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Abstract

Ensuring safe drinking water depends not only on infrastructure but on effective regulatory compliance. This paper studies compliance with drinking water quality regulations through a three-layer framework that distinguishes among whether providers report monitoring data at all, whether those that do report collect the required number of samples, and whether the samples collected reveal violations of regulatory quality thresholds. Because each layer is a necessary condition for the next, failures in reporting and sampling can prevent official statistics from accurately reflecting underlying water quality risks. Using comprehensive administrative data from Brazil covering more than 5,500 municipalities between 2010 and 2022, we show that failures at each compliance layer are widespread, non-random, and systematically correlated with municipal characteristics. Non-reporting and under-sampling are concentrated in poorer and lower-capacity municipalities, while over-sampling is prevalent among larger providers. Over-samplers report fewer violations than municipalities that comply exactly with the prescribed sample count, a pattern that admits several interpretations and that the administrative record alone cannot adjudicate. The reported violation share is therefore jointly determined with sampling behavior, and this joint determination is systematically related to the municipal characteristics that also predict contamination risk. Treating reported violations as the sole measure of regulatory performance yields a misleading picture of drinking water safety and obscures the importance of monitoring compliance with reporting and sampling requirements alongside quality thresholds.

JEL Codes:I18; Q25; Q53; L51; D82; H75.

Keywords: Drinking water quality; regulatory compliance; self-monitoring and enforcement; administrative data; public health; Latin America and the Caribbean.

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1 Introduction

Safe drinking water is a fundamental determinant of public health, yet ensuring its quality remains an unresolved challenge in both developing and developed countries. Contaminated water is associated with a range of severe health outcomes, including gastrointestinal disease, low birth weight, child mortality, and multiple forms of cancer (Prüss-Ustün et al., 2019; WHO, 2022; Kremer et al., 2023). In Latin America and the Caribbean (LAC), unsafe water and inadequate sanitation account for a disproportionate share of child deaths (Wolf et al., 2023), and the expansion of piped water has been shown to reduce infant mortality (Gamper-Rabindran et al., 2010). Yet infrastructure alone is not enough: the health gains from piped water depend critically on whether the water delivered through those pipes meets quality standards set by the corresponding national regulation (Hutton and Chase, 2016). Whether that regulatory system actually works, that is, whether providers report information, whether they sample at the required frequency, and whether official records accurately reflect the drinking water quality that reaches households, is therefore a first-order public health concern.

Most countries have established formal drinking water quality regulations that set maximum permissible levels for microbiological and chemical contaminants and mandate regular testing and public reporting by water providers (WHO, 2022). In LAC, nearly all countries have such rules in place, yet monitoring and enforcement remain persistently weak (Larocque, 2018; Couleau et al., 2025). The underlying reason is that most regulatory systems rely on self-monitoring: providers are themselves responsible for collecting, testing, and submitting the data used to assess their own compliance. This creates a classic principal-agent problem. Regulators must rely on entities that bear the direct costs of compliance and hold private information about their own water quality. The problem is particularly acute when the regulated entity controls not only what is reported, but also how much is tested and when, giving agents facing regulatory penalties both the incentive and the discretion to manipulate the information used to evaluate them. Understanding compliance with water quality regulation, therefore, requires looking beyond the official violation record.

We organize compliance into three sequentially conditional layers: whether providers report any data at all; whether those that do report collect the required number of samples; and whether the samples collected reveal violations of quality standards. Each layer is a necessary condition for the next, and failures at any stage can prevent official statistics from reflecting the true extent of water quality problems. If the characteristics of non-reporters differ systematically from those who report, official violation rates will be biased downward, with the bias likely largest precisely where water quality risks are greatest. Beyond non-reporting, deviations in sampling volume introduce a further source of distortion. Under-sampling may reflect limited provider capacity, but it also reduces the probability of detecting contamination, meaning violations go unrecorded, not because the water is safe but because the testing is insufficient. Over-sampling, by contrast, may reflect genuine quality consciousness among better-resourced providers, but can also serve to dilute the share of positive results, thereby keeping reported violation rates below regulatory thresholds even when underlying contamination is present. Both mechanisms bias official violation statistics in ways that are difficult to detect without observing all three compliance layers simultaneously.

To study these compliance dynamics empirically, we turn to Brazil. Brazil's regulatory framework (Portaria GM/MS No. 888/2021) makes all three compliance layers simultaneously observable in a single administrative system covering more than 5,500 municipalities over 13 years.[1] Brazil is particularly well suited for this analysis: its advanced information systems and binding regulatory framework make it one of the few developing countries where reporting and sampling behavior can be observed separately and consistently across a large number of providers over a long time period. At the same time, there is substantial heterogeneity in provider capacity, income, and institutional quality across municipalities, which allows us to observe the full range of compliance behaviors within a single regulatory environment and to trace how those behaviors relate to population health outcomes. We use a balanced panel of 5,565 municipalities observed annually from 2010 to 2022.

We rely on the National Sanitation Information System (SNIS, in Portuguese), managed by the Ministry of Cities, as our source of data for water quality and sampling adequacy. Brazil also maintains a parallel water quality database, Water Quality Surveillance System (SISAGUA, in Portuguese), operated by the Ministry of Health. While SISAGUA records individual sample results and is used for surveillance purposes, it does not include information on the number of samples

[1] This regulation establishes an obligation to report sample results, specifies the minimum number of samples providers are required to collect, and sets clear thresholds for water to be considered safe for human consumption. It also mandates reporting through the National Sanitation Information System (SNIS), which records both the number of samples collected and the regulatory minimum required, making it possible to assess sampling adequacy directly.

each provider was required to collect under the regulation. Because assessing sampling adequacy requires comparing observed sample counts to the regulatory minimum, SNIS is the appropriate data source for the second compliance layer.

Our empirical analysis focuses on total coliform compliance. While the regulation prohibits E. coli in all samples without exception, the compliance threshold subject to empirical variation, the 5% rule, applies exclusively to total coliforms, which constitute the binding and measurable regulatory standard governing distribution network performance. Total coliforms are also the most widely and consistently tested microbiological indicator across Brazilian municipalities, making them the most tractable outcome for large-scale empirical analysis.

Evidence from both high- and low-income countries suggests that failures at each compliance layer are widespread and non-random. At the reporting layer, non-reporting is a serious problem even in countries with robust oversight infrastructure: in the United States, between 26 and 38 percent of detected health-based violations are never formally reported to the relevant authority, and the providers most likely to go silent are those serving rural, low-income, and otherwise disadvantaged communities (Allaire et al., 2018; Mueller and Gasteyer, 2021). At the sampling layer, both under-sampling and over-sampling are common and non-random. Under-sampling is more prevalent among smaller and financially constrained providers, consistent with limited capacity rather than deliberate evasion (Crocker and Bartram, 2014). Over-sampling is concentrated among larger, better-resourced systems. Bennear et al. (2009) shows that in U.S. water utilities, over-sampling was concentrated in months when early contamination had already been detected, pointing to deliberate threshold management rather than a precautionary response.

