Internet Use and Business-Start Occupational Preference in Nigeria: Linking Afrobarometer Survey Data to Geospatial Broadband Performance

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ABSTRACT: This study brings national survey evidence together with an independent spatial measure of broadband performance to examine a specific occupational choice: whether Nigerians would rather start a business than work for an organisation. Afrobarometer Round 10 interviewed 1,600 adults between 19 June and 17 July 2024. We matched respondents by local government area (LGA) to Ookla mobile Speedtest tiles for the second quarter of 2024 and estimated household-weighted generalised estimating equations with standard errors clustered by LGA. Among the 1,544 respondents who selected one of the four occupational alternatives, 62.3% preferred to start a business. In the full survey model, movement to the next internet-use category was associated with lower odds of choosing business start-up (OR = 0.766, 95% CI [0.673, 0.872]). Estimates for the separate use categories point mainly to a difference between users and non-users rather than a regular dose-response pattern. The geospatial model covered 1,158 respondents in 47 LGAs. A one-standard-deviation increase in logged download performance produced an imprecise estimate (OR = 1.120, 95% CI [0.897, 1.399]). The corresponding interval from 1,999 stratified cluster-bootstrap replications was [0.864, 1.446], while leave-one-LGA-out estimates ranged from 1.048 to 1.169. Results for upload speed, latency and the cross-level interaction were similarly inconclusive. The findings show why reported internet use, measured local network performance, occupational preference and actual business entry should not be treated as interchangeable indicators.

KEYWORDS: Afrobarometer; Geospatial Broadband Performance; Internet-Use Frequency; Business-Start Occupational Preference; Occupational Choice; Mobile Network Performance

I. INTRODUCTION

Internet connectivity reduces many of the costs attached to information, communication, payments, coordination and contact with customers. These benefits have encouraged an appealing proposition: as internet use rises, entrepreneurship should rise with it. The proposition is incomplete. The same technology broadens access to vacancies, training, professional networks, platform work and remote employment. Connectivity may make it easier to start a business while also making jobs in established organizations more attractive. Our concern is therefore not whether broadband has economic value. We ask a narrower question: when several occupations are available, how is connectivity related to the preference for business ownership? This distinction carries particular weight in Nigeria. Self-employment includes opportunity-seeking ventures, but it also includes livelihood activity undertaken because paid employment is limited. Some people value ownership for autonomy and expected returns; others may see it as the least unattractive option in a difficult labour market. Better connectivity can help an existing firm

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without changing anyone's preferred occupation. It may even weaken stated interest in ownership if it reveals better employment opportunities. In practice, the value obtained from a connection also depends on devices, data prices, electricity, skills, payments, logistics, finance and trust (World Bank, 2019). Broadband belongs to a wider productive system. It is not a uniform intervention with one predictable behavioural effect.

The dependent variable comes from an Afrobarometer question asking respondents where they would choose to work if any sector were open to them. The alternatives were government or public-sector employment, a private company, a non-governmental organization (NGO), starting one's own business, and residual responses. This is a question about occupational preference. It does not reveal how strongly the preference is held, whether preparations have begun, whether a firm is owned or registered, or whether a venture survives, innovates or grows. Research on entrepreneurial intention has long shown that attitudes and preferences translate imperfectly into conduct (Kautonen et al., 2015). We therefore use the term business-start preference throughout. Calling the outcome entrepreneurial participation would overstate what the survey records.

A substantial Nigerian literature on digital enterprise draws evidence from entrepreneurs, students or residents of particular locations, often using respondents' perceptions of technology. Such studies offer insight into practice, yet they cannot compare business ownership with rival occupations in a national probability sample. This study adds something different. It links a nationally representative Afrobarometer survey to an independently observed, geospatial measure of local broadband performance from Ookla and keeps the two connectivity concepts separate: reported individual internet use and measured LGA-level network performance. The novelty is therefore not merely the use of two datasets; it is the ability to examine personal use, local technical performance and occupational preference in the same empirical framework while making the geographic support and test-density limitations visible. Afrobarometer provides individual internet use, occupational preference and personal characteristics. Ookla supplies spatial evidence from tested mobile connections. The join is made at LGA level rather than at household coordinates. This arrangement allows reported use and surrounding network performance to appear in the same model without treating them as interchangeable constructs.

The empirical work addresses three questions. First, is internet-use frequency positively or negatively associated with business-start preference, and does the relationship resemble a straight-line progression? Second, after individual characteristics and geopolitical zone are taken into account, is measured mobile broadband performance in the LGA related to that preference? Third, does local download performance change the association between personal internet use and occupational choice? The contribution lies in linking national probability-survey responses to an external geospatial infrastructure measure while preserving a strict construct distinction between individual use, local network performance, occupational preference and actual entrepreneurial behaviour. Unlike studies based only on perceived access or entrepreneur samples, the design places business-start preference alongside competing organisational occupations and subjects the contextual broadband estimate to coverage audits, density thresholds, cluster-bootstrap intervals and leave-one-LGA-out checks. These features clarify what the linkage can and cannot support; they do not turn the cross-section into a causal design.

