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Behavioural reporting noise in digital tax administration: Compliance signal distortions under the UK making tax digital for income tax regime

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Abstract

Digital tax reforms that increase reporting frequency alter not only the reporting frequency of taxpayers but also the behavioural conditions that produce compliance information. This paper introduces behavioural reporting noise (BRN), defined as systematic distortions of reported compliance signals generated by adaptation to a reporting regime rather than underlying noncompliance. Using Making Tax Digital for Income Tax Self-Assessment (MTD-ITSA) as a motivating example, the paper develops a theoretical framework around three mechanisms: compressed categorisation under deadline pressure, precautionary underclaiming under uncertainty, and misalignment between quarterly submissions and annual declarations. Drawing on research on default effects, cognitive scarcity, and administrative burden, the paper argues that these mechanisms can generate directional and correlated bias in compliance data. The paper also outlines a research design for future empirical testing using HMRC's pilot population. It contributes to behavioural public administration by identifying BRN as a distinct analytical construct with implications for the design, interpretation, and evaluation of digital governance reforms.

Keywords: Digital Tax Administration; Behavioural Public Administration; Administrative Burden; Default Effects; Reporting Frequency; Compliance Signal Distortion; Making Tax Digital

1. Introduction

Behavioural public administration scholarship has examined how cognitive biases, defaults, and institutional architecture shape individual decision-making within administrative systems (Grimmelikhuijsen et al., 2017; Battaglio et al., 2019). Less attention has been paid to a related question: how changes in administrative reporting design can alter the statistical properties of the data that governance systems depend on, independently of any change in underlying behaviour. This article addresses that gap.

Making Tax Digital for Income Tax Self-Assessment (MTD-ITSA) requires sole traders and landlords with qualifying income above £50,000 to submit quarterly digital updates to HMRC from April 2026, replacing the single annual self-assessment return. The reform is the most fundamental change to the UK personal tax reporting cycle since self-assessment was introduced in 1996. Under the existing annual regime, returns are typically professionally reviewed with full-year context before submission. Under quarterly reporting, figures are likely to be prepared under compressed timelines, with heavier reliance on software defaults and partial records. This change is not merely procedural: it alters the conditions under which categorisation and reconciliation decisions are made, and those conditions are argued here to systematically distort the resulting compliance signals.

This article introduces the concept of *behavioural reporting noise* (BRN): systematic, directional variation in reported financial data generated by the conditions of the reporting process, as distinct from random measurement error or

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deliberate non-compliance. The concept draws on default effect theory (Thaler & Sunstein, 2008; Madrian & Shea, 2001), cognitive scarcity (Shah et al., 2012; Kahneman, 2011), and administrative burden theory (Herd & Moynihan, 2018; Moynihan et al., 2015). It extends established findings on third-party reporting and under-claiming (Kleven et al., 2011; Chetty et al., 2013) to the novel domain of software-mediated quarterly reporting.

This article develops a conceptual and theory-building framework. Its purpose is to define the BRN construct, ground it in established theory, derive testable propositions, specify boundary conditions, and design an empirical programme, not to test it. Three contributions are made. First, BRN is established as a construct distinct from measurement error, strategic under-reporting, and random compliance variation. Second, six formal propositions are derived with explicit boundary conditions. Third, a falsifiable empirical research design is proposed using HMRC's MTD pilot data.

The article proceeds as follows. Section 2 reviews four bodies of literature and identifies the analytical gap. Section 3 defines BRN and its properties. Section 4 develops the theoretical mechanism and derives the propositions. Section 5 illustrates the mechanisms through stylised taxpayer archetypes. Sections 6 and 7 address compliance operations and tax gap measurement implications. Section 8 proposes the empirical research design. Section 9 presents comparative evidence and boundary conditions. Section 10 concludes.

2. Literature Review and Analytical Gap

The article sits at the intersection of four bodies of literature, each capturing part of the relevant phenomenon without developing the construct that unifies them.

