes minor processing post harvest. It is consumed mainly as grain (field-to-plate crop), and as such, visual attributes are important and often drive demand and price [10]. One attribute defining 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 is 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. For many reasons, including the genetic characteristics of a rice variety, the growing conditions (e.g., high temperature and other abiotic stresses), and both on-farm and post-harvest management practices, a percentage of rice kernels break, which is separated from the whole (head) rice and segregated into different categories of broken.

While broken rice mixed with head rice in different proportions is sold for human consumption, there is a potential leakage of broken rice out of the human food system and into other uses, for example, animal feed and the energy sector. It was estimated that around 9.7 million metric tons, or 36.6% of the broken rice globally in 2020, was used for animal feed and other non-human food uses [1]. This volume is enough to feed 158 million additional people yearly at the average global per-capita rate of 61.2 kg/year [11]. This represents a loss of food and inefficient use of production resources, equating to an estimated 3.2 million hectares of rice produced for non-human consumption because of poor perceived quality.

1.1. Rice in Colombia

Rice consumption in Colombia grew by approximately 25% in the last decade (2011-2021), given the combination of population growth and an 11% increase in per-capita consumption [12]. Per-capita consumption was estimated at 37.4 kg annually in 2021, accounting for 11.2% of the average caloric intake [1]. Despite being the third largest producer in the LAC region behind Brazil and Peru, Colombia is a residual rice importer depending on domestic production performance [13]. Colombia protects its domestic rice market with an 80% import tariff on rice from all World Trade Organization (WTO) members. Still, it grants preferential access through regional trade agreements such as the Andean Accord and the U.S.-Colombia Trade Promotion Agreement [14]. As regional trade agreements open the rice market, rice imports could create competition for domestic rice producers in Colombia through competitive pricing, quality, or both, potentially affecting the total rice demand. Rice imports in Colombia could benefit consumers by increasing the number 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. It is estimated that 15.5 million Colombians, or 30% of the population, are food insecure, 2.1 million of whom are severely food insecure [15]. 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, including affordable options for the poorest segments of the population.

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 49% 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) [16]. Broken rice carries a lower economic 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 [17]. 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 [1].

Milled rice is graded based on several criteria, including the percentage of broken kernels in the total 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 [16]. 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.

1.2. Rice quality preferences

Previous studies underline rice preferences' geographic and cultural heterogeneity and the relative price variation of 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) [18]. Even among low-income households, there is increasing evidence, primarily from Asia and Africa, indicating consumers' awareness of rice quality attributes [18]. Studies examining consumer perception and preference for rice quality have highlighted appearance, taste, aroma, and texture as significant determinants of consumer choices. Previous literature emphasizes the global variation in rice grain quality by assessing the major rice quality trait characteristics [19]. 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 [19]. A rice quality study conducted in the Democratic Republic of Congo (DRC), Ghana, and Mozambique [20] highlighted that 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, research has found that rice prices in Bangladesh are driven by broken rice percentages above the threshold of 24.9 percent [10].

Research has also explored consumer willingness to pay (WTP) for high-quality rice, indicating the economic implications of rice quality preferences. A WTP for parboiled rice study conducted in Haiti found that respondents showed inconsistency regarding their WTP for broken grains, which led to broken percentage not being a strong attribute in consumers' purchasing decisions [21]. A study in the Philippines using a hedonic price model revealed that middle- and high-income classes discount a greater percentage of broken rice [18]. 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, consumers could not differentiate between milled rice with different levels of broken (varying from 5% to 40%) when assessing the appearance of cooked rice [22].

While previous studies highlight consumer preference for rice attributes, few analyze the economic value consumers place on rice quality attributes, especially in LAC. Therefore, an assessment of the economic value of rice quality in Colombia is novel in the literature. This study uniquely combines hedonic price analysis (a revealed preference methodology) and consumer choice experiments (a stated preference methodology) to better understand the revealed preference and stated preference for milled rice with different broken percentages. The general literature comparing stated and revealed preferences has found that individuals tend to inflate their stated valuation of a particular good, service, or outcome, leading to misleading relative value estimates [23]. This is important in the context of food security in Colombia regarding rice. If consumers were to inflate their WTP for rice with low broken percentages in their stated preferences, then wholesalers may increase the price, leaving the poorest of the poor priced out of the market.

This study analyzes consumer preference for broken rice in Colombia using stated and revealed preference methodologies. 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 siphoning broken rice into the brewing industry, animal feed, or energy use without price penalties. Broken rice contains the same nutritional value as a whole grain of rice [24]. 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.