Analogous strategic responses to monitoring requirements have been documented in air quality regulation, where local agencies strategically shut down monitors before high-pollution events (Mu et al., 2021), and in surface water monitoring in China, where contamination distributions are bunched just below regulatory thresholds (Zhao et al., 2021). At the violation layer, even among providers that report and sample adequately, official violation rates will be biased downward if selection into the preceding layers is correlated with underlying water quality (Gray and Shimshack, 2011; Shimshack, 2014), meaning the communities facing the greatest risks are precisely those least visible in the official record. Existing evidence on these mechanisms, however, comes predominantly from the United States; whether similar patterns obtain in middle-income country settings, where provider heterogeneity and institutional capacity constraints are more severe, remains an open question.

This paper makes two contributions. First, we introduce a three-layer compliance framework that explicitly distinguishes reporting, sampling adequacy, and threshold reported violations as sequentially conditional behaviors. Prior work has focused almost exclusively on the third layer (Gray and Shimshack, 2011; Shimshack, 2014), treating official violation rates as the relevant outcome. We show that this restriction is consequential: the selection processes governing who clears the first two layers are non-random and systematically related to the underlying water quality risk. Second, we provide the first large-scale evidence on all three compliance layers in a middle-income country. The United States evidence, while valuable, operates in a setting with comparatively strong institutional capacity; our findings document that compliance failures are sharper and more unequally distributed when provider heterogeneity is more pronounced.

Our findings are consistent with systematic downward bias in official compliance statistics. At the reporting layer, between 5 and 17 percent of municipalities submit no water quality data in a given year; non-reporters are concentrated in poorer, smaller, and less-developed municipalities, precisely those facing the highest risk of poor water quality. At the sampling layer, over-sampling is the dominant behavior among reporters, accounting for approximately 45 percent of reporting municipalities, while under-sampling has declined but remains prevalent, particularly in lower-income and more rural areas; exact compliance with the prescribed sample count is the least common outcome. At the violation layer, under-samplers exhibit persistently higher coliform violation rates than exact-samplers or over-samplers, consistent with degraded water quality constrained by limited testing. Over-samplers report fewer violations than exact-samplers, a result that admits several interpretations, including genuinely better water quality, dilution of positive results through excess testing, and the mechanical effect of the mandatory resampling protocol triggered by any positive coliform detection. The administrative record alone cannot separate these mechanisms. What the evidence does establish is that official violation statistics, which capture only the third compliance layer, conditional on passing the first two, reflect not just underlying water quality but also the sampling decisions that precede measurement, and that these decisions are themselves systematically related to the municipal characteristics that predict contamination risk. The communities least visible in the official record, and least adequately represented within it, are those facing the greatest underlying risk.

The remainder of the paper proceeds as follows. Section 2 presents the three-layer compliance framework and describes Brazil's regulatory environment. Section 3 describes the data. Section 4 presents the empirical analysis of each compliance layer. Section 5 concludes.

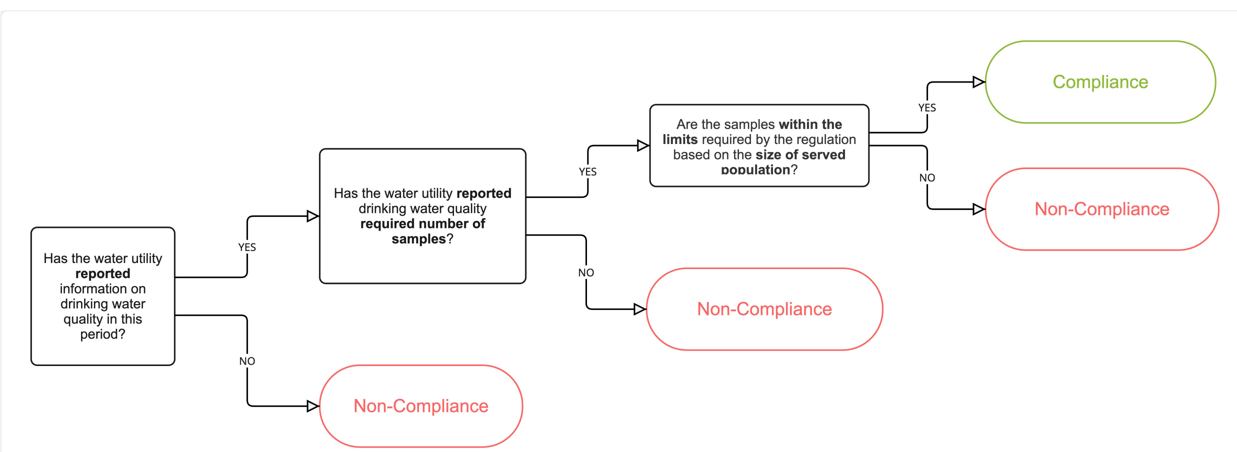
2 Compliance with Drinking Water Quality Regulation

2.1 A Three-Layer Compliance Framework

Assessing compliance with drinking water quality standards must go beyond looking at the reported share of violations. In most regulatory systems, drinking water quality is governed through a self-monitoring arrangement: regulated providers are responsible for collecting, testing, and reporting the data used to evaluate their own compliance. This creates a multi-stage process in which failures can occur at each step, so a clean record in official data does not necessarily reflect safe water in practice.

We organize compliance into three layers, illustrated in Figure 1. Each layer is a necessary condition for the next: a provider cannot be assessed on sampling adequacy without first reporting, and cannot be evaluated on threshold violations without adequate sampling.

Figure 1: Drinking water quality regulation compliance diagram



The first layer is reporting. Providers are required to submit water quality monitoring data to the relevant surveillance authority at prescribed frequencies. Failure to report constitutes non-compliance in its own right, independent of the actual quality of the water supplied. Crucially, non-reporting removes a provider from the observable compliance record, making it impossible to assess water quality using official data alone.

The second layer is sampling adequacy. Among providers that do report, regulations typically specify a minimum number of samples to be collected per period, determined by the size of the population served. We define under-sampling as submitting fewer samples than the regulatory minimum. This represents a compliance failure because it reduces the statistical power to detect contamination events, meaning violations may go undetected, not because the water is safe but because the testing is insufficient. We define over-sampling as submitting more samples than the regulatory minimum. Over-sampling is not a regulatory violation, and under Portaria GM/MS No. 888/2021 it is in fact required following any positive coliform detection. It may also reflect genuine quality consciousness or excess institutional capacity on the part of better-resourced providers. Collecting more samples than required can nonetheless dilute the share of positive results, lowering the measured violation rate below what a minimum-compliant sampling regime would have recorded. For the purposes of our framework, then, over-sampling is not treated as compliance in a substantive sense. It clears the regulatory minimum but introduces variation in the denominator of the violation share that is itself a choice variable of the provider, and one whose determinants and consequences we discuss in the empirical analysis.

