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Heterogeneous demand for agricultural lime in Tanzania: Recent empirical evidence and implications for policy

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Bisrat Gebrekidan[1], Moti Jaleta[1], Jordan Chamberlin[1], Nicholaus M. Kuboja[2]

[1] CIMMYT (International Maize and Wheat Improvement Center)

[2] Tanzanian Agricultural Research Institute (TARI)

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Abstract

Soil acidity and related agricultural productivity constraints have re-emerged as a policy priority in several countries in Sub-Saharan Africa in recent years. However, despite well-documented agronomic benefits, the use of agricultural lime to address soil acidity remains limited by farmers, and value-chains for agricultural lime remain poorly developed in most acidic areas. As countries with acidity constraints evaluate their policy options – which may include targeted extension, investments in lime production and market development, or inclusion of lime in input subsidy schemes – they are constrained by limited evidence on how farmers value lime, what drives their demand, and how demand would respond to pricing changes in local markets. To address this gap in one country with significant soil acidity constraints, Tanzania, we estimate the willingness of smallholder farmers to pay for lime using a double bounded dichotomous choice contingent valuation method. Our analysis is based on survey data from 600 randomly selected farm households in Iringa District, Tanzania, an area characterized by high soil acidity, an existing lime supply chain, but limited lime uptake by local farmers. The estimated mean willingness to pay was found to be 4.67 US dollars per 50 kilogram bag of lime, closely aligning with the prevailing market prices. However, the willingness to pay varies considerably among farmers. Social exposure, measured by the number of known lime users, is the strongest predictor of demand, with the willingness to pay significantly higher for farmers who know more than five other users. WTP is higher for farmers with prior lime experience, exposure to training, level of education, landholding size, and livestock ownership, and is negatively correlated with the degree of present bias. Inverse demand curves show that only about half of farmers are willing to pay the current market price. An effective intervention requires simultaneous investments in demand creation, improved access to liquidity, and coordination across the lime supply chain. Our results not only provide useful guidance to policymakers in Tanzania but also to governments and private sector actors in similar settings in the region.

Keywords: Willingness to pay; demand heterogeneity; agricultural lime; soil acidity; contingent valuation; smallholder farmers; Tanzania

Contents

1 Introduction

Soil acidity is a widespread and intensifying constraint on agricultural productivity across sub-Saharan Africa (SSA). It is estimated to affect approximately 32.7 million hectares - equivalent to 23% of the total cropland of the region (Silva et al., 2025). Soil acidity directly undermines agricultural productivity, thereby affecting the livelihoods of millions of smallholder farmers. It restricts plant growth due to a combination of physical, chemical and biological factors. Physically, it causes problems such as soil erosion and reduced water retention, delaying crop development. Chemically, it can lead to aluminium toxicity and reduce the availability of essential nutrients, such as calcium, magnesium and phosphorus. Biologically, acidity suppresses the activity of beneficial soil microorganisms, which affects the decomposition of organic matter, the mineralisation of nutrients, and the ability of plants to absorb and utilise nutrients. These effects combined contribute to reduced crop yields in acidic soils (N. Fageria & Baligar, 2008; Sanchez, 2019; Sharma, Datta, & Sharma, 2025). The total economic burden of soil acidity in SSA is staggering, estimated at an annual loss of $6.0 billion (Silva et al., 2025).

The problem is worsened by the reduced effectiveness of fertilizers. Even when farmers apply inorganic fertilizers, crops respond minimally to acidic soils, resulting in poor returns on investment and increased production risk. For resource-constrained smallholders, this perpetuates a cycle of low productivity, income stagnation, and soil degradation. In Ethiopia, over 40% of arable land is estimated to be acidic, resulting in significant national yield losses and undermining efforts to ensure food security (Oumer, Diro, Taye, Mamo, & Jaleta, 2023). Similar patterns are seen in the southern highlands of Tanzania, central Kenya, and parts of Rwanda and Malawi, where acidic soils dominate high-potential agricultural zones.

Agricultural lime, comprising finely ground calcium carbonate ($CaCO_3$) or dolomitic lime ($CaMg(CO_3)_2$), is the most established and effective input for correcting soil acidity (Enesi et al., 2023; N. K. Fageria & Nascente, 2014; Hijbeek, van Loon, Ouaret, Boekelo, & van Ittersum, 2021; Luna & Larrea, 2024). Lime neutralizes excess hydrogen (H^+) and aluminum ions in the soil solution, thereby raising pH, reducing toxic element solubility, and improving nutrient availability, particularly phosphorus, sulfur, and molybdenum (Barber, 1984). Beyond its chemical effects, liming also enhances soil structure, increases microbial activity, and promotes root growth, creating favorable conditions for crop productivity and fertilizer efficiency (Enesi et al., 2023; Regasa, Haile, & Abera, 2025).

Studies in Ethiopia, Kenya, and Rwanda report yield gains ranging from 30% to over 100% in maize, wheat, and legumes following lime application, especially when combined with nitrogen and phosphorus fertilizers (Agegnehu et al., 2021; Hijbeek et al., 2021; Jaleta et al., 2024; Kibet et al., 2023; Warner, Mann, Chamberlin, & Tizale, 2023). These effects are particularly pronounced in areas with low pH (≤ 5.5) and high exchangeable aluminum, where lime can unlock nutrient availability and reduce input waste (Chander, Mishra, RK, M, & P, 2020; Codling, 2008; Vanlauwe et al., 2023).

However, in spite of its agronomic effectiveness, lime remains underused in acidic areas of SSA due to a range of economic, logistical, and behavioral constraints (Enesi et al., 2023; Jaleta et al., 2024; Luna & Larrea, 2024; Bizoza, 2021; Esilaba et al., 2023; Oumer et al., 2023). High transport costs, lack of market infrastructure, poor awareness of lime's benefits, and the delayed nature of its yield response have all been cited as contributing factors in low lime adoption rates across the region. Addressing these bottlenecks requires a deeper understanding of farmer preferences, demand patterns, and willingness to pay, particularly in areas where lime is available but underutilized.

Southern Tanzania presents a relevant context for such inquiry. The region has relatively well-established supply channels, and a history of public investment in soil health interventions. Yet uptake remains low, raising important questions about the demand-side dynamics at play. Understanding how farmers in this setting value lime offers a useful lens for exploring broader adoption constraints. Despite substantial public and donor interest in soil acidity management in Tanzania, including demonstration plots, promotional campaigns, and input subsidies, effective farmer demand remains weak. At the same time, private sector participation in lime markets has yet to scale (Kilimo-Kwanza, 2025a, 2025b). While recent efforts have focused on expanding production and improving delivery logistics, sustained uptake will ultimately depend on whether smallholders are willing and able to pay for lime at market or subsidized prices. However, Tanzania still lacks rigorous evidence on farmers' willingness to pay for lime.

This study responds to that gap and contributes to the literature and policy dialogue in three key ways: First, it provides country-specific, econometrically estimated WTP for agricultural lime in Tanzania . Such a context-specific study shades light on the importance of considering differences in soil conditions, market structures, cropping systems, and farmer profiles in estimating smallholders' demand for agricultural lime. Second, it complements the ongoing discussion on the supply-side investments by generating demand-side evidence critical for assessing the commercial viability of lime value chains. Our estimates help decide whether current price levels are affordable for most farmers or whether price support mechanisms (e.g., targeted subsidies, credit, bundling with other options) are needed to stimulate agricultural-lime adoption. Third, it analyzes the heterogeneity in WTP across socio-economic, behavioral, and informational dimensions. Understanding how WTP varies by wealth, education, past exposure, and time preferences enables the designing of more effective and fair interventions in scaling ag-lime use.

The rest of the paper is organized as follows. Section 2 describes the study area and contextual background. Section 3 outlines the data sources and methodological approach. Section 4 presents empirical results and discussion, and Section 5 concludes with key insights and policy implications.

2 Data and methodology

2.1 Context and Data

The study was conducted in Kilolo District, located in the eastern part of Iringa Region in Tanzania's Southern Highlands (see Figure 1. The district lies at altitudes ranging from 1,200 to over 2,000 meters above sea level and is characterized by a subtropical highland climate. It receives annual rainfall between 800 and 1,600 mm, concentrated during a well-defined rainy season from November to May, followed by a cool dry season from June to September. Average temperatures range from 10°C in the cold season to around 25°C in the warmest months (Anyango, Begasha, Kweka, et al., 2019; KDC, 2022). The district's topography, altitude, and rainfall patterns contribute to microclimatic variation and to the development of highly leached, acidic soils.