2. Materials and methods

We used a combination of choice experiments and hedonic price modeling to elicit the potential discount associated with broken rice in Colombia. The conceptual foundation for choice experiments is found in hedonic methods, where demand for goods arises from demand for attributes [25]. 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 for those goods. By combining the information from both approaches, researchers can better understand individuals' trade-offs between different attributes and more accurately estimate their values [25]. Fig. 1 shows the methodology chart flow used in this study. Answering our research questions about the valuation of broken rice entails comparing the results from the choice model (stated preferences) and the hedonic price model (revealed preferences). The left-right arrows indicate the cross-model comparisons of interest.

2.1. Data

A total of 400 surveys (stated preferences) and 200 consumer rice samples (revealed preferences) were collected from four major supermarkets and one small outlet store across Cali and Palmira, Colombia, in April 2022. The locations were selected based on the distribution of socioeconomic strata by the administrative division of Cali [26] in an effort to obtain a representative sample by socioeconomic strata using the most recent distribution data for 2020 [27]. Colombia uses a system of socioeconomic strata to categorize neighborhoods by labeling houses from one through six, one being the lowest and six being the highest [28]. 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 pays a premium for utilities [28].

2.2. Choice experiment

2.2.1. Experimental design

Defining attributes and their respective levels is crucial in designing choice experiments to reveal consumer preference [29]. In this study, we selected only relevant factors based on the consultation of local rice millers and guidance from the Latin American Fund for Irrigated Rice (FLAR) team at CIAT. The chosen attributes were rice price and the percentage of broken rice. Keeping the number of attributes and attribute levels small is preferable because the more attributes and attribute levels, the greater the cognitive burden for respondents to choose the most preferred alternative accurately [30]. Price levels (COP/kg) were derived from retail prices from five supermarkets in Cali collected a week before the experiment was conducted. All prices were expressed in Colombian Pesos (COP). Broken percentage levels were derived using expert opinion from millers and FLAR, as well as the five rice grades as defined in the Colombian Technical Standard for Processed Rice: 5%, 12%, 18%, 25%, and 35% for Grades 1 through 5, respectively [16]. A summary of attributes and attribute levels is outlined in Table 1. The rice samples were created in the CIAT/FLAR Rice Quality Laboratory. Creating the rice samples involved separating the whole and broken rice

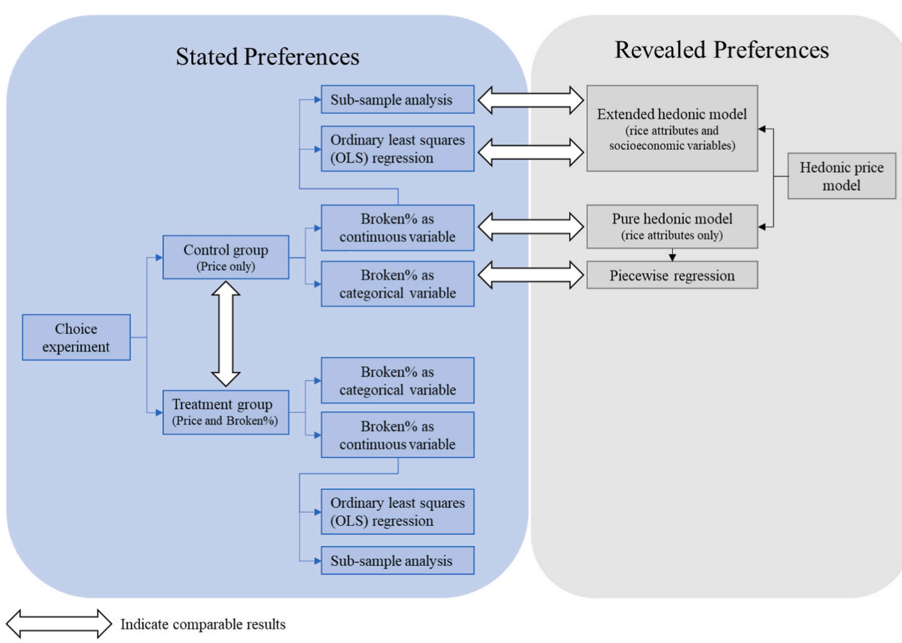

Fig. 1. Flowchart of methodology and models estimated.
Figure footnote. Stated preferences are derived from a controlled hypothetical choice experiment, and revealed preferences are derived from rice collected from survey participants who had just purchased rice independently from a market.

Table 1
Attributes and attribute levels selected for this study.

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

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

kernels and mixing them back at the correct proportions by weight.

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 [31]. 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 [31]. 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 rice products with different combinations of price and broken percentage (Table 2). Based on the results of the Bayesian efficiency design method, five choice tasks were presented in our survey.