The third layer is threshold compliance. Among providers that report and submit adequate samples, compliance is determined by whether test results fall within permissible limits. In most regulatory systems, this is the only layer that is routinely measured and reported as a violation. But as the first two layers make clear, this measure is conditional on a provider having cleared the previous hurdles.

This framework applies broadly to any regulatory system that relies on self-monitoring by providers. At each stage, some providers are excluded from the observable record. If the characteristics of those who are excluded differ systematically from those who remain, then standard violation statistics, which capture only the third layer, will be systematically biased. Specifically, if selection into the first and second layers is correlated with underlying water quality conditions, official violation rates will not accurately reflect the true extent of non-compliance. We document empirically whether such selection exists.

2.2 The Brazilian Case

Brazil offers a rich setting to study all three compliance layers simultaneously. It combines a comprehensive and well-specified regulatory framework with substantial heterogeneity in provider capacity and enforcement intensity across its more than 5,500 municipalities, allowing us to observe the full range of compliance behaviors within a single national system.

Brazil's regulatory framework for drinking water quality is anchored in the National Sanitation Law (Law No. 11.445/2007, updated by Law No. 14.026/2020), which mandates a universal and safe water supply and establishes clear responsibilities for monitoring and oversight. Drinking water quality standards are set by the Ministry of Health, with the most recent regulation stablished by Portaria GM/MS No. 888/2021. This regulation defines health-based maximum limits, mandatory monitoring frequencies, and reporting obligations for all water suppliers, covering microbiological, physical, and chemical parameters.

Data on compliance are collected through two national information systems. Water Quality Surveillance System (SISAGUA, in Portuguese), operated by the Ministry of Health, is the official platform for drinking water surveillance and integrates both provider-reported control data and independent surveillance results. National Sanitation Information System (SNIS, in Portuguese), managed by the Ministry of Cities, collects annual aggregated service and water quality indicators from providers, with participation effectively mandatory due to federal funding incentives tied to regular data submission. While both systems contain information on water quality, they operate at different levels of aggregation and are not directly comparable. We rely primarily on SNIS for two reasons. First, it offers a longer time and municipal coverage. Second, and most importantly for our purposes, SNIS includes information on the minimum number of samples providers are required to collect, which is essential for assessing compliance with the second layer of our framework.

The regulatory framework establishes precise sampling requirements for microbiological quality. According to Portaria 888/2021, all entities supplying water for human consumption, including public utilities, private operators, and collective alternative systems, are required to sample and analyze the water distributed to the population regularly. Microbiological testing focuses on the detection of Escherichia coli (E. coli) and total coliforms as indicators of faecal contamination and system integrity. For water providers that supply water to 20,000 or more inhabitants, up to 5% of monthly samples from the distribution network are allowed to test positive for total coliforms, while the presence of E. coli remains strictly prohibited in all samples at all times. Any detection of total coliforms triggers an operational response, requiring immediate collection of additional samples to confirm whether the contamination is isolated or persistent. While the regulation prohibits E. coli in all samples without exception, the compliance threshold subject to empirical variation, the 5% rule, applies exclusively to total coliforms. Our analysis therefore focuses on total coliform compliance, which constitutes the binding and measurable regulatory standard governing distribution network performance.

The regulatory framework makes the three compliance layers directly observable within the Brazilian data. The first layer is captured by whether a municipality submitted any water quality data to SNIS in a given year. The second layer is assessed by comparing the number of samples submitted against the minimum requirement specified in Portaria 888/2021, which varies by population served. Providers submitting fewer samples than required are classified as under-samplers, while those submitting more are classified as over-samplers. The third layer is measured by the reported share of coliform samples exceeding the 5% regulatory threshold, representing the standard definition of a violation in Brazilian law.

3 Data

Our analysis draws on four data sources, combined into a panel of 5,565 Brazilian municipalities observed annually from 2010 to 2022 [2]. The primary source is the SNIS, which provides municipal-level drinking water quality data and constitutes the foundation of our compliance measures [3]. We complement SNIS with municipal socioeconomic and demographic characteristics from Brazil's 2010

[2]All data in this study are at the municipality level. The SNIS database reports at the provider level and was aggregated to the municipality level for this analysis. Even though providers can supply water to multiple municipalities, they are required to submit sample results for each water system serving a given municipality, so the unit of observation always respects municipal boundaries. Municipalities served by multiple providers will, however, have multiple observations in the same year, and since providers within the same municipality may adopt different sampling strategies, it is not possible to infer a single sampling adequacy measure for such cases. We therefore excluded municipality-year observations where more than one provider uploaded water sample data, a restriction that affects less than 1% of the total sample.

[3]SNIS closed its data collection cycle at the end of 2023, with reference year 2022 as the last published report. The National System of Basic Sanitation Information (SINISA, in Portuguese) is SNIS's legal successor. However, SINISA focuses on data relating to the operation and management of water supply and sanitation systems, and therefore discontinued the collection of water quality sampling data. As a result, this study relies solely on information available through SNIS.

Demographic Census, produced by IBGE. Finally, we incorporate municipal-level diarrheal hospitalization records from DATASUS, Brazil's national health information system. The construction of each source and the variables derived from them are described below.

3.1 SNIS

We rely on SNIS as our primary data source for two reasons. First, it offers broader municipal coverage and a longer time series than SISAGUA, the alternative national platform for drinking water surveillance operated by the Ministry of Health.[4] Second, and most importantly for our framework, SNIS dataset includes information on the minimum number of samples each provider is required to collect under Brazil's regulatory standards, which is essential for evaluating the second layer of compliance.

Within SNIS, observations are recorded at the provider level, but since the universe of active providers per municipality is not fully known, we construct a balanced panel at the municipal level. We aggregate total samples collected and total samples with positive results to the municipality level by summing across providers. The first is the total number of samples collected for microbiological analysis in a given year. The second is the total number of samples with positive results for total coliforms, that is, results exceeding the regulatory limit. From these two variables, we construct the *share of violations*, defined as the reported ratio of positive samples to total samples collected.

