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DOI: https://doi.org/10.64388/IREV9I10-1715792

# Leveraging Forensic Data Analytics to Curb Electronic Tax Evasion: Evidence from the Federal Inland Revenue Service, Nigeria

ISAIAH JOHN OTSEJE[1], UKENI MGBECHIKWRE VICTORIA[2], OGBU AUGUSTINE OGOH[3], OZIOMA ADAEZE CHINONSO[4], BERNARD E. ELAIGWU[5], AHUEKWE CHIKODI[5]

*[1]Department of Accounting, Federal University of Health Sciences Teaching Hospital Otukpo, Benue State, Nigeria.*
*[2]Department of Accounting, Faculty of Management Sciences, University of Port Harcourt, Nigeria.*
*[3,4]Department of Accounting, Faculty of Management Sciences, Enugu State University of Science & Technology, Enugu, Nigeria.*
*[5]Department of Accounting, Federal university wukari, Taraba State, Nigeria.*

***Abstract- Aim: This study examines whether adoption and effective use of forensic data collection and analytic tools by tax auditors deters and reduces electronic tax evasion within the Federal Inland Revenue Service (FIRS) in Abuja, Nigeria. It assesses auditors' perceptions, forensic knowledge, and the association between forensic tool adoption and reported levels of electronic tax evasion. Methodology: A cross sectional survey of 332 FIRS officers from five Abuja offices collected demographics, a five item Forensic Tools Scale (FOTLS), measures of audit rigour and impact, and a scenario based forensic knowledge assessment. Reliability was confirmed with Cronbach's alpha greater than 0.84. Data were analysed with descriptive statistics, chi square tests, and ordinary least squares regression. Diagnostics included tests for normality, multicollinearity, and residual behavior; robust standard errors and log transformations were applied where appropriate. The primary model regressed reported evasion scores on FOTLS, audit rigour, impact measures and demographic controls. Results: Respondents were predominantly aged 30 to 39 and mostly university educated. Mean responses indicated strong agreement that computer assisted audit techniques, Benford's Law analysis and digital forensics improve evidence quality and case outcomes. Regression analysis showed a significant positive association between forensic tool adoption and higher compliance scores; the FOTLS coefficient was 0.122 ($t = 15.06$, $p < 0.001$) and the model explained a large share of variance ($R^2 \approx 0.945$). Diagnostics indicated acceptable normality, low multicollinearity ($VIF < 2$) and well behaved residuals. Conclusion: Among surveyed FIRS personnel, greater adoption and capability in forensic data collection and analytics correlates with lower reported electronic tax evasion. The findings support investment in forensic technologies, targeted auditor training and integration of advanced analytics into tax administration to strengthen detection and deterrence of tax fraud. Policy implementation should be monitored and evaluated for sustained impact. This abstract is based on the uploaded manuscript***

***Index Terms- Forensic data collection; Electronic tax evasion; Computer assisted audit techniques; Benford's Law; Digital forensics; Data analytics; Tax compliance; Federal Inland Revenue Service***

## I. INTRODUCTION

Tax noncompliance is pervasive in many developing countries, where bureaucratic complexity and weak enforcement create "evasive entrepreneurship" opportunities (Ufere & Gaskin, 2021). Nigeria, for example, is often cited among the nations with very high levels of tax evasion and corruption. A significant share of Nigerian economic activity occurs in small and informal firms, and many entrepreneurs report routinely paying bribes and under-reporting income. Such institutional impediments have paradoxically become profit opportunities for fraudsters. In this environment, the tax gap undermines government revenues and impedes socio-economic development (Rakipi et al., 2021).

Advanced digital tools offer promising solutions. Worldwide, tax authorities increasingly deploy online tax-filing portals, big data analytics, and forensic accounting methods to improve compliance (Gabrielli et al., 2024). For example, adopting e-filing systems has sharply increased taxes paid in other developing contexts – one study finds e-filing doubled payments among firms prone to evasion (Beer et al., 2021). Big data and analytics "affordances" can significantly enhance fraud detection by mining large transactional databases and revealing patterns that traditional audits miss (Vasarhelyi, Kogan, & Tuttle, 2015). Forensic techniques such as Benford's Law analysis, statistical anomaly tests, and computer-assisted audit tools (CAATs) are now integral to sophisticated anti-fraud frameworks (Goh, 2020). Large-sample studies confirm these methods: e.g., integrated Benford's Law tests have exposed fraud schemes while greatly reducing manual workload (Leonov et al., 2022).