Agriculture is the dominant livelihood activity in Kilolo, with most households engaged in maize, beans, and paddy cultivation. The district also shows strong potential for high-value horticultural crops such as avocados, tomatoes, and onions. Although Kilolo has substantial arable land, only a part is under active cultivation. Soil acidity is still a key constraint to productivity, particularly in upland zones. Notably, Kilolo is one of the few areas in Tanzania with local lime availability, making it a strategic location for evaluating smallholders' willingness to pay for lime use and informing targeted soil acidity management interventions. Primary data were collected using a multistage sampling approach designed to ensure representativeness across the district's diverse agroecological and socioeconomic contexts. In the first stage, 40 villages were randomly selected using probability proportional to size (PPS) sampling, based on village population data. In the second stage, one enumeration area (EA) was randomly selected from each sample village. Finally, in the third stage, 15 households were randomly selected from each EA using simple random sampling techniques, yielding a total sample of 600 households.

Trained enumerators from the Tanzania Agricultural Research Institute collected data using computer-assisted personal interviewing (CAPI). In addition to the core sections on household demographics, farm attributes, knowledge of soil acidity, and lime adoption practices, three incentive-compatible modules were included. First, data collection for the Willingness-to-Pay component began with enumerators reading a standardized script on the agronomic benefits of lime (20–30% yield gains lasting multiple seasons) before presenting a delivery scenario for a 50 kg bag of standard powdered agricultural lime. Respondents then participated in an unfolding bids sequence: an initial offer randomly selected from 5,000; 7,500; 10,000; 12,500; 15,000; 17,500 TSH (2–7 USD at the time of survey), a second bid adjusted by ±2,500 TSH, and a final open-ended question about their maximum payable amount. To mitigate hypothetical bias, we included a cheap talk script emphasizing that this was not a promotional or subsidy program, and that we were interested in their true valuation if they had to spend their own money.

Second, risk preferences were elicited using a five-step adaptive "coin flip" task. Each choice offered a guaranteed payment versus a 50% chance of winning 40,000 TSH (win the full amount on heads, lose nothing on tails). After each response, the sure sum increased or decreased by half

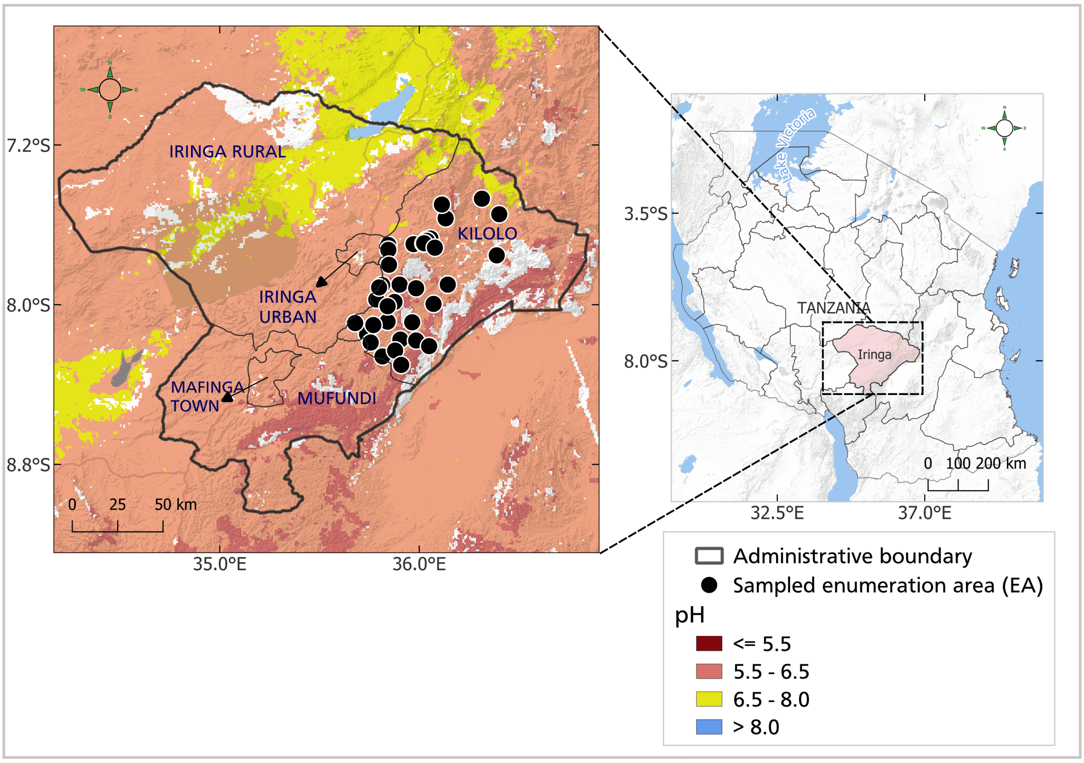

Figure 1: Map of the study area in Kilolo District, Iringa Region, Tanzania

Note: The map shows the spatial distribution of sampled enumeration areas (EAs) overlaid on soil pH classifications (Hengl et al., 2015). The inset map indicates the location of Iringa Region within Tanzania.

to converge on the indifference point. The midpoint between the last accepted offer and the first rejected offer was taken as each household's certainty equivalent. Then, these were converted into a CRRA-style risk-aversion index via the standard logarithmic inversion (see (Falk, Becker, Dohmen, Huffman, & Sunde, 2023)).

Third, our estimation of time Preferences employed a consistent halving-step design across two horizons: "now" versus three months and "now" versus six months. This approach yielded two certainty equivalents for each respondent. From these, we calculated a constant-rate discount factor and a present bias measure to capture overall patience and extra short-term impatience. Full details on the design, wording, and step-size rules are available in (Falk et al., 2023).

To capture farmers' ability to pay for agricultural lime, we constructed a household wealth index using principal component analysis (PCA). The index was derived from variables capturing ownership of key productive and durable assets, such as farm tools, and mobile phones, as well as housing characteristics, such as roof, wall, and floor materials. This approach provides a multidimensional measure of economic status, which complements income data and offers a more robust indicator of household liquidity and purchasing power in rural areas.

Table 1 displays summary statistics for the full sample of 600 respondents. A wide range of demographic, agronomic, and socioeconomic variables are reported to provide context for the heterogeneity in WTP. On average, respondents were 49 years old and had 22 years of farming experience. Sixteen percent were classified as young (35 years old). Most households were male-headed (80%), with an average of 5.07 family members. Approximately 21% were small-scale farmers, and 51% had access to credit, which are factors that directly influence liquidity constraints and investment capacity. On average, respondents owned or controlled 2.24 plots and walk an average of 41 minutes to reach their main plot from homestead, which may affect input application logistics and labor allocation. Livestock ownership, a proxy for asset wealth, was high at 80%. Generally, education levels were low: 5.8% of respondents had no formal education, 81% had completed primary school, and 13% had completed secondary school or higher. These variables are hypothesized determinants of perceived returns to lime use and the financial flexibility needed for adoption.

Exposure to lime-related information and prior use of lime in their vicinity were limited. Although respondents reported knowing an average of about one other farmer (0.93 people) who had used lime (SD = 1.70), only 5.5% had applied lime themselves. Roughly 23% had received personalized soil test results, and only 9.7% had taken part in lime training or demonstration activities. The use of organic fertilizer (21%) suggests limited investment in improving soil fertility. These indicators capture informational and experiential constraints that may influence respondents' valuation of lime. Additionally, behavioral preferences, proxied by a discount factor of 0.35 (SD = 0.24) and a CRRA risk aversion index, reflect heterogeneity in time and risk preferences. These preferences are theoretically and empirically linked to the adoption of long-term, productivity-enhancing inputs, such as lime. Together, these variables provide a context for interpreting variations in WTP across the sample and for identifying constraints that limit market-based demand for agricultural lime.