Each compliance layer in our framework is directly observable in SNIS dataset. The first layer, reporting, is captured by whether a municipality submitted any water quality data in a given year. The second layer, sampling adequacy, is constructed by comparing the number of samples collected against the regulatory minimum specified in Portaria GM/MS No. 888/2021, which varies by population served. SNIS itself provides a variable indicating the minimum number of samples required.[5]Municipalities submitting fewer samples than required are classified as under-samplers;

[4] In 2022, 95% of Brazilian municipalities reported sampling results to SNIS, compared with 77% to SISAGUA. SISAGUA data are also only available starting in 2014, whereas SNIS coverage extends back to 2010. Appendix figure 13 maps reporting municipalities in both systems for 2022, illustrating the greater geographic reach of SNIS. Both systems nonetheless underrepresent Brazil's North region, a pattern we document and account for in the analysis.

[5] The minimum required number of samples is defined at the provider level because it depends on the population served by the provider and cannot be directly aggregated to the municipal level when multiple providers operate within a municipality in the same year. In practice, approximately 1% of municipalities in SNIS are served by more than one provider in the same year; for the remaining 99%, the provider-level requirement is equivalent to a municipal-level requirement. Our sampling adequacy analysis is therefore restricted to single-provider municipalities, a sample that is broadly representative of the full population.

those submitting more are classified as over-samplers; and those meeting the requirement exactly constitute the reference group (exact-samplers). The third layer, threshold compliance, is measured directly by the violation share, corresponding to the standard definition of a violation in Brazilian law.

It is important to note that the SNIS data record sampling behavior at the annual level, whereas Brazil's regulatory framework specifies sampling requirements and the five percent violation threshold at the monthly level. To map annual sampling shares to monthly compliance, we assume that sampling behavior is persistent within municipalities over time, so that a municipality's annual sampling ratio is informative about its typical monthly behavior. This assumption is supported empirically: Appendix Table 4 reports persistence regressions in which lagged sampling status strongly predicts current sampling status. Under this assumption, the annual measure constitutes a reasonable approximation of the underlying monthly sampling pattern, and the classification of municipalities into under-, exact-, and over-sampling categories reflects a stable behavioral disposition rather than transitory deviations from the regulatory requirement.

3.2 Supplementary Data Sources

We merge the SNIS panel with municipal socioeconomic and housing indicators from Brazil's 2010 Demographic Census, produced by IBGE. These variables, including average nominal income, household size, total population, and shares of households with access to piped water and piped sewage, serve as controls for baseline differences in living conditions, infrastructure access, and income across municipalities.

3.3 Final Panel

Merging these sources yields a balanced panel of 5,565 municipalities observed annually from 2010 to 2022, for a total of 72,345 municipality-year observations. The panel is balanced in the sense that all municipalities appear every year, regardless of whether they submitted data to SNIS. Non-reporting municipalities are retained with the reporting indicator set to zero, [6] consistent with our

[6] Municipalities are classified as non-reporting under any of the following conditions: they do not appear in SNIS in a given year; they appear in SNIS but report zero samples collected; or they appear in SNIS but have missing values for either the total samples with positive results for total coliforms or the minimum required sample variable. In addition, municipalities where the reported information is clearly inconsistent, specifically, where the total number of samples collected is lower than the total number of positive results, are also classified as non-reporting.

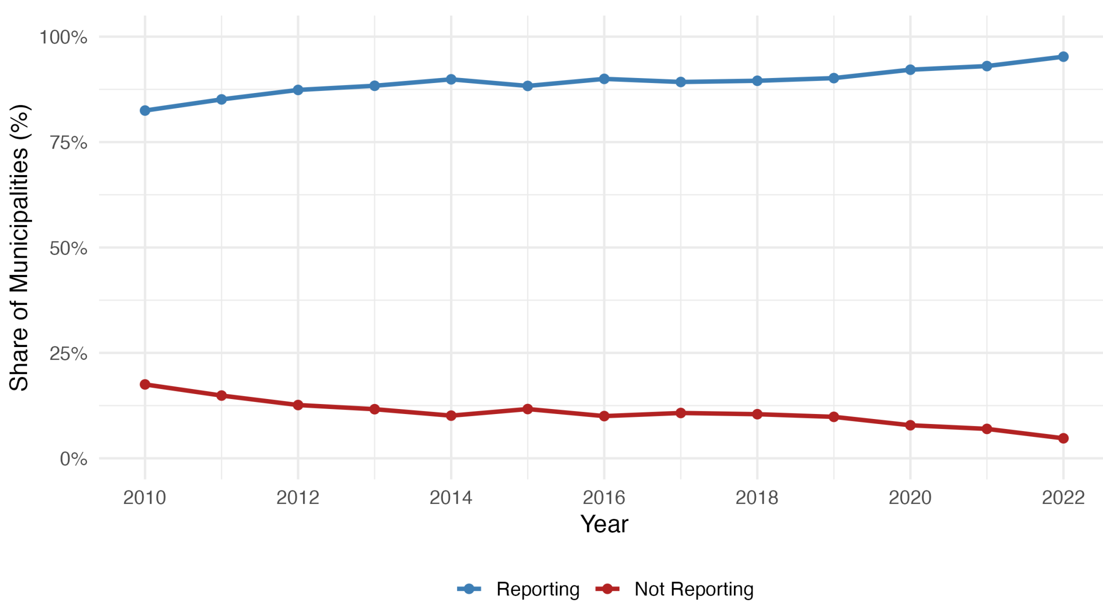
treatment of non-reporting as the object of analysis in the first compliance layer rather than as missing data to be discarded. Conditioning on reporters only, as is standard in analyses that take the administrative record at face value, would introduce the selection bias that this paper aims to document and quantify.

4 Analysis

4.1 Reporting

The first layer of compliance consists of providers reporting any sampling information to SNIS in a given year. Despite the legal requirement, reporting is far from universal. As shown in Figure 2, reporting rates improved steadily from 82.5% in 2010 to a peak of 95.3% in 2022, suggesting that federal funding incentives tied to data submission have gradually brought more municipalities into the reporting system. Nevertheless, around 5% of municipalities still do not report any water quality data.

Figure 2: Share of Municipalities Reporting to SNIS by Year



Reporting rates among municipalities vary substantially by region, with some areas approaching near-universal reporting while others lag persistently behind (Figures 3 and 4). While reporting increased across all five regions over the period, the pace of improvement varied substantially. The

South and Southeast maintained consistently high reporting rates, exceeding 95% by 2022. In contrast, the North region displayed persistently lower compliance throughout the period, starting at 57.5% in 2010 and reaching only 82.6% by 2022. The Center-West and Northeast regions occupied an intermediate position, reaching 94.4% and 93.5% respectively by 2022.