Each choice task consisted of three rice products with different prices and percentages of broken rice and a no-buy option. Having a no-buy alternative is important in the experiment design because it more closely emulates a real-world scenario in which the respondent is not required to choose. Each participant was presented with the same five choice sets (Appendix A), except that half of the participants were randomly assigned to a control group that only received information about the price of the rice products, and the other half received information about the price and percentage of broken rice in each of the rice products as shown in Appendix B. The goal of adding the information 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 without knowing the exact broken percentage in each product.

2.2.2. Implementation

The research protocol was approved by the University of Arkansas's Institutional Research Board. The survey was available to participants in Spanish. Thirty pre-test surveys were conducted at the International Center for Tropical Agriculture (CIAT) for question validation, and the estimated parameters were employed as priors of the Bayesian design. The survey team, composed of eight Colombian natives fluent in Spanish, approached potential participants exiting supermarkets. Adults (over 18 years old) who oversaw household grocery purchasing, including rice, were invited to participate in the study. Participants who voluntarily agreed to participate 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 (Appendix A), participants who had purchased rice from the supermarket were asked to voluntarily provide a sample (around 50 grams) of rice and state the price they just paid (which was converted to COP/kg), and received another voucher for COP 10,000 or roughly US$ 2.5. Our final sample comprised 400 choice experiment surveys and 200 rice samples collected.

As part of the choice experiment, participants were presented with the five choice tasks/questions discussed in the previous section, and were asked to choose their most preferred alternative in each of the five choice tasks. The rice products were presented in clear, commercial-grade plastic bags containing half-kilo (500 grams) of rice (Appendix B). The experiments were conducted outside the selected supermarkets to engage consumers leaving the sites. The same setting of the experiment was maintained across all locations (e.g., tables covered with dark-green tablecloths to keep the contrast between the background and the rice samples constant) to control the experiment conditions as much as possible.

Table 2
The 14 rice products and prices included in the choice experiment following a Db-efficient design.

Rice Product	Price (COP/kg)/% broken	Rice Product	Price (COP/kg)/% broken
1	COP 4000/15%	8	COP 5500/20%
2	COP 8500/5%	9	COP 7000/15%
3	COP 7000/10%	10	COP 5500/5%
4	COP 5500/30%	11	COP 2500/15%
5	COP 2500/20%	12	COP 4000/30%
6	COP 2500/30%	13	COP 7000/20%
7	COP 4000/10%	14	COP 8500/10%

2.2.3. Empirical model

Choice experiments follow the Random Utility Theory [32], which states that, given a set of alternatives, individuals choose the alternative that generates the highest level of utility U, which for an individual i with j alternatives and t choices can be represented as:

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

where x_{ijt} represents a vector of the explanatory variables, β_i represents the vector of parameters, and ε_{njt} represents the error term. $x_{ijt}\beta_i$ represents the deterministic or observable portion of the individual utility function, while the random error component, ε_{njt}, represents the unobserved portion [33].

A random parameter logit (RPL) model was 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 [34]. 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:

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

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) by dividing the attribute coefficient by the price coefficient as represented in the following way [34]:

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

where $\frac{\beta}{\alpha}$ is the WTP vector. 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 from the RPL model. The vector created represents the WTP for each respondent. An Ordinary Least Squares (OLS) regression using this vector and socioeconomic variables was estimated as follows:

$$WTP = \beta_0 + \beta_1 Edu + \beta_2 MiddleStrata + \beta_3 HighStrata + \varepsilon \quad \text{(iv)}$$

where *WTP* represents the individual WTP vector for broken from (iii), β_0 is a constant, β_1, β_2, and β_3 are the estimated coefficients for covariates *Education* (*Edu*), *MiddleStrata*, and *HighStrata*, respectively, and ε is the error term.

2.3. Pure hedonic price model

The quality of the 200 rice samples collected from participants who had independently purchased rice at the supermarket before the survey was assessed to estimate the revealed value of the selected quality attributes. Based on consumer theory [35], hedonic price modeling postulates that goods possess attributes that, when combined, provide a price value to the consumer [36]. Lancaster's theory [35] 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:

$$P_i = aX_i + \varepsilon_i \quad \text{(v)}$$

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 [10]. The rice quality attributes included in this study are broken percentage (*Broken*), chalk percentage (*Chalk*), average length (*AvgLength*), average width (*AvgWidth*), and breakdown viscosity (*Breakdown*). Breakdown viscosity refers to the stickiness of cooked rice [37]. The model was estimated with socioeconomic variables, education and strata, and interactions with the broken percentage attribute to analyze the effect of various socioeconomic variables' perception of broken rice on price per kilogram. The econometric equation is as follows:

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

2.3.1. Measurement of physical attributes of rice

The rice samples collected from consumers who purchased rice independently at a supermarket were processed for physical analysis at CIAT. The rice samples were processed using the Vibe QM3 Rice Analyzer and a Rapid Viscosity Analyzer (RVA) (Perten 4500) to determine the broken percentage (*Broken*), chalk percentage (*Chalk*), average length (*AvgLength*), average width (*AvgWidth*), and breakdown viscosity (*Breakdown*). 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 an accuracy of less than 50 μm, and abnormal color and damaged kernels analysis using 3000 color pixels per kernel [38]. The Vibe QM3 was calibrated following the Colombian standard [16], by which a whole kernel of rice is at least 75% of the average length of the corresponding whole kernel, and a broken kernel is less than 75% of the average length of the corresponding whole kernel. The average size of the samples processed was 50 grams or between 400 and 500 grains of rice.[1]

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

$$Broken_i = \frac{WB_i}{weight\ of\ working\ sample\ i} * 100 \quad \text{(vii)}$$

where WB_i is the weight of broken rice in sample *i* [10].[1]

A chalky kernel is defined as a whole or broken rice kernel with half or more of its area chalky [39]. The chalk percentage is measured as:

$$Chalk_i = \frac{WC_i}{weight\ of\ working\ sample\ i} * 100 \quad \text{(viii)}$$

where WC_i is the weight of chalk rice in sample *i* [10]. 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*.

$$AvgLength_i = \sum_{j=1}^{n} \frac{length_{ji}}{n} \quad \text{(ix)}$$

$$AvgWidth_i = \sum_{j=1}^{n} \frac{width_{ji}}{n} \quad \text{(x)}$$

The rice samples collected from consumers were processed to assess their cooking characteristics, specifically, the amylose content, gelatinization temperature, and paste viscosity represented by the breakdown, final viscosity, and setback points. Although consumers can only evaluate the cooking characteristics after eating cooked rice and not when buying raw rice, these attributes where included to control for their potential impact on consumer choices in other proxy ways, such as purchasing rice based on a brand or another credence attribute (e.g., taste associated with a specific brand) that consumers could associate with specific cooking characteristics. Appendix C describes the procedure followed to assess the culinary attributes of rice considered in this study.

2.3.2. Piecewise analysis

Given the emphasis on broken rice, we tested whether the relationship between rice price and broken had a breaking point, consistent with recent literature [10,20]. That is, is there a threshold at which the impact of percent broken on the price of milled rice changes in one way or another, which could be understood as a change in consumer WTP for milled rice based on its broken percentage? This is important as consumers may not discount broken rice to a specific percentage and then require a price discount above that breakpoint.

A piecewise, or segmented, regression analysis estimates linear models with one or more relationship segments in the predictor model [40]. A piecewise regression is used to understand how independent variables affect the dependent variable over certain thresholds. In relation to this study, understanding these thresholds is important because the relationship between price and the covariates may be nonlinear (e.g., the marginal effect of broken rice on rice price changes with the level of broken percentage), and therefore identifying the relevant segments is important from a marketing point of view. This analysis was performed using the NL command in Stata®.

3. Results and discussion

3.1. Descriptive statistics

Table 3 outlines the socioeconomic characteristics of the sample (400 participants) and the Colombian population. Almost 80% of the respondents in the sample were female, compared to 53.9% in the population, as observed in 2020 by the Administrative Department of Planning in Cali, Colombia, and the Ministry of Education of Cali [41, 42]. 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.

[1] The Vibe QM3 uses a proprietary algorithm to estimate the weight of a sample based on digital imaging. To calculate the broken percentage and the chalk percentage, the algorithm first estimates the total weight of a sample and then the weight of that sample which is classified as broken or chalky. Using these estimates and equations (*vii* and *ix*) the percentage of each sample classified as chalky or broken could be estimated by weight.

Table 3
Sociodemographic characteristics (in percentage) of the sample and Colombian population.

Characteristic	Sample (n = 400)	Colombian 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
Socioeconomic 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

Therefore, the population proportion reflects the distribution of the workforce by education level for all of Colombia [43]. We conclude that our sample is overeducated compared to the population. While monthly income data was collected, socioeconomic strata were used in this study because it is significantly and positively correlated with income, and Colombians know, the strata to which 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 [27]. The correlation by socioeconomic strata between our sample and the population is high (90.9%). 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.

The socioeconomic characteristics of the subsample used for the hedonic price model (200 participants that share a sample of their rice) reported similar proportions to the entire sample using a Welch two-sample *t*-test.