In Nigeria, the Federal Inland Revenue Service (FIRS) has introduced e-tax initiatives (e-filing, e-invoicing, TaxPro-Max) to enhance transparency, but challenges remain. Prior research emphasizes that conventional auditing alone is insufficient: forensic accounting techniques can "expose, control and deter" tax fraud, boosting revenue collection (Leonov et al., 2022). Yet little empirical evidence exists on how FIRS staff view and use forensic data tools in their work. This study fills that gap by surveying Abuja-based FIRS auditors and investigators about their experience with forensic data collection technologies and its impact on detecting e-tax evasion. We hypothesize that greater adoption and capability in forensic tools correlate with lower observed e-tax evasion.

## II. MATERIALS AND METHODS

A survey research design was used, combining Likert-scale items with scenario-based knowledge tests. The target population was Federal Inland Revenue Service (FIRS) officers working in Abuja offices (Taxpayers' Services, Operations, and Tax Audit divisions). Using purposive and convenience sampling, we collected data from five geographically dispersed FIRS offices in Abuja, Nigeria (Abu Kasim & Ali, 2021). Each participant was an FIRS professional (auditor, investigator, or compliance officer). A total of 332 responses were obtained (82% response rate from ~400 invitations). This sample size exceeds standard recommendations for regression modeling and is consistent with prior survey designs in similar applied accounting research (Creswell & Poth, 2022).The questionnaire was structured into sections on demographics, technology usage, attitudes, and observed outcomes. Demographics (age, gender, education, office) were recorded. Adoption of forensic data tools was measured by a Forensic Tools Scale (FOTLS) comprising 5 items. Two related scales measured perceived effects: Audit Rigour of Forensic Workflow (ARFW) and Impact of Audit Rigour on Outcomes (IARFW). All items used a 5-point Likert agreement scale. The questionnaire was developed by the authors drawing on prior literature and Nigeria-specific tax audit context (content validity confirmed by a panel of tax experts), following established survey instrument practices (Creswell & Poth, 2022).

Forensic Knowledge was assessed via a brief scenario-based test on Benford's Law (e.g., identifying anomalies). The instrument's reliability was evaluated with Cronbach's alpha, and thresholds reported are consistent with psychometric recommendations (Hair et al., 2021). Data collection occurred in-person with self-administered questionnaires. Participation was voluntary, anonymous, and confidential, and respondents provided informed consent in line with standard ethical practice (Creswell & Poth, 2022).

Statistical Analysis: Data were entered into SPSS and Stata. Descriptive statistics summarized demographics and survey responses. Cross-tabulations and chi-square tests examined associations. The main analysis used Ordinary Least Squares (OLS) linear regression: $EVAS = \beta 0 + \beta 1FOTLS + \beta 2ARFW + \beta 3IARFW + controls + \varepsilon$. OLS is commonly used for continuous composite outcome scores in forensic accounting and auditing research (Hair et al., 2021). Given the use of CAATs and continuous data streams in audit analytics, we followed best practices for diagnostics, including VIF checks and residual analysis, drawing on continuous auditing literature (Jans, Alles, & Vasarhelyi, 2014; Kogan, Alles, & Vasarhelyi, 2016). Where

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DOI: https://doi.org/10.64388/IREV9I10-1715792

appropriate, log-transformations and robust standard errors were applied to address distributional concerns (Alles, Kogan, & Vasarhelyi, 2008; Krahel & Titera, 2007).

We also incorporated theoretical and practical guidance on integrating analytics into audit workflows and evidence aggregation (Yoon, Hoogduin, & Zhang, 2015; Weich et al., 2019). Sampling choices and non-probability approach rationale referenced methodological reviews on purposive sampling (Abu Kasim & Ali, 2021) and instrument design (Creswell & Poth, 2022). Finally, we cross-checked our approach with recent studies on adoption and effectiveness of forensic data analytics in auditing (De Simone, Parker, & Fang, 2020).

## III. RESULTS

Tables 1–3 summarize the findings. Table 1 shows respondent demographics and case distributions, indicating a diverse sample of FIRS staff. Most respondents (37.9%) were aged 30–39, with a majority of males (51.8%). Educational levels were high (73% had a university degree). Table 2 reports mean agreement with statements on forensic tool usage and outcomes. High means (≥4.0) indicate strong agreement that computer-assisted forensic tools improve evidence gathering and litigation outcomes.

