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Willingness to Pay for Shared and Digitally Booked Transport among Low-Income Commuters after Fuel Price Increases

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Abstract
When Nigeria removed its fuel subsidy at the end of May 2023 the pump price rose by 129.2 percent in a month, and transport fares followed unevenly: within-city bus fares rose 116.4, 67.9 and 95.4 percent in Lagos, Osun and Kwara while motorcycle fares rose only 20.0, 46.2 and 5.3. That pass-through differential frames the question: what would a low-income commuter pay for shared and digitally booked transport at fares like these? We answer it with a stated preference experiment administered in the final quarter of 2023 to 1,080 low-income commuters across the three states, yielding 8,640 choices, whose design and estimation are reported in full. The paper's contribution is methodological. Multinomial logit, mixed logit and latent class specifications were fitted to identical choices. The multinomial logit holds preferences homogeneous, so it yields one willingness to pay for the whole market rather than a share of it, and it ranks last on every information criterion. Of the three specifications that spread willingness to pay across the market, the mixed logit puts 48.2 percent below an assumed 431 naira cost of provision, a two-class latent class model 54.6 and a three-class one 62.6, fourteen points on specification alone. Goodness of fit does not order those figures usefully: the criteria rank the three-class model first, the two-class second and the mixed logit last of the three, the reverse of their order on the share, so the model chosen on fit is the one that would justify the largest subsidy and nothing inside any single estimation says whether it should. Reporting a range across specifications, rather than a point from whichever fits best, is the practical conclusion.

Keywords: Stated Preference, Willingness to Pay, Mixed Logit, Latent Class, Fuel Subsidy Removal, Shared Mobility, Transport Affordability, Nigeria

1. Introduction

Nigeria removed its petrol subsidy at the end of May 2023 and the pump price rose by 129.2 percent within a month, from 238.11 to 545.83 naira a litre on the unweighted mean of the 37 state averages. Across the three states in this study the increase was larger still: 151.6 percent in Lagos, 138.8 in Osun and 154.1 in Kwara, so a litre of petrol ended June costing about two and a half times what it cost at the end of May.

What happened to fares is more interesting than what happened to fuel. Within-city bus fares rose 116.4, 67.9 and 95.4 percent in the three cities, while motorcycle fares rose only 20.0, 46.2 and 5.3 percent. In Kwara the bus rose eighteen times as far as the motorcycle, in Lagos not quite six times as far, and in Osun only half again as far, which tells us the market did not simply reprice the fuel: something about how each mode is organized absorbed the shock differently (Rentschler 2016; Siddig *et al.* 2014) [35, 44].

Into that setting arrives shared and digitally booked transport, which is established in Lagos (Williams *et al.* 2015) [49] and newly present in the smaller cities. The planning question is what low-income commuters will pay for it, and the conventional answer is a mean willingness to pay estimated from a choice model (Louviere *et al.* 2000; Train 2009) [27, 45].

What this paper offers is the design, reported in full, and a question that does not depend on any one specification being the right one: given a choice experiment of this size and shape, how much of the answer to the affordability question is decided by the analyst rather than by the respondents? The mixed logit and latent class literatures exist because homogeneous specifications can mislead (Revelt and Train 1998; McFadden and Train 2000; Greene and Hensher 2003) [36, 30, 15], and the transport affordability literature establishes that in low-income settings the distribution matters more than its center (Carruthers *et al*. 2005; Litman 2021; Venter *et al*. 2018; Lucas *et al*. 2016) [10, 25, 47, 28]. Neither literature says how far apart those specifications land on the one number a subsidy designer would act on.

The setting sharpens the question in ways a hypothetical fare exercise could not:

- *The shock is large and recent.* State-level bus and motorcycle fares are published monthly, so the movement is read straight off the series.
- *Modes absorbed it differently*, so relative prices moved, and a commuter's alternatives changed as much as their budget did.
- *Incomes are low relative to fares.* At the observed post-shock within-city bus fare, two paid trips a day for twenty working days cost about 67 percent of the median monthly income in these cities, which is arithmetic on the published fare.
- *The service is new outside Lagos*, so there is no revealed-preference record to estimate from and a stated preference instrument is the only available route.

The contribution runs from the design through to that one number. First, we design and report a stated preference experiment anchored to an observed price shock rather than to a hypothetical one, and we report the design itself, including the efficiency cost we accepted to keep every attribute level identifiable. Second, we set out the quantity a subsidy designer needs, which is not a mean willingness to pay but the share of a market whose willingness to pay falls below the cost of provision, and we show how to compute it from a choice experiment of this design and size. Third, we estimate homogeneous, continuous-heterogeneity and discrete-segment specifications on identical choices. The homogeneous one prices the market at a single point and yields no share below cost at all; across the three that place a distribution over the market the estimate of that share moves by fourteen percentage points, ranking those three by goodness of fit gives no purchase on it because the ordering runs opposite to it, and the information criteria prefer a three-class solution the separation diagnostics reject. Those results are properties of the estimators on data of this size and shape.

Section 2 reviews the design, estimation and affordability literatures. Section 3 sets out the study inputs, Section 4 gives the experimental design and Section 5 the specifications. Section 6 reports the models and the willingness-to-pay distributions, Section 7 how far apart the specifications land on the quantity that matters and how the headline quantities check against published measurement, and Section 8 what follows.

2. Related Work

2.1 Designing a choice experiment

Louviere *et al*. (2000) [27] is the standard reference and Rose and Bliemer (2009) [37] and Bliemer and Rose (2011) [8] the modern treatment of efficient design. Huber and Zwerina (1996) [20] established the value of design efficiency over orthogonality, Sándor and Wedel (2001) [40] developed designs robust to prior misspecification, and Walker *et al*. (2018) [48] examines what D-efficiency does and does not buy. Rose and Bliemer (2013) [38] gives the sample size machinery we use, and Fifer *et al*. (2014) [14] treats hypothetical bias, which is the standing objection to any stated preference result.

2.2 Estimating heterogeneity

McFadden (1974) [29] supplies the conditional logit and Train (2009) [45] the modern text. Continuous heterogeneity comes from Revelt and Train (1998) [36] and McFadden and Train (2000) [30], with Bhat (2003) [7] on simulation methods, Hensher and Greene (2003) [16] on practice and Hess and Train (2017) [18] on correlated parameters. Discrete heterogeneity comes from Greene and Hensher (2003) [15], Boxall and Adamowicz (2002) [9] and Shen (2009) [43].