3.2. Estimates from choice experiment

Table 4 shows the results of the RPL model for stated preferences in which *Broken* is a continuous and sole explanatory variable for the control and treatment groups. The scale represents the average heterogeneity of WTP [34]. No-buy can be described as the utility (in COP) consumers lose by not purchasing a kilogram of rice. The standard deviation represents the coefficient distribution for the continuous variable *Broken* among individuals. Tau represents the variance of the random effect parameter in the RPL model and is negative and statistically significant in both models, indicating heterogeneity in the preferences for broken rice among individuals.

The negative coefficient on *Broken* suggests that consumers are willing to pay COP 2.45/kg less for each percentage point increase in broken rice when they do not know for certain the broken rate of milled rice (control), but their WTP decreases to COP 6.24/kg when they know precisely how much broken rice is in the milled rice (treatment). A likelihood ratio test ($p<0.01$) confirmed that the coefficients on Broken from the control and treatment models differ significantly. This interesting finding highlights that providing the broken percentage on a label could lead to more price variability and greater market disaggregation. However, in combination, the results suggest that the impact of broken percentage on the overall price of milled rice is relatively small. For instance, considering the range of broken percentage values used in this study (5% to 30%) and the estimated economic value of *Broken* from Table 4, data indicate that the price of milled rice can vary by as much as COP 61.25/kg between milled rice with 5% and 30% broken (the latter having a lower price) for the control group, and up to COP 156.00/kg for the treatment group. These variations in milled rice prices due to changes in broken percentages translate into a maximum change in the price of milled rice of 1.1% and 2.8%, considering that the average market price of rice used in the experiment (Table 1) was COP 5500/kg.

We conducted ordinary least square (OLS) regression analysis and sub-sample RPL analysis to assess whether the WTP for Broken varies based on the socioeconomic characteristics of the respondents (Appendix D). The results show that the education and strata do not significantly explain WTP for broken rice.

To ascertain whether the marginal value of broken percentage changes with the levels of broken percentage, we estimated an RPL model with broken rice entered as a set of binary variables rather than a continuous variable. Four binary variables were created, one for each of the following four levels of broken percentage: 5%, 10%, 15%, and 20%. A bootstrap method was used by simulating 10,000 parameters [44]. We tested the statistical difference between coefficients using the Poe test [45]. Figs. 2 and 3 show the average estimated marginal value for each level of broken percentage relative to 30% broken (the highest level used in the study), which serves as the benchmark for both control and treatment groups.

The results from Figs. 2 and 3 (positive values for all broken percentages relative to 30% broken percentage) are consistent with the previous literature that indicates that broken percentage negatively impacts the price of milled rice. The coefficients, understood as price differences relative to milled rice with 30% broken rice, are positive (indicating consumers are WTP a premium for rice with a low broken percentage) and negatively correlated with the percentage of broken rice (indicating that the premium increases as the percentage of broken decreases), and they are larger for the information treatment than the control. For the treatment group (Fig. 2), the premium for milled rice with 5% broken ($p<0.05$), 10% broken ($p<0.10$), and 15% broken ($p<0.10$) are significant. However, a Poe test (not shown) indicates that there are no significant differences ($p>0.10$) in the price premiums between the 5%, 10%, 15%, and 20% broken percentages. Based on these combined results, it appears that consumers perceive rice with 15% broken or less as different from that with 30% broken, but their WTP for all broken percentages below 30% are statistically the same. These results are surprising and contradict the hypothesis that consumers who receive information about broken percentages will be willing to pay a premium for rice with a lower broken percentage.

For the control group (Fig. 3), 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 significant. Poe test results (not shown) indicate that there is no statistical difference ($p>0.10$) 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 ($p>0.10$) between the premiums for 15% and 20% broken. These results indicate that the control group could visually perceive the differences in broken percentage and are willing to pay a significantly higher premium for higher quality rice (5% and 10%

Table 4
RPL model results showing the willingness to pay for broken percentage for the control and treatment groups.

	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.