Table 1: Descriptive Statistics by DBDC Response Category

Characteristic	Overall N = 600[1]	No-No N = 152[1]	No-Yes N = 92[1]	Yes-No N = 154[1]	Yes-Yes N = 202[1]	p-value[2]
		DBDC responses				
Knows Others Who Used Lime	0.93 (1.70)	0.67 (1.22)	0.63 (1.36)	0.79 (1.68)	1.38 (2.06)	0.001
Used Lime Before	33 (5.5%)	7 (4.6%)	4 (4.3%)	8 (5.2%)	14 (6.9%)	0.73
Received personalized soil-test result	135 (23%)	31 (20%)	18 (20%)	45 (29%)	41 (20%)	0.15
Used Organic Fertilizer	127 (21%)	33 (22%)	25 (27%)	30 (19%)	39 (19%)	0.44
Gender of Household Head	477 (80%)	119 (78%)	70 (76%)	116 (75%)	172 (85%)	0.094
Age of the household head	49 (13)	49 (14)	53 (13)	48 (14)	48 (13)	0.007
Is household head young (=35)	93 (16%)	27 (18%)	9 (9.8%)	26 (17%)	31 (15%)	0.37
Years of Farming Experience	22 (13)	22 (13)	25 (12)	22 (12)	22 (14)	0.029
Household Size	5.07 (2.25)	4.78 (2.20)	5.50 (2.43)	4.75 (1.99)	5.33 (2.33)	0.011
Received Lime Training/Demo	58 (9.7%)	9 (5.9%)	8 (8.7%)	16 (10%)	25 (12%)	0.23
Number of Owned/Controlled Plots	2.24 (1.04)	2.09 (0.92)	2.11 (0.98)	2.21 (1.14)	2.44 (1.05)	0.004
Has access to credit	303 (51%)	66 (43%)	52 (57%)	81 (53%)	104 (51%)	0.19
Small-Scale Farmer	127 (21%)	21 (14%)	25 (27%)	36 (23%)	45 (22%)	0.057
Risk Preference (CRRA)	0 (8)	0 (7)	-1 (11)	0 (8)	1 (8)	0.37
Time Preference (Discount Factor)	0.35 (0.24)	0.38 (0.24)	0.36 (0.24)	0.34 (0.25)	0.34 (0.25)	0.40
Plot Travel Time (Minutes)	41 (45)	43 (45)	47 (52)	34 (44)	43 (43)	0.22
Soil pH value	5.89 (0.27)	5.92 (0.26)	5.95 (0.26)	5.88 (0.27)	5.86 (0.27)	**0.015**
Owns Livestock	481 (80%)	118 (78%)	71 (77%)	119 (77%)	173 (86%)	0.12
Wealth group						0.64
Poor	200 (33%)	55 (36%)	27 (29%)	54 (35%)	64 (32%)	
Middle	199 (33%)	49 (32%)	33 (36%)	55 (36%)	62 (31%)	
Rich	200 (33%)	47 (31%)	32 (35%)	45 (29%)	76 (38%)	
Education level						0.53
No Education	35 (5.8%)	12 (7.9%)	8 (8.7%)	7 (4.5%)	8 (4.0%)	
Primary Education	488 (81%)	119 (78%)	74 (80%)	129 (84%)	166 (82%)	
Secondary or more	77 (13%)	21 (14%)	10 (11%)	18 (12%)	28 (14%)	

[1] Mean (SD); n (%)

[2] Kruskal-Wallis rank sum test; Pearson's Chi-squared test

Note: Sub-samples were defined on the basis of respondent choices under the Double-Bounded Dichotomous Choice (DBDC) elicitation, described in section 2.2 below.

2.2 Empirical estimation strategy

To make an empirical estimation of WTP, we combine the Double-Bounded Dichotomous Choice (DBDC) elicitation method with econometric modelling based on maximum likelihood estimation (MLE). The DBDC approach is efficient and well-suited to non-market valuation in smallholder settings, enabling us to capture farmers' willingness to pay more accurately than single-bounded methods (Carson & Hanemann, 2005; Hanemann, Loomis, & Kanninen, 1991; Lopez-Feldman, 2012). It improves statistical efficiency by collecting more information per respondent than the single-bounded format, thereby narrowing the WTP interval and reducing variance in the estimated WTP distribution.

Let $U(Y,Z)$ be the indirect utility function of a representative farmer with income Y, and Z as a vector of individual and household characteristics. Suppose the farmer is asked whether they would be willing to buy a good (here, a 50kg bag of lime) at a given price P. The farmer accepts if the utility with the good at the cost of P is greater than or equal to the utility without the good:

$$U(Y-P,Z,1) \geq U(Y,Z,0) \tag{1}$$

where the last argument (1 or 0) denotes the state with or without the good. Let the difference in utility be denoted:

$$\Delta U(P;Z) = U(Y-P,Z,1) - U(Y,Z,0) \tag{2}$$

Then the respondent will accept the bid P if $\Delta U(P;Z) \geq 0$ which defines an unobserved threshold WTP. We assume $\Delta U(P;Z)$ is monotonic and continuous in P, and WTP is a latent variable WTP^* such that the probability of accepting a bid P is:

$$\Pr(\text{Yes} \mid B,Z) = \Pr(WTP^* \geq P) = 1 - F(P;Z) \tag{3}$$

where $F(.)$ is the cumulative distribution function of WTP conditional on covariates Z.

In the double-bounded format, each respondent is first presented with an initial bid P_1, randomly selected from a set of pre-defined values. Based on their response, if the respondent accepts P_1, they are then offered a higher bid $P_{2H} > P_1$. If the respondent rejects, they are then offered a lower bid $P_{2L} < P_1$. Thus, four response patterns are observed:

Response Pattern	WTP Interval	Interpretation
Yes – Yes	$WTP^* \geq P_{2H}$	WTP exceeds even the higher bid
Yes – No	$P_1 \leq WTP^* < P_{2H}$	WTP between initial and higher bid
No – Yes	$P_{2L} \leq WTP^* < P_1$	WTP between lower and initial bid
No – No	$WTP^* < P_{2L}$	WTP below the lowest bid

This creates an interval-censored data structure, where each respondent's WTP is known to lie within one of the following bounds WTP_{Li}, WTP_{Ui} depending on their response sequence. To model this censored structure, we specify the respondent's latent (unobserved) WTP as:

$$WTP_i^* = X_i'\beta + \varepsilon_i \tag{4}$$

where X_i is a vector of explanatory variables, β is a parameter vector to be estimated and $\varepsilon_i \sim N(0,\delta^2)$ is a normally distributed error term.

Under the normality assumption, the likelihood contributions for the four response outcomes are:

$$\text{Yes–Yes:} \quad \Pr(WTP_i^* \geq P_{2H}) = 1 - \Phi\left(\frac{P_{2H} - X_i'\beta}{\sigma}\right) \tag{5}$$

$$\text{Yes–No:} \quad \Pr(P_1 \leq WTP^* < P_{2H}) = \Phi\left(\frac{P_{2H} - X_i'\beta}{\sigma}\right) - \Phi\left(\frac{P_1 - X_i'\beta}{\sigma}\right) \tag{6}$$

$$\text{No–Yes:} \quad \Pr(P_{2L} \leq WTP^* < P_1) = \Phi\left(\frac{P_1 - X_i'\beta}{\sigma}\right) - \Phi\left(\frac{P_{2L} - X_i'\beta}{\sigma}\right) \tag{7}$$

$$\text{No–No:} \quad \Pr(WTP^* < P_{2L}) = \Phi\left(\frac{P_{2L} - X_i'\beta}{\sigma}\right) \tag{8}$$

The log-likelihood function is constructed from these probabilities, and the parameters $\hat{\beta}$ and σ are directly estimated via maximum likelihood estimation (MLE):

$$\sum_{i=1}^{N} \left[\begin{array}{l} d_i^{yy} \ln\left(1 - \Phi\left(\frac{P_{2H} - X_i'\beta}{\sigma}\right)\right) + \\ d_i^{yn} \ln\left(\Phi\left(\frac{P_{2H} - X_i'\beta}{\sigma}\right) - \Phi\left(\frac{P_1 - X_i'\beta}{\sigma}\right)\right) + \\ d_i^{ny} \ln\left(\Phi\left(\frac{P_1 - X_i'\beta}{\sigma}\right) - \Phi\left(\frac{P_{2L} - X_i'\beta}{\sigma}\right)\right) + \\ d_i^{nn} \ln\left(\Phi\left(\frac{P_{2L} - X_i'\beta}{\sigma}\right)\right) \end{array} \right] \tag{9}$$

Where $d_i^{yy}, d_i^{yn}, d_i^{ny}, d_i^{nn}$ are indicator variables that equal one if the observation falls into the corresponding case and zero otherwise. Each individual respondent contributes to only one of the four components of the log-likelihood function.