Figure 3: Share of Municipalities Reporting to SNIS by Region and Year

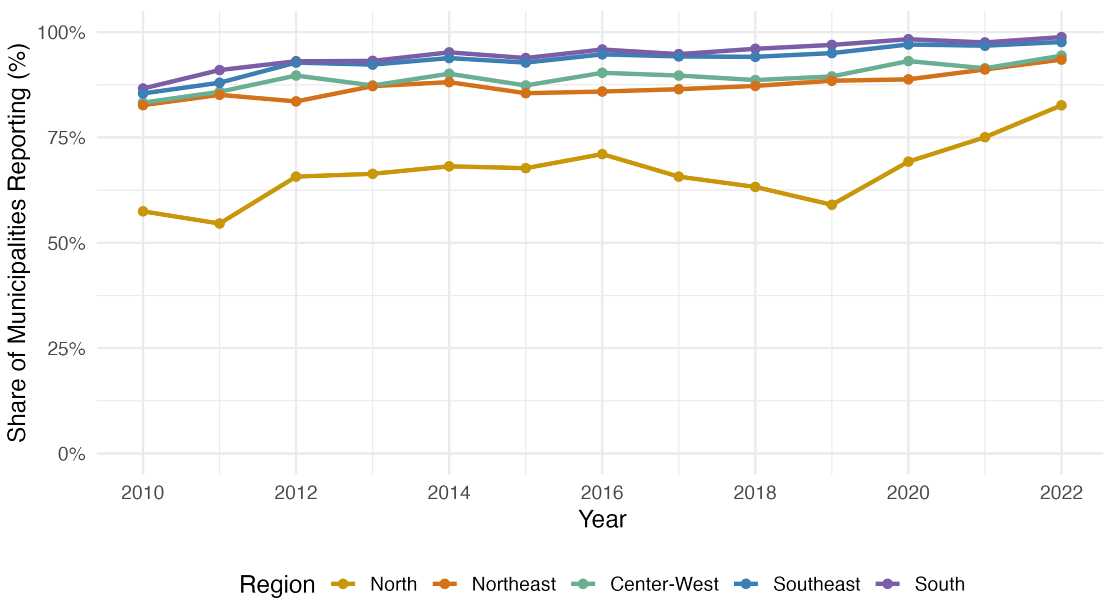
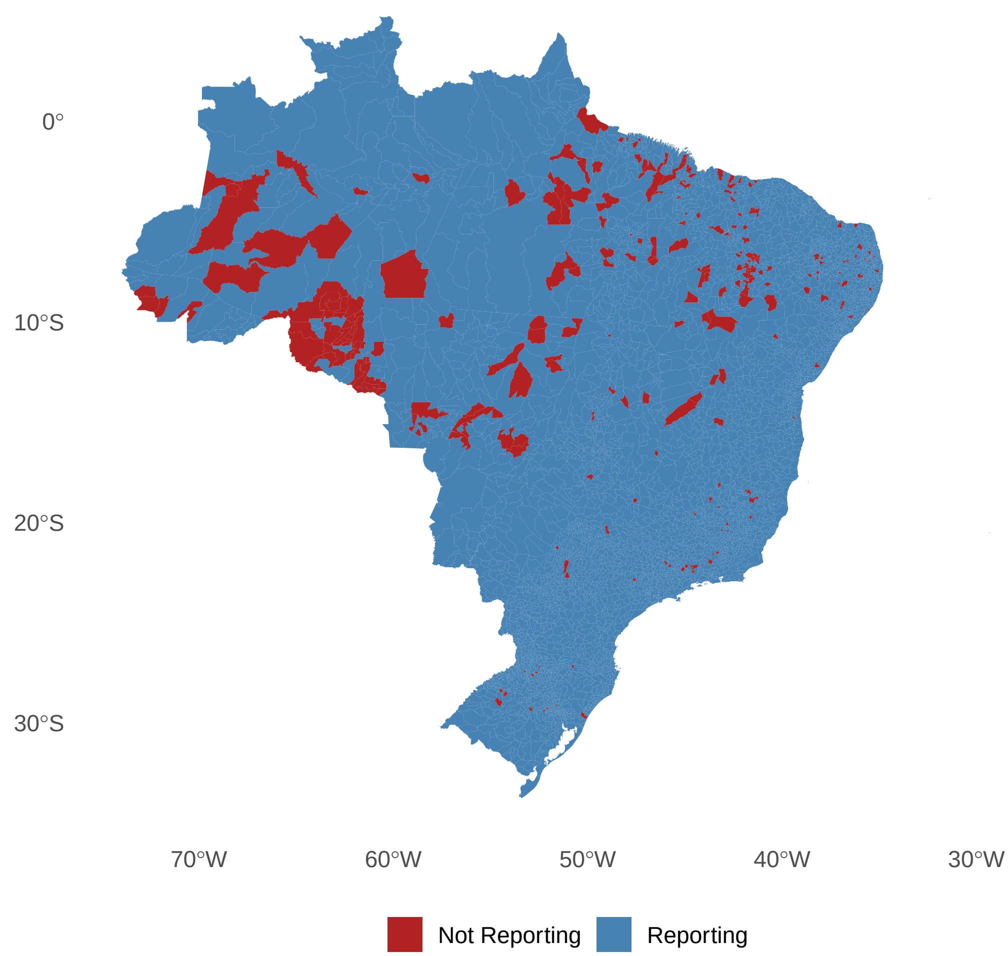
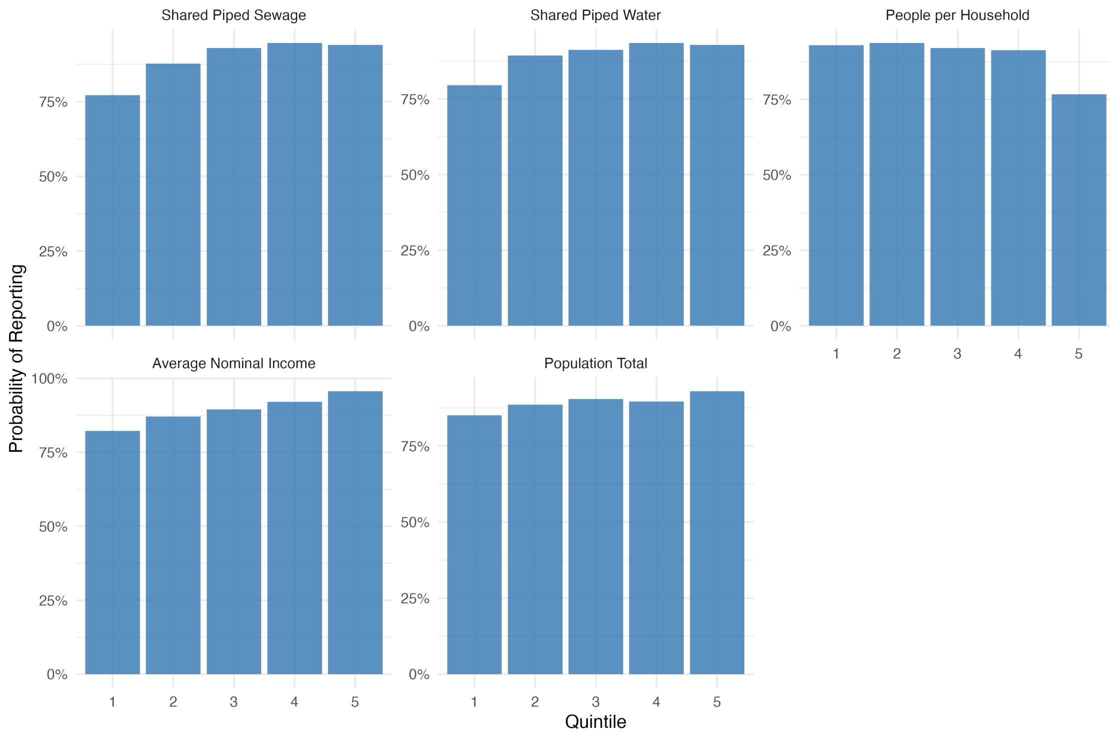