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II. RELATED WORKS

A. Internet Use, Local Broadband Performance and Effective Use

Digital-entrepreneurship research explains how programmable technologies, platforms and shared infrastructure can loosen geographical and organizational constraints on entrepreneurial activity (Nambisan, 2017; Sussan & Acs, 2017). They may lower the cost of experimentation, coordination and distribution and reshape the development of entrepreneurial ecosystems (Autio et al., 2018). More recent reviews place infrastructure within a system that also contains capabilities, institutions, finance and demand (Camps et al., 2026; Cruz & Zhu, 2023). That broader view is especially important where electricity, devices, skills, logistics and confidence in digital transactions remain uneven. There is also a difference between a conventional enterprise that uses digital tools and an enterprise whose product or business model is digital. The Afrobarometer item identifies neither category. It asks about occupational preference before entry and gives no indication of how a prospective business might use technology. Digital-entrepreneurship theory can suggest an enabling route, but the observed outcome remains a preference to start a business of any kind. Reviews of digital transformation among small firms in sub-Saharan Africa describe operational and resilience gains alongside continuing constraints in skills, cost, infrastructure and organizational readiness (Achieng & Malatji, 2022). Evidence about established firms should not be carried over mechanically to the choice of an occupation. Infrastructure has consequences through use, not simply through presence. A faster network expands what is technically possible, but users differ in devices, electricity, data budgets, knowledge and complementary services. The World Development Report 2016 referred to these conditions as analogue complements (World Bank, 2016). Nigerian evidence likewise shows that physical access does not automatically confer digital capability, and that both vary by place, education, wealth and gender (De Simone & Manolio, 2024). Ookla's indicators summarize tested connections within an LGA. They cannot show that service reached every resident, that households could afford it, or that it was used effectively. Individual frequency of use and local technical performance are related ideas, but they are not the same construct.

B. Business-start Occupational Preference and Rival Theoretical Accounts

Occupational-choice models regard entrepreneurship and paid employment as competing uses of a person's time and resources. Expected income, autonomy, risk, effort, entry costs and the opportunities forgone all enter the comparison (Amit et al., 1995; Douglas & Shepherd, 2002). A preference for business ownership follows when its expected utility exceeds that offered by the best organizational job. Internet use and network quality can alter both sides of this calculation. A positive relationship with business preference should arise only where their contribution to entrepreneurial utility is greater than their contribution to employment utility. The enablement account predicts a positive association with business-start preference. Faster and more reliable connections can lower information, search and coordination costs, widen market reach, support digital payments and permit more flexible production. If these gains raise the expected utility of self-employment more than they improve the best organisational alternative, respondents who use the internet more frequently, or who live in better-performing network environments, should be more likely to prefer starting a business. Longitudinal evidence from Nigeria associates mobile broadband coverage with gains in household welfare and labour-force participation, indicating that connectivity can alter the opportunity set (Bahia et al., 2024). The spread of fast internet has also changed employment outcomes elsewhere in Africa (Hjort & Poulsen, 2019). These studies establish that connectivity can alter available opportunities, but they do not imply that the entrepreneurial margin must dominate.

The outside-option account predicts the opposite sign. Connectivity can improve access to vacancies, professional networks, online training, platform work and remote employment. If those gains raise the

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expected value of organisational employment more than they raise the expected value of a new venture, the relative preference for business ownership can decline even while connectivity remains economically beneficial. Afrobarometer contains no measure of expected earnings, job-search intensity, occupational motive or subsequent transition, so the models cannot identify this mechanism directly. The two accounts are therefore rival interpretations of the sign of the association, not observed mediators. The two accounts produce competing hypotheses. H1a (enablement) predicts a positive association between internet-use frequency and business-start preference; H1b (outside option) predicts a negative association. H2a predicts that higher LGA download and upload performance will be positively associated with business-start preference, while H2b predicts that higher latency will be negatively associated. H3 predicts that better local download performance will strengthen the association between personal internet use and business-start preference if infrastructure makes individual use more economically productive. Because an ordinal score can conceal threshold or non-monotonic patterns, internet use is estimated both as a linear term and as separate categories. In the interpretation, support for H1b is taken as evidence that the observed sign is more consistent with the outside-option account than with simple enablement; it is not treated as proof that internet use causes an employment-oriented preference.

C. Construct Definitions and Model Alignment

The analysis contains three focal constructs. Internet-use frequency is a reported individual behaviour. It records how often the respondent goes online. It says nothing about availability, digital skill, purpose, quality, business use or the return obtained from connectivity. This distinction follows the effective-use literature, which separates a physical connection from the capability and complementary resources needed to benefit from it (World Bank, 2016; De Simone & Manolio, 2024). Empirically, the construct is the five-category Afrobarometer Q90J item. We first treat it as an ordinal score and then estimate four category indicators against never-use. Local mobile broadband performance belongs to the LGA, not to the individual respondent. It represents the technical performance observed among user-initiated mobile tests within that area. The principal measure is the standardized logarithm of test-weighted mean download speed. Upload speed and latency enter as secondary dimensions in joint and sensitivity models (Ookla, 2024). The indicator is not a measure of coverage, subscription, affordability, device ownership, household speed or universal service quality. These limits matter because testing is voluntary and very uneven across space.

