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Assessing the socioeconomic and heterogeneous impacts of noise pollution on food markets in Akure metropolis, Nigeria

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Abstract
As urbanization intensifies across sub-Saharan Africa, noise pollution has emerged as a critical yet underexplored environmental and economic stressor for informal market economies. While prior studies have largely focused on the health impacts of noise, limited empirical research exists on its direct effect on market vendors' economic performance, particularly in rapidly urbanizing African cities. This study addresses this gap by examining the socioeconomic and heterogeneous impacts of noise pollution on food markets in Akure Metropolis, Nigeria. Using primary data collected from 120 food vendors across four major markets, noise levels were measured with a sonometer, while a well-structured questionnaire captured the marketers' socioeconomic characteristics and perceptions. Unconditional Quantile Regression (UQR) was employed to analyze the heterogeneous impacts of noise pollution on vendors' income levels. The results show that noise pollution significantly reduces income at the 50th and 75th quantiles, while noise perception has a significant negative effect at lower income levels. The socioeconomic factors, such as sex, education, shop size, and market experience, were also found to significantly influence income levels. The study highlights the need for market zoning regulations, noise control policies, and targeted trader support programs to mitigate noise pollution's adverse effects and promote sustainable urban commerce.

Keywords Noise pollution, Income disparity, Unconditional quantile regression, Food markets, Urban resilience, Akure metropolis

1 Introduction

The interplay between environmental factors and socioeconomic dynamics remains a critical research area, especially in developing urban centers where economic activities and environmental challenges coexist [1–4]. Akure Metropolis has undergone significant urbanization over the past few decades, transitioning from a mid-sized agrarian community into a bustling metropolis [5–7]. While this growth has stimulated economic activity, it has also exacerbated environmental challenges, including noise pollution [1, 8, 9]. Urban noise primarily stems from vehicular traffic, industrial operations, and market activities, often surpassing the World Health Organization's (WHO) recommended thresholds for health and productivity [5]. The proximity of markets to high-traffic roads and densely populated residential areas further intensifies this issue [6].

Food marketers play an essential role in the urban economy, providing access to staple foods and driving local commerce [10–12]. However, these marketers often operate under precarious conditions characterized by limited education, low income, and constrained access to financial resources. These vulnerabilities amplify their exposure to environmental risks such as noise pollution [1]. The disparity in economic resilience among food marketers reveals a sharp divide between larger vendors with access to capital and smaller traders who struggle to survive. This stratification not only reflects broader socioeconomic inequalities but also influences how noise pollution impacts their businesses [7].

Noise pollution is not only a health hazard but also an economic deterrent [13, 14]. Studies indicate that noise levels in many markets exceed safe limits, disrupting communication, reducing customer satisfaction, and causing stress-related health issues among traders [9, 15–17]. Empirical evidence from similar contexts shows a direct correlation between elevated noise levels and reduced market activity, which can lead to income losses among marketers [18]. Noise pollution also exacerbates broader environmental challenges, such as land degradation and air pollution, in urban areas [19, 20]. In an urban city like Akure metropolis, these interconnected issues further strain the resilience of market-based economies [4, 6].

Income inequality within the food marketing sector is both a cause and a consequence of environmental stressors. Larger vendors often have the resources to mitigate the impacts of noise pollution by relocating to less affected areas or investing in adaptive strategies. Conversely, smaller traders are more likely to bear the brunt of these challenges, deepening existing disparities [8]. Furthermore, marketers' perceptions of noise pollution highlight its pervasive impact on their livelihoods [21]. Many traders view noise as a significant barrier to effective communication, customer retention, and overall productivity [5]. In response, they employ various coping mechanisms, such as adjusting operating hours, lobbying for noise regulations, and relocating stalls. However, these strategies often fail to address the root causes of noise pollution, leaving many marketers in a vulnerable position [5].

Despite growing concerns about the impact of environmental stressors on urban markets, there remains a significant gap in understanding how noise pollution affects food vendors' economic activities, particularly in developing urban centers such as Nigeria. While previous studies have extensively explored the health implications of noise pollution [13, 20] and its general environmental consequences [19], little attention has been given to its direct economic effects on informal food vendors. Existing research has primarily focused on noise pollution's influence on residential property values and urban liveability [9], yet empirical studies quantifying its impact on vendors' income and market activity remain scarce. Also, a critical limitation of past studies is the lack of investigation into the heterogeneous economic impacts of noise pollution among market vendors. The extent to which traders experience income losses due to noise-induced disruptions varies according to socioeconomic factors and financial resilience. However, most existing studies have not adequately examined how these disparities influence vendors' ability to cope with noise pollution. Additionally, prior research has been largely qualitative, relying on subjective perceptions rather than integrating measured noise levels with variations in sales performance. Without empirical data linking noise exposure to vendors' income, it remains challenging to assess the magnitude of the problem and propose targeted interventions.

Therefore, this study makes a significant contribution to the existing literature by providing empirical evidence on the economic impact of noise pollution on urban food vendors. Unlike previous studies that rely on generalized mean-based estimations, this research employs Unconditional Quantile Regression (UQR) to capture distributional variations and understand how different income groups experience the effects of noise pollution. The study also advances knowledge by integrating theoretical perspectives such as the Environmental Stress Theory (EST) and the Socioeconomic Disparity and Market Resilience Theory to explain how noise pollution interacts with economic vulnerabilities. Therefore, the primary aim of this study is to investigate the socioeconomic and heterogeneous impacts of noise pollution on food markets in Akure Metropolis, Nigeria.

The study specifically seeks to:

1. Describe the socioeconomic characteristics of food vendors in selected markets in Akure;
2. Assess vendor perceptions of the impact of noise pollution on their market activities;
3. Measure and compare noise pollution levels across different market environments; and.
4. Determine the heterogeneous impact of noise pollution on the income of the food marketers in the area.

2 Theory and concept of the study

The study on the heterogeneous impacts of noise pollution and socioeconomic factors on food markets in urban centers is grounded in multiple theoretical perspectives that examine environmental stressors, urban market economies, and socioeconomic stratification. The Environmental Stress Theory (EST) posits that exposure to adverse environmental factors, such as noise pollution, leads to physiological and psychological stress, ultimately affecting productivity and well-being [20]. Noise pollution disrupts cognitive functions, communication, and decision-making, which are critical for market traders in a densely populated urban setting. High noise levels in food markets impact traders' capacity to interact with customers, maintain focus, and operate efficiently [21].