Figure 4: Reporting Municipalities to SNIS in 2022



Beyond regional patterns, non-reporting is not randomly distributed across municipal characteristics. Figure 5 shows the probability of reporting across quintiles of six municipal characteristics: average nominal income, total population, share of households with piped water, share of households with piped sewage, people per household. Reporting probability rises monotonically with income and population size, and falls for municipalities with more people per household, a pattern consistent with reporting failure being concentrated at the lower end of the development distribution. Access to piped water and sewage also correlate positively with reporting, suggesting a complementarity between infrastructure provision and regulatory compliance.

Figure 5: Probability of Reporting by Quintile of Municipal Characteristics



To assess the conditional correlations between municipal characteristics and reporting behavior, Table 1 presents estimates from a logit model of the form:

$$Report_{it} = \alpha + \beta_1 \ln Wage_i + \beta_2 HHsize_i + \beta_3 \ln Pop_i + \beta_4 WaterAccess_i + \beta_5 SanitationAccess_i + \gamma_t + \epsilon_{it}$$

where $Report_{it}$ is an indicator equal to one if municipality i reported any drinking water quality data to SNIS in year t; $\ln Wage_i$ is the log of the average formal wage; $HHsize_i$ is the average household size; $\ln Pop_i$ is the log of municipal population; $WaterAccess_i$ and $SanitationAccess_i$ are the shares of the population with access to piped water and sanitation services, respectively; γ_t denotes year fixed effects. Municipality fixed effects are not included because all regressors are drawn from the 2010 Demographic Census and therefore do not vary within municipalities over the sample period, making them perfectly collinear with municipality fixed effects.

Table 1: Logit estimates of the probability of reporting water quality data to SNIS.

	(1)	(2)
Dependent variable: Report		
ln Pop	0.500***	0.508***
	(0.015)	(0.015)
HHsize	-1.354***	-1.384***
	(0.032)	(0.032)
Sanitation Access	0.273***	0.272***
	(0.052)	(0.053)
Water Access	1.606***	1.635***
	(0.063)	(0.063)
ln Wage	0.026	0.020
	(0.043)	(0.044)
Year Fixed Effect	No	Yes
Observations	72,345	72,345
AIC	43,315	
Log-Likelihood		-21,225.5
R^2	0.120	0.137

Notes: Standard errors in parentheses. Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

The estimates reveal a clear and consistent pattern across both specifications. Water and sanitation coverage rates are positive and significant predictors of reporting, pointing to a complementarity between service provision and regulatory compliance: municipalities that have already invested in infrastructure are better positioned to operate the quality monitoring systems that regulation requires. Population size enters positively and significantly, reflecting the well-documented scale advantages that larger municipalities enjoy in public service delivery. The one coefficient that moves in the opposite direction is household size, which enters negatively and significantly across both specifications. Conditional on wages and service coverage, municipalities where households are larger tend not to report. Household size in this context is best read as an inverse proxy for socioeconomic development, i.e. larger households are associated with greater overcrowding and poverty in the Brazilian context, and its negative sign reinforces the interpretation that reporting failure is concentrated at the lower end of the development distribution.

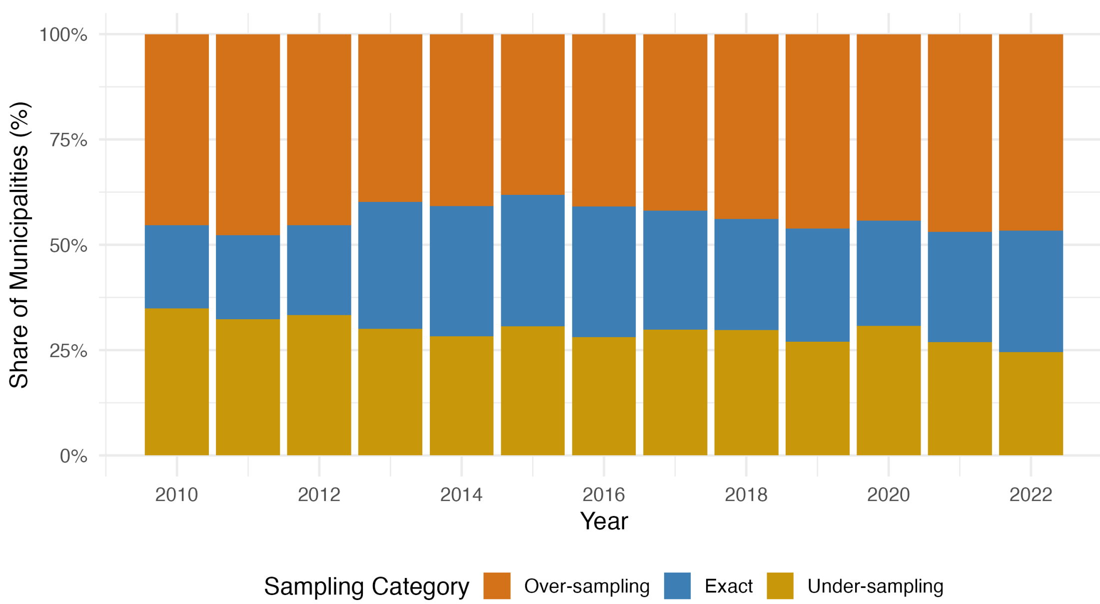
These results indicate that non-reporting compliance (first layer of regulation) is far from random. The same municipalities that are least likely to report i.e. those that are poorer, smaller, less urbanized, and with lower water and sanitation coverage, are precisely those where the underlying population faces the greatest risk of exposure to unsafe drinking water. Non-reporting is therefore not a statistical nuisance to be corrected away; it is itself a signal of capacity and infrastructure disadvantage, and any analysis that restricts to reporting data will produce estimates that are downward biased with respect to the true prevalence of unsafe water.