Following estimation of the WTP distribution, we construct an empirical inverse demand curve by plotting the share of farmers whose predicted WTP (from the estimated model) is greater than or equal to a given price point. This yields a curve that approximates demand under real-world price uncertainty and can be disaggregated by subgroups (e.g., lime training, education level, or asset class) to examine heterogeneity. In addition to subgroup comparisons, we used local polynomial smoothing techniques to examine how predicted WTP varies across continuous variables. This nonparametric approach allows us to detect flexible, non-linear associations between willingness to pay and characteristics such as peer exposure, landholding size, and time preferences, providing a more detailed understanding of the drivers of lime demand.

3 Result and discussion

3.1 Descriptive analysis and determinants of Willingness to Pay

Figure 2 shows how respondents distributed their choices across four DBDC response sequences (Yes-Yes, Yes-No, No-Yes, and No-No) at six initial bid levels ranging from \$2 to \$7. In the

DBDC design, respondents who accept (reject) the initial bid are shown a follow-up bid that is $1 higher (lower), which allows for a more precise identification of willingness-to-pay intervals. The number of respondents at each bid level is reported beneath the corresponding bar. The response patterns are consistent with rational, utility-maximizing behavior under posted price offers. As the initial bid increases, the likelihood of accepting the offered price decreases monotonically, reflecting a downward-sloping latent willingness-to-pay (WTP) distribution. At the lowest bid level of $2, 63.3% of respondents accepted both the initial and higher follow-up bids (Yes-Yes), while 1.0% rejected both (No-No). In contrast, at the highest bid level of $7, only 16.7% accepted both bids, while 64.4% rejected both, indicating that most respondents had reservation prices below $7. This transition is particularly sharp in the mid-range of bid levels. At $4, 42.4% of respondents chose "Yes-Yes," while 7.6% rejected both bids. At $5, however, the percentage of "Yes-Yes" responses falls to 19.4%, while the percentage of "No-No" responses rises to 26.2%. This discontinuity suggests that many respondents have WTP values mainly concentrated in the $4–5 range and that they are particularly sensitive to prices near this threshold. While this doesn't allow us to estimate the Marshallian price elasticities, the pattern indicates that even modest price increases in this range result in a disproportionately large decline in acceptance, suggesting a steep segment of the cumulative WTP distribution.

The intermediate categories, "Yes-No" and "No-Yes," provide further behavioral insights. At the $4 price point, 32.2% of respondents selected Yes-No, while 17.8% chose No-Yes. At $5, however, this pattern reverses. Thirty-two percent of respondents accepted the lower follow-up bid (No-Yes), while 22.3 percent accepted the initial bid but rejected the higher follow-up bid (Yes-No). This shift suggests that many respondents have WTP values close to the bid threshold and would respond positively to modest price reductions. This reinforces the potential role of targeted subsidies or price negotiation mechanisms. The asymmetry between the two categories across bid levels is consistent with anchoring effects and reference-dependent preferences, in which the initial bid influences subsequent valuation (Bateman et al., 2002; Herriges & Shogren, 1996) . These behavioral patterns are common in contingent valuation settings and imply that respondents may be more reluctant to revise their valuation upward than downward (Bateman et al., 2002; Herriges & Shogren, 1996; Johnston et al., 2017; Tversky & Kahneman, 1991).

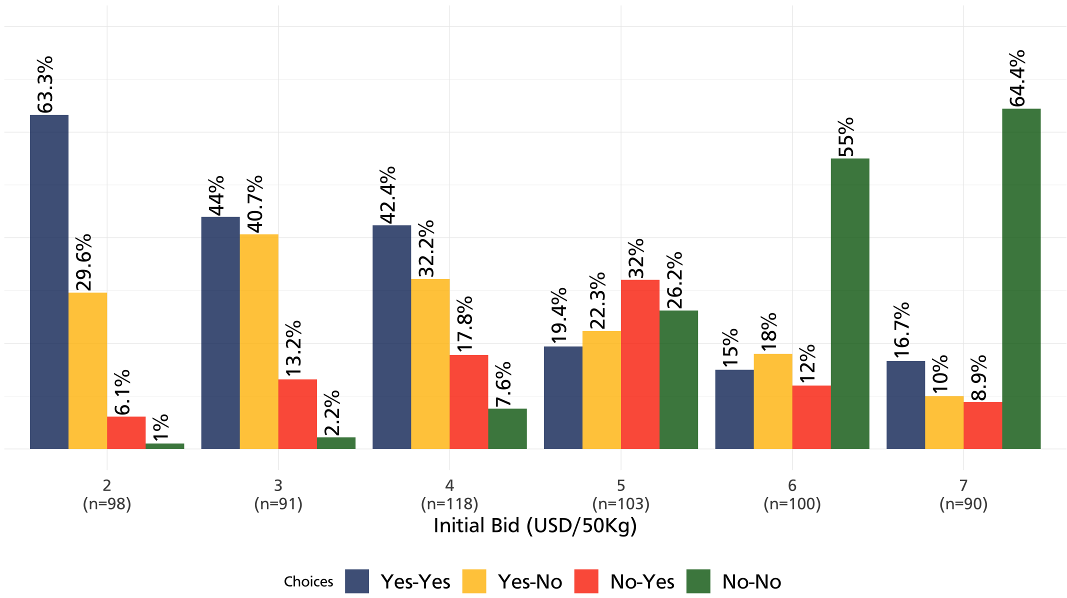

Figure 2: Distribution of DBDC Responses by Initial Bid Level ($ per 50kg Bag of Lime)

Table 2 presents the results of two models that estimate farmers' willingness to pay (WTP) for a 50-kilogram bag of agricultural lime using single-bounded (SBDC) and double-bounded dichotomous choice (DBDC) formats. The SBDC model provides a baseline, while the DBDC approach is more statistically efficient because it uses follow-up responses to determine each individual's WTP. The discussion below focuses on the DBDC specification. The estimated mean WTP is 4.67 USD, which is closely aligned with prevailing market prices in the study area. On average, this suggests that farmers perceive lime as a worthwhile investment. However, substantial variation in WTP across households highlights the need for targeted approaches to improve adoption. Social exposure is the most robust determinant of WTP. Each additional known lime user is associated with a 0.28 USD increase in WTP. This reflects the importance of peer learning and social networks in technology adoption under uncertainty. This effect is large in magnitude and statistically significant, indicating that farmers are more likely to value lime when they observe its use among peers. While previous personal use of lime is also positively associated with WTP, the effect is not statistically significant, possibly due to collinearity with peer exposure or limited variation in prior use.

Productive asset ownership is another strong predictor. Farmers with more agricultural plots report significantly higher WTP; each additional plot is associated with a 0.20 USD increase. Livestock ownership is also positively associated with WTP at conventional significance levels. These findings are consistent with models of investment under liquidity constraints, in which asset-rich households are better able to finance medium-term soil fertility investments, such as lime. However, variables related to formal information, such as receiving a personalized soil test result or participating in lime-related training, do not significantly influence WTP in this model. While these coefficients are directionally consistent with expectations, their lack of statistical significance suggests that information alone may be insufficient to increase perceived value, unless it is delivered through trusted channels or yields visible results. Interestingly, the coefficient in receiving a soil test result is negative, though not significant, which may reflect confusion or skepticism about the recommendations provided. Behavioral characteristics show no statistically significant effects. The negative sign on the time preference variable aligns with theoretical expectations—more impatient individuals place a lower value on long-term benefits—but the effect is imprecisely estimated. Similarly, risk aversion, household demographics, and travel time to fields do not exhibit significant associations with WTP. This suggests that observable economic constraints and social learning dominate psychological traits in shaping lime valuation.

Education and wealth indicators, while positively associated, are not significant either. While these variables may affect the adoption of lime use or the ability to implement it effectively, they appear to be less relevant in shaping the stated willingness to pay at the valuation stage.