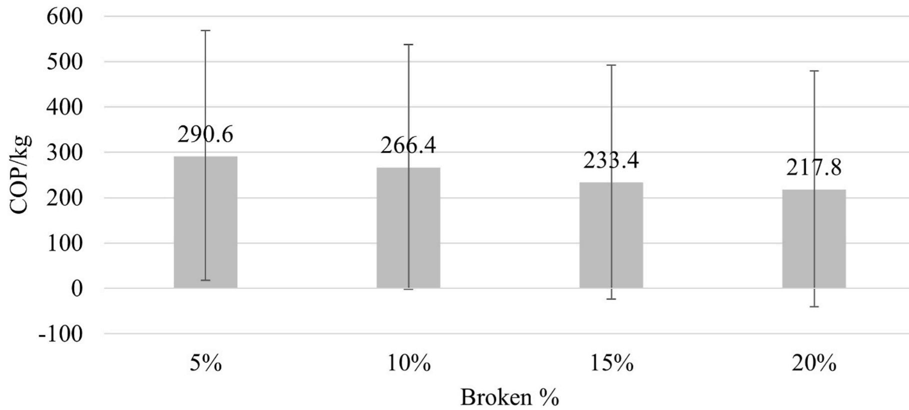

Fig. 2. Treatment group. Mean and 95% confidence interval of willingness to pay for rice with different broken percentages (relative to 30% broken rice). Figure footnote: The treatment group was provided information about the actual percentage (5, 10, 15, 20, and 30) of broken rice in each sample.

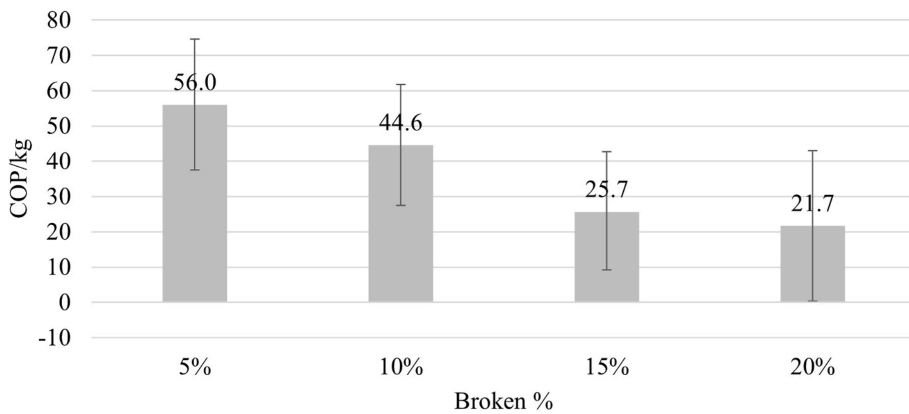

Fig. 3. Control Group. Mean and 95% confidence interval of willingness to pay for rice with different broken percentages (relative to 30% broken rice). Figure footnote: The control group was not provided with the information about the actual percentage (5, 10, 15, 20, and 30) of broken rice in each sample and relied on visual assessment alone.

broken). These findings align with the hypothesis that consumers will pay considerably higher premiums for rice with a low broken percentage and can have implications for marketing in that different thresholds can be identified and used as a reference for pricing. The control group most accurately reflects how consumers receive information, or lack thereof, regarding broken rice in shopping settings 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 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 shows the descriptive statistics for the price of rice and the rice quality variables considered in this study estimated from the 200 rice samples collected from participants after they had purchased rice independently from a supermarket and prior to the survey being conducted. Six observations were dropped from the initial sample due to issues with the price paid reported by participants (four prices too low and two too high), leaving 194 rice samples. The average price paid by consumers was COP 3670/kg (0.8 US$/kg), with a minimum and maximum price of COP 1327/kg and COP 9800/kg (0.29 to 2.12 US $/kg) reported. The average broken percentage was 17.5%, ranging from 1.5% to 46.3%. By U.S. rice milling standards, rice with this average broken percentage is classified as between US No. 3 and US No. 4 grade, or 15-25% broken [46].

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	1327.0	9800.0
Broken (%)	17.5	7.7	1.5	46.3
Chalk (%)	20.0	6.1	3.8	35.4
Length (mm)	6.9	0.2	6.5	7.5
Width (mm)	2.1	0.0	2.0	2.2
Amylose (%)	31	1.5	27.1	33.0
Gelatinization Temperature (degrees Celsius)	68.2	1.1	65.6	70.7
Final Viscosity	4164.6	528.6	3114	5655.0
Setback	1295.1	340.8	317.0	2571.0
Breakdown	1017.2	243.4	344.0	1667.0

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%). According to the ranges for gelatinization temperatures [47] (low <70 °C, intermediate between 70 °C and 74 °C, and high>74 °C) as, 193 samples fell in the low range. Final viscosity is correlated with setback and breakdown, however, within the setback measurements, all but one sample fell in the low range (<750). Breakdown was instrumentalized as a dummy variable equal to 1 if breakdown <1000 and zero otherwise.

Table 6 presents the results of the pure hedonic price model (Model 1) and a model that includes the socioeconomic variables representing strata and education. *High Education* and *High Strata* are defined as explained in the previous section, while *Middle Strata* equal 1 is respondents belonging to strata 3 and 4, zero otherwise.