Again, the heterogeneous effects of noise pollution on food vendors align with the Socioeconomic Disparity and Market Resilience Theory, which explains how economic stratification influences exposure to environmental risks. Higher-income traders might mitigate noise pollution by relocating, using improved infrastructure, or lobbying for regulations, while lower-income traders remain vulnerable [22]. This disparity in economic resilience among vendors creates a dynamic where noise pollution perpetuates existing economic inequalities. Likewise, the Urban Market Sustainability Framework explores how environmental factors, including noise, interact with urban food supply chains and socioeconomic structures [23]. Noise pollution, alongside other urban stressors, affects market sustainability by reducing vendor efficiency, influencing consumer behaviour, and potentially leading to income disparities among traders [24].

The conceptual framework in Fig. 1 integrates socioeconomic factors, noise pollution effects, and market activities to understand the dynamics affecting food vendors in urban markets. Noise pollution serves as the independent variable in this study, measured through decibel levels across various market locations. It originates from multiple sources, including vehicular traffic, industrial activities, and market congestion [1, 8]. The impact of noise pollution on market dynamics is influenced by several socioeconomic characteristics that act as mediating factors. Among the mediating factors, income levels might distinguish the experiences of higher-income vendors from those of lower-income traders. Vendors with greater financial stability might often implement measures to mitigate the effects of noise, while those with fewer resources remain vulnerable to its adverse consequences [7]. Educational background plays a crucial role, as traders with higher literacy levels might be more adept at adopting effective coping mechanisms to counteract the impact of noise pollution. The market type also introduces disparities, as formal (structured) markets and informal (open-air) markets experience noise differently due to their spatial arrangements and levels of organization [22].

The net income constitutes the dependent variable in this framework. Noise pollution might negatively affect vendors by reducing sales and revenue, as communication barriers hinder customer interactions [13]. Prolonged exposure to high noise levels also leads to increased stress-related health issues among traders, thereby affecting their overall well-being and capacity to operate efficiently [15]. Additionally, noise pollution contributes to consumer dissatisfaction, ultimately decreasing foot traffic and lowering market engagement [9].

Coping strategies and regulatory policies function as moderating variables that influence the extent to which noise pollution affects market vendors. Traders employ adaptive strategies such as relocating their stalls, adjusting operating hours, or installing noise barriers to mitigate the disruptive effects of environmental noise [5]. Government interventions, including the enforcement of noise regulations, implementation of zoning laws, and urban planning reforms, play a crucial role in reducing noise pollution and

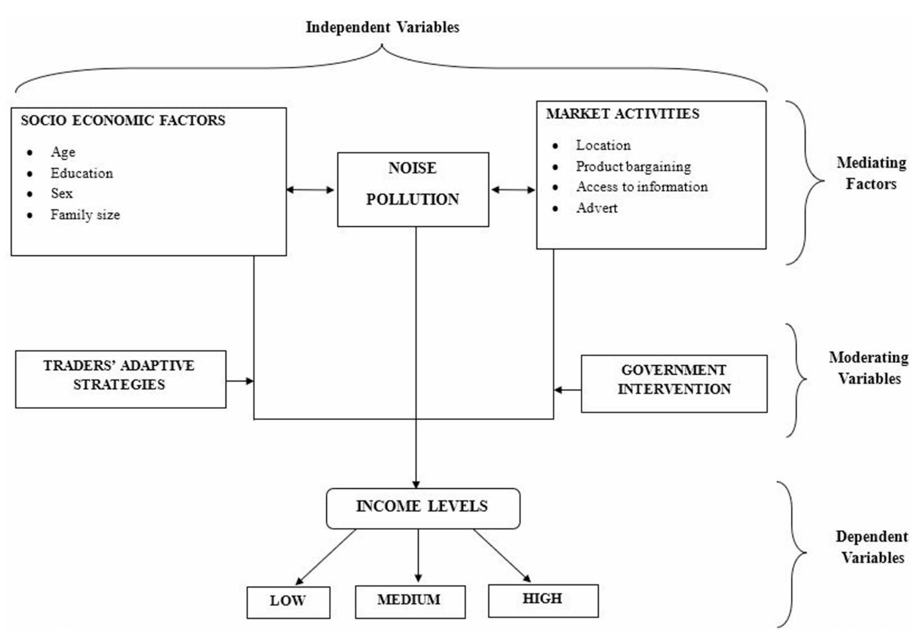

Fig. 1 Conceptual Framework for the Heterogeneous Impacts of Noise Pollution on Income. Source: Authors, 2024

ensuring a more conducive trading environment [4]. These moderating factors determine how successfully vendors can adapt to or mitigate the impact of noise pollution.

3 Justification and transition from OLS to unconditional quantile regression (UQR)

Statistical regression models have evolved significantly over time to address the limitations of conventional mean-based estimation techniques. Traditional methods, such as Ordinary Least Squares (OLS), while foundational, often fail to capture the full complexity of data distributions, particularly in the presence of heteroscedasticity, skewness, and outliers [25]. Recognizing these challenges, researchers have advanced from OLS to Quantile Regression (QR), then to Conditional Quantile Regression (CQR), and ultimately to Unconditional Quantile Regression (UQR). Each of these methods provides a more refined analytical framework for addressing issues of distributional heterogeneity and robustness in statistical modeling.

OLS is the most widely applied method in econometrics and statistical modeling, designed to estimate the conditional mean of a dependent variable given a set of independent variables. Its popularity is largely due to its computational efficiency and interpretability. However, OLS is based on strong assumptions, including homoscedasticity (constant variance of residuals) and normality of errors. These assumptions rarely hold in real-world data, leading to inefficiencies and biased estimates in cases of non-normal or skewed distributions [25, 26].

A major limitation of OLS is its inability to capture the effects of independent variables across different points of the outcome distribution. When the interest lies beyond the mean response—such as in cases of income disparity, educational outcomes, or health distributions—OLS falls short [27]. Moreover, OLS results are particularly sensitive to extreme values, as it minimizes squared residuals, disproportionately weighting large deviations. This limitation has led to the development of regression techniques that analyze the entire distribution of the dependent variable rather than just its central tendency.