Business-start occupational preference is the outcome. It records whether starting a business is the respondent's first choice when considered alongside government, private-company and NGO employment. The concept is intentionally narrower than entrepreneurship. It is not a validated intention scale and does not demonstrate preparation, entry, ownership, registration, survival, innovation or growth (Kautonen et al., 2015). The binary variable equals one for business start-up and zero for the three organizational-employment alternatives among respondents who supplied a valid modelled choice. Enablement and employment outside options are interpretive accounts, not observed variables, mediators or latent constructs. One expects connectivity to raise the relative value of starting a business; the other allows it to raise the value of organizational employment by more. The internet-by-download term asks whether the association between personal use and preference changes with local performance. It cannot identify either explanation. Keeping this boundary visible aligns the theory with the measurements, models and data-linkage claim made in the title.

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III. METHODOLOGY

A. Survey Source, Fieldwork, and Samples

NOIPolls, Afrobarometer's Nigerian fieldwork partner, interviewed a stratified probability sample of 1,600 citizens aged 18 years or older from 19 June to 17 July 2024 (Afrobarometer, 2025a, 2025b). Under the published design, national percentages have an approximate sampling margin of ±2.5 percentage points. The anonymized public file includes `withinwt_hh`, the Round 10 within-country household weight. We use that weight for national estimates, as directed by the survey manual, because it adjusts for enumeration-area population and household size. It was not multiplied by the older `withinwt_ea` weight. Of the 1,600 interviewees, 1,544 chose one of the four occupations included in the analysis. The survey-only model had complete information for 1,496 respondents living in 67 LGAs. Requiring a Q2 mobile-performance measure reduced the sample to 1,158 respondents in 47 LGAs. Missing survey variables therefore removed 3.1% of otherwise valid occupational choices; the loss associated with contextual coverage was much larger. Model 1R repeats the survey-only specification within the Q2-covered subsample, allowing a change in geographic composition to be distinguished from the addition of broadband performance.

B. Measures

Business-start Occupational Preference

The dependent variable takes the value one for respondents choosing “starting your own business” and zero for those choosing government, a private company, or an NGO. We excluded “none of the above,” refusals, don’t-know answers, and out-of-range codes before constructing the variable. The weighted proportion preferring business start-up is reported for both all 1,600 interviews and the 1,544 modelled choices. Reporting both denominators avoids the appearance of inconsistent percentages.

Internet-use Frequency and Individual Controls

Q90J records internet use as 0 = never, 1 = less than monthly, 2 = a few times monthly, 3 = a few times weekly, and 4 = daily. The main specification assumes equal spacing between these categories. A second specification uses four indicator variables, with never-use as the reference, to examine that assumption. The controls are community mobile-service availability, sex, urban residence, age in decades, a four-level education measure, and the average of five lived-poverty items concerning shortages of food, water, medical care, cooking fuel, and cash income. Binary indicators were constructed only from valid responses; missing and indeterminate answers were not treated as zeros.

C. Linking Afrobarometer to Geospatial Broadband Performance

The spatial data are Ookla mobile-performance tiles for the second quarter of 2024. This period runs from 1 April to 30 June, preceding most interviews and overlapping only the opening days of fieldwork. The source files contain zoom-level 16 tiles, approximately 610.8 metres at the equator, and retain tests with GPS-quality locations. For each tile they report mean download speed, upload speed, latency, test count and contributing devices (Ookla, 2024). Since users decide whether to run a test, the data describe tested connections. They are not a representative household census and should not be read as a direct measure of service availability. We placed the WGS84 centroid of each tile's bounding box within Nigeria's 2022 ADM2 polygons from geoBoundaries, which contains 774 LGAs (Runfola et al., 2020). Test and device counts were summed by LGA. Download, upload and latency were averaged using test counts as weights, consistent with Ookla's aggregation example. Afrobarometer and geoBoundaries LGA names were harmonized for case and punctuation and the resulting matches were checked. Respondents then inherited the aggregate for their matched LGA; no household coordinate or individual Speedtest record entered the

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analysis. Logged performance measures were standardized across the 501 Nigerian LGAs with at least one Q2 mobile observation, rather than across survey respondents. Accordingly, each odds ratio refers to a one-standard-deviation difference in the national distribution of covered LGAs.

Coverage of the linkage is materially incomplete and must condition interpretation of every broadband coefficient. Only 47 of the 67 sampled LGAs had a Q2 mobile observation, leaving 1,158 respondents in the principal contextual models rather than the 1,496 used in the complete survey model. The quantity of Ookla evidence also differs sharply between covered areas: the median covered LGA supplied only 13 tests, with an interquartile range of 3.5-46. Figure 1 therefore distinguishes sampled LGAs with no observation from those supported by fewer than five tests. The broadband results should be read as evidence from a geographically restricted, unevenly tested subset of the national survey, not as nationally complete estimates of local network quality. We repeat the analysis at minimum thresholds of 5, 10 and 20 tests, after pooling Q2 and Q3 mobile records, and with Q2 fixed-broadband performance. A centroid can assign a boundary tile to the wrong LGA, and an LGA mean can conceal substantial within-area inequality. Aggregation solves neither problem.