Two methodological cautions matter for what we report. Daly *et al*. (2012) [12] shows that a lognormal cost coefficient is required if willingness-to-pay moments are to exist at all, which is why our fare parameter is specified that way. And Train and Weeks (2005) [46], Scarpa *et al*. (2008) [42] and Hess and Rose (2012) [17] set out the argument for estimating in willingness-to-pay space rather than preference space, along with the scale confound that motivates it. We estimate in preference space and derive willingness to pay by simulation with Krinsky and Robb (1986) [21] intervals, following Hole (2007) [19], and we flag in Section 7 the specific place where that choice appears to cost us.

2.3 Shared and digitally booked transport

Rayle *et al*. (2016) [34] compares ride-hailing with taxis, Sarriera *et al*. (2017) [41] and Lavieri and Bhat (2019) [24] study willingness to share a vehicle with strangers, and Alonso-González *et al*. (2020) [4] and Alonso-González *et al*. (2021) [3] estimate the value of shared ride attributes directly. Those last two are the closest comparators for our attribute-level results.

For African paratransit, Cervero and Golub (2007) [11] and Behrens *et al*. (2015) [6] frame the sector, Ehebrecht *et al*. (2018) [13] covers motorcycle taxis, Nkurunziza *et al*. (2012) [31] models mode choice in an East African city, and Kumar and Barrett (2008) [23], Kumar (2011) [22] and Olubomehin (2012) [32] give the Nigerian and West African picture. Williams *et al*. (2015) [49] documents digital platform arrival in African cities and Poku-Boansi and Adarkwa (2013) [33] paratransit demand in Ghana.

2.4 Affordability and price shocks

Carruthers *et al*. (2005) [10] and Litman (2021) [25] establish transport affordability measurement, Venter *et al*. (2018) [47] and Lucas *et al*. (2016) [28] its equity dimension. Litman (2022) [26] supplies the elasticity evidence. Rentschler (2016) [35] and Siddig *et al*. (2014) [44] analyze fuel subsidy removal incidence, which is the shock this study is set inside.

For Nigerian fares and earnings specifically, Wojuade (2017) [50] reports transport pricing, Arosanyin (2010) [5] operator earnings, Salau *et al*. (2018) [39] household travel, Aderamo and Abolarin (2014) [2] modal choice and Adedotun *et al*. (2016) [1] the Osogbo case.

2.5 What is missing

No study we located estimates willingness to pay for shared or digitally booked transport in Nigeria against an observed fuel price shock, and none reports the share of a low-income market falling below a stated cost of provision, which is the quantity an operator or a subsidy designer needs. The affordability literature measures burden and the choice literature measures preference; the crossing of the two is the gap.

What the results here can be checked against is shaped by what is absent. We could verify no Nigerian value of travel time study, so the time valuations are benchmarked against the conventional international appraisal bands rather than against a local measurement. Nor could we verify any Nigerian or West African stated preference willingness-to-pay study for transport: the nearest comparators, Nkurunziza *et al*. (2012) [31] for Dar es Salaam and Poku-Boansi and Adarkwa (2013) [33] for Kumasi, are not choice experiments.

3. Study Inputs

Twenty-four monthly national statistical workbooks for 2023, covering the petrol price watch and the transport fare watch at state level, were retrieved and cached. From these come the May to June 2023 price and fare movements reported in the introduction and in Fig 1. Two of the workbooks also carry a monthly fare series back to January 2016 for each state, which we extracted for the three study states and read only as context on the pre-shock trend; no parameter in this paper is fitted to it and no result depends on it.

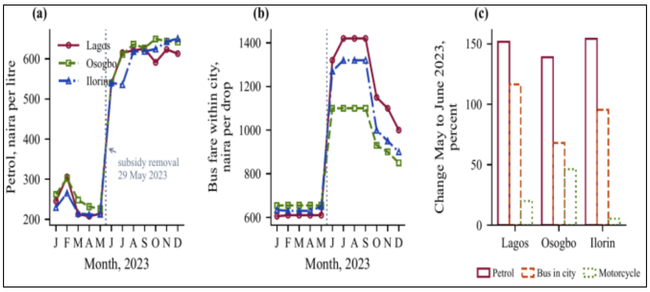

Fig 1: The 2023 fuel price shock and the fare response by mode and city, from the monthly national price and fare series

The recruitment frame was set against published Nigerian sources. Income band quotas follow Wojuade (2017) [50], with the band edges carried from 2016–17 to 2023 by the growth in the national minimum wage rather than by consumer prices, because indexing incomes by a price index in the middle of a price shock is circular; usual-mode quotas follow Salau *et al*. (2018) [39] for Lagos and Aderamo and Abolarin (2014) [2] for Ilorin.

The attribute levels and the 431 naira cost of provision are analyst-set. The fare levels bracket the observed post-shock within-city fares. The cost of provision is built from the observed September 2023 petrol price of 623.51 naira per litre, the mean of the three study states, plus assumed vehicle, driver and platform components, and because those components are assumed every share-below-cost figure below is reported at 0.75 and 1.30 times the central case as well as at the central case itself.

4. Experimental Design

Table 1 reports the design and Fig 2 shows a choice task as a respondent would see it.

Table 1: Attributes, levels and diagnostics of the stated-preference design. Three unlabeled service options and an opt-out, 24 choice tasks in 3 blocks of 8

Attribute	Levels	Rows
Fare, naira per trip	300; 650; 1,000; 1,350	18
Waiting time, minutes	3; 10; 20; 35	18
In-vehicle time, minutes	15; 35; 60	24
Other passengers sharing	0; 3; 8	24
How the trip is booked	roadside hail; phone call; smartphone app	24
On-time arrival, percent	60; 80; 95	24
Design diagnostics		
Full factorial, profiles per option		1,296
D_p-error, level-balanced design		0.0723
D_p-error, same search without level balance		0.0626
A-error		0.4788
S-estimate, largest over coefficients		165
Realized sample, respondents		1,080
Largest attribute correlation, booking dummies excluded		0.203
Correlation between the two booking dummies		-0.500
D_p-error by block		0.3040; 0.2556; 0.2684
Dominated tasks		none
Block indicator orthogonality score		5.2e-33

Note. The design is found by a swap search that minimizes the D_p-error of the multinomial logit information matrix evaluated at non-zero priors, subject to exact attribute-level balance. Level balance costs efficiency: the same search without the balance constraint, on the same priors and the same levels, reaches a D_p-error of 0.0626, so the balanced design's 0.0723 is 15.5 percent higher. What the unconstrained design buys that efficiency with is coverage. Its rarest level, the middle of the three on-time arrival levels, appears in 0 of the 72 design rows against 18 to 24 under balance, so that level is never shown to anyone and its effect cannot be identified at all. The S-estimate is the number of respondents at which the least well identified coefficient reaches a t ratio of 1.96 under the priors; the realized sample of 1,080 is well above it. The two booking dummies code one three-level attribute and are therefore structurally correlated at -0.5; that pair is excluded from the correlation diagnostic above it. Blocks are assigned to minimize the correlation between each block indicator and every design column.