To address the limitations of OLS [28], introduced Quantile Regression (QR), which extends conventional regression analysis by estimating the conditional quantiles of the dependent variable rather than its mean. QR is particularly useful in understanding the impact of explanatory variables at different points in the distribution, such as the lower or upper quantiles, making it a powerful tool for studying inequality and heterogeneous treatment effects [29]. QR provides robust estimates in the presence of heteroscedasticity and skewed distributions, allowing for a more comprehensive understanding of variable relationships. By focusing on different quantiles, QR reveals effects that OLS would otherwise obscure, offering insights into policies that target specific population segments, such as lower-income or high-achieving individuals [30]. However, QR is still conditional in nature, meaning that the estimated quantiles depend on specific values of the independent variables. This limitation means that while QR can provide valuable distributional insights, it does not fully capture the general effect of an independent variable across the entire unconditional distribution [25, 31]. Additionally, estimation at multiple quantiles can introduce computational complexity, particularly when extending QR to nonlinear models or large datasets.

Thus, CQR refines QR by focusing on the estimation of quantiles conditional on particular characteristics of the independent variables. This method allows researchers to evaluate how distributions shift based on changes in explanatory variables while maintaining a focus on specific subpopulations. CQR is especially useful in fields such as labour economics, where wage distributions and policy interventions can have differential impacts depending on individual characteristics such as education level, gender, or experience [32]. While CQR enhances QR by providing more precise quantile estimates, it remains limited by its conditional nature. The methodology assumes that estimated quantiles change based on specific covariates, making it difficult to assess broader distributional effects. Furthermore, the interpretation of CQR coefficients is often complex, as they reflect shifts in the conditional distribution rather than changes in the overall distribution of the outcome variable [26].

Recognizing the limitations of QR and CQR [33], introduced Unconditional Quantile Regression (UQR), a method designed to estimate the impact of explanatory variables on the entire distribution of the dependent variable rather than within specific conditional distributions. UQR achieves this by utilizing Recentered Influence Functions (RIF), which allow researchers to estimate quantile treatment effects without conditioning on specific covariates [25, 34]. One of the key advantages of UQR is its policy relevance. By estimating how changes in explanatory variables shift the unconditional distribution, UQR provides insights that are crucial for understanding broad economic and social phenomena, such as wage inequality or the impact of educational attainment on income distribution [35]. This makes UQR particularly powerful in policy analysis, where understanding shifts in entire distributions is often more relevant than understanding shifts within conditional subgroups. UQR also provides a more comprehensive assessment of distributional effects, overcoming the major limitation of QR and CQR by ensuring that results are not contingent upon specific covariate values. This feature makes it particularly useful in cases where the primary interest lies in evaluating the overall effect of policy interventions, market shocks, noise pollution, or structural economic changes [25, 36].

Moreover, UQR is robust to outliers and extreme values, as it does not rely on minimizing squared residuals but rather evaluates distributional shifts using influence functions. This property ensures that UQR provides more stable estimates in the presence of heavy-tailed distributions or influential data points [30]. Based on the facts, UQR emerges as the most robust method, offering an unconditional assessment of explanatory variables across the entire outcome distribution, making it particularly valuable for policy analysis and inequality research [26]. Given its ability to provide richer and more meaningful distributional insights, UQR has gained traction in empirical research across disciplines, including labour economics, education, and environmental studies.

4 Materials and methods

4.1 Description of Akure metropolis

The study was conducted in the Akure Metropolis. Akure is the capital city of Ondo State, located in the southwestern region of Nigeria. As a growing urban centre, it serves as the state's administrative, commercial, and cultural hub. The city holds historical, economic, and social significance, making it a vital part of Ondo State's identity and development. Akure lies within latitudes 7°15'N and 7°25'N and longitudes 5°10'E and 5°15'E, positioned strategically in the tropical rainforest zone of Nigeria (Fig. 2). It shares borders with several Local Government Areas, including Idanre to the South, Akure North to the North, and Ifedore to the West. The city benefits from a warm and humid tropical climate characterized by distinct wet and dry seasons. The annual rainfall ranges between 1,200 mm and 1,500 mm, with peak rainfall occurring from April to October while the average daily temperatures range from 22 °C to 34 °C, making the climate conducive for various agricultural and economic activities.

The geographical and climatic conditions of Akure contribute to its suitability for agriculture and commerce, particularly the operation of vibrant local markets. Akure has experienced rapid urbanization and population growth over the past few decades. Akure Metropolis, with an estimated population exceeding 700,000, serves as a regional economic hub, particularly for food and agricultural trade. Yet, informal market vendors, who account for over 60% of local retail food distribution, face mounting environmental risks. Studies estimate that over 30% of traders in high-traffic areas report declining daily sales due to environmental disturbances, with noise being a key factor [1, 6]. The population is predominantly Yoruba, with Akure serving as one of the core cultural centers of the Yoruba ethnic group. The city is also home to other ethnic groups, fostering cultural diversity and a dynamic social environment. The economy of Akure revolves around a mix of traditional and modern sectors. Agriculture remains a primary economic activity, with farmers producing crops such as cassava, maize, yam, cocoa, and oil palm. Akure hosts several markets, including Oja Oba, Oja Arakale, Oja Oshodi, and Oja Araromi, where food items, textiles, and household goods are traded. These markets are central to the livelihoods of many residents.

The city has a growing service sector, including transport, education, banking, healthcare, and public administration, supported by its role as the state capital. Again, rapid urbanization and economic activities in Akure have led to growing environmental challenges, particularly noise pollution.