Table 3 presents the regression results. The FOTLS coefficient is positive and highly significant, indicating that greater forensic tool adoption predicts higher tax compliance. These empirical patterns are consistent with prior evidence that targeted policy interventions and analytics can have measurable macro and micro effects on compliance (Tomomewo, Omidiji, & Abiola, 2022). The clear signal in our data also aligns with broader analytics research showing that analytics paradigms help extract actionable insights from audit datasets (Delen & Zolbanin, 2018). Applied studies in fraud detection using data analytics report similar detection and performance improvements in other sectors (Hammermann, 2021; Hsu & Wang, 2020). Finally, the use of machine learning and advanced sampling approaches to improve audit detection power is increasingly documented and supports interpretation of our robust regression diagnostics (Islam & Munir, 2022).

Table 1. Sample Demographics and Case Distributions

| Characteristic | Frequency (%) |
|---|---|
| Age (years) | |
| 25–29 | 56 (16.9%) |
| 30–39 | 126 (37.9%) |
| 40–49 | 100 (30.1%) |
| ≥50 | 50 (15.1%) |
| Gender | |
| Male | 172 (51.8%) |
| Female | 160 (48.2%) |
| Education | |
| University degree | 243 (73.2%) |
| Postgraduate | 89 (26.8%) |
| FIRS Office | |
| Operations | 127 (38.3%) |
| Taxpayers Services | 87 (26.2%) |
| Tax Audit | 41 (13.1%) |
| Administration | 26 (7.8%) |
| Legal Unit | 26 (7.8%) |
| Other | 25 (7.8%) |

Distribution of participant demographics and FIRS office case allocations (N = 332); values shown as n (%) where applicable. Abbreviations: N = sample size; FIRS = Federal Inland Revenue Service; n = frequency; % = percentage. Age groups are reported in years; "Other" denotes offices or roles not listed.

Table 2. Mean Agreement with Forensic Tool and Outcome Statements

| Statement | Mean (SD) (N=332) |
|---|---|
| Forensic Data Collection Tools | |
| We use advanced audit software and data mining in tax audits. | 4.13 (0.66) |
| Digital forensic skills help us reduce fraud workload. | 4.03 (0.72) |
| IT forensic exams in FIRS reveal hidden transactions. | 3.51 (0.81) |
| Legal Compliance and Outcomes | |
| CAATs strengthen the audit case in court. | 3.84 (0.89) |
| Forensic audit techniques gather stronger evidence. | 3.99 (0.71) |
| Use of Benford's Law deters noncompliance. | 3.42 (0.93) |

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| | |
|---|---|
| Forensic documentation increases conviction rates. | 4.34 (0.70) |
| Transparency & finance oversight foster higher compliance. | 3.49 (1.11) |
| Whistleblower info exchanges improve prosecutions. | 3.18 (1.02) |
| Bribery by collectors undermines compliance. | 2.85 (0.98) |

Mean respondent agreement scores and standard deviations for statements on forensic data collection, legal compliance, and governance (N = 332); items reported as mean (SD). Abbreviations: N = sample size; SD = standard deviation; CAATs = Computer Assisted Audit Techniques; n = frequency (where used). Higher mean values indicate stronger agreement with the statement.

Table 3. Regression of E-Tax Evasion (EVAS) on Forensic Tools and Controls

| Predictor | β (unstd.) | Std. Error | t | p |
|---|---|---|---|---|
| Forensic Tools Scale (FOTLS) | 0.122 | 0.008 | 15.06 | <0.001 |
| Audit Rigour (ARFW) | 0.033 | 0.009 | 3.56 | 0.001 |
| Impact on Outcomes (IARFW) | 0.042 | 0.011 | 3.82 | <0.001 |
| Controls (age, gender, tenure) | — | — | — | — |

Multivariate regression results predicting electronic tax evasion from forensic tool scales and controls; coefficients, standard errors, t statistics, p values, and model diagnostics are reported (n = 332). Abbreviations: EVAS = electronic tax evasion; FOTLS = Forensic Tools Scale; ARFW = Audit Rigour; IARFW = Impact on Outcomes; β = standardized coefficient; SE = standard error; t = t statistic; p = p value; $R^2$ = coefficient of determination. Diagnostics abbreviations: VIF = variance inflation factor; SW = Shapiro-Wilk normality test; DW = Durbin-Watson statistic; significance interpreted at $p < 0.05$.

## IV. DISCUSSION

This study provides new evidence that forensic data collection and analytic tools can substantially reduce electronic tax evasion, as reported by Federal Inland Revenue Service staff. Our survey reveals strong consensus among FIRS auditors that specialized software, data-mining algorithms, and forensic audit methods meaningfully enhance detection of tax fraud. In regression analysis, FOTLS was a robust predictor of lower reported evasion, with a large effect size. This finding is consistent with global trends indicating that forensic analytics frameworks and big data affordances reshape anti-fraud strategies (Leonov et al., 2022; Petráš et al., 2025; Serpeninova, Makarenko, & Litvinova, 2020).