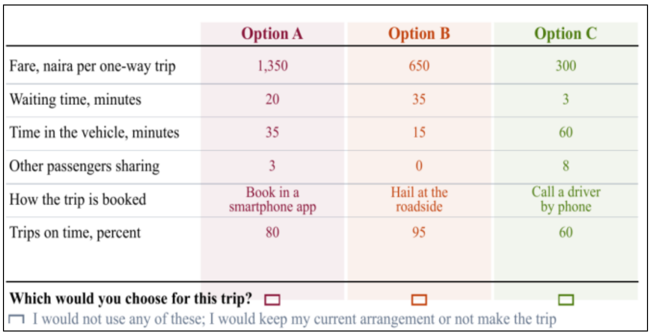

Fig 2: A choice task as presented: three unlabeled service alternatives plus an opt-out, across six attributes

The experiment is unlabeled, presenting three service alternatives plus an opt-out. Six attributes vary: fare at 300, 650, 1,000 and 1,350 naira; waiting time at 3, 10, 20 and 35 minutes; in-vehicle time at 15, 35 and 60 minutes; sharing at

0, 3 and 8 co-passengers; booking method as roadside hail, phone call or app; and reliability at 60, 80 and 95 percent on-time. There are 24 tasks in three blocks of eight.

One design decision is worth reporting because the efficiency literature would push the other way. Our level-balanced design achieves a D_P-error of 0.0723. The same search without the balance constraint, on the same priors and the same levels, reaches 0.0626, so the balanced design's error is 15.5 percent higher than the unbalanced one's, and the unbalanced design is 13.4 percent better measured from ours. It buys that efficiency by dropping the middle on-time arrival level to zero appearances across all 72 rows, which makes that level unidentifiable. We accepted the worse efficiency and report the cost, because a design that cannot identify a level it contains is not efficient in any sense that matters.

The design is dominance-free, its largest attribute correlation excluding the two structurally correlated booking dummies is 0.203, and block-attribute orthogonality is exact to numerical precision. The sample size estimate implied by the design is 165 against our 1,080, so the study is not sample-limited.

The experiment was administered in the final quarter of 2023 to 1,080 respondents across the three study states, recruited at markets, motor parks and campuses in Lagos, Osogbo and Ilorin, and yielding 8,640 choices. Table 2 reports the respondent sample. Its composition was managed against published Nigerian sources: the income band quotas follow Wojuade (2017) [50] with the band edges carried from 2016–17 to 2023 by the growth in the national minimum wage, and the usual-mode quotas Salau *et al*. (2018) [39] for Lagos and Aderamo and Abolarin (2014) [2] for Ilorin, while occupation, trip purpose and smartphone ownership were left to fall out of recruitment rather than quotaed. Three features of it do work later in the paper and are worth pointing at. The median monthly income is 75,961 naira over the whole sample and 69,116 naira in Ilorin against 88,099 in Lagos, which is what makes the 431 naira cost of provision a demanding figure rather than a trivial one. A fifth of the sample, 20.8 percent, sits in the lowest band. And 52.5 percent own a smartphone, ranging from 57.7 percent in Lagos to 48.7 in the two smaller cities, which matters twice over: the app booking attribute is only meaningful to a smartphone owner, and smartphone ownership is one of the two covariates in the class membership function estimated below. The Osogbo column is the weakest anchored of the three, because no published Osogbo fare or intra-city travel survey could be verified to quota against or to check it against afterwards.

Against this sample and this design, 39.5 percent of the 8,640 choices land on the opt-out. A design whose opt-out is almost never taken cannot price a service at all, and one whose opt-out is almost always taken cannot either.

Table 2: Composition of the respondent sample, by city

	Lagos	Osogbo	Ilorin	All
Respondents	456	312	312	1,080
Choice observations	3,648	2,496	2,496	8,640
Monthly income, naira				
Median	88,099	70,174	69,116	75,961
Mean	104,076	88,401	87,260	94,690
Income band, percent				
under 45,000	15.4	22.8	26.9	20.8
45,000 to 85,000	32.7	38.1	34.0	34.6
85,000 to 130,000	25.9	21.8	20.8	23.2
130,000 to 200,000	17.8	12.5	15.1	15.5
over 200,000	8.3	4.8	3.2	5.8
Usual mode, percent				
Minibus	52.6	18.3	23.7	34.4
Motorcycle	16.2	29.2	31.7	24.4
Tricycle	13.4	38.8	32.1	26.1
Shared taxi	8.3	8.3	4.8	7.3
Walk	9.4	5.4	7.7	7.8
Occupation, percent				
Informal trade	34.2	36.5	39.4	36.4
Formal employee	28.7	18.9	23.1	24.3
Artisan or driver	18.4	17.9	12.5	16.6
Student	14.5	19.9	17.6	16.9
Unemployed or casual	4.2	6.7	7.4	5.8
Owns a smartphone, percent	57.7	48.7	48.7	52.5
Has household vehicle access, percent	14.7	11.9	11.2	12.9

Note. Income band quotas follow Wojuade (2017) [50], with the band edges carried from 2016–17 to 2023 by the growth in the national minimum wage rather than by consumer prices; usual-mode quotas follow Salau *et al.* (2018) [39] for Lagos and Aderamo and Abolarin (2014) [2] for Ilorin. No published fare or travel survey for Osogbo could be verified, so the Osogbo column has no published profile to be set against and is the least well anchored of the three. Occupation, trip purpose and smartphone ownership were not quotaed. Each respondent answers eight of the twenty-four choice tasks, one design block.

Fig 3 shows the three diagnostics that decide whether the design is usable. Panel (a) confirms that outside the structural -0.5 between the two booking dummies, which code one three-level attribute and must be correlated, no pair of attributes correlates above 0.21 in absolute value; the largest is fare against sharing at -0.203, so no attribute is close to standing in for another. Panel (b) is the balance constraint made visible: every level of every attribute appears either 18 or 24 times across the 72 rows, with no level below or above that, which is what the unbalanced search would have destroyed. Panel (c) shows the three blocks reaching D_P-errors of 0.304, 0.256 and 0.268 against 0.072 for the full design, which is the expected penalty for seeing a third of the tasks and is why the blocks are pooled in estimation rather than analyzed apart. All three panels are properties of the design matrix and were computed before the experiment was fielded.