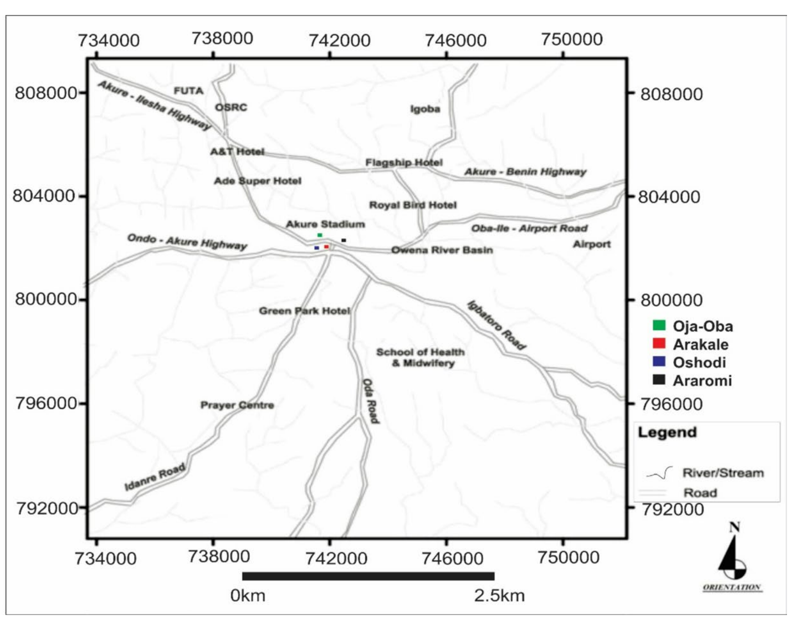

Fig. 2 Major Roads and Landmarks in Akure Metropolis. Source: Adapted from Google Maps

4.2 Sampling design and data collection

Questionnaire survey: A structured questionnaire was designed to collect socio-economic data, awareness levels, and perceptions of noise pollution among food market vendors. The questionnaire was pre-tested to ensure clarity and reliability. A two-stage sampling procedure was used to select the respondents. Firstly, the research focused on four purposively selected markets, which were Oja Oba and Oja Arakale markets located in busy areas with high vehicular traffic, and Oja Araromi and Oja Oshodi markets located in less busy areas with minimal vehicular traffic. These markets were chosen to capture variations in noise pollution levels based on market location and activity levels. Using a simple random sampling approach, 10 food vendors were selected from each location within each market, resulting in 30 respondents per market. A total of 120 respondents participated in the study, providing insights into the awareness and impact of noise pollution on their livelihoods.

A pilot study involving 10 food vendors (excluded from the main sample) was conducted to pre-test the questionnaire. Feedback from the pilot informed adjustments to question phrasing, Likert scale balance, and logical flow. These pilot respondents were not included in the main dataset used for analysis. To assess internal consistency, the reliability of Likert-scale items used for noise perception was evaluated using Cronbach's Alpha. The resulting coefficient ($\alpha = 0.81$) indicates good reliability, confirming that the scale items were consistently measuring the intended construct.

Noise pollution data collection: A sonometer machine was used to measure the noise decibels at the three locations within each market, spaced 50 m apart to ensure spatial variability. The locations were selected based on areas with the highest vendor concentration to provide representative readings while the readings were taken at the market peak day. The measurements were taken during peak market hours to reflect decibel levels under typical operating conditions.

4.3 Data analysis

Descriptive statistics and analysis of variance (ANOVA) were used to analyze the data obtained from the Sonometer machine to determine noise pollution levels across sampled market locations. Again, questionnaire responses were coded and analyzed using descriptive statistics to assess the perceived impacts of noise pollution on market activities, while Unconditional Quantile Regression (UQR) was used to determine the heterogenous impact of noise pollution, socioeconomic variables, and market activities on the sales (income) of the marketers.

Analysis of Variance (ANOVA).

In this study, an Analysis of Variance (ANOVA) was used to assess the variability in sales and noise pollution across the four selected markets. The model is specified in Eq. (1) as follows:

$$Y_{ij} = \mu + \tau_i + \varepsilon_{ij}. \tag{1}$$

where: Y_{ij} = Observed value of the dependent variable (sales or noise pollution) for the j-th sample in the i-th market; μ = overall mean of the dependent variable across all markets; τ_i = effect of the i-th market (treatment effect); and ε_{ij} = random error term, assumed to be normally distributed with mean 0 and variance $\sigma^2 \left(\varepsilon_{ij} \sim N\left(0, \sigma^2\right)\right)$.

Equations (2) and (3) are the One-way ANOVA representation for sales (income) and noise pollution, respectively.

$$For\ Sales:\ S_{ij} = \mu + \tau_i + \varepsilon_{ij} \tag{2}$$

$$For\ Noisepollution:\ NP_{ij} = \mu + \tau_i + \varepsilon_{ij} \tag{3}$$

All of the data were treated with one-way ANOVA in SPSS. The SPSS Duncan multiple range test was used to find discrepancies between the treatment means ($P < 0.05$).

Unconditional Quantile Regression (UQR).

Following [25], the general form of the UQR model is specified in Eq. (4) as:

$$Q_Y(\tau) = X\beta(\tau). \tag{4}$$

where $Q_Y(\tau)$ is the $\tau - th$ quantile of the income distribution, X represents the matrix of independent variables (including the intercept), and $\beta(\tau)$ is the vector of quantile-specific coefficients.

For the estimation of the UQR, the recentered influence (RIF) approach as proposed by [33] is employed. The RIF creates a pseudo-outcome as shown in Eq. (5):

$$RIF(Y, Q_Y(\tau)) = Q_Y(\tau) + \frac{\tau - I(Y \leq Q_Y(\tau))}{\int (Q_Y(\tau))} \tag{5}$$

where I is an indicator function that equals 1 if $Y \leq Q_Y(\tau)$ and zero otherwise, and $\int$ is the density of Y at $Q_Y(\tau)$. The regression of these pseudo-outcomes against the independent variables provides the estimates for $\beta(\tau)$.

The RIF for a quantile is calculated in Eq. (6) as follows:

$$RIF(y, q_\tau) = q_\tau + \frac{\tau - I(y \leq q_\tau)}{\int q_\tau}. \tag{6}$$

where y is the income (dependent variable), q_τ is the $\tau - th$ quantile of income, τ is the quantile of interest (0.25, 0.50, and 0.75 for low, median, and high, respectively), $I(y \leq q_\tau)$ is an indicator function that equals 1 if y is less than or equal to q_τ and 0 otherwise, and $\int q_\tau$ is the estimated density of income at q_τ which can often be estimated using kernel density estimation.

After calculating the RIF for the desired quantile of income, we use this as the dependent variable in a regression model. The independent variables include noise pollution, socioeconomic and market activity factors that could affect income.