D. Estimation and Inferential Scope

Population-averaged logistic models were estimated by generalized estimating equations. We used a binomial family, an independence working correlation, `withinwt_hh`, and robust standard errors clustered by LGA. Model 1 uses all complete survey observations. Model 1R applies the same equation to the Q2-covered LGAs. Model 2 adds geopolitical-zone indicators and standardized logged mobile download performance. Model 3 enters download, upload and latency together. Model 4 centres internet use and interacts it with download performance. In each case the mean model is a conventional logit; the sandwich covariance allows residual dependence among respondents from the same LGA. This procedure does not reproduce every stratum and enumeration-area feature of Afrobarometer's full survey design. The choice of weighted GEE is deliberate because the principal estimand is population-averaged and the contextual exposure is assigned at LGA level. The household weight `withinwt_hh` corrects unequal selection in national descriptive and regression estimates, while the sandwich covariance permits residual dependence among respondents sharing the same LGA-level broadband exposure. A conventional design-based survey logit would represent strata and primary sampling units more fully, but it would not by itself solve dependence created by attaching a common contextual measure to all respondents within an LGA; multilevel logistic models would instead estimate conditional rather than population-averaged effects and would rely on distributional assumptions for the random effects. GEE therefore provides a transparent compromise aligned with the population-averaged research question and the level of contextual assignment. Its limitation is the relatively small number of contextual clusters: 47 in the principal broadband models and only 20 under the strictest density rule. For that reason, cluster-sandwich intervals are supplemented with a zone-stratified LGA bootstrap and leave-one-LGA-out analysis, and interval width is given more weight than a simple significant-insignificant label. Zone indicators absorb broad regional differences but cannot account for confounding within zones.

Additional equations compare business start-up separately with government, private-company and NGO employment. This shows whether the combined result is driven by one comparator. For the categorical internet model, average marginal predictions are obtained by assigning each use category to every observation in turn and calculating the `withinwt_hh`-weighted mean probability. The result is population standardized; it is not a prediction for a fictional person with average characteristics. Tests are two-sided and intervals are 95%, with exact p-values retained. The sensitivity exercises are diagnostic, so an isolated p-value is not treated as an independent discovery. Two further exercises examine how strongly the download estimate depends on the available LGAs. Model 2 is first re-estimated 47 times, omitting a

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different covered LGA on each run. A second exercise draws 1,999 bootstrap samples of LGAs with replacement within geopolitical zones. Regional representation is thereby retained, while the respondent composition of sampled clusters is allowed to recur. The percentile bootstrap interval supplements the prespecified cluster-sandwich interval; it does not replace it.

Table 1: Analytic Sample Flow

Stage	Respondents	LGAs
Survey observations	1,600	67
Valid four-alternative outcome	1,544	67
Complete survey model (M1)	1,496	67
Q2 mobile-covered models	1,158	47
Q2–Q3 mobile sensitivity	1,257	53
Q2 fixed-broadband sensitivity	661	23

Source: Verified reanalysis of Afrobarometer Nigeria Round 10 and Ookla 2024 Q2–Q3 files.

IV. RESULTS AND DISCUSSION

A. Survey Profile and Geospatial Linkage Support

Starting a business was preferred by 60.5% of the weighted full sample and by 62.3% of respondents who chose one of the four modelled occupations. The percentages differ only because their denominators differ. Within the sampled LGAs covered in Q2, median test-weighted mobile download performance was 26.28 Mbps (IQR 15.12–36.83). Median upload performance was 13.55 Mbps (IQR 9.43–17.22), and median latency was 54.2 ms (IQR 39.62–70.82). These are summaries of voluntary tests in covered locations, not measurements of respondents' own connections. Figure 1 displays the geographic basis of the Afrobarometer–Ookla join. Twenty sampled LGAs had no Q2 mobile observation, while several of the covered areas contributed fewer than five tests. The pattern shows where users happened to run Speedtests, not how the survey sample was allocated. The figure is therefore a measurement audit rather than a map of national broadband coverage. It makes the evidential base of the contextual models visible: 47 covered locations, unevenly observed.