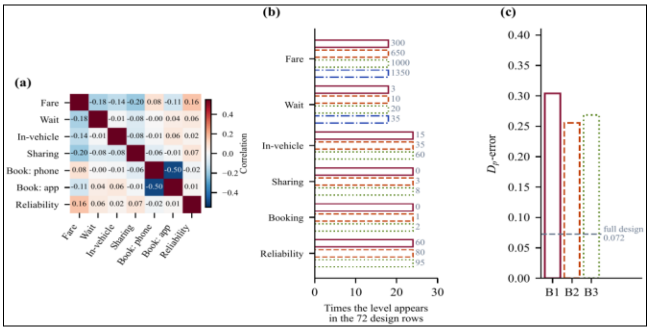

Fig 3: Diagnostics of the design we use. Panel (a) is the attribute correlation matrix, where the only entry above 0.21 in absolute value is the structural -0.5 between the two booking dummies that code one three-level attribute. Panel (b) counts how often each attribute level appears across the 72 design rows, which is 18 for the two four-level attributes and 24 for the four three-level ones. Panel (c) is the D_p-error of each block of eight tasks against the full design. The unbalanced alternative discussed in the text is not drawn here

5. Specifications

All three estimators were implemented for this study, because the Python stack available to us carries no mixed logit with a lognormal price coefficient and no latent class model with a covariate-driven membership function. Three specifications are estimated on the same 8,640 observations. Every design column is scaled before estimation so that the reported coefficients sit on a readable range. Fare is divided by 1,000, so its coefficient is per 1,000 naira; waiting time, in-vehicle time and on-time arrival are divided by 10, so their coefficients are per ten minutes and per ten percentage points. Sharing and the two booking dummies enter unscaled. Every coefficient reported in Section 6 is on those units, and every willingness-to-pay figure there is converted back to naira per natural unit of the attribute.

Multinomial logit. Maximum likelihood with an analytic gradient and a sandwich covariance clustered on the respondent, which is the homogeneous baseline the other two are measured against.

Mixed logit. Simulated maximum likelihood over 1,000 modified Latin hypercube draws per respondent. The panel is respected: a respondent's eight tasks enter as a product taken inside the integral over the mixing distribution rather than outside it, so the eight answers are treated as coming from one person with one draw of coefficients rather than from eight people. The fare coefficient is lognormal-negative, $\beta_{fare} = -exp(m + sz)$, following Daly *et al*. (2012) [12], who show that a normal, uniform, triangular or truncated-normal price coefficient leaves willingness to pay, a ratio with that coefficient in the denominator, with no finite moments, and that truncating at zero does not repair it. The other six attribute coefficients and the opt-out constant are normal. Standard deviations enter the parameter vector unconstrained and are reported as absolute values, because taking an absolute value inside the objective puts a kink at zero and stalls a quasi-Newton search. The analytic gradient was checked against a central-difference approximation to a maximum relative error of 3.9×10^{-8}. Optimization is L-BFGS-B, run twice from the second solution; the largest absolute gradient element at the reported optimum is 5.7×10^{-5}.

Latent class. Expectation maximization, with a weighted multinomial logit per class in the M step and a multinomial logit membership function in the E step. Membership is a function of a constant, standardized log income, smartphone ownership and two city dummies for Osogbo and Ilorin, with Lagos as the reference city, and those five terms are reported with the class coefficients in Section 6. Standard errors come from the outer product of the complete-data scores. Two through five classes are estimated and compared on AIC, BIC, CAIC and entropy R^2.

Willingness to pay. Derived by simulation rather than as a ratio of point estimates. Two distributions are reported and they answer different questions. The *unconditional* distribution is 200,000 draws from the estimated mixing distribution and describes the population the model implies; it is the basis of every attribute willingness-to-pay figure reported below. The *individual conditional* distribution assigns each of the 1,080 respondents the mean of their own coefficients given the eight choices they made, and describes this sample; it is the basis of every share-below-cost figure, because that quantity is a headcount of people rather than a property of a distribution. The two are stated separately wherever they appear, because they do not agree. Confidence intervals on the unconditional quantiles are Krinsky and Robb (1986) [21] intervals: 400 draws of the parameter vector from its estimated asymptotic distribution, each propagated through 20,000 draws of the mixing distribution.

The three specifications are then set against one another on the quantity a subsidy designer acts on rather than on fit alone. Section 7 reports that comparison, and it is where the most useful methodological result in this paper appears.

6. Results

6.1 What the specifications do to the same choices

Table 3 reports the comparison. The multinomial logit reaches a log likelihood of $-10{,}923.31$ with a Bayesian information criterion of 21,919.1 and a McFadden ρ^2 of 0.088. The mixed logit reaches $-10{,}051.00$, an information criterion of 20,247.0 and a ρ^2 of 0.161, an improvement of 872.3 log likelihood points on eight extra parameters, or a likelihood ratio statistic of 1,744.6 on eight degrees of freedom. Because the null places all eight variance parameters on the boundary of the parameter space, the reference distribution is a mixture of chi-squared rather than chi-squared; the statistic exceeds every conventional critical value under either. Making the opt-out constant random rather than fixed buys a further 11.4 on one degree of freedom, $p = 0.0004$, which is why the random-constant specification is the one carried forward.

What the comparison shows is that a mixed logit estimated on 1,080 respondents answering eight tasks apiece detects preference heterogeneity decisively rather than marginally, and that the homogeneous specification is rejected outright. That is a statement about the power of a design of this size.

The latent class results are more interesting than they first appear. Two classes reach an information criterion of 20,060.8 and three classes 20,042.9, so the criterion selects three. But entropy R^2 falls from 0.852 to 0.701 between them, and the mean maximum posterior probability falls from 0.958 to 0.862, which together are the signature of over-splitting: the third class is not well separated from the others. This is therefore a case where the information criterion prefers a solution the separation diagnostics reject, which is a property of the criterion rather than of these choices. Both solutions are reported, and the two-class one carries wherever a discrete reading is needed.