The explicit function of the model specification is stated in Eq. (7):

$$\begin{aligned} RIF(y, \tau) = \beta_0 + \beta_1 NIP + \beta_1 NPR + \beta_2 SEX + \beta_3 EDU + \beta_4 MEX + \beta_5 MAC \\ + \beta_6 SPS + \beta_7 WHR + \beta_8 MSA + \beta_9 LOC + \beta_{10} AGE + \beta_{11} FMS + \varepsilon \end{aligned} \tag{7}$$

where $RIF(y, \tau)$ is the income in Naira (dependent variable) created from the RIF calculation. It is worth noting that the natural logarithm of Sales (income) was used for the analysis for easy interpretation. $\beta_0 - \beta_{12}$ are the coefficients to be estimated. ε is the error term.

NIP = Noise pollution (decibels).

NPR = Noise perception (mean perception using a 5-point Likert scale).

SEX = Sex of the vendor (male = 1 and female = 0).

EDU = Education level of the vendor (number of years spent in school).

MEX = Marketing experience (years).

MAC = Market access (access = 1 and 0, otherwise).

SPS = Shop size (meter square).

WHR = Work hours (hours).

MSA = Membership of association (member = 1 and 0, otherwise).

LOC = Location (1 = high traffic and 0, otherwise).

AGE = Age of the marketers (years).

FMS = Family size (numbers).

The acceptability and robustness of the Ordinary Least Squares (OLS) regression results were evaluated using diagnostic tests such as R-Square, F-value, VIF, Breusch – Pagan – Godfrey test, and Ramsey test. These tests ensured that the model meets the required assumptions, provides meaningful estimates, and avoids common pitfalls such as multicollinearity or specification errors.

5 Results and discussion

5.1 Socioeconomic characteristics of the respondents

The summary statistics of the socioeconomic variables of food marketers in the area are presented in Table 1. The results indicate that the majority of food marketers in the study area are female, accounting for 78.3% of the total sample. This finding is consistent with existing literature on informal market economies in developing countries, where women predominantly engage in food retailing due to its relatively low capital requirement and flexible working conditions [10, 12]. Studies in Nigeria and other sub-Saharan African countries have highlighted that women's participation in informal food markets is often driven by economic necessity, family responsibilities, and limited access to formal employment opportunities [11, 36]. Fewer male traders (21.7%) likely reflects their preference for more capital-intensive or wholesale operations over small-scale food vending. Also, the age distribution of food marketers reveals that the majority of respondents (74.2%) fall within the 31–60 years age bracket, with a mean age of 46.9 years. This suggests that food vending in the area is dominated by middle-aged marketers. According to [22], younger individuals are more likely to explore alternative income-generating activities, including digital entrepreneurship and formal employment, rather than engaging in traditional market trading. The average household size among respondents is 5.5 persons, with 62.5% of food marketers having families of 1–5 members and 34.2% having between 6 and 10 members. Large family sizes may influence vendors' financial responsibilities and business sustainability, as income from food vending often serves as the primary source of household livelihood [7]. The majority (92.5%) of respondents are married, reinforcing the notion that food marketing serves as a critical economic activity for supporting family needs. Previous studies have demonstrated that married women, in particular, rely on informal vending as a means of supplementing household income and maintaining financial independence [1]. The results further indicate that 12.5% of food marketers have no formal education, while 87.5% have attained at least primary education. This distribution reflects the general educational profile of informal market vendors, who often have limited access to higher education due to financial constraints

Table 1 Socioeconomic characteristics of food vendors in Akure metropolis

Variable	Frequency	Percent	Mean	SD
Sex				
Male	26	21.7		
Female	94	78.3	0.78	0.43
Age (years)				
≤30	16	13.3		
31–40	29	24.2		
41–50	35	29.2	46.9	13.1
51–60	25	20.8		
61–70	9	7.5		
>70	6	5.0		
Family size (numbers)				
1–5	75	62.5		
6–10	41	34.2	5.5	2.5
11–15	3	2.5		
>15	1	0.8		
Marital Status				
Married	101	92.5	0.93	0.47
Non-married	9	7.5		
Educational Level				
No formal education	15	12.5		
Primary school education	33	27.5		
Secondary school education	45	37.5	3.2	4.5
Tertiary education	27	22.5		
Member of association				
Yes	95	79.2	0.79	0.33
No	25	20.8		
Market Experience (years)				
1–10	46	38.3		
11–20	46	38.3	16.6	9.8
21–30	18	15.0		
31–40	9	7.5		
>40	1	0.8		
Total	120	100.0		

or early entry into trading activities [13]. However, traders with higher education levels may be better positioned to adopt modern business strategies, such as digital payment systems and market diversification, which could enhance their resilience to external shocks, including noise pollution [6]. About 79.2% of respondents belong to a traders' association, suggesting a strong network of market-based social capital. Membership in such associations provides several benefits, including access to credit facilities, collective bargaining power, and advocacy for better market conditions [8]. Associations may also serve as platforms for implementing noise mitigation strategies, such as lobbying for market zoning regulations or advocating for infrastructural improvements. The result of the market experience indicates that 76.6% of food marketers have been in business for at least 10 years, with an average experience of 16.6 years. The high level of experience suggests that many traders might have developed adaptive strategies to cope with market challenges, including environmental stressors. Experienced traders are likely to have better knowledge of market dynamics, customer preferences, and risk mitigation strategies, which can influence their ability to sustain their businesses despite environmental stressors like noise pollution [15].

5.2 Perception of marketers regarding the impact of noise pollution on their market activities

The Table 2 highlights the perceptions of marketers regarding the impact of noise pollution on their market activities, based on the mean responses for various statements. The highest-ranked issue in the results is the statement that "noise pollution impacts conversations with customers during transactions", with a mean score of 4.69. This suggests that communication difficulties are the most pressing concern for marketers. It implies that noise pollution severely disrupts interactions between marketers and their customers, which can directly affect sales and overall customer satisfaction. Following closely with a mean of 4.61, marketers also reported that noise pollution affects their general ability to communicate with customers, reinforcing communication as a critical area of concern. The use of perception scores reinforces the findings of [21, 37], who identified stress, communication breakdown, and shortened customer stay as primary noise-induced disruptions. Another concern raised by marketers is that noise pollution influences the amount of time customers spend at their stalls, as reflected in the third highest score (mean: 4.20). This suggests that noise may make the shopping environment uncomfortable for customers, potentially causing them to spend less time at individual stalls, which could result in fewer sales or less engagement. Marketers also perceive noise pollution as having a notable impact on their well-being. The statement regarding the physical discomfort or stress caused by market noise had a mean score of 4.07. This result indicates that noise pollution not only affects the business environment but also contributes to stress and fatigue among marketers, which could lead to reduced productivity or job satisfaction over time. Similarly, some health issues experienced by marketers are believed to be related to noise in the market, as reflected in the mean score of 3.56. Interestingly, the impact of noise pollution on overall market operations, with a mean of 3.47, was ranked lower. This suggests that while noise pollution is acknowledged as a problem, its direct effect on daily operations is not perceived as severely as its impact on communication and customer interactions. The perception of changes in customer behaviour due to noise pollution was also ranked low, with a mean score of 3.01. Marketers may not strongly associate noise pollution with noticeable changes in customer behaviour, or the effects may be too subtle to recognize clearly in daily activities. The lowest-ranked statement, with a mean score of 2.59, is the perception that noise pollution affects the pricing or quality of products. This indicates that marketers do not view noise pollution as having a direct connection to the inherent value of their goods. Noise may be seen as an external disturbance, but it does not affect the quality or pricing of products in the same way it affects interpersonal communication and customer experience [37, 38].