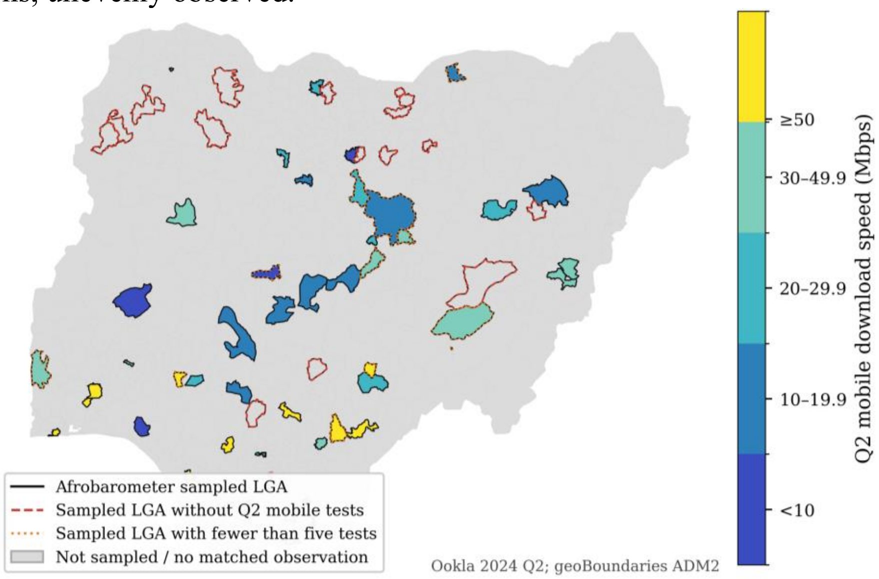

Figure 1: Geospatial Broadband Performance Linked to Afrobarometer Sampled LGAs: Q2 2024 Mobile Download Speed, Coverage and Test-density Flags

Source: Verified linkage of Afrobarometer Nigeria Round 10 sampled LGAs to Ookla 2024 Q2 mobile tiles using geoBoundaries Nigeria ADM2 polygons.

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B. Primary Associations

Model 1 associates a one-category rise in internet-use frequency with 23.4% lower odds of preferring business start-up (OR = 0.766, 95% CI [0.673, 0.872], $p < .001$). In practical terms, moving one step up the five-category use scale—for example, from never to less-than-monthly use or from monthly to weekly use—is associated, on average, with multiplying the odds of choosing business start-up by 0.766 rather than leaving those odds unchanged. This should not be read as a 23.4-percentage-point reduction in probability, because odds ratios and probabilities are not the same. When the same survey equation is restricted to respondents in Q2-covered LGAs, the estimate changes little (M1R OR = 0.739, 95% CI [0.641, 0.852], $p < .001$). The inverse relationship is therefore not an artefact created by adding the broadband variables, nor is it explained by the geographic restriction alone. After adjustment for geopolitical zone, a one-standard-deviation rise in logged Q2 mobile download performance gives an odds ratio of 1.120 (95% CI [0.897, 1.399], $p = .317$) in Model 2. The point estimate corresponds to roughly 12% higher odds of preferring business start-up, but the confidence interval ranges from about 10% lower odds to about 40% higher odds. The data therefore do not locate the association precisely enough to support either a positive or a negative substantive claim. With download, upload and latency entered together, the odds ratios are 1.199 [0.900, 1.598], 0.894 [0.695, 1.151] and 1.028 [0.867, 1.220], respectively. Every interval includes one. This is not evidence that the effects are equivalent to zero; it means that associations of modest size in either direction remain compatible with the data. Community mobile-service availability is imprecisely estimated in the full sample and negative in the Q2-covered equations. Its coefficient changes with sample support and adjustment, making a substantive claim that mobile service reduces business preference untenable. Age passes the .05 threshold only in contextual models, while education is marginal in Models 1 and 1R. These isolated movements among correlated controls are not treated as central findings.

Table 2: Household-weighted GEE Estimates for Primary Models

Predictor	M1	M1R	M2	M3
Internet-use frequency	0.766 [0.673, 0.872]	0.739 [0.641, 0.852]	0.735 [0.636, 0.850]	0.735 [0.636, 0.849]
Community mobile service	0.847 [0.598, 1.199]	0.619 [0.447, 0.856]	0.629 [0.434, 0.913]	0.630 [0.430, 0.925]
Mobile download (log SD)	-	-	1.120 [0.897, 1.399]	1.199 [0.900, 1.598]
Mobile upload (log SD)	-	-	-	0.894 [0.695, 1.151]
Mobile latency (log SD)	-	-	-	1.028 [0.867, 1.220]
Woman	1.224 [0.951, 1.576]	1.108 [0.843, 1.458]	1.176 [0.888, 1.556]	1.176 [0.888, 1.558]
Urban	1.063 [0.765, 1.477]	1.290 [0.873, 1.908]	1.287 [0.852, 1.946]	1.298 [0.860, 1.959]
Age (10 years)	1.053 [0.946, 1.172]	1.098 [0.978, 1.234]	1.134 [1.008, 1.274]	1.134 [1.008, 1.275]
Education (four levels)	0.816 [0.666, 1.000]	0.813 [0.660, 1.000]	0.837 [0.690, 1.016]	0.839 [0.692, 1.019]
Lived poverty	0.961 [0.799, 1.155]	1.002 [0.800, 1.254]	0.984 [0.781, 1.240]	0.982 [0.777, 1.242]
Zone indicators	No	No	Yes	Yes
N / LGA clusters	1,496 / 67	1,158 / 47	1,158 / 47	1,158 / 47

Source: Verified reanalysis. Entries are odds ratios [95% confidence intervals].