Table 3: Model comparison. All models are estimated on the same 8,640 choice observations from 1,080 respondents

Model	Parameters	lnL	ρ^2	AIC	BIC	CAIC
Multinomial logit	8	-10,923.31	0.0880	21,862.6	21,919.1	21,910.5
Mixed logit, opt-out constant fixed	15	-10,056.71	0.1604	20,143.4	20,249.4	20,233.2
Mixed logit, opt-out constant random	16	-10,051.00	0.1608	20,134.0	20,247.0	20,229.8
Latent class, 2 classes	21	-9,935.23	0.1705	19,912.5	20,060.8	20,038.1
Latent class, 3 classes*	34	-9,867.35	0.1762	19,802.7	20,042.9	20,006.2
Latent class, 4 classes	47	-9,857.17	0.1770	19,808.3	20,140.4	20,089.6
Latent class, 5 classes	60	-9,847.60	0.1778	19,815.2	20,239.0	20,174.3

Note. ρ^2 is against the equal-shares null of $-11{,}977.6$. $*$ marks the number of classes selected by the Bayesian information criterion. The likelihood ratio statistic for the multinomial logit against the mixed logit is 1,744.6 on 8 degrees of freedom, which corresponds to a log likelihood improvement of 872.3; because the null places all 8 variance parameters on the boundary of the parameter space, the reference distribution is a mixture of chi-squared rather than chi-squared, and the statistic exceeds every conventional critical value under either. Making the opt-out constant random buys a further 11.4 on one degree of freedom, $p = 0.0004$. Entropy R^2 falls from 0.852 at two classes to 0.701 at three and the mean maximum posterior probability from 0.958 to 0.862, which is the usual sign that the extra class is splitting a segment rather than finding one. BIC is computed on the 8,640 choice observations while CAIC as reported here is computed on the 1,080 respondents, which is why every CAIC sits below its BIC; the two columns are not on a common scale and only differences within a column are meaningful. The mixed logit uses 1,000 modified Latin hypercube draws; the largest absolute element of the gradient at the reported optimum is 5.7e-05.

Table 4: Estimated coefficients. Standard errors in parentheses; those for the multinomial logit are clustered on the respondent

	MNL	Mixed logit		Latent class, 2	
	Coefficient	Location	Scale	Class 1	Class 2
Fare, per 1,000 naira†	-1.4089	0.5290	0.9053	-0.9021	-2.6140
	(0.0492)	(0.0476)	(0.0494)	(0.0524)	(0.0912)
Waiting time, per 10 minutes	-0.0968	-0.1186	0.0644	-0.1033	-0.1022
	(0.0107)	(0.0128)	(0.0439)	(0.0148)	(0.0194)
In-vehicle time, per 10 minutes	-0.0426	-0.0551	0.0579	-0.0409	-0.0612
	(0.0070)	(0.0080)	(0.0175)	(0.0090)	(0.0131)
Other passengers sharing, per passenger	-0.0579	-0.0678	0.0252	-0.0590	-0.0588
	(0.0041)	(0.0047)	(0.0136)	(0.0053)	(0.0073)
Booking: phone call	0.1214	0.1084	0.1865	0.1740	0.0154
	(0.0364)	(0.0396)	(0.1250)	(0.0468)	(0.0657)
Booking: smartphone app	0.1145	0.0591	0.6101	0.3969	-0.4649
	(0.0388)	(0.0480)	(0.0575)	(0.0435)	(0.0686)
On-time arrival, per 10 points	0.0483	0.0516	0.0632	0.0552	0.0446
	(0.0089)	(0.0114)	(0.0160)	(0.0120)	(0.0169)
Opt-out constant	-0.4453	-1.1283	0.7920	-1.5121	-0.5419
	(0.0857)	(0.1081)	(0.1206)	(0.1229)	(0.1576)
Class share	–	–	–	0.454	0.546
Class membership, class 2 relative to class 1					
const	–	–	–	0.5694	
log income z	–	–	–	-0.7624	
smartphone	–	–	–	-0.6274	
Osogbo	–	–	–	-0.1684	
Ilorin	–	–	–	0.0626	

Note. Coefficients are on scaled design columns: fare enters per 1,000 naira, waiting time and in-vehicle time per ten minutes, on-time arrival per ten percentage points, and sharing and the two booking dummies unscaled. For the seven rows whose mixed-logit coefficient is normal, the columns headed Location and Scale are the mean and the standard deviation of that normal. † The fare coefficient is not normal: it is lognormal-negative, $\beta_{fare} = -exp(m + sz)$, so its two entries are the location m and the scale s on the log scale, and the fare coefficient itself is negative at every draw rather than positive as a mean of 0.5290 would imply. The lognormal is chosen so that willingness to pay, which is a ratio with the fare coefficient in the denominator, has finite moments; Daly *et al*. (2012) [12] show that a normal, uniform, triangular or truncated-normal fare coefficient leaves those moments undefined. The class membership rows are coefficients of a multinomial logit on a constant, standardized log income, smartphone ownership and city dummies for Osogbo and Ilorin with Lagos as the reference. The income coefficient of -0.7624 places higher-income respondents in class 1, which is the less fare-sensitive of the two classes and the one that values booking in an app positively.

Table 5: Willingness to pay, in naira, as a distribution across the estimated population rather than as a point

		Mixed logit					Latent class	
Attribute	**Unit**	**10th**	**Median**	**95% interval**	**90th**	**Negative**	**Class 1**	**Class 2**
Waiting time, minutes	minute	-24.1	-6.2	[-7.9, -4.7]	-1.1	0.97	-11.5	-3.9
In-vehicle time, minutes	minute	-13.2	-2.6	[-3.4, -1.9]	1.0	0.83	-4.5	-2.3
Other passengers sharing	passenger	-131.8	-37.4	[-44.2, -31.7]	-9.9	1.00	-65.4	-22.5
Booking: phone call	trip	-78.8	47.1	[13.5, 95.9]	326.6	0.28	192.9	5.9
Booking: smartphone app	trip	-548.2	22.7	[-18.3, 59.0]	686.2	0.46	440.0	-177.9
On-time arrival, percent	percentage point	-1.6	2.3	[1.3, 3.6]	13.2	0.21	6.1	1.7
Reference service, whole	per trip	-150	549	[486, 619]	2,739	0.16	2,212	6

Note. Every column in this table is computed on the *unconditional* distribution implied by the estimated mixing distribution, simulated with 200,000 draws, and describes the population the model implies rather than the 1,080 respondents; the share-below-cost figures in Table 6 are computed on the individual conditional distribution instead and the two do not agree. The column headed 95 percent interval is the Krinsky–Robb interval on the mixed-logit median in the column to its left, from 400 draws of the parameter vector from its asymptotic distribution, each propagated through 20,000 draws of the mixing distribution; it qualifies no other column. The column headed Negative is the share of the estimated population whose willingness to pay for that attribute is negative, not a headcount of respondents. The reference service is a pooled ride booked in an app with 8 minutes of waiting, 30 minutes in the vehicle, 3 other passengers and 85 percent of trips on time; its willingness to pay is the fare at which a respondent is indifferent between taking it and taking the opt-out. Its unconditional mean is 1,026 naira against the median of 549 shown here, and its median on the individual conditional distribution is 471. Latent class columns are the two-class solution.

6.2 Why a mean is the wrong summary of this output

See Table 4 and Table 5 report the parameters and the derived willingness to pay, and Fig 4 shows the distributions.

The reference service these figures are priced against has to be stated, because four headline numbers depend on it. It is a pooled ride booked in a smartphone app, with eight minutes of waiting, thirty minutes in the vehicle, three other passengers on board, and 85 percent of trips arriving on time. Its willingness to pay is the fare at which a respondent is indifferent between taking it and taking the opt-out.