Table 2 Mean perceptions of the impact of noise pollution on market activities

Statement	Mean	Rank
Noise pollution impacts your conversations with customers during transactions	4.69	1st
Noise pollution influences the time customers spend at your stall	4.20	2nd
The noise level in the market causes you physical discomfort or stress	4.07	3rd
Some health issues experienced are related to noise in the market	3.56	4th
The high level of noise in the market affects your market operation	3.47	5th
There is a change in customer behaviour due to noise pollution	3.01	6th
Noise pollution affects the pricing or quality of your products	2.59	7th

5.3 Measurement of noise pollution levels and sales/day in the study area

The ANOVA results presented in Table 3 reveal the variation in sales performance and noise pollution levels across different market locations in the study area. The results indicate that the average daily sales of food vendors across the four markets are ₦17,550.42, with variations among individual markets. Oja Oba recorded the highest mean daily sales of ₦19,716.7, followed by Oja Oshodi (₦18,275.9), Oja Araromi (₦16,533.3), and Oja Arakale (₦15,700.0). These variations can be attributed to differences in market size, customer footfall, location, and the types of food sold [7, 12, 22, 39].

Again, the noise pollution results reveal significant variations in environmental noise levels across the four markets. Oja Arakale recorded the highest mean noise level of 70.1 dB, followed by Oja Oshodi (60.1 dB), Oja Araromi (58.9 dB), and Oja Oba (56.6 dB). These values exceed the World Health Organization (WHO) recommended safe threshold of 55 dB for commercial areas [20], indicating that traders and customers in these markets are exposed to potentially harmful noise levels. The high noise level in Oja Arakale can be linked to its proximity to major road networks, high vehicular traffic, and the presence of transport hubs, which contribute significantly to urban noise pollution [13, 37, 38, 40]. Studies have shown that market areas located near high-traffic roads tend to experience elevated noise levels, which negatively impact business operations by reducing customer satisfaction and increasing stress-related health issues among traders [1, 37]. Further, Oja Oba, which recorded the highest average daily sales, reported the lowest mean noise level (56.6 dB). This suggests that markets with lower noise levels may provide a more conducive business environment, facilitating effective communication between traders and customers, and thereby enhancing sales performance [21, 37]. reported that excessive noise pollution in markets disrupts vendor-customer interactions, leading to communication barriers, reduced customer engagement, and ultimately lower sales. The ANOVA test confirms that the differences in noise levels among markets are statistically significant ($p < 0.05$). Markets such as Oja Arakale, where noise levels are higher, may experience lower sales due to customer discomfort and reduced vendor productivity. Vendors operating in these high-noise areas may require adaptive strategies, such as adjusting their trading hours, relocating to quieter sections of the market, or advocating for noise regulations to mitigate the adverse effects of noise pollution on their businesses [41].

Table 3 ANOVA results for daily sales and noise pollution across markets

Variable	Mean	SD	Min	Max
Sales/day in Naira				
Oja Arakale	15,700.0^{a}	12,559.2	3,000.0	60,000.0
Oja Oshodi	18,275.9^{a}	17,614.7	1,000.0	70,000.0
Oja Oba	19,716.7^{a}	35,834.3	2,000.0	200,000.0
Oja Araromi	16,533.3^{a}	12,516.8	3,000.0	60,000.0
Average total	17,550.42	21,654.9	1,000.0	200,000.0
Noise pollution (decibel)				
Oja Arakale	70.1^{a}	10.7	59.0	84.3
Oja Oshodi	60.1^{b}	4.8	53.8	65.0
Oja Oba	56.6^{b}	5.0	52.9	63.5
Oja Araromi	58.9^{b}	6.37	54.5	67.8
Average total	61.4	8.7	52.9	84.3

^{a},^{b} – Means with different superscripts within columns are significantly different at $p < 0.05$ using Duncan's Multiple Range Test. Sales are measured in Nigerian Naira (₦). Noise levels are expressed in decibels (dB).

Table 4 Unconditional quantile regression estimates of noise pollution effects on vendor income

Explanatory Variable	OLS	25th	50th	75th
Noise pollution	− 0.001 (0.006)	− 0.009 (0.007)	− 0.006*** (0.002)	− 0.009** (0.005)
Noise Perception	− 0.183*** (0.030)	− 0.156*** (0.037)	− 0.151*** (0.034)	0.079** (0.039)
Age	0.002 (0.002)	0.003 (0.002)	− 0.081* (0.047)	0.003 (0.002)
Sex	− 0.186*** (0.031)	− 0.019* (0.011)	− 0.018** (0.008)	− 0.163* (0.092)
Education	0.011* (0.006)	0.050** (0.022)	0.076*** (0.019)	0.070** (0.031)
Family size	− 0.201*** (0.071)	− 0.022* (0.013)	− 0.135* (0.078)	0.185** (0.091)
Market access	0.231 (0.221)	0.115 (0.085)	0.002 (0.002)	0.012*** (0.002)
Shop size	0.199*** (0.070)	0.135*** (0.038)	0.037** (0.015)	0.015 (0.036)
Work hours	0.091 (0.076)	0.099 (0.085)	0.003 (0.025)	0.015*** (0.006)
Membership	0.014 (0.010)	− 0.115 (0.102)	0.011 (0.010)	− 0.037 (0.056)
Location	− 0.201** (0.096)	− 0.115** (0.052)	− 119*** (0.035)	− 0.085** (0.041)
Constant	0.929 (0.122)	0.898 (0.148)	0.922 (0.135)	0.744 (0.159)
F-value	3.91***	2.74***	3.43***	1.00
R-squared	0.378	0.299	0.347	0.134
Sample Mean RIF	–	0.672	0.736	0.813