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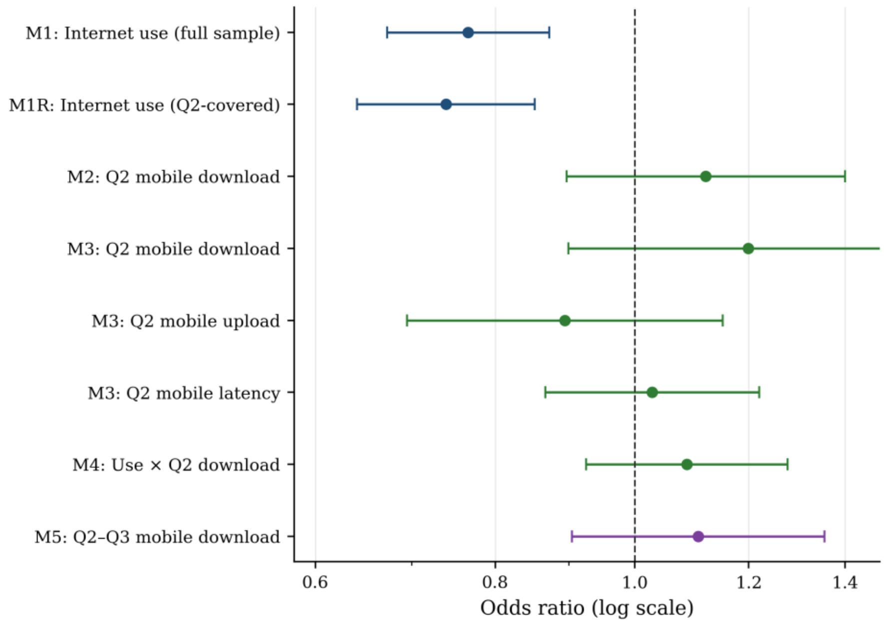

Figure 2: Selected Connectivity Coefficients from Primary and Pooled-Quarter Models
Source: Verified reanalysis; points are odds ratios and bars are 95% confidence intervals.

The contextual point estimate is not being held in place by one LGA. Across the 47 leave-one-LGA-out versions of Model 2, the odds ratio ranges from 1.048 to 1.169, with a median of 1.118. The 1,999-replicate bootstrap, stratified by geopolitical zone, yields a 95% percentile interval of [0.864, 1.446]. That interval is wider than the cluster-sandwich interval, although the substantive reading is unchanged: a modest negative association and a moderate positive association are both compatible with the evidence. Figure 3 separates the stability of the point estimate from the uncertainty surrounding it.

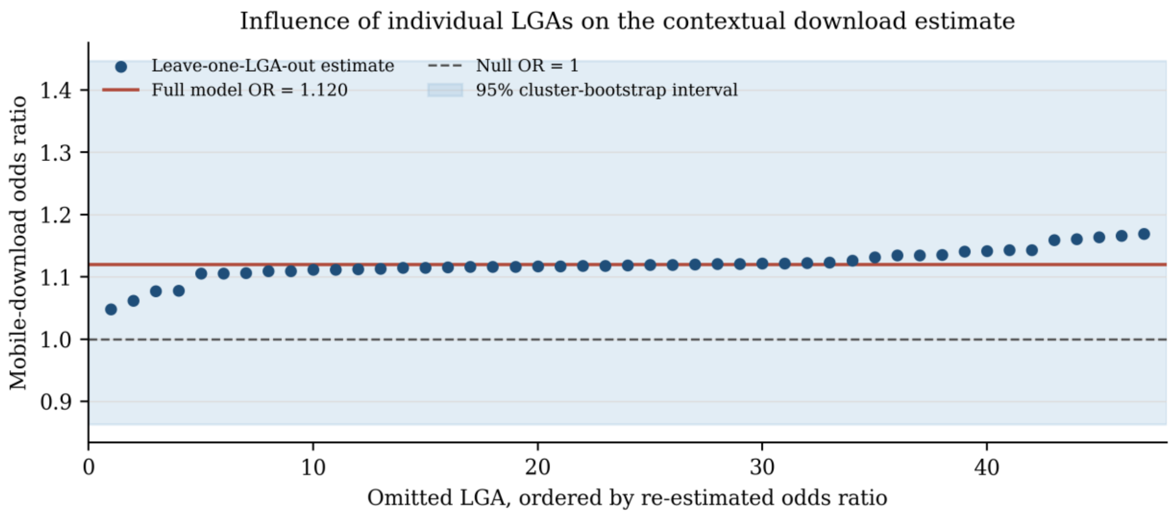

Figure 3: Leave-one-LGA-out Influence and Cluster-bootstrap Uncertainty for the Q2 Mobile-Download Estimate
Source: Verified reanalysis of Model 2; the shaded band is the 95% percentile interval from 1,999 zone-stratified LGA-cluster bootstrap samples.