Table 2: Mean WTP and its Determinants

	(1)	(2)
VARIABLES	SBDC	DBDC
Mean WTP	4.64***	4.67***
	(0.0862)	(0.0831)
Initial bid (USD/50kg)	-0.138***	
	(0.00687)	
Knows Others Who Used Lime	0.0545***	0.289***
	(0.0130)	(0.0570)
Used Lime Before	0.0486	0.331
	(0.0829)	(0.414)
Recived personalized soil-test result	0.0288	-0.117
	(0.0389)	(0.199)
Used Organic Fertilizer	-0.0714*	-0.253
	(0.0413)	(0.210)
Gender of Household Head	0.0101	0.228
	(0.0439)	(0.217)
Is household head young (<=35)	-0.0189	-0.0302
	(0.0525)	(0.260)
Years of Farming Experience	-0.00250*	-0.00510
	(0.00129)	(0.00697)
Household Size	-0.00607	0.0429
	(0.00793)	(0.0401)
Received Lime Training/Demo	0.00374	-0.182
	(0.0709)	(0.312)
Number of Owned/Controlled Plots	0.0340*	0.177*
	(0.0189)	(0.0913)
Has access to credit	-0.0101	-0.139
	(0.0353)	(0.176)
Small-Scale Farmer	0.0298	0.130
	(0.0459)	(0.219)
Risk Preference (CRRA)	0.00191	0.00435
	(0.00219)	(0.00963)
Time Preference (Discount Factor)	-0.0995	-0.406
	(0.0705)	(0.350)
Plot Travel Time (Minutes)	-0.000409	0.00179
	(0.000429)	(0.00186)
Owns Livestock	0.0444	0.418*
	(0.0447)	(0.216)
Soil pH value	-0.115*	-0.374
	(0.0665)	(0.343)
Wealth Status: Middle	0.00667	0.0558
	(0.0414)	(0.211)
Wealth Status: Rich	0.00387	0.115
	(0.0459)	(0.230)
Education: Primary	0.148**	0.625
	(0.0744)	(0.386)
Education: Secondary or Higher	0.0901	0.581
	(0.0916)	(0.471)
Observations	596	596
LR ^{2}	175.9	
Prob < ^{2}	0	

3.2 Price responsiveness and heterogeneity in Willingness to Pay

Building on the estimated WTP distribution from the DBDC model, we next explore how these valuations translate into demand under varying price scenarios. Specifically, we construct an empirical inverse demand curve that maps the proportion of farmers willing to pay at or above each price point. This approach allows us to visualize the price responsiveness of the population and to assess how demand varies across relevant subgroups.

Figure 3 illustrates the proportion of farmers who would be willing to pay for lime at different price points. As expected, the demand curve is downward sloping, reflecting decreasing willingness to pay across the population. At the market price of approximately 4.67 USD, just under half of the sample has a predicted WTP above this threshold, suggesting that current pricing excludes a substantial share of farmers from the lime market.

The steepness of the curve at the upper and lower ends reflects heterogeneity in valuation. At high price levels (above 6 USD), only a small minority of respondents are willing to pay, while the long, flatter middle segment between 4 and 6 USD indicates that modest price changes in this range could substantially affect the share of adopters. This implies a high degree of price sensitivity in the zone near the market price, reinforcing findings from the DBDC model.

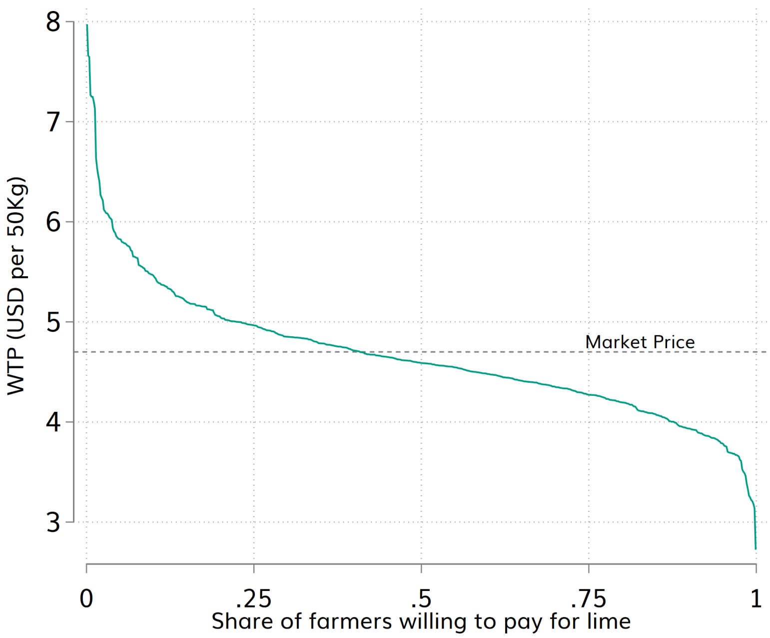

Figure 3: Empirical Inverse Demand Curve for Agricultural Lime (50kg Bag)

Note: The figure shows the empirical inverse demand curve derived from the estimated distribution of individual willingness to pay (WTP) for lime. The vertical axis shows the predicted WTP in USD per 50kg bag, while the horizontal axis shows the cumulative share of farmers with WTP at or above a given price. The dashed horizontal line denotes the prevailing market price

The empirical inverse demand curve provides a practical tool for visualizing how adoption rates might respond to changes in price and allows for subgroup comparisons to assess heterogeneity in demand. It also has direct policy relevance: identifying the proportion of farmers priced out at current levels supports the case for targeted subsidies, cost-sharing schemes, or differentiated pricing models to expand adoption among marginal buyers.

As shown in Figure 5, substantial heterogeneity exists in farmers' willingness to pay for lime, consistent with theoretical models of adoption under uncertainty, liquidity constraints, and learning. Experience-based factors strongly predict higher valuation. Among farmers who have used lime before, approximately 72 percent are willing to pay at market price, compared to 44 percent among those who have not. Similarly, 63 percent of farmers who received lime-specific training are willing to pay at market price, versus 46 percent of those who did not. These differences reflect the role of experiential and informational learning in reducing perceived risk and enhancing expected returns. They align with theoretical predictions that posterior beliefs about profitability improve with direct exposure or credible information.

Education level also significantly differentiates demand. At the market price, only 38 percent of farmers with no formal education are willing to pay, compared to 51 percent with primary education and 65 percent among those with secondary education or higher. This supports the hypothesis that education increases comprehension of agronomic benefits and lowers cognitive frictions in valuing long-term investments like lime.

We observe similar patterns across asset indicators. Among wealthier farmers (top tercile), 64 percent are willing to pay at the market price, compared to 48 percent of middle-income and 37 percent of poor farmers. Likewise, 58 percent of livestock-owning households are willing to pay, compared to 36 percent among those without livestock. These gaps reflect liquidity constraints and investment capacity, consistent with household investment models under budget limitations and incomplete credit markets. Smaller differences are observed for other factors. For instance, gender of household head shows only minor differences: 49 percent of male-headed and 46 percent of female-headed households are willing to pay at market price. This suggests that gender-related constraints may influence actual adoption through access or implementation frictions, but not necessarily valuation. Farmers who used organic fertilizer show slightly lower WTP, with 44 percent willing to pay compared to 51 percent among non-users, possibly reflecting perceived input redundancy or substitution.

These demand curves reveal that while the average WTP is close to the market price, actual adoption potential is highly segmented. At current prices, adoption is likely to be concentrated among more experienced, wealthier, better-educated, and asset-rich farmers. Expanding adoption would require demand-side strategies that target liquidity constraints, amplify social learning, or tailor pricing structures to heterogeneous demand. This could include input credit, targeted subsidies, or bundled extension with trusted peer demonstration.