Mean VIF = 2.53; Breusch – Pagan – Godfrey test: Chi2 (1) = 3.59 with prob > Chi2 = 0.091; Ramsey test: F (3, 100) = 1.61 (0.192); Sample size = 120

Standard errors are in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% respectively. RIF = Recentered Influence Function; OLS = Ordinary Least Squares; UQR = Unconditional Quantile Regression

5.4 Heterogeneity effect of noise pollution on the sales (Income) of food marketers in the area

The regression results presented in Table 4 provide a detailed analysis of the impact of noise pollution and various socioeconomic factors on the income of food marketers in the study area. Using Ordinary Least Squares (OLS) and Unconditional Quantile Regression (UQR) at the 25th, 50th, and 75th quantiles, the study examines how noise pollution and other independent variables influence vendor income across different income levels. This approach allows for a distributional assessment of the effects rather than focusing solely on the mean impact, thereby capturing heterogeneity in the economic experiences of food marketers. To start with, the diagnostic tests were conducted for the reliability and validity of the regression model by assessing potential issues such as multicollinearity, heteroskedasticity, and model specification errors. The Variance Inflation Factor (VIF) has a mean value of 2.53, which is well below the commonly accepted threshold of 10. This indicates that multicollinearity among the independent variables is not a concern, suggesting that the estimated coefficients are stable and not distorted by high correlations between predictors. The Breusch-Pagan-Godfrey test ($Chi^2 = 3.59$, $p = 0.091$) assesses the presence of heteroskedasticity, which occurs when the variance of residuals is not constant across observations. The result indicates that there is no strong evidence of heteroskedasticity in the model. The Ramsey RESET test ($F = 1.61$, $p = 0.192$) is used to detect specification errors, including omitted variable bias or incorrect functional form.

The result suggests that there is no significant evidence of model misspecification. The F-value results indicate the overall significance of the regression models in explaining variations in income among food marketers. The OLS model ($F = 3.91$, $p < 0.01$), as well as the 25th ($F = 2.74$, $p < 0.01$) and 50th ($F = 3.43$, $p < 0.01$) quantile models, are statistically significant, suggesting that the independent variables collectively explain a substantial portion of income variation. However, the 75th quantile model ($F = 1.00$) is not statistically significant, implying that income determinants among high-earning traders may be influenced by unobserved factors. The R-squared values further reinforce these findings, with the OLS model explaining 37.8% of the variation in income, while the 25th and 50th quantile models explain 29.9% and 34.7%, respectively. The 75th quantile model exhibits a low R-squared value (13.4%), indicating that the explanatory power of the model diminishes among top-income vendors. This suggests that while noise pollution and socioeconomic factors significantly impact lower- and middle-income vendors, high-income traders are less affected by these variables. Again, the sample mean RIF values increase across quantiles, from 0.672 at the 25th quantile to 0.813 at the 75th quantile.

The coefficient for noise pollution is negative across all quantiles, indicating that higher noise levels are associated with lower income among food marketers. However, its significance varies. The OLS estimate (-0.001, $p > 0.05$) is statistically insignificant, suggesting that when the entire sample is considered on average, noise pollution does not have a strong explanatory power in determining income. However, the UQR results indicate that noise pollution has a significant negative effect at the 50th (-0.006, $p < 0.01$) and 75th (-0.009, $p < 0.05$) quantiles. These findings imply that noise pollution disproportionately affects mid-to-high-income vendors rather than lower-income traders. Based on the UQR results, a one-decibel increase in measured noise pollution reduces median vendor income by approximately ₦105 (0.6%) per day. Over a typical 25-day working month, this translates to a potential loss of ₦2,625 per vendor, equivalent to over ₦31,000 annually. Extrapolated across just 1,000 traders in Akure's busiest markets, total estimated income losses could exceed ₦31 million annually, underscoring the urgent need for noise mitigation policies. The finding that noise pollution significantly reduces income at the 50th and 75th quantiles aligns with [3, 9], who also documented adverse economic consequences of elevated noise levels in Nigerian urban centers. Similarly, the disproportionate impact on middle- and high-income vendors is echoed in [13, 19, 21], which found that environmental degradation exacerbates inequality in market productivity and resilience. Further, noise perception, which measures traders' subjective experience of noise pollution, is also negatively associated with income across most quantiles. The OLS estimate (-0.183, $p < 0.01$) and the UQR results at the 25th (-0.156, $p < 0.01$) and 50th (-0.151, $p < 0.01$) quantiles indicate a significant negative relationship. However, at the 75th quantile, the effect turns positive (0.079, $p < 0.05$), suggesting that wealthier traders may adopt adaptive measures to mitigate noise impacts, such as relocating stalls, investing in noise reduction technologies, or benefiting from established customer bases [22].