The pure hedonic price model (Model 1) shows that a one-point increase in broken percentage leads to a reduction of COP 29.62/kg in the price of milled rice. This negative and significant ($p<0.05$) estimate is consistent with the findings from the RPL models (stated preferences), but the magnitude is larger. Holding all other attributes constant, the discount estimated in Model 1 applied to the range of broken percentages in our sample (Table 6) leads to a maximum variability of COP 1327/kg, or a 35.9% change considering the average price of COP 3700/kg of milled rice. This is significantly larger than the discount associated with stated preference results of between 1.1% and 2.8%. 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 1000 per millimeter in length. However, this large premium is relative, considering there is limited length variability (1 mm difference between the minimum and maximum values in the sample).

Model 2 in Table 6 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, which shows the robustness of the results. All else constant, socioeconomic strata reveal a price increase of COP 612/kg and COP 562/kg for middle and high strata, respectively. This indicates 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.

Comparing the coefficients for broken percentage from the choice experiment (stated preferences) in Table 4 (- COP 2.45/kg for the control and – COP 6.24/kg for the treatment group) and the pure hedonic model (revealed preferences) in Table 6 (-COP 29.62/kg), we find that the magnitudes of the slopes are statistically different (Z score -29.7 and -25.6 for control and treatment versus hedonic, respectively, $p>0.01$ for both pair comparisons). This finding highlights that the current market pricing based on broken percentage overstates what consumers state they would pay. In other words, the price differences by quality, based on broken percentage, observed in the market are unjustifiably large considering consumers' stated preferences. In other words, what consumers say they would pay (stated via choice experiment) for broken rice is significantly less than the value observed in the market, which can lead to market inefficiencies. In practice, rice retailers can use this finding to set prices across rice qualities differently, narrowing the price premiums and discounts. However, our results cannot be used to define the actual price level to set the premiums and discounts, and further studies are needed to identify the rice price levels that can help achieve the desired outcome (e.g., maximize profits and rice consumption). Our findings could positively impact food security if the smaller premiums/discounts are applied based off the market price of low-quality rice because the new price scheme will result in lower market prices overall.

Table 6
Impact of rice quality attributes and selected socioeconomic variables on the price of milled rice estimated using a hedonic (revealed preference) 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
High 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.

3.4. *Piecewise regression analysis*

Table 7 reports the results of a segmented regression analysis that models the relationship between broken percentage and price taken from the rice samples provided by consumers who had purchased rice independently at the grocery store prior to the stated preference survey. The segmented regression analysis divides the range of the independent variable into segments and estimates a separate regression line for each segment.

The analysis suggests an inflection point at a broken percentage of 10.72, which means a significant change in the slope/relationship between price and broken percentage at this point. The first segment ranges from 0 to 10.72 broken percentage with a slope of -170.91 ($p<0.01$), which indicates that the rice price decreases by COP 170.91/kg for every percentage increase in the broken percentage to 10.72%. The second segment shows an insignificant slope ($p>0.10$), therefore, the consumers appear indifferent to broken percentage above the threshold of 10.72 percent (Fig. 4).

These results and those for the control group from the RPL model with broken rice entered as a set of binary variables (Fig. 3) suggest a non-linear relationship between milled rice price and broken percentage, with an inflection point around 10% broken. Unfortunately, we cannot test the statistical difference between coefficients from both models because the coefficients from the RPL model with broken as binary variables are discounted relative to 30% broken. In contrast, the coefficients from the stepwise regression are average changes in milled rice prices with respect to broken percentage. But the fact that both approaches find a similar breakpoint is important and grants support for using that broken percentage as a threshold. For example, the rice industry can use this threshold to segment the rice market by quality, for instance, by pricing rice with 10% or less broken higher and using a different price schedule for lower quality rice that could help sell more broken rice for human consumption. Another potential use of these findings is for policy formulation, specifically adjusting the milled rice standard to incorporate consumers' preferences in determining the different grades of rice commercialization. As discussed in the introduction, the Colombian standard currently considers 5%, 12%, 18%, 25%, and 35% broken as thresholds for the five commercialization grades, which could be adjusted based on our findings.

4. Conclusion

Rice is an important staple food globally and is increasingly important across LAC. The growing importance of rice as a caloric source and the persistently high levels of food insecurity in Colombia highlight the importance of improving the efficiency of the rice market. Functioning markets that reveal consumers' preferences and price the products accordingly are essential for promoting food security for the vulnerable populations of Colombia.

Table 7
Results of segmented regression analysis.