4.2 Sampling Adequacy

Among municipalities that do report, the second layer of compliance relates to whether the number of samples submitted matches the regulatory requirement. In principle, providers should report exactly the mandated number of samples each year. In practice, however, both under-sampling and over-sampling are widespread, and exact compliance is relatively rare.

As shown in Figure 6, the share of exactly-sampling municipalities rose from 19.7% in 2010 to 28.8% in 2022, reflecting a gradual improvement over time. Over-sampling remained the most prevalent pattern throughout the period with around 45%, while under-sampling declined from 34.9% to 24.5%.

Figure 6: Sampling Behaviour Among Reporting Municipalities by Year



The spatial distribution of sampling groups, shown in Figure 7, reveals clear geographic clustering in reporting behavior. Over-sampling municipalities form extensive and continuous regions, especially across the South, Southeast, and portions of the Center-West. Exact reporters also exhibit noticeable clustering across several parts of the country. Under-sampling is more scattered, though prominent concentrations appear in the North and parts of the Northeast. Municipalities displayed as *No Information* are those where more than one water provider reported sample results to SNIS for that municipality in a given year, and municipalities with no report.

Figure 7: Municipality Sampling Behaviour in SNIS in 2022

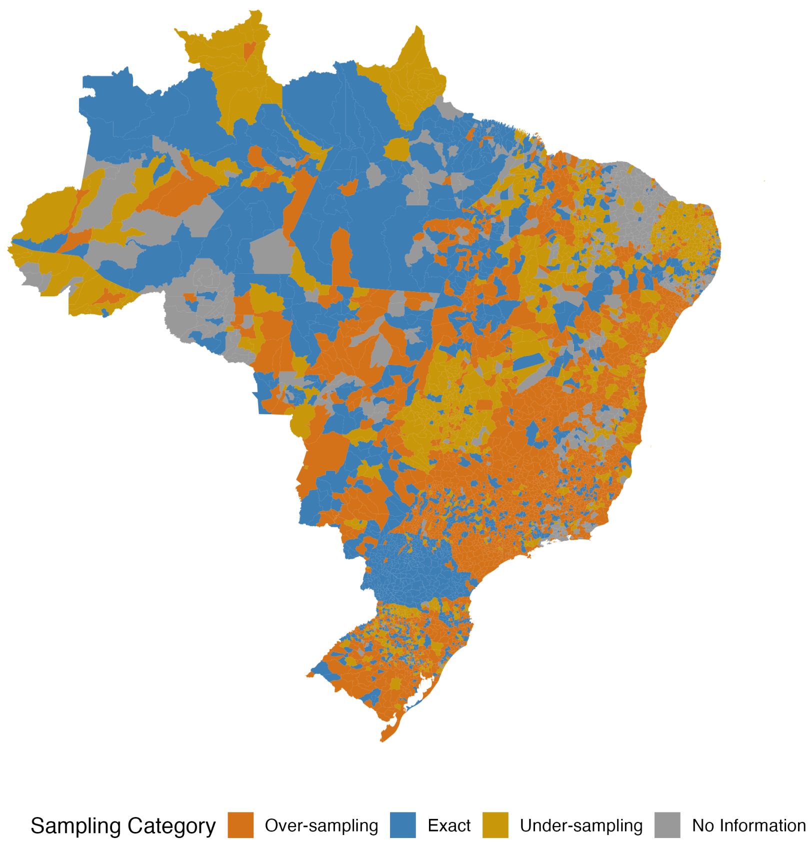
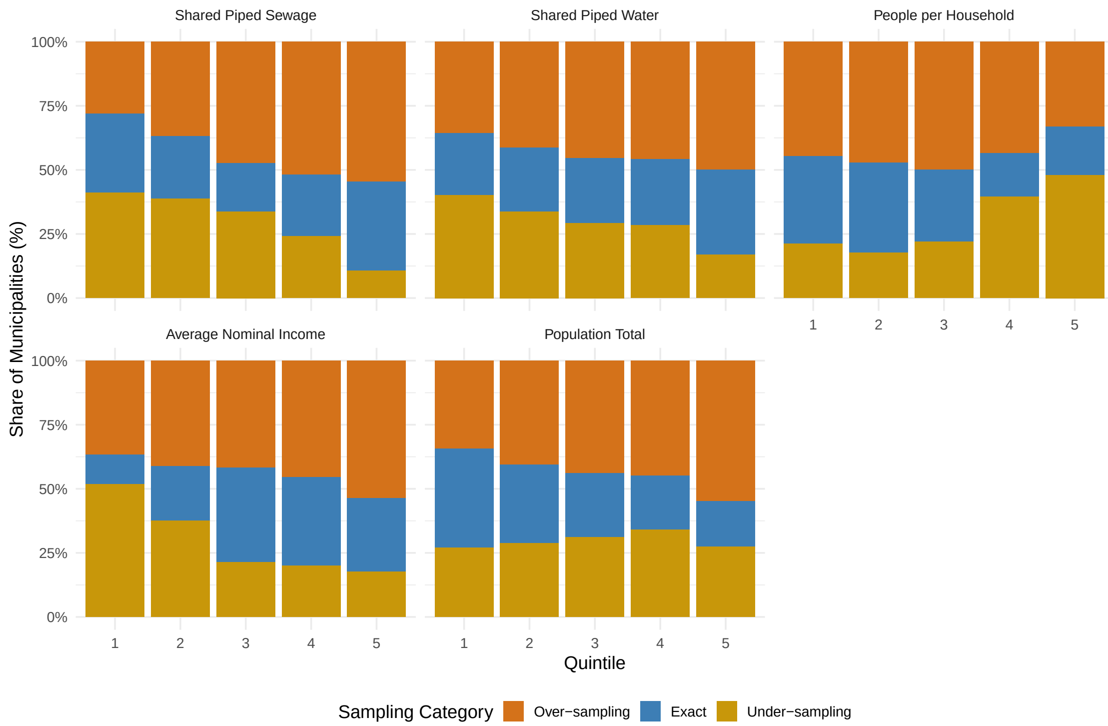


Figure 8 documents how sampling behavior varies across quintiles of the same six municipal characteristics examined in the reporting analysis. Over-sampling is the dominant pattern across all quintiles but grows more prevalent at higher quintiles of income, population, and infrastructure access. Under-sampling is disproportionately concentrated in the lower quintiles of income, piped water coverage, and piped sewage coverage, and in the upper quintiles of household crowding and diarrheal disease burden. These patterns suggest that, as with reporting, the capacity to achieve or exceed sampling requirements might be linked to underlying socioeconomic and infrastructural conditions.