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C. Functional Form, Interaction and Sensitivity

The internet-use-by-download interaction is also imprecise (OR = 1.087, 95% CI [0.925, 1.276], p = .312). Pooled Q2–Q3 mobile download produces OR = 1.107 [0.905, 1.354], and Q2 fixed download produces OR = 1.103 [0.910, 1.337]. Imposing minimum test counts leaves the sign positive but reduces the available clusters: OR = 1.155 [0.850, 1.569] for at least 5 tests, 1.103 [0.798, 1.524] for at least 10, and 1.202 [0.827, 1.746] for at least 20. The intervals widen as sparsely tested LGAs are removed, which is the expected price of demanding denser spatial evidence. The negative internet-use association persists when business start-up is compared separately with government employment (OR = 0.847, 95% CI [0.727, 0.985]), private-company employment (OR = 0.711, 95% CI [0.580, 0.873]) and NGO employment (OR = 0.685, 95% CI [0.563, 0.833]). No single employment alternative accounts for the result obtained from the pooled comparison. The separate use categories do not describe a smooth dose-response relationship. Relative to never-use, the odds ratios are 0.466 [0.299, 0.726] for less-than-monthly use, 0.341 [0.206, 0.564] for monthly use, 0.277 [0.162, 0.474] for weekly use and 0.333 [0.194, 0.573] for daily use. The standardized probability falls from 0.777 among non-users to 0.620, 0.546 and 0.494 over the next three categories, before rising to 0.540 for daily users. The pronounced difference is between no use and some use. Daily use is not associated with a lower probability than weekly use.

Table 3: Prespecified and Diagnostic Sensitivity Analyses

Analysis	Focal estimate	N / LGAs
Internet × Q2 mobile download	1.087 [0.925, 1.276]	1,158 / 47
Q2–Q3 mobile download	1.107 [0.905, 1.354]	1,257 / 53
Q2 fixed download	1.103 [0.910, 1.337]	661 / 23
Q2 mobile, ≥5 tests	1.155 [0.850, 1.569]	914 / 34
Q2 mobile, ≥10 tests	1.103 [0.798, 1.524]	763 / 27
Q2 mobile, ≥20 tests	1.202 [0.827, 1.746]	593 / 20
Internet: business vs government	0.847 [0.727, 0.985]	1,238 / 67
Internet: business vs private company	0.711 [0.580, 0.873]	1,111 / 67
Internet: business vs NGO	0.685 [0.563, 0.833]	1,043 / 67

Source: Verified reanalysis. Estimates are odds ratios [95% confidence intervals].

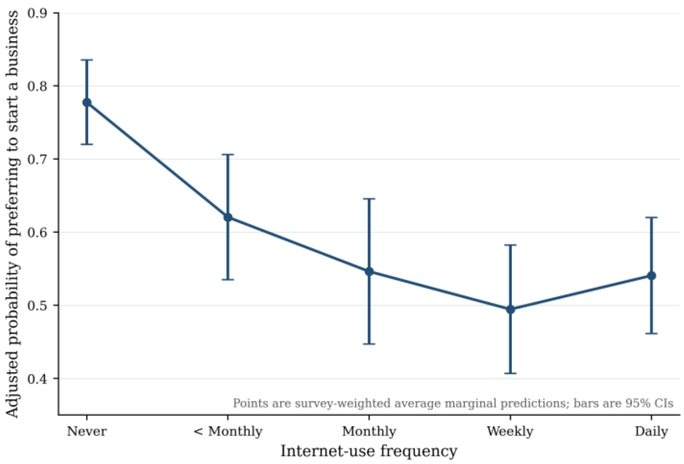

Figure 4: Survey-Weighted Average Predicted Probability of Business-start Preference by Internet-use Category

Source: Verified reanalysis; bars are 95% confidence intervals.

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For this occupational-choice outcome, the evidence fits the outside-option account better than a simple enablement story. Internet users are less likely than non-users to state that they would prefer starting a business over working for an organisation. The result concerns relative occupational preference only. It does not show that internet use discourages entrepreneurship, reduces business formation, harms existing entrepreneurs or caused the stated preference. Indeed, connectivity may improve entrepreneurial productivity while simultaneously making paid employment more attractive. Several relevant influences are absent from the data, including income, present occupation, digital capability, job-search behaviour, local labour-market conditions and subsequent entrepreneurial action. The negative coefficient therefore supports H1b only at the level of observed occupational preference; it does not identify the outside-option mechanism itself. The form of the relationship is as important as its direction. Treating frequency as a linear score gives a concise average, but the categorical estimates place the main division between respondents who never use the internet and those who use it at least occasionally. Weekly and daily use do not continue a descending sequence. A theory based solely on progressively greater digital exposure is therefore hard to defend. User status may instead capture a bundle of literacy, device access, networks, income prospects and attachment to the labour market. Future surveys need measures of purpose, task complexity, device constraints, data costs and skill if they are to explain this pattern convincingly. The objective network measures are not precise enough to decide between enablement and outside options. Several features of the design help explain this. Exposure is assigned at LGA level, the main contextual equation rests on 47 clusters, Speedtest participation is selective, and an area mean may hide large neighbourhood differences. The leave-one-LGA-out exercise shows that the positive point estimate does not depend on a single locality. The broader bootstrap interval, however, confirms substantial uncertainty. Download, upload and latency in Model 3 are correlated properties of the same service. Ranking their p-values, or interpreting them as proof of no infrastructural effect, would be misleading. The linkage also clarifies what is gained, and what remains unknowable, when a national survey is joined to external geospatial infrastructure data. Reported personal use is kept separate from the performance of tested connections in the surrounding LGA. At the same time, gaps in coverage and thin testing become part of the reported evidence. This brings occupational choice into analysis of the digital environment before entry. Connectivity may change several returns simultaneously: the return to starting a firm, running an existing enterprise, accepting salaried or remote work, and acquiring training. Such simultaneous effects help reconcile the inverse preference association with Nigerian evidence of welfare and employment gains from broadband (Bahia et al., 2024). The outcome cannot distinguish these movements and should not be presented as evidence of a general decline in entrepreneurship.