2.1. Behavioural Tax Compliance

The dominant compliance framework derives from Allingham and Sandmo's (1972) expected utility model, extended by work incorporating social norms, intrinsic motivation, and procedural fairness (Kirchler, 2007; Luttmer & Singhal, 2014). Most of this literature treats the reporting system as a stable background. Of particular relevance to BRN is the third-party reporting literature: Kleven et al. (2011) demonstrate that compliance rates are dramatically higher for income subject to third-party reporting, partly because it removes categorisation discretion. MTD-ITSA introduces an intermediate case of software-mediated reporting that automates data capture while preserving categorisation discretion. This intermediate case has not been analysed in the third-party reporting literature. Chetty et al. (2013) document persistent under-claiming of EITC entitlements attributable to eligibility uncertainty; the BRN framework extends this logic to quarterly deductibility decisions. Field experimental evidence on compliance nudges (Hallsworth et al., 2017; Kettle et al., 2017) confirms that structural features of reporting systems function as behavioural architecture shaping outcomes independently of taxpayer intent. Classic syntheses of tax compliance behaviour also support this broader framing (Andreoni et al., 1998; Torgler, 2007).

2.2. Default Effects, Cognitive Load, and Administrative Burden

Samuelson and Zeckhauser (1988) establish status quo bias as a pervasive decision feature under uncertainty; Madrian and Shea (2001) demonstrate its scale in retirement savings. Thaler and Sunstein (2008) formalise these effects within a choice architecture framework. Applied to tax categorisation, software defaults for transaction classification function as choice architecture that shapes categorisation outcomes when advisers resolve ambiguous items under deadline pressure. Shah et al. (2012) demonstrate that cognitive scarcity narrows attention toward the immediate constraint; Bertrand et al. (2004) show that cognitive load under resource pressure impairs complex financial decisions. The administrative burden literature (Herd & Moynihan, 2018; Moynihan et al., 2015; Burden et al., 2012) conceptualises burden as comprising learning, compliance, and psychological costs. MTD-ITSA increases reporting frequency without reducing categorisation complexity, a combination predicted to increase coping-strategy-driven inaccuracy (Evans et al., 2014; Alm, 2019).

2.3. Digital Tax Administration

The digital tax administration literature generally treats digitisation as compliance-improving (OECD, 2020; Okunogbe & Tourek, 2024). These assessments largely conflate two distinct effects: improvements in submission mechanics and changes in the behavioural conditions of data production. An improvement in mechanics may co-occur with degraded categorisation accuracy if digitisation simultaneously increases reporting frequency and embeds default categorisation architectures. The BRN framework argues this combination, not digitisation per se, is the key risk condition. Slemrod (2007) documents that categorisation complexity reduces compliance accuracy; MTD-ITSA increases the frequency at which complex categorisation decisions must be made under constrained conditions, without reducing their complexity.

Related work on e-filing adoption and electronic invoicing also links digitisation to compliance administration changes (Klun & Trkman, 2016; Barreix & Zambrano, 2018).

2.4. Administrative Signal Validity

Shadish et al. (2002) formalise construct validity: a measure has construct validity if it captures what it is designed to measure rather than the conditions of its production. The tax gap is designed to measure the behavioural difference between legal liability and reported figures. If the reporting process systematically shifts submitted data uncorrelated with true compliance behaviour, the tax gap will capture a mixture of behavioural and process-level variance, a validity problem, not merely a precision problem. Manski (1995) analyses identification problems in administrative data from selection and behavioural effects; these apply directly when quarterly data are produced under structurally different conditions from annual data. The analytical gap: none of these four literatures develops a construct isolating the reporting process itself as a source of systematic, directional distortion in compliance signals. BRN addresses this gap. Classic selection concerns in observational administrative data reinforce this identification problem (Heckman, 1979).

3. Defining Behavioural Reporting Noise

BRN refers to systematic, directional distortion in reported compliance signals generated by adaptation to a reporting system rather than by underlying non-compliance. It differs from intentional evasion because BRN does not require dishonest intent; from ordinary clerical error because clerical errors are isolated and unsystematic, whereas BRN is correlated and directional across a class of cases; and from measurement error, because measurement error describes a discrepancy without specifying the behavioural pathway, whereas BRN identifies the reporting process itself as the source.

Formally, let y* denote the true reportable liability under conditions of full information and professional support, and let y^h denote the figure actually submitted under quarterly reporting. BRN is the systematic component of the difference between the two: BRN = y^h − y*, where random measurement error is represented separately by ε. Four properties distinguish BRN from random error. First, directionality: E(BRN) ≠ 0. Second, correlation: BRN is positively correlated across taxpayers using the same software platform. Third, predictable concentration: BRN is concentrated in particular groups, categories, and reporting periods. Fourth, persistence followed by decay: BRN is expected to be greatest in the initial period and to decline over time as defaults are corrected and familiarity increases.