The clearest case is app-based booking. Its estimated mean coefficient is 0.0591 with a standard error of 0.0480, indistinguishable from zero at $t = 1.23$, while the standard deviation of that coefficient is 0.6101 with a standard error of 0.0575, emphatic at $t = 10.6$. A homogeneous model fitted to the same choices would report a population indifferent to app booking. The heterogeneous model reports a population that is not indifferent but divided. A large estimated standard deviation beside a near-zero mean is also consistent with an estimator that cannot locate the center of a single population, which is why the two-class solution reported below, stating the division as two valuations, is the more direct reading.

The unconditional willingness-to-pay distribution makes the spread concrete. Its median is $+23$ naira with a Krinsky–Robb interval from -18 to 59, its tenth percentile is -548 and its ninetieth is $+686$, and 46.2 percent of the estimated population values app booking negatively. That 46.2 percent is a share of the 200,000 draws from the estimated mixing distribution, not a headcount of the 1,080 respondents, and the two are different quantities.

The other attributes are reported for completeness, all as medians of the same unconditional distribution: waiting time at -6.2 naira per minute, in-vehicle time at -6.2, sharing at -37 naira per additional co-passenger, and reliability at $+2.3$ naira per percentage point of on-time performance. The reference service as a whole carries an unconditional median of 549 naira with an interval from 486 to 619, a tenth percentile of -150 and a ninetieth of 2,739. Its mean is 1,026 naira, nearly twice its median, which is what a long right tail does to an average and the reason the median is quoted throughout. Computed instead on the individual conditional distribution, over the 1,080 respondents rather than over the mixing distribution, the median for the same service is 471 naira. Both are correct answers to different questions, and each is labeled where it appears.

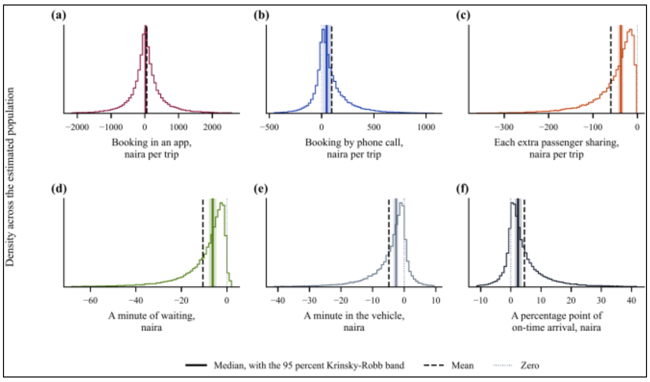

Fig 4: Unconditional willingness-to-pay distributions by attribute, from 200,000 draws of the estimated mixing distribution. The app-booking panel is a single peak centered near zero: 46.2 percent of the draws are negative, 28.5 percent fall within 100 naira of zero, and only 14.2 percent exceed 500 naira. The mixed logit specifies a normal coefficient on app booking, so a single peak is the only shape available to it

6.3 The share below the cost of provision, and how far the specification moves it

Table 6 and Fig 5 report the quantity a subsidy designer needs: the share of a market whose willingness to pay for the reference service falls below the cost of providing it, taken here as 431 naira. That cost is a design parameter. Its arithmetic is given in Section 3, and every figure in this subsection is conditional on the assumed cost base, which the table varies from 0.75 to 1.30 times the central case for that reason.

All the shares in Table 6 are headcounts over the 1,080 respondents, computed on the individual conditional distribution described in Section 5. On the unconditional mixing distribution the same central-case figure would be 43.9 rather than 48.2 percent, and we report the conditional version because a subsidy is paid to people rather than to draws.

What matters is how much the answer moves for no reason a respondent supplied. The mixed logit gives 48.2 percent, the two-class latent class model 54.6 and the three-class model

62.6. Nothing separates those three numbers except the analyst's choice of specification, and the distance between the extremes is 14.4 percentage points. A subsidy sized on the first would cover three quarters of the population a subsidy sized on the third would cover, and no diagnostic available inside a single specification says where in the range to stand.

The gradient across income bands is steep, running from 66.2 percent in the lowest band to 6.3 percent in the highest under the mixed logit, and all three specifications reproduce that ordering and its rough magnitude. Where they part company is at the bottom of the income distribution, which is where a subsidy would be aimed. In the lowest band the mixed logit puts 66.2 percent below cost, the two-class model 77.9 and the three-class model 88.0, so for the poorest fifth of the sample the choice of specification moves the estimate further than it moves the sample-wide figure.

Table 6: Share of respondents whose willingness to pay for the reference service falls below the cost of providing it, by income band and by model, with the design-block standard deviation of the central-case figure reported separately

	n	**Mixed logit**	**Latent class, 2**	**Latent class, 3**
Central cost of provision, 431 naira per passenger trip				
under 45,000	225	0.662	0.779	0.880
45,000 to 85,000	374	0.551	0.633	0.717
85,000 to 130,000	251	0.398	0.437	0.518
130,000 to 200,000	167	0.371	0.386	0.444
over 200,000	63	0.063	0.048	0.086
All respondents	1080	0.482	0.546	0.626
Sensitivity to the cost of provision				
Low, 323 naira	–	0.410	0.546	0.626
Central, 431 naira	–	0.482	0.546	0.626
High, 560 naira	–	0.536	0.546	0.626
Variability of the central-case figure, reported separately				
Design-block standard deviation, 3 blocks	–	0.069	0.026	–

Note. Shares are headcounts over the 1,080 respondents, computed on the individual conditional distribution of willingness to pay rather than on the unconditional mixing distribution reported in Table 5; on the unconditional distribution the central-case overall figure would be 0.439 rather than 0.482. The cost of provision is built from the observed September 2023 petrol price of 623.51 naira per litre, the mean of the three study states, plus assumed vehicle, driver and platform components; the low and high cases are 0.75 and 1.30 times the central figure. The mixed logit is the only one of the three whose figure moves with the cost of provision over this range, because a continuous mixing distribution has mass everywhere while a two- or three-class solution moves only when a cost level crosses one of its class valuations. The design-block figure is reported apart from the estimates it qualifies rather than folded into them. It is a standard deviation, taken across the 3 blocks of the sample, 360 respondents each, and therefore carries the sampling noise of a third-sized sample as well as any block effect, which makes it an upper bound on the design's contribution rather than an estimate of it.