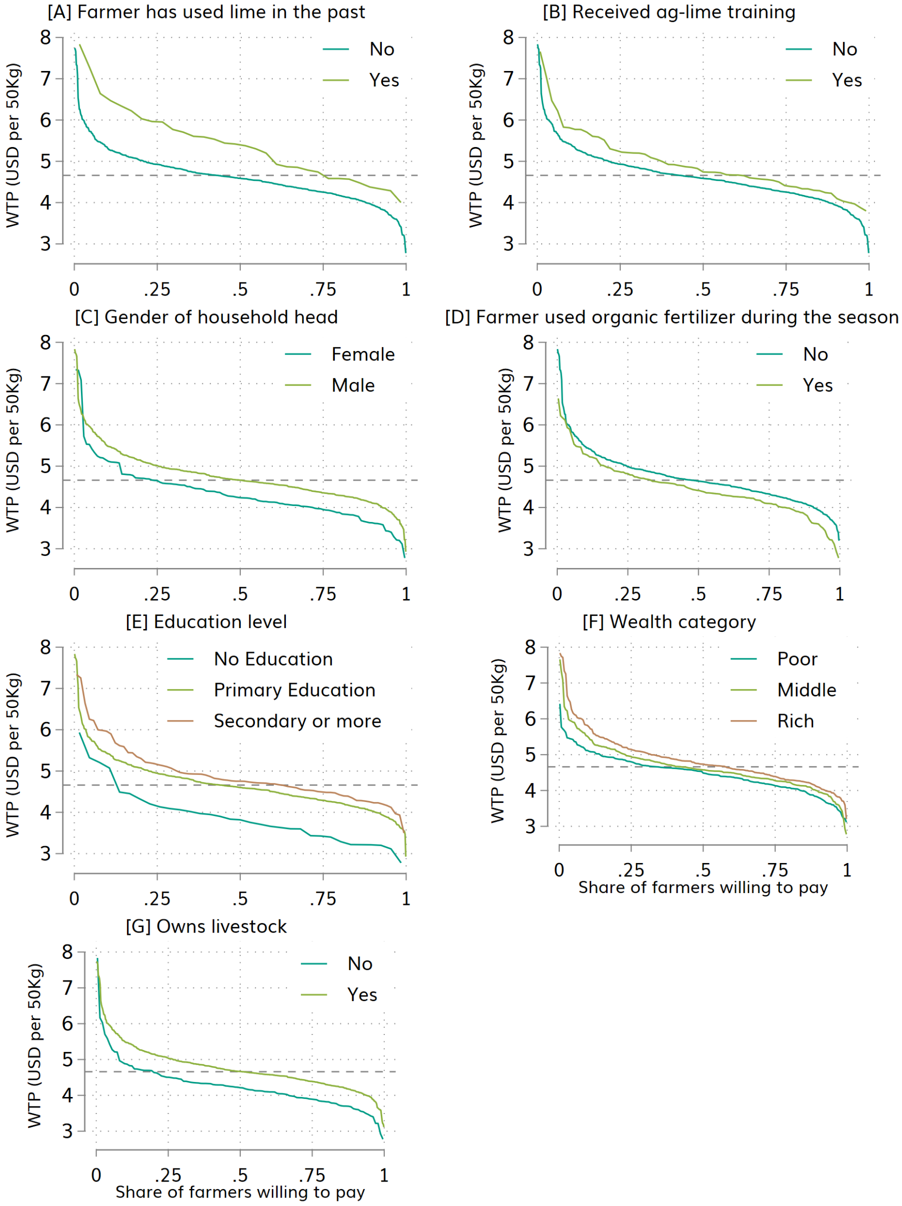

Figure 4: Inverse Demand Curves for Agricultural Lime by Farmer Characteristics

Note: This figure presents subgroup-specific inverse demand curves derived from predicted willingness to pay (WTP) for a 50kg bag of agricultural lime. Each curve plots the share of farmers with WTP at or above each price level. Subgroups include prior lime use, training exposure, gender of household head, organic fertilizer use, education level, wealth tercile, and livestock ownership. The horizontal dashed line indicates the current market price (approximately 4.67 USD). These curves illustrate variation in demand and highlight how agronomic experience, human capital, and asset endowments shape valuation.

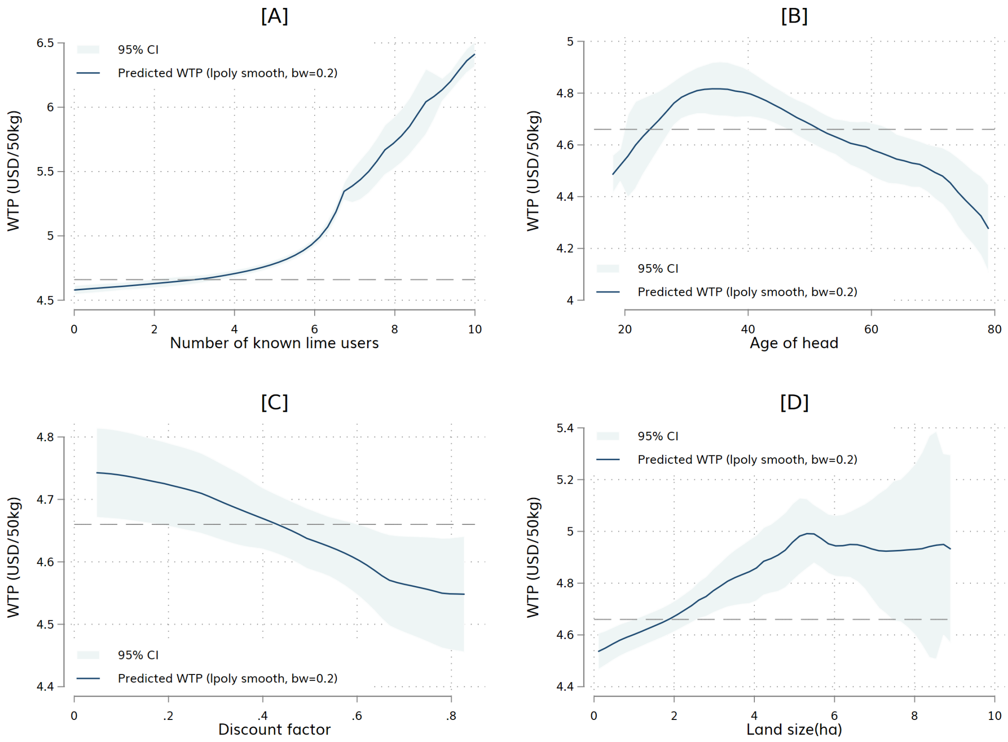

Figure 5: Nonparametric relationship between predicted WTP and key continuous variables

Note: This figure displays the smoothed relationship between predicted willingness to pay (WTP) for a 50kg bag of agricultural lime and four continuous variables: age of household head, number of known lime users, time preference (discount factor), and land size. Local polynomial smoothing is used to visualize the functional form of these relationships, with shaded bands representing 95 percent confidence intervals.

Panel A shows a steep positive relationship between the number of known lime users and WTP, especially beyond five known users. This nonlinear increase suggests strong peer effects and social learning dynamics. Early exposure may build awareness, but valuation accelerates once lime use becomes more common within a farmer's social network. This is consistent with threshold models of diffusion, where beliefs about returns and trust in technology grow as more peers adopt.

Panel B shows a nonlinear relationship between age and WTP. WTP rises from early adulthood, peaks around age 40, and gradually declines thereafter. This inverted U-shape suggests that middle-aged farmers may be at the optimal stage of their life cycle to invest in productivity-enhancing inputs. Younger farmers may lack experience or authority to make input decisions, while older farmers may face shorter planning horizons or greater liquidity constraints, consistent with lifecycle investment models and declining marginal utility of long-term soil fertility gains.

Panel C, the discount factor is negatively associated with WTP, meaning more impatient farmers (lower discount factors) are less willing to pay. This relationship supports standard dynamic investment theory: lime application has delayed payoffs through improved soil structure and nutrient availability, so farmers with high time preference (who heavily discount future benefits) place less value on the input. The relationship is relatively linear, suggesting no sharp threshold in intertemporal valuation but a consistent gradient.

Panel D reveals a positive association between land size and WTP up to approximately 6 hectares, after which the relationship flattens. This reflects diminishing marginal benefit of applying lime beyond a certain scale or nonlinearities in how land-rich farmers perceive input investment. Larger landholders likely face fewer liquidity constraints, benefit from economies of scale in lime application, or have higher return expectations from productivity-enhancing inputs. The plateau at larger scales may reflect heterogeneity in land quality or opportunity cost of capital allocation across plots.

Together, these smoothed plots highlight the complex, nonlinear nature of demand heterogeneity. Key determinants of WTP operate through experience (social exposure), intertemporal preferences, productive capacity, and age-related lifecycle effects. These insights reinforce the value of flexible estimation techniques in capturing behavioral responses and have clear implications for targeting: peer-based interventions, intertemporal incentives (such as credit or delayed payment), and outreach to middle-aged, land-rich, and socially connected farmers may be the most cost-effective strategies to expand lime adoption.