4. Theoretical Mechanism and Propositions

The theoretical mechanism is sequential: administrative redesign increases reporting frequency and narrows preparation windows; narrower windows change how taxpayers and intermediaries assemble figures; changed behaviour alters the reliability of observed compliance signals; and risk systems treating altered signals as equivalent to mature annual data may misclassify adaptation artefacts as non-compliance. Three pathways operate.

4.1. Pathway 1: Compressed Categorisation Under Deadline Pressure

Under the annual system, the adviser observes the full year of transactions before committing to categorisation. Under quarterly reporting, the adviser faces a backlog of auto-categorised items and must resolve them within approximately one month. Applying cognitive scarcity theory (Shah et al., 2012) and dual-process theory (Kahneman, 2011), deadline-driven scarcity predicts that advisers narrow attention toward submission completion, resolving ambiguous items using the least cognitively demanding option: the software default. This produces correlated directional errors across taxpayers using the same platform.

- **Proposition 1.** As reporting frequency increases, the probability should rise that submitted figures reflect categorisation decisions made under time pressure rather than fully reconciled judgements, with this effect expected to be stronger where software default categories diverge materially from the professionally correct categorisation.
- **Proposition 2.** Categorisation errors arising from deadline compression are expected to be correlated within the software platform, producing systematic within-platform anomaly clustering in expense distributions that should be absent from annually reviewed data.

4.2. Pathway 2: Precautionary Under-Claiming Under Uncertainty

Loss aversion under uncertainty (Kahneman & Tversky, 1979) predicts that individuals will accept a small certain loss (a foregone deduction) to avoid a potentially larger loss (penalty or investigation). Under quarterly reporting, the

adviser is unavailable for pre-submission review in many cases. Under incomplete information, the probability of allowance is systematically underestimated and the probability of challenge overestimated (consistent with prospect theory), making precautionary omission the dominant strategy even for genuinely allowable expenses.

- **Proposition 3.** Taxpayers with high deductibility uncertainty, those without continuous professional support, those managing mixed-use assets, and those in sectors with complex expense structures are predicted to systematically under-claim legitimate deductions in quarterly submissions relative to their correctly calculated liability.
- **Proposition 4.** Precautionary under-claiming is predicted to compress the lower tail of the sector expense ratio distribution relative to the pre-MTD baseline, such that risk models calibrated on annual data may classify taxpayers who correctly claim full allowable expenses as relatively anomalous.

4.3. Pathway 3: The Structural Quarterly–Annual Gap

MTD design excludes year-end adjustments, accruals, prepayments, depreciation, and private-use restrictions from quarterly submissions. For any business with significant year-end adjustments, the sum of quarterly submissions is expected to systematically exceed the final declared liability. The risk arises where compliance systems compare quarterly totals against the annual return without modelling the expected adjustment range.

- **Proposition 5.** The distribution of annual adjustment magnitudes is predicted to be systematically skewed toward downward year-end corrections, with magnitude expected to be positively correlated with business complexity, asset intensity, and dual-purpose expenditure.
- **Proposition 6.** During implementation transitions, risk systems comparing quarterly submissions against annual benchmarks are predicted to generate false positive compliance flags at a rate exceeding the steady-state baseline, with this elevated rate expected to decline as risk models are recalibrated.

Table 1 Taxonomy of Behavioural Reporting Noise Mechanisms

Mechanism	Process origin	Direction of bias	Affected metric
Compressed categorisation	Deadline pressure; software default acceptance	Default-skewed misclassification; correlated within platform	Expense category distributions; income classification
Precautionary under-claiming	Penalty-aversion + deductibility uncertainty before professional review	Overstated profit; systematic under-claiming of allowable deductions	Sector expense benchmarks; measured tax gap
Structural quarterly–annual gap	Year-end adjustments excluded from quarterly totals by design	Quarterly sum systematically exceeds final declared liability	Reconciliation anomaly rates; triage false-positive rate

Note. Each mechanism produces directional rather than random bias. The three mechanisms may operate simultaneously, with reinforcing or partially offsetting effects.