Age is insignificant in the OLS and most quantiles, except for a weak negative effect at the 50th quantile (-0.081, $p < 0.10$). This suggests that aged medium-income traders may experience slightly lower income due to greater vulnerability to noise-induced stress or fatigue [1]. Sex is negatively associated with income across all quantiles, indicating that male traders earn significantly less than their female counterparts. The OLS coefficient (-0.186, $p < 0.01$) and UQR estimates confirm this trend, particularly at the 25th (-0.019, $p < 0.10$), 50th (-0.018, $p < 0.05$), and 75th (-0.163, $p < 0.10$) quantiles. These findings align with previous studies highlighting gender disparities in informal markets [10, 12]. Education has a positive and significant effect on income across most quantiles, reinforcing the idea that higher education enhances business acumen and adaptive capacity. The OLS estimate (0.011, $p < 0.10$) and the UQR results at the 25th (0.050, $p < 0.05$), 50th (0.076, $p < 0.01$), and 75th (0.070, $p < 0.05$) quantiles confirm that traders with more education earn higher incomes. These results suggest that literacy and numeracy skills may help traders optimize pricing strategies, maintain better records, and explore digital payment solutions [13]. Family size exhibits a mixed effect, with a negative impact in lower quantiles (-0.201, $p < 0.01$ at OLS, -0.022, $p < 0.10$ at 25th, and −0.135, $p < 0.10$ at 50th) but a positive impact at the 75th quantile (0.185, $p < 0.05$). This suggests that for lower-income traders, larger families may impose financial constraints that limit business expansion, while for wealthier traders, family support structures may provide labour or financial stability [7]. Market access is insignificant in most models except for the 75th quantile (0.012, $p < 0.01$), suggesting that higher-income traders possibly benefit from better location advantages and customer traffic [12]. Shop size has a significant positive effect on income across all quantiles, with stronger effects at lower quantiles (OLS: 0.199, $p < 0.01$; 25th: 0.135, $p < 0.01$; 50th: 0.037, $p < 0.05$). This confirms that vendors with larger shop spaces attract more customers, offer a diverse product range, and experience higher turnover [10]. Work hours have an insignificant effect at lower quantiles but a positive impact at the 75th quantile (0.015, $p < 0.01$), indicating that higher-income traders benefit from extended working hours, possibly due to their ability to operate in safer or regulated spaces [22]. Location exhibits a strong negative impact on income across all quantiles, with highly significant coefficients at the 50th (-0.119, $p < 0.01$) and 75th (-0.085, $p < 0.05$) quantiles. This suggests that vendors operating in high-traffic, high-noise areas face income losses, likely due to customer discomfort, communication barriers, and increased competition [13, 41].

6 Conclusion and policy implications

This study provides empirical evidence on the heterogeneous impact of noise pollution on food vendors' income in Akure Metropolis, Nigeria. Using Unconditional Quantile Regression (UQR), the findings reveal that noise pollution significantly affects market vendors, particularly those in the middle and upper-income quantiles. Food marketers at the 50th quantile and 75th quantile experience substantial income reductions due to noise pollution, highlighting its disruptive effects on business transactions and customer interactions. Noise perception also negatively impacts income, particularly among lower-income vendors, suggesting that traders with fewer resources are more vulnerable to environmental stressors. Socioeconomic characteristics play a crucial role in income distribution among vendors. Education, shop size, and market experience positively influence income, reinforcing the importance of knowledge, business structure, and operational expertise in mitigating external shocks such as noise pollution. However, gender disparities persist, with female traders earning significantly more than their male counterparts, pointing to broader inequalities in informal markets. Furthermore, the location of the market confirms that traders operating in high-noise areas experience lower sales performance, reinforcing the need for strategic market planning. Based on the main findings, the study recommends that given the significant impact of noise pollution on vendors' income, policymakers should enforce market zoning regulations that separate high-noise activities (such as motor parks and industrial operations) from food trading areas. Establishing noise reduction measures, such as designated quiet zones within markets, sound barriers, and noise limits for public address systems, can help create a more conducive business environment. The study also highlights persistent gender disparities in income, necessitating targeted programs to support male traders. Policies should focus on improving access to credit, market literacy training, and business expansion opportunities for men in informal markets to enhance their economic participation and competitiveness. Also, women's economic empowerment initiatives can help enhance their resilience to environmental stressors. The significant role of shop size in income generation shows the need for investments in modern market infrastructure. Government and private sector partnerships should focus on expanding trading spaces, improving market layouts, and creating structured trading zones that minimize exposure to external noise disturbances. Incentives for vendors to operate in structured, low-noise environments could enhance business sustainability and productivity. The negative perception of noise among traders highlights the need for awareness campaigns on the effects of noise pollution and coping strategies. Market associations and local governments should train vendors on adaptive strategies, such as optimizing business hours, utilizing noise-absorbing materials, and advocating for regulatory enforcement to reduce market noise. Additionally, public education on the importance of noise regulation in commercial areas can help foster community support for noise reduction initiatives. Urban planning authorities should integrate noise pollution assessments into market development plans and enforce stricter noise pollution control laws. Routine monitoring of noise levels in commercial zones, penalties for excessive noise, and incentives for noise reduction practices can ensure compliance. The establishment of a noise pollution monitoring system within markets would provide data for informed policymaking and long-term urban sustainability strategies. Lastly, to mitigate the impact of noise on business transactions, policymakers should encourage digital payment systems and e-commerce solutions for market vendors. Integrating mobile payment options, online sales platforms, and digital marketing strategies can help vendors expand their customer base while reducing reliance on face-to-face transactions in noisy environments. Government and non-governmental organizations should also explore subsidized access to digital business tools for small-scale traders.

7 Limitations and prospects

The study's reliance on self-reported data introduces the possibility of recall or response bias, particularly in reported income and perceived noise impacts. Its focus on Akure Metropolis may also limit the generalizability of findings to other urban contexts. Moreover, certain potentially relevant variables, such as household income and seasonal trading fluctuations, were not included. Despite these limitations, the study provides a robust empirical basis for future research. Longitudinal and multi-city studies are recommended to validate these findings, explore causal pathways, and inform targeted interventions addressing environmental stressors in informal market economies.

Author contributions

O.A.I.: Conceptualization, methodology, formal analysis, writing, reviewing, writing-original draft preparation, and supervision. O.L.O.: Methodology, survey design, reviewing, editing, preparing and providing data. O.M.M.: Conceptualization, Survey design, writing, plotting, reviewing, editing and supervision. O.A.S.: Conceptualization, Methodology, reviewing, editing, resources, validation, investigation and supervision. O.A.F.: Conceptualization, Survey design, writing, plotting, reviewing, editing and supervision. A.E.A.: Survey design, resources, reviewing and supervision. O.P.O.: Reviewing, editing, resources, and supervision.A.I.A.: Reviewing, editing, validation, preparing and providing data. All authors have read and agreed to the published version of the manuscript.

Funding

The research was not funded.

Data availability

All data and materials not included in the manuscript are available on request.

Declarations

Ethics approval and consent to participate

Ethics approval was obtained from the Faculty of Agriculture's IRB committee, Adekunle Ajasin University, Akungba-Akoko, Ondo State, Nigeria, following the law and the country's national ethical guidelines. In addition, the participants gave their informed consent to participate in this study.

Consent to publish

All authors have read and agreed to the published version of the manuscript.

Competing interests

The authors declare no competing interests.

Received: 28 February 2025 / Accepted: 26 June 2025

Published online: 07 July 2025

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