3.3 Socioeconomic and behavioral gradients across WTP quintiles

To explore heterogeneity in farmers' valuation of agricultural lime , we partition households in five groups based on the empirical distribution of their estimated WTP. Specifically, farmers were assigned to WTP quintiles defined by the 20th, 40th, 60th, and 80th percentiles of predicted WTP (USD per 50 kg bag). In this sample, these cut-off points correspond to $4.18, $4.49, $4.71, and $5.08, respectively. From an economic perspective, the transition from the lowest to the highest quintile is analogous to a shift in the demand curve, characterised by farmers whose reservation prices are significantly below prevailing market prices. Consequently, these farmers would require price support or complementary interventions. In contrast, the highest quintile represents farmers with strong demand, who are willing to purchase lime at current prices. The intermediate quintiles, whose WTP lies close to the market price, are of particular policy relevance because they represent the segment most responsive to modest price reductions or targeted subsidy programmes.

Table 3 shows the patterns across WTP gradient are monotonic. As WTP increases, indicators of exposure, productive capacity and investment orientation rise while constraints related to limited information, smaller land holdings, and present bia decline. Social exposure demonstrates the most pronounced gradient. The mean number of known lime users increases from 0.14 in the lowest quintile to 3.23 in the highest quintile ($p < 0.001$). The proportion of individuals who have previously engaged in lime use increased from less than 1 percent to 16 percent, while the

Table 3: Heterogeneity in household characteristics across WTP quintiles for agricultural lime

Characteristic	**Overall** N = 596[1]	**Q1 (Lowest 20%)** N = 120[1]	**Q2 (Low–Mid)** N = 119[1]	**Q3 (Middle)** N = 119[1]	**Q4 (Mid–High)** N = 119[1]	**Q5 (Highest 20%)** N = 119[1]	**p-value**[2,3]
Number of known farmers using aglime	0.93 (1.70)	0.14 (0.45)	0.19 (0.47)	0.44 (0.72)	0.65 (0.82)	3.23 (2.48)	0.001***
Past use of aglime[=Yes]	32 (5.4%)	1 (0.8%)	4 (3.4%)	3 (2.5%)	5 (4.2%)	19 (16%)	0.001***
Used organic fertilizer[=Yes]	126 (21%)	38 (32%)	30 (25%)	21 (18%)	18 (15%)	19 (16%)	0.006**
Gender of the household head[=Male]	474 (80%)	65 (54%)	95 (80%)	101 (85%)	110 (92%)	103 (87%)	0.001***
Age of household head[=Young (35)]	93 (16%)	16 (13%)	15 (13%)	20 (17%)	19 (16%)	23 (19%)	0.61
Household size (number of members)	5.06 (2.24)	4.28 (2.17)	4.83 (2.25)	5.23 (2.01)	5.35 (2.15)	5.61 (2.38)	0.001***
Received aglime training/demo[=Yes]	57 (9.6%)	6 (5.0%)	9 (7.6%)	10 (8.4%)	12 (10%)	20 (17%)	0.028*
Number of plots owned	2.23 (1.03)	1.52 (0.61)	2.00 (0.77)	2.29 (0.86)	2.58 (0.93)	2.80 (1.32)	0.001***
Access to credit[=Yes]	301 (51%)	60 (50%)	60 (50%)	63 (53%)	64 (54%)	54 (45%)	0.73
Is smallholder (<2.5ha)[=Yes]	125 (21%)	11 (9.2%)	17 (14%)	25 (21%)	37 (31%)	35 (29%)	0.001***
Exponential discount factor	0.35 (0.24)	0.41 (0.27)	0.35 (0.23)	0.38 (0.23)	0.29 (0.23)	0.33 (0.24)	0.006**
Own livestock[=Yes]	479 (80%)	63 (53%)	90 (76%)	106 (89%)	110 (92%)	110 (92%)	0.001***
Wealth group							0.001***
Poor	199 (33%)	57 (48%)	43 (36%)	42 (35%)	36 (30%)	21 (18%)	
Middle	199 (33%)	38 (32%)	41 (34%)	43 (36%)	36 (30%)	41 (34%)	
Rich	198 (33%)	25 (21%)	35 (29%)	34 (29%)	47 (39%)	57 (48%)	
Education level							0.001***
No Education	33 (5.5%)	25 (21%)	4 (3.4%)	0 (0%)	1 (0.8%)	3 (2.5%)	
Primary Education	486 (82%)	90 (75%)	101 (85%)	105 (88%)	96 (81%)	94 (79%)	
Secondary or more	77 (13%)	5 (4.2%)	14 (12%)	14 (12%)	22 (18%)	22 (18%)	

[1] Mean (SD); n (%) [2] Kruskal-Wallis rank sum test; Pearson's Chi-squared test [3] *p<0.05; **p<0.01; ***p<0.001

participation rate in lime training rose from 5 percent to 17 percent within the same range. The findings suggest that both direct experience and peer learning increase perceived returns to lime investment. However, low WTP farmers remain relatively isolated from information. Economic capacity also increases systematically with WTP. Average landholding rises from 1.5 plots in the lowest quintile to 2.8 plots in the highest quintile ($p < 0.001$), and livestock ownership increases from 53 percent to 92 percent ($p < 0.001$). Wealth gradients are equally pronounced, with the share of poor households falling from 48 percent to 18 percent and the share in the richest tercile rising from about one fifth to nearly one half. Access to formal credit does not differ significantly across groups, suggesting that existing credit mechanisms are not well aligned with lime investment.

Behavioral preferences and human capital vary in parallel. The exponential discount factor declines from 0.41 to 0.33 ($p = 0.006$), implying greater patience among higher WTP farmers. Education improves markedly, with no schooling falling from one fifth of farmers in the lowest quintile to less than 3 percent in the highest, where 18 percent have secondary education or more. Male headed households increase from 54 percent to over 87 percent.

These gradients show that higher WTP is associated with greater exposure, assets, education, and patience. From a policy perspective, farmers in the middle WTP quintiles, whose valuations lie just below the market price, are potentially most responsive to modest subsidies, while the lowest quintile faces deeper information and liquidity constraints that require complementary support beyond price reductions alone.

3.4 Implications for smart subsidy design

The estimated willingness to pay distribution allows simulation of adoption responses to alternative price support schemes within a partial equilibrium framework, conditional on price being the primary constraint to lime adoption (see Appendix A). At the prevailing market price of 4.67 USD per 50 kg bag, approximately 50 percent of farmers have a reservation price at or above this level and would therefore be expected to purchase lime. A reduction in the effective price to 3.50 USD, corresponding to a subsidy of about 25 percent, increases the share of farmers who are willing to pay to roughly 75 percent. Conversely, an increase in price to 6 USD reduces this share to around 20 percent. These large shifts in expected demand changes for relatively small changes in price indicate that a substantial mass of farmers have reservation prices clustered near the current market price.

To underscore this, we may use these willingness-to-pay changes to derive an approximate price elasticity of demand at the extensive margin in our sample (see Appendix A5 for derivation): a 25 percent reduction in price is associated with a 40 percentage point increase in adoption, which corresponds to an elasticity of demand of approximately -1.4 evaluated at the market price. This extensive margin response suggests that relatively small price reductions can induce sizable increases in uptake among farmers whose reservation prices lie just below the market price.

The economic rationale for such price support depends on the magnitude and persistence of productivity gains. Assuming a 50 kg bag of lime typically treats about 0.1 hectares and is associated with yield increases of approximately 300 kg per hectare under acidic soil conditions. At a maize price of 0.25 USD per kilogram, this corresponds to an additional gross value of output of about 7.5 USD per season. Given that lime effects generally persist for at least two seasons, the cumulative expected gross benefit per bag is approximately 10 to 15 USD. These figures suggest that the social value of increased lime use potentially exceeds the fiscal cost of the subsidy, even before accounting for longer term soil health benefits, risk reduction, or spillovers to fertilizer efficiency.

The willingness to pay distribution further highlights the scope for improved targeting. Average willingness to pay among wealthier farmers is approximately 5.40 USD, compared with about 3.60 USD among poorer farmers. At the market price, simulated adoption is therefore much lower among poorer households. Reducing the effective price to around 3.60 USD, corresponding to a subsidy of roughly 23 percent, raises predicted participation among poorer farmers to about 60 percent. Restricting such support to poorer households would achieve a large share of the potential adoption gains at substantially lower fiscal cost than a universal subsidy.