5. Stylised Illustrations

This section illustrates the mechanisms through stylised taxpayer archetypes, composite figures representative of recurring patterns, not individual cases.

Archetype A (self-employed tradesperson, Pathway 1) uses cloud accounting software with a bank feed. Approximately 200 transactions per quarter are captured automatically; an estimated 20–25% require categorisation decisions at which the software default diverges from the professionally correct classification. At the quarterly deadline, the accountant resolves ambiguous items by accepting defaults for van servicing to vehicle maintenance without checking whether it constitutes a capital improvement and a trade subscription to professional fees without verifying period alignment. The resulting submission systematically over-claims revenue expenditure, consistent with Propositions 1 and 2.

Archetype B (residential landlord, Pathway 2) faces deductibility uncertainty over travel to inspect properties, the treatment of a new door as a repair or improvement, and the business proportion of her mobile phone bill. Under quarterly reporting, and consistent with loss aversion under incomplete information (Kahneman & Tversky, 1979), she

omits uncertain items rather than claiming and risking a query. Across the population of similar landlords, this compresses sector expense ratios and distorts the benchmarks used by risk models, consistent with Propositions 3 and 4.

Archetype C (asset-holding sole trader, Pathway 3) uses a vehicle 70% for business. Quarterly submissions record full vehicle costs; the private-use restriction (30% add-back) is applied only at annual finalisation. If risk systems compare quarterly totals against the annual return without modelling this expected adjustment, the year-end correction is likely to be flagged as an unexplained reduction in claimed costs, consistent with Propositions 5 and 6.

6. Operational and Measurement Implications

At the triage stage, the volume of risk-flagged cases is expected to rise during the initial quarters of MTD-ITSA implementation (Proposition 6). In the first year, a higher share of these flags is likely to reflect artefacts generated by the three BRN mechanisms rather than genuine anomaly signals. Triage teams will therefore need to distinguish process-driven patterns from underlying non-compliance in the absence of established benchmarks. At the risk-banding stage, cases assigned elevated risk scores on the basis of quarterly anomalies may no longer justify those scores once annual declarations are received, thereby reducing average yield per case. At the case-allocation stage, BRN-driven cases are likely to require examination of transaction-level data, bank feeds, and categorisation histories rather than simple comparison of declared figures with sector norms. This is a more time-intensive process and one that rewards familiarity with software default behaviour. More broadly, this is consistent with work showing that randomness in observed enforcement and compliance signals can distort case selection (Scotchmer & Slemrod, 1989).

The implication for tax gap measurement is, more formally, a problem of construct validity (Shadish et al., 2002). The precautionary under-claiming mechanism (Propositions 3–4) implies that some quarterly submitters will report taxable profits that systematically exceed their correctly calculated liability. If these overstated profits enter the dataset used to estimate the tax gap for the self-employment and landlord population, the measured gap may be artificially compressed. This would not reflect genuine improvement in compliance; rather, it would indicate that the reporting process has generated data biased toward making compliance appear stronger than it is. HMRC's tax gap estimation methodology for 2026–27 and 2027–28 should therefore incorporate explicit sensitivity analyses before first-year quarterly reporting data are used in published estimates. This interpretation should be read alongside HMRC's published tax gap series and methodological annex (HM Revenue & Customs, 2025a; HM Revenue & Customs, 2025b).

7. Proposed Empirical Research Design

The six propositions are falsifiable using data HMRC holds or is collecting. Table 2 summarises the proposed design, which comprises three quantitative phases and one qualitative arm. HMRC's upstream compliance research on reporting errors also provides a relevant baseline for this empirical programme (HM Revenue & Customs, 2020).