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

***indicate significance at 1%.

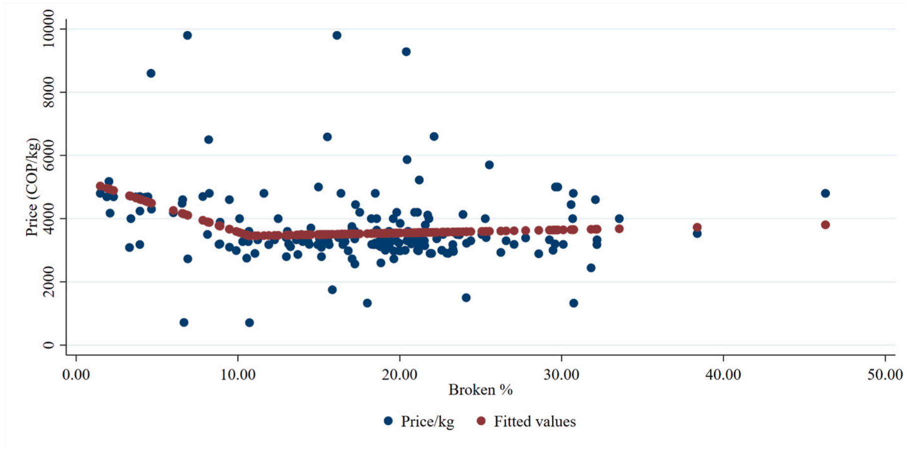

Fig. 4. The estimated relationship between broken percentage and the price of milled rice using a segmented regression estimation.

Our study highlights that consumers can perceive differences in rice quality regarding broken percentage and require a discount for broken rice, which was expected based on the existing literature and the general perception of broken rice as a sign of lower quality. Importantly, we find that the discount revealed in the market (using samples that consumers independently purchased in a market) is significantly higher than that stated experimentally, which can have implications for pricing rice based on quality. Adjusting the pricing system based on consumer preferences can help improve the profitability throughout the rice supply chain and the food security situation in Colombia by better matching the rice pricing system to the consumer's preferences. Furthermore, this information can also facilitate formulating of food policies regulating prices according to rice qualities and/or potentially making prices of some kinds of rice more accessible to low-income populations.

The findings from the stated (experimental via choice experiment) and revealed (by actual purchases analyzed via hedonic model) methods also support the non-linear relationship between broken percentage and the price of milled rice. These results can inform and help industry leaders and policymakers design better marketing strategies, such as defining the thresholds of quality based on what is relevant for consumers, and policy strategies, such as redefining the commercial grades of rice based on consumer preferences for broken percentage.

The significant difference between the discounts for broken rice stated (experimental) and revealed (by actual purchases) by consumers can be understood as a loss of consumer welfare. That is, consumers are forced to accept the premiums and discounts for rice based on broken percentage, which are different than their stated preferences. 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. By not aligning prices with consumer demands, the market may miss 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.

The results of this study can be used by the Colombian rice industry in one of two ways in combination with the current Colombian standard of 5%, 12%, 18%, 25%, and 35% broken as thresholds for the five commercialization grades. First, the rice industry could make use of the 10-11% broken threshold found in both models (10.72% in the pure hedonic model and 10% in the choice experiment) in this analysis to simplify the marketing strategies for rice with more than 10% broken (e.g., not producing, tracking and differentially pricing four quality levels greater than 10% broken), which could result in cost savings, a portion of which could be passed to consumers as price reductions. Instead, the industry could market just two types of rice, "premium" (<10%), and "standard" (11-30%broken). This would allow the industry to funnel more brokens into the food human food supply and provide consumers a greater supply of lower priced rice. The second option is that the rice industry could price all rice above 10.72% broken at the *relatively high* 12% broken price, as the industry could benefit from the fact that above 10.72%, consumers no longer discount broken rice. Thus, current discounts for rice at 18%, 25% and 35% could be eliminated. While there are confounding factors to calculate welfare gains, such as the responsiveness of producers and consumers to changes in rice prices, it is likely that the profit maximizing rice industry would gravitate to a policy more closely resembling the second option, which can be problematic from a food-security point of view as consumers currently buying low-quality rice may be priced out of the market.

The differences in the results from the stated (choice experiment) and revealed (the hedonic price model) preference models emphasize the importance of considering consumer preferences and market outcomes when assessing market efficiency. Differences in stated and revealed preferences can be understood as a sign of market inefficiency. 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 the rice industry in Colombia needs to be proactive in understanding and meeting consumer expectations. For instance, our results do not support the current breakdown of milled rice grades used in Colombia and could be used to simplify the standard into fewer grades.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jafr.2023.100884.

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