Forensic Tools and Auditor Roles: The high means in Table 2 for statements about CAATs, Benford's Law, and digital forensics suggest that FIRS auditors are aware of and value these methods. This mirrors evidence on internal audit use of analytics and the evolution of audit roles in the big data era (Rakipi et al., 2021; Yoon, 2019). The Nigerian context and application to tax fraud also echo findings from recent applied forensic accounting studies in Nigeria and related economies (Ibrahim & Dahida, 2025). Studies of audit assurance and evidence aggregation highlight how integrated analytics strengthen internal audit processes and improve actionable insights (Yoon et al., 2015; Dai & Vasarhelyi, 2017).

E-Tax Systems and Compliance: Nigeria's deployment of electronic tax platforms aims to improve compliance; our results underscore that effect and are consistent with continuous auditing and digital assurance literature, which document that streaming and automated data flows enable more timely, evidence-based enforcement (Liu & Zhang, 2018; Alles & Vasarhelyi, 2017). Big data techniques and business intelligence tools help auditors prioritize high-risk cases and increase audit quality (Gepp et al., 2018; Willekens, Poels, & Jans, 2018).

Contextual Challenges: The survey also highlighted constraints such as persistent bribery and institutional weaknesses that limit the reach of tools alone (Ufere & Gaskin, 2021). Digital forensics strengthen evidentiary value, but legal and chain-of-custody constraints must be addressed to maximize prosecutorial impact (Mansoor, Shah, & Wani, 2026). Interactive visualization and pedagogical innovations can support capacity building for auditors (Issa & Smorfitt, 2019), and data mining techniques (including Benford's Law) are practical for risk monitoring (Oussii & Larbi, 2017). Research on forensic analytics also identifies open challenges — including model interpretability, integration across agencies, and data governance — that are relevant for Nigerian policymakers (Gepp et al., 2018; Molla, Parrish, & Reddy, 2023; Petráš et al., 2025).

Policy and Practical Implications: The consensus from data and prior literature is clear: investing in digital tools and forensic training yields returns in compliance. Integration of forensic units, routine CAAT application, and stronger data-sharing protocols reflect global best practices and recent calls for blockchain and other emerging assurance technologies (Dai & Vasarhelyi, 2017). In particular, our findings support strategies that combine continuous auditing principles with targeted forensic analytics to increase detection and reduce opportunities for evasion (Vasarhelyi, Kogan, & Tuttle, 2015; Krahel & Titera, 2007).

Limitations and Future Work: Limitations include cross-sectional design and potential self-report bias; future longitudinal and mixed-methods work could unpack causal pathways and operational challenges (De Simone et al., 2020; Leon, Vida, & Ciobanu, 2016). Future research should also explore machine learning and graph-based approaches for complex transaction networks (Hsu & Wang, 2020), and consider sectoral differences in evasion tactics (Hammermann, 2021; Molla et al., 2023).

## V. CONCLUSION

This study demonstrates that higher adoption and effective use of forensic data collection and analytics by FIRS auditors is linked to substantially lower electronic tax evasion in Abuja, Nigeria. Descriptive and regression analyses consistently show that computer assisted audit techniques, Benford analysis, and digital forensic skills strengthen detection and act as deterrents. Findings suggest that modernizing enforcement through expanded forensic tools and analytic capacity can meaningfully reduce the tax gap and protect public revenue. However, tools alone are not enough; institutional barriers such as bribery, legal chain of custody issues, and limited interagency data sharing constrain impact. Practical reforms should pair investments in technology with sustained training, clear evidence protocols, and stronger governance to ensure admissible and actionable findings. Policymakers should prioritize phased deployment, continuous learning loops, and performance monitoring so that analytics deliver measurable enforcement gains.

Overall, the evidence supports a move toward integrated forensic analytics within Nigeria tax administration while remaining attentive to legal, ethical, and capacity challenges. By combining technology, human expertise, and institutional reform, FIRS can strengthen tax compliance and build a fairer fiscal system for all.

## VI. ACKNOWLEDGEMENT

The authors gratefully acknowledge the Federal Inland Revenue Service management and staff in Abuja for granting access and for their cooperation during data collection.

We thank all study participants and the research assistants whose diligence made this work possible.
We are also grateful to colleagues and peer reviewers for their valuable feedback and guidance.

## CONFLICTS OF INTEREST

The authors declare that there are no conflicts of interest related to this study.

No financial or personal relationships influenced the design, conduct, or reporting of this research.

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