4 Conclusion and Recommendation

This study has provided detailed empirical evidence on smallholder farmers' WTP for agricultural lime, using a DBDC approach combined with parametric and nonparametric analysis. The results show that the mean WTP is closely aligned with current market prices, suggesting a latent market potential for lime. However, these average masks significant heterogeneity in demand, shaped by differences in agronomic exposure, social networks, asset endowments, behavioral traits, and education levels.

The most consistent and economically meaningful predictor of WTP is peer exposure. Farmers who know others using lime are significantly more likely to value it highly, especially when that exposure exceeds a critical threshold. Similarly, prior personal experience and lime-related training are associated with elevated WTP, particularly in the upper quantiles of distribution. These findings align with well-established models of learning under uncertainty and adoption dynamics in the presence of incomplete information. Nonparametric analysis further shows that time preferences, landholding, and education also influence valuation, with more patient, better-educated, and land-rich farmers expressing higher demand.

These findings reinforce the idea that lime is a lumpy, investment-type input with intertemporal and informational barriers to adoption. The inverse demand curves and subgroup disaggregation clearly indicate that while some segments (especially those with assets and prior exposure) are willing to adopt lime at current prices, a large share of the population is still price sensitive or uncertain about its benefits. Without targeted support, uptake is likely to remain concentrated in relatively advantaged groups.

The heterogeneity in demand is not only a micro-level behavioral issue; it is also linked to structural constraints within the larger agricultural lime value chain. In several sub-Saharan African countries, the lime sector is trapped in a vicious cycle. This cycle is characterized by low effective demand from farmers. This low demand is caused by high costs, logistical challenges, and delayed returns. As a result of this cycle, private suppliers prioritize industrial clients over agricultural markets. Consequently, governments often intervene through public production and subsidy programs. However, these initiatives often exhibit characteristics such as bureaucracy, underfunding, and inefficiency. The supply chain is characterized by fragmentation and high costs, which serve to exacerbate the initial issues of low and unpredictable demand. This dynamic prolongs a self-reinforcing cycle, further compounding the challenges faced by all stakeholders. In order to disrupt this cycle, it is necessary to make coordinated efforts to simultaneously enhance demand and reduce supply-side obstacles. While the DBDC method provides strong internal consistency and leverages follow-up responses to better estimate individual valuation intervals, some limitations warrant caution. Stated WTP may not translate directly into revealed behavior, especially in settings where liquidity constraints or risk aversion are salient. In addition, farmers' responses may reflect current beliefs and exposure levels, which are themselves endogenous to past interventions, peer networks, and extension coverage. Finally, although we see clear patterns of heterogeneity, these are correlational, and future work could strengthen causal identification through experimental variation in exposure or pricing.

The findings have implications for designing and targeting policy interventions. Encouraging the adoption of lime requires approaches that extend beyond price reductions alone. Strategies that build social credibility through peer demonstrations, ease liquidity constraints via credit or voucher mechanisms, and specifically target less experienced farmers are likely to deliver greater impact and cost-effectiveness than broad, untargeted subsidy programs typically advocated. Furthermore, initiatives aimed at developing the lime sector should take into account both demand-side behavioral limitations and supply-side structural deficiencies. A viable market for agricultural lime cannot be created through isolated interventions. Rather, it will require coordinated strategies that address behavioral, institutional, and logistical barriers impeding scale.

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A Appendix A: Step by step calculations for price support simulations

These simulations are conducted under partial equilibrium assumptions and characterize predicted adoption responses conditional on the estimated willingness to pay distribution. They do not account for supply responses, endogenous price adjustments, administrative costs, imperfect pass through, or general equilibrium effects. The calculations should therefore be interpreted as transparent benchmarks for adoption incidence and fiscal cost under demand side price support.

A1. Inputs from the estimated willingness to pay distribution

Let WTP_i denote the estimated willingness to pay of farmer i for one 50 kg bag of agricultural lime, measured in USD. Let P denote the effective price paid by the farmer after any subsidy.

Define the predicted adoption indicator at price P as

$$A_i(P) = \mathbf{1}(WTP_i \geq P),$$

where $\mathbf{1}(\cdot)$ is an indicator function.

The predicted adoption rate at price P is given by

$$a(P) = \frac{1}{N} \sum_{i=1}^{N} A_i(P).$$

From the estimated WTP distribution, the predicted adoption rates at selected price points are

$$a(4.67) \approx 0.50, \quad a(3.50) \approx 0.75, \quad a(6.00) \approx 0.20.$$

These rates are interpreted as extensive margin purchase probabilities under a partial equilibrium framework.

A2. Price support instrument and per unit subsidy

Let P_0 denote the market price and P_1 the subsidized price faced by farmers. In the baseline scenario,

$$P_0 = 4.67.$$

Under the subsidy scenario,

$$P_1 = 3.50.$$

The per bag subsidy is therefore

$$s = P_0 - P_1 = 4.67 - 3.50 = 1.17.$$

The proportional subsidy rate is

$$\tau = \frac{s}{P_0} = \frac{1.17}{4.67} \approx 0.25.$$

A3. Adoption effects in a representative population

To express adoption impacts and fiscal costs transparently, consider a representative population of $N = 100$ farmers.

The predicted number of adopters without subsidy is

$$Q_0 = N \cdot a(P_0) = 100 \cdot 0.50 = 50.$$

The predicted number of adopters with subsidy is

$$Q_1 = N \cdot a(P_1) = 100 \cdot 0.75 = 75.$$

The number of additional adopters induced by the subsidy is therefore

$$\Delta Q = Q_1 - Q_0 = 75 - 50 = 25.$$

A4. Government fiscal outlay and cost per additional adopter

Assuming the subsidy is paid on all subsidized purchases, total government expenditure is

$$G = s \cdot Q_1 = 1.17 \cdot 75 = 87.75.$$

The average fiscal cost per additional adopter is

$$\frac{G}{\Delta Q} = \frac{87.75}{25} = 3.51,$$

which is reported as approximately 3.5 USD per additional adopter. This measure includes transfers to inframarginal adopters who would have purchased lime even in the absence of the subsidy.

A5. Demand responsiveness and elasticity benchmark

An arc elasticity benchmark is computed using the midpoint formula. The percentage change in adoption is

$$\%\Delta a = \frac{a(P_1) - a(P_0)}{\frac{a(P_1)+a(P_0)}{2}} = \frac{0.75 - 0.50}{(0.75 + 0.50)/2} = 0.40.$$

The percentage change in price is

$$\%\Delta P = \frac{P_1 - P_0}{\frac{P_1+P_0}{2}} = \frac{3.50 - 4.67}{(3.50 + 4.67)/2} \approx -0.286.$$

The implied arc elasticity is therefore

$$\varepsilon = \frac{\%\Delta a}{\%\Delta P} \approx -1.40.$$

This elasticity should be interpreted as a local extensive margin responsiveness derived from the estimated WTP distribution rather than a structural demand elasticity.

A6. Benefit calculation per bag

Assume one 50 kg bag treats 0.1 hectares. Assume a yield gain of 300 kg per hectare per season and a maize price of 0.25 USD per kg.

The yield gain attributable to one bag per season is

$$\Delta y_{\text{bag}} = 300 \times 0.1 = 30 \text{ kg}.$$

The gross value of additional output per season is

$$B_1 = 30 \times 0.25 = 7.50 \text{ USD}.$$

Assuming benefits persist for two seasons, the total gross benefit per bag is

$$B_2 = 2 \times 7.50 = 15.00 \text{ USD}.$$

A7. Benefit to cost ratios

From the government perspective, the benefit to subsidy ratio is

$$\frac{B_2}{s} = \frac{15.00}{1.17} \approx 12.8,$$

reported as approximately 13 USD of additional gross output per 1 USD of subsidy.

From the farmer perspective, the private benefit to cost ratio at the subsidized price is

$$\frac{B_2}{P_1} = \frac{15.00}{3.50} \approx 4.3,$$

reported as approximately four to one.

These are gross output comparisons and do not net out labor, application costs, or complementary input costs.

A8. Targeted subsidy calibration for poorer households

Let $\overline{WTP}^{poor} \approx 3.60$ denote the average willingness to pay among poorer households. To reach this effective price from the market price,

$$s_{poor} = P_0 - 3.60 = 4.67 - 3.60 = 1.07.$$

The implied subsidy rate is

$$\tau_{poor} = \frac{1.07}{4.67} \approx 0.23,$$

corresponding to approximately 23 percent.

This calibration illustrates how heterogeneity in willingness to pay can inform subsidy levels for specific population groups.