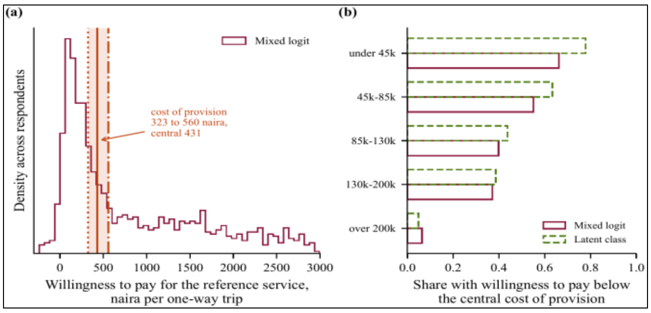

Fig 5: Estimated willingness to pay against the assumed cost of provision, overall and by income band. The estimated share below cost falls from 66.2 percent in the lowest band to 6.3 percent in the highest

Fig 6 turns the estimated model into demand curves, tracing predicted uptake of the reference service against the fare charged for it. The fare that maximizes margin per rider times uptake is 2,100 naira, at which 17.9 percent of the modeled market takes the service. At a fare equal to the 431 naira cost of provision the model predicts 52.6 percent uptake and, by construction, zero margin per rider: when the fare equals the unit cost, margin is zero at every level of uptake, so break-even is a point on the fare axis rather than a threshold uptake to be cleared. The distance between 2,100 and 431 naira, and between 17.9 and 52.6 percent uptake, is the whole of the tension between an operator pricing for margin and one pricing for access. It is arithmetic on an estimated demand curve and an assumed cost base, and the cost base is the more fragile of the two.

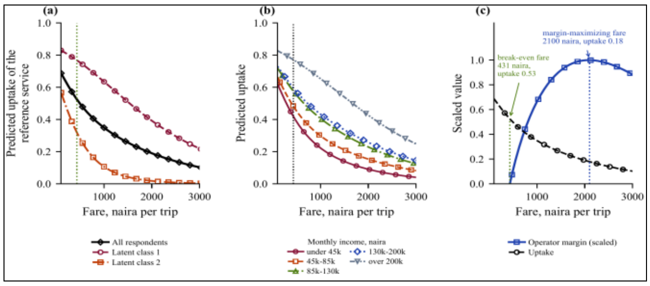

Fig 6: Predicted uptake of the reference service against the fare charged for it, with the margin-maximizing fare of 2,100 naira and the 431 naira cost of provision both marked. Uptake at the cost of provision is 52.6 percent, where margin per rider is zero

7. Comparison Across Specifications, and External Checks

7.1 Fit, and the quantity the fit statistics do not order

The three specifications are fitted to the same 8,640 choices and differ only in what they allow preferences to do. Ranked by information criterion they run three-class latent class first at a BIC of 20,042.9, two-class second at 20,060.8 and mixed logit third at 20,247.0. Ranked by the share of the market they place below the cost of provision they run mixed logit lowest at 48.2 percent, two-class next at 54.6 and three-class highest at 62.6. The second ordering is the reverse of the first, and it is the second one a subsidy designer acts on. Nothing in either ordering says which of the three figures to believe: an information criterion measures how well a specification reproduces the choices that were made, not how well it locates the lower tail of a willingness-to-pay distribution, and the whole of the fourteen-point spread sits inside a set of models every one of which fits these choices acceptably.

The over-splitting result belongs here too. The information criterion selects three classes while entropy R^2 falls from 0.852 to 0.701 and the mean maximum posterior probability from 0.958 to 0.862 between two classes and three. A study reporting the criterion alone would have profiled a third segment that its own posterior probabilities cannot separate from the other two, and that solution is also the one sitting at the top of the fourteen-point range. Fig 7 profiles the two-class solution instead. The two classes differ most on app booking, which class 1 values at 440 naira a trip and class 2 at -177.9, and membership turns steeply on income: class 2 holds most of the lowest income band and class 1 most of the highest.

The cost of estimating in preference space shows up in the tail. With a lognormal fare coefficient the implied willingness-to-pay distribution is heavily right-skewed, and the reference service carries an unconditional median of 549 naira against a mean of 1,026 and a ninetieth percentile of 2,739. On the same fitted model the unconditional and the individual conditional readings of the share below cost part company, 0.439 against 0.482, because the unconditional reading carries the full spread of the mixing distribution while the conditional one is anchored on each respondent's own eight answers. Estimating in willingness-to-pay space (Train and Weeks 2005; Scarpa *et al.* 2008) [46, 42] is the standard way to stop a policy quantity depending on the shape of that tail, and we did not implement it.

None of this is visible from inside a single estimation. The mixed logit converged cleanly, its largest gradient element at the optimum was 5.7×10^{-5}, its ρ^2 of 0.161 sits in the conventional range for a stated preference model with an opt-out, and every diagnostic a referee would ask for is satisfied. Estimated on its own it would have returned 48.2 percent, and nothing in its output would have hinted that a latent class model on the same choices returns 62.6. That is the argument for the range rather than the point, and it is the most transferable thing in the paper.

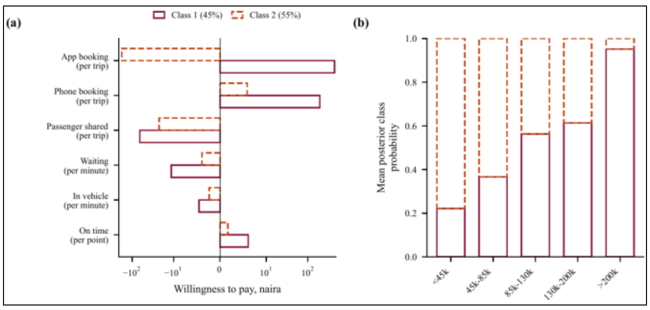

Fig 7: The two-class latent class solution. Panel (a) gives each class's willingness to pay by attribute on a symmetric logarithmic axis, and panel (b) the mean posterior class probability within each income band. The two classes differ most on app booking, which class 1 values at 440 naira a trip and class 2 at -177.9, and class membership turns steeply on income

The design-block figure is reported apart from the estimates it qualifies and is never folded into them. Across the three design blocks of 360 respondents the standard deviation on the share below cost is 0.069 under the mixed logit, and that figure is an upper bound because block and subsample are confounded at this size.

7.2 Checking the headline quantities against published measurement

The comparison above is internal. It says how far three specifications fitted to the same choices land from one another, and nothing about whether any of the three describes a plausible world: a model can fit a set of answers closely and still imply behavior no commuter would exhibit. We therefore checked eleven headline quantities against published values for comparable systems: the size of the price shock, the value of in-vehicle time against the wage rate, the ratio of waiting time to in-vehicle time, the value of a travel minute against a prevailing fare, the sharing penalty per passenger, the value of reliability against the value of waiting, the monthly fare burden measured at the observed post-shock fare and again at the design's own fare mid-point, the arc fare elasticity of uptake, the cost of provision as a fraction of the incumbent bus fare, and the McFadden ρ^2 of the preferred model. Nine fall inside the published range and none sits on its edge.