Table 2 Proposed Empirical Research Design

Phase	Data / method	BRN indicator
Pre-rollout baseline	HMRC SA administrative data 2020–2025; sector expense ratios; annual–quarterly adjustment ranges from MTD-VAT analogues	Expected expense ratio ranges; baseline false-positive rates under current risk models
Pilot comparison	MTD-ITSA pilot cohort (voluntary, 2024–2025); matched non-pilot SA controls; difference-in-differences design	Categorisation variance; expense ratio compression; quarterly–annual adjustment magnitude
Post-rollout validation	First four quarters of mandatory submissions (April 2026–April 2027); compliance investigation outcome data	Triage false-positive rate; investigation yield per case; annual adjustment distribution
Qualitative arm	Semi-structured interviews: accountants (n ≥ 50), sole traders/landlords (n ≥ 50), HMRC compliance officers (n ≥ 20)	Mechanism validation; decision processes under time pressure

The primary identification challenge is separating BRN-driven changes from genuine changes in taxpayer compliance. Three strategies address this. First, *difference-in-differences* using the MTD pilot cohort as the treatment group and matched non-pilot Self Assessment taxpayers as the control group tests Propositions 1–4 directly. Second, *within-taxpayer comparison* of first-year MTD submissions against the same taxpayer's pre-MTD annual returns tests whether first-year quarterly figures show distributional characteristics predicted by BRN even when underlying income and expenditure are unchanged. Third, *software-platform clustering analysis* tests Proposition 2: if compressed categorisation errors are correlated within platform, anomalies should cluster by software provider in first-quarter data.

8. Comparative Evidence and Boundary Conditions

HMRC's evaluation of MTD for VAT (2021) found elevated error rates in the first two quarters, followed by substantial improvement as software defaults were corrected and adviser familiarity increased, consistent with the BRN property of persistence then decay. However, VAT-registered businesses were already accustomed to quarterly filing; MTD-ITSA changes both the cycle and the mechanism for a population with no prior quarterly reporting experience. BRN intensity under MTD-ITSA is therefore predicted to be substantially greater. Estonia's e-Tax system and Norway's pre-populated returns achieve high compliance rates by reducing categorisation burden; Australia's Single Touch Payroll increased frequency but removed categorisation discretion from employees entirely. These reforms confirm the broader generalisation: digitisation improves compliance data quality when it reduces categorisation burden; it risks generating BRN when it transfers that burden to a time-pressured intermediary. This pattern is consistent with HM Revenue & Customs (2021).

BRN is predicted to be weakest where bookkeeping is continuous, software defaults closely match the correct categorisation, year-round adviser support enables pre-submission review, and transactions are primarily discrete. It is predicted to be strongest where the taxpayer has a complex mix of business and personal transactions in shared accounts, professional advisory support is episodic, large year-end adjustments are structurally necessary, and income is irregular. These conditions are most prevalent among sole traders in construction, hospitality, and property, and among landlords managing properties without professional agents. Alternative explanations like deliberate evasion, misunderstanding of rules, and ordinary clerical error remain possible; the most informative discriminating tests are whether anomalies cluster within software platforms (Proposition 2) and whether they reverse predictably at the annual reconciliation point (Propositions 5–6).

9. Policy Implications

Two implications are time-sensitive and traceable directly to the propositions. Proposition 6 implies that triage thresholds may benefit from upward adjustment during the initial quarters of MTD operation, treating first-year quarterly data as a calibration period. Proposition 5 implies that risk-selection systems may benefit from explicit configuration to model the expected year-end adjustment range by taxpayer type before first submissions arrive. Additional operational implications, sector-specific seasonal income profiling, mandatory pre-submission validation checks in approved software, and a formal within-year correction window follow directly from the mechanisms developed above.

10. Conclusion

This article has developed behavioural reporting noise (BRN) as a theoretically grounded framework for understanding how digital reporting design can systematically distort compliance signals independently of taxpayer behaviour. Three pathways compressed categorisation under deadline pressure, precautionary under-claiming under uncertainty, and the structural quarterly–annual gap each derive from established behavioural theory and generate directional, falsifiable predictions. Six formal propositions are derived with explicit boundary conditions. The empirical research design proposed in Section 8 can test these propositions using HMRC's existing administrative data.

The contribution to behavioural public administration is to establish reporting regime architecture as a variable of independent importance alongside the incentives and norms that have dominated the compliance literature. Any administrative reform that changes the conditions under which reporting decisions are made will alter the data-generating process in ways that compliance statistics may not reveal until models are applied to the new data. Digital visibility and compliance signal validity must be studied together. The BRN framework, grounded in the core behavioural and institutional mechanisms of the field, provides a foundation for doing so with the UK MTD-ITSA transition as the motivating case and a research agenda applicable to digital governance reforms internationally.

Compliance with ethical standards

Disclosure of conflict of interest

The author declares that there is no conflict of interest.

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