D. Policy and Research Implications

Nothing in the findings supports slower broadband investment or treating non-users as a reserve of latent entrepreneurs. The survey result shows only that internet users are less likely to prefer business start-up relative to organisational employment; it does not show that connectivity reduces actual entrepreneurship. The imprecise LGA-performance estimates also provide no basis for claiming that faster local broadband alone raises business-start preference. The policy implication is therefore one of complementarity rather than retrenchment. Broadband investment should continue, but enterprise policy should pair connectivity with the factors that can convert access into productive entrepreneurial use—reliable electricity, affordable devices and data, digital and commercial skills, secure payments, logistics, finance and consumer trust. This recommendation follows directly from the empirical separation between individual use and local network performance: neither is sufficient evidence of entrepreneurial conversion. Evaluation should likewise distinguish employment effects, occupational preferences, nascent activity and actual business entry rather than treating them as one outcome. The stronger next step is longitudinal.

Repeated observations could follow the movement from preference to search, nascent activity, registration, entry, survival, job creation, innovation and performance. More persuasive studies of infrastructure might exploit dated network rollout, signal coverage, outages or price changes at a finer spatial scale. Multinomial models could preserve the occupational alternatives instead of collapsing them. Administrative links or panel surveys could then reveal whether connectivity changes actual transitions, while qualitative evidence could explain why users favour one occupation over another.

E. Limitations

Six limitations define the reach of the study. First, cross-sectional evidence cannot establish sequence or causation. The timing of Q2 performance is useful, but it is not exogenous. Second, the outcome is one hypothetical occupational choice, not a validated intention measure or observed entrepreneurial behaviour. Third, internet-use frequency contains no information about purpose, digital skill or business use. Fourth, the geospatial join is contextual and incomplete: only 47 of 67 sampled LGAs enter the main broadband models, covering 1,158 respondents, and the median covered LGA has only 13 Ookla tests. An LGA mean is not the respondent's connection, and voluntary Speed tests are not a representative sample of residents. Fifth, the weighting/GEE strategy is a population-averaged approximation aligned with LGA-level contextual exposure; it does not reproduce every Afrobarometer stratum and enumeration-area feature, and inference with 47 contextual clusters remains finite-sample sensitive despite bootstrap and leave-one-cluster checks. Sixth, unmeasured income, employment status, digital capability, local labour demand and other confounders may influence both internet use and occupational preference.

V. CONCLUSION

Within those limits, two descriptive findings stand out. First, internet users report a lower relative preference for business start-up than non-users. The magnitude is substantial in the odds-ratio models and persists across occupational comparators, but it is a finding about stated occupational preference, not evidence that internet use suppresses actual entrepreneurship. Second, the LGA broadband-performance measures do not yield a precise independent association. The first result is more consistent with the outside-option hypothesis than with simple enablement, while the second leaves the infrastructure hypothesis unresolved. The broadband result remains uncertain when quarter, connection type and minimum test density are altered, and after 47 leave-one-LGA-out estimations and a zone-stratified cluster bootstrap. Taken together, the findings reinforce the manuscript's central distinction: reported internet use, local technical performance, occupational preference and realised business entry are related but analytically different outcomes.

Data Availability, Reproducibility and Ethics

Afrobarometer Nigeria Round 10 public-use data, its questionnaire and supporting survey records are available at https://www.afrobarometer.org/survey-resource/nigeria-round-10-data-2024/. The analysis used `NIG_R10.Data_18Nov24.wtd_.final_.release_updated.13Feb25.csv`. Ookla files and documentation are available through https://github.com/teamookla/ookla-open-data and the AWS Open Data Registry. The principal archive was `2024-04-01_performance_mobile_tiles.zip`; Q3 mobile and Q2 fixed records were used only for sensitivity checks. The Nigeria ADM2 layer was geoBoundaries `NGA-ADM2-59680162`, representing 2022 boundaries. All sources were accessed on 2 August 2026. Ookla notes that its aggregates may later change in response to data-subject requests, so the access date and exact filename form part of the reproducibility record. Only anonymized public-use records were analyzed. The researchers had no contact with respondents and made no attempt to identify them. LGA names served solely as keys for attaching contextual measures. Afrobarometer's questionnaire records voluntary informed consent, confidentiality and the right to decline participation. The authors declare no conflict of interest and received no specific funding for the study.

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