Two checks remain outside, and they are the same fact seen twice. The value of a travel minute comes to 0.002 of one prevailing bus fare against a published band of 0.05 to 0.15 taken from Nkurunziza *et al.* (2012) [31] for Dar es Salaam. The conventional appraisal normalization, the value of in-vehicle time against the wage rate, passes comfortably at 0.355 against a band of 0.30 to 0.60, and we report both because the gap between them is the point: normalizing by a fare compares two fare-to-income regimes, and a Nigerian within-city bus fare of 1,280 naira in September 2023 is not the nineteen-cent daladala fare the band was built on. The second failure is the monthly fare burden at the observed post-shock fare, 0.674 against a band of 0.20 to 0.55 whose upper edge is Carruthers *et al.* (2005) [10] reporting over 54 percent for a poor Lagos worker. That row uses the observed post-shock fare and the sample median income: two paid trips a day for twenty working days at that fare cost about two thirds of a median monthly income. The design's own fare mid-point sits inside the band at 0.434, so the attribute levels themselves describe a budget a respondent could plausibly consider, and the failure attaches to the incumbent fare rather than to the instrument.

8. Discussion

8.1 What this study establishes

The central results are methodological. A stated preference design of this size and shape produces the share-below-cost quantity at all, and the answer moves by 14.4 percentage points across three standard specifications fitted to identical choices. The ranking of those specifications by information criterion runs opposite to their ranking on the quantity itself, so the model selected on fit is the model that puts the largest share of the market below the cost of provision, and nothing in its own output says whether it should. A mixed logit that converges cleanly and passes every routine diagnostic returns a figure fourteen points from the one a latent class model returns on the same choices, without either estimation giving a sign of it. And an information criterion selects three latent classes on choices whose entropy R^2 and mean maximum posterior probability both fall sharply at that third class. These are properties of estimators on data of this size and shape.

8.2 What follows, and for whom

The audience for the methodological result is anyone who will estimate willingness to pay for a new service in a low-income market and hand a single number to someone who will act on it. For that reader the recommendations are about how an estimate is produced and reported.

First, report the share below the cost of provision as a range across specifications rather than as a point from whichever specification fits best. In this study the range is 48.2 to 62.6 percent, its two ends are the worst-fitting and the best-fitting of the three specifications, and nothing in either model's own output indicates which end a subsidy should be sized on.

Second, do not select the number of segments on an information criterion alone. Entropy R^2 and the mean maximum posterior probability cost nothing to compute and both flagged the over-split solution the criterion preferred here.

Third, treat a mean coefficient that is indistinguishable from zero as a diagnostic rather than a result. In this study that pattern appeared for app booking, where an estimated mean of 0.0591 at $t = 1.23$ stands beside a standard deviation of 0.6101 at $t = 10.6$. A large estimated standard deviation alongside a near-zero mean is consistent with a divided population, but it is equally consistent with an estimator that cannot locate the center of one. The two-class model fitted to the same choices states the division directly instead, at 440 and -177.9 naira a trip.

One point belongs to the regulators of the three states. Bus fares and motorcycle fares absorbed the same fuel shock at very different rates, and the difference is not uniform across cities: in Kwara the within-city bus fare rose 95.4 percent while the motorcycle fare rose 5.3, a factor of eighteen; in Lagos the two rose 116.4 and 20.0 percent, a factor of just under six; in Osun 67.9 and 46.2, a factor of one and a half. Whatever explains that spread, and this study does not establish it, a single assumed pass-through applied across modes or across states will misstate who carried the burden of the subsidy removal.

8.3 Transferability

The design transfers directly and cheaply: six attributes, 24 tasks, three blocks, and a sample size requirement of 165 that any modest survey can meet. The estimation is standard and is described in Section 5 in enough detail to rebuild.

The numbers do not transfer. They are estimates for three Nigerian cities at fare levels set in the year of the subsidy removal.

The methodological result transfers furthest. Its short form is that on a choice experiment of this design and size the analyst's choice of specification moved the affordability answer by 14.4 percentage points, and that no diagnostic available inside a single estimation said which end of that range to act on.

8.4 Limitations

The cost of provision, 431 naira per passenger trip, is set by the analyst rather than taken from an operator's accounts, and every share-below-cost figure in the paper is conditional on it. The low and high cases, at 0.75 and 1.30 times the central figure, are reported beside it throughout for that reason, and any reuse of these shares should carry the same range.

The Osogbo quotas are the weakest part of the recruitment. No published Osogbo fare or intra-city travel survey could be verified, so the Osogbo usual-mode quotas were set between Ilorin's and a more tricycle-dominated profile, against Lagos and Ilorin quotas that follow Salau *et al.* (2018) [39] and Aderamo and Abolarin (2014) [2]. Roughly a third of the sample therefore rests on an interpolated quota rather than on a source, and any city-level comparison involving Osogbo should be read with that in mind.

9. Conclusion

We designed, fielded and reported a stated preference experiment on willingness to pay for shared and digitally booked transport, set inside the observed 2023 Nigerian fuel subsidy removal in which petrol rose between 138.8 and 154.1 percent across the three study states while within-city bus fares rose 67.9 to 116.4 percent and motorcycle fares only 5.3 to 46.2. Those movements are read from the published monthly series.

The result we would carry elsewhere is about how much of an affordability answer the analyst supplies. A multinomial logit, a mixed logit and two- and three-class latent class models were fitted to identical choices. The multinomial logit holds preferences homogeneous and returns a single willingness to pay rather than a share of the market, and across the other three the estimated share falling below an assumed 431 naira cost of provision is 48.2 percent under the mixed logit, 54.6 under the two-class model and 62.6 under the three-class one, a spread of 14.4 percentage points that no respondent contributed to. Goodness of fit does not order those three figures usefully: on every information criterion the three-class latent class model ranks first of the three, the two-class second and the mixed logit third, which is the exact reverse of their order on the share below cost, so the specification the criteria select is the one that would justify the largest subsidy.

A second finding sits in the same estimation. The information criterion selects three latent classes on choices whose entropy R^2 falls from 0.852 to 0.701 and whose mean maximum posterior probability falls from 0.958 to 0.862 at that third class, so the criterion prefers a solution its own separation diagnostics reject, and that solution sits at the top of the fourteen-point range.

Reporting a range across specifications rather than a point from whichever fits best therefore costs little and prevents a specific, demonstrable class of error.

What would improve on this is a second fielding at a different fare level, and a revealed preference record to check the stated answers against once the service has run long enough outside Lagos to leave one.

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