Figure 8: Distribution of Sampling Category by Quintile of Municipal Characteristics



To characterize the determinants of sampling behavior more formally, Table 2 presents estimates from a multinomial logit model in which the outcome is sampling category relative to the exact-sampling baseline. All coefficients are statistically significant, indicating that municipalities that over-, under-, and exactly-sample differ systematically in their underlying conditions rather than being randomly distributed across categories. This is consistent with our central hypothesis that failures at each compliance layer are non-random and systematically correlated with underlying water quality risk.

Comparing the two over and under sampling categories to the exact-sampling baseline, the results suggest that municipalities that comply precisely with the prescribed sample count tend to have lower population, higher average income, less crowded households, and better access to piped water relative to both over- and under-samplers. The one characteristic that moves in opposite directions across the two groups is sanitation access, which is higher among over-samplers and lower among under-samplers relative to exact-samplers.

One finding from the over-sampling column deserves particular attention. Over-samplers exhibit lower average income and lower water access coverage relative to exact-samplers. This weakens the

Table 2: Determinants of Sampling Category (Baseline: Exact Sampling)

	Over	**Under**
	Multinomial Logit (Baseline: Exact)	
Sanitation Access	0.076^{*}	-1.412^{***}
	(0.033)	(0.041)
Water Access	-0.148^{*}	-0.267^{***}
	(0.065)	(0.067)
HHsize	-0.767^{***}	-0.337^{***}
	(0.037)	(0.036)
ln Wage	-1.201^{***}	-2.028^{***}
	(0.038)	(0.041)
ln Pop	0.528^{***}	0.484^{***}
	(0.011)	(0.012)
Observations	63,647	63,647

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.
Baseline category: Exact sampling. Sample restricted to municipalities with one water provider.

interpretation that over-sampling is driven by superior socioeconomic and infrastructural conditions, since the municipalities collecting excess samples are not uniformly in better conditions than those that comply exactly.

4.3 Water Quality Violations

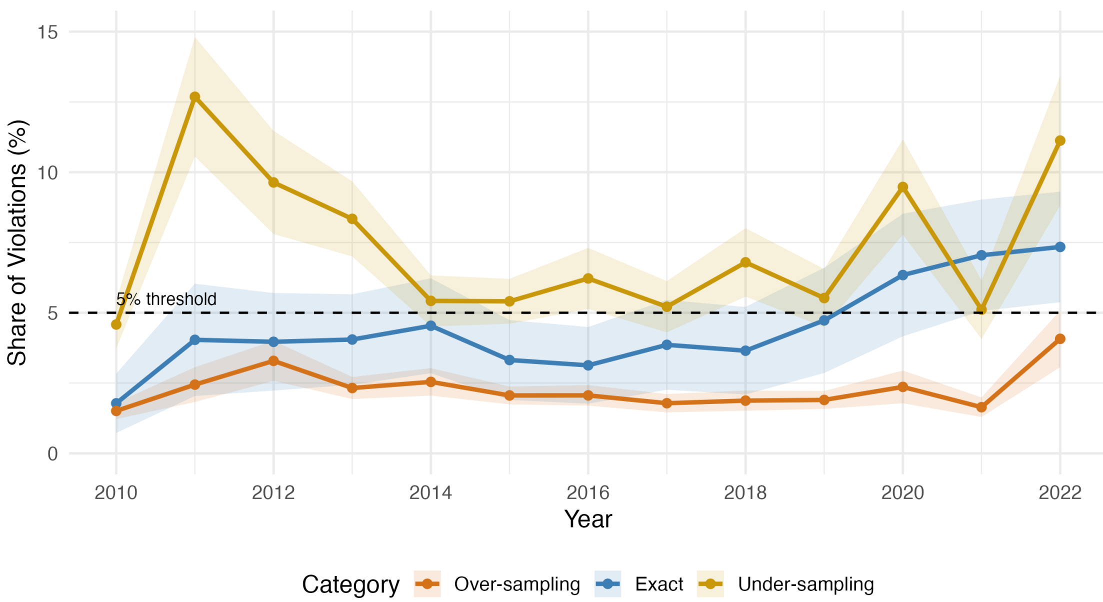
The analysis of reported water quality violations differs from the preceding two layers in one important respect. While all water systems are required to report water quality data and to collect a minimum number of samples, the 5% rule for total coliforms applies only to water systems serving populations with 20,000 or more inhabitants. The econometric analysis of violations is therefore restricted to this subset of water systems. This restriction is not a sample selection choice but a reflection of the regulatory framework: for smaller water systems, different standards apply, and the 5% threshold is not the relevant benchmark.[7]

[7]For systems serving fewer than 20,000 inhabitants, Portaria GM/MS No. 888/2021 adopts a presence-absence standard: no more than one sample among all samples collected in a given period may return a positive result for total coliforms. In 2022, 29% of the municipalities were subject to the five percent rule.

4.3.1 Does Sampling Behavior Distort the Violation Measure?

A natural concern is whether heterogeneity in sampling behavior distorts measured violation rates. To examine this, Figure 9 plots average violation rates by sampling category across the sample period.

Figure 9: Average Share of Reported Violations by Sampling Category



Notes: Confidence intervals correspond to 5% significance level.

Under-samplers exhibit higher violation rates than both exact reporters and over-samplers throughout the period, frequently exceeding the 5 percent legal threshold, while over-samplers display the lowest violation rates of the three groups, remaining consistently below it. These patterns are suggestive, but the confidence intervals overlap substantially across groups and periods, making it difficult to draw firm conclusions from the raw series alone and motivating the regression analysis in Table 3.

Results in column 1 confirm the raw ranking even when controlling for municipal characteristics. In column 2, over-samplers report fewer violations than exact samplers conditional on observables, while under-samplers do not show a statistically different share of violations than exact samplers.

For over-samplers, three mechanisms are consistent with the negative coefficient. First, municipalities that exceed the sampling requirement may simply have better underlying water quality than exact-samplers with similar observable characteristics. Second, excess testing may dilute the

Table 3: OLS estimates of the effect of sampling compliance on the share of water quality violations.

	(1)	(2)
Dependent variable: Share of violations		
Over-sampling	-0.023***	-0.012*
	(0.005)	(0.005)
Under-sampling	0.027***	0.009
	(0.007)	(0.006)
ln Pop		0.003
		(0.002)
HHsize		0.087***
		(0.011)
Sanitation Access		-0.031***
		(0.007)
Water Access		-0.002
		(0.016)
ln Wage		-0.007
		(0.008)
Observations	19,210	19,210
Fixed effects	No	Year
Adj. R^2	0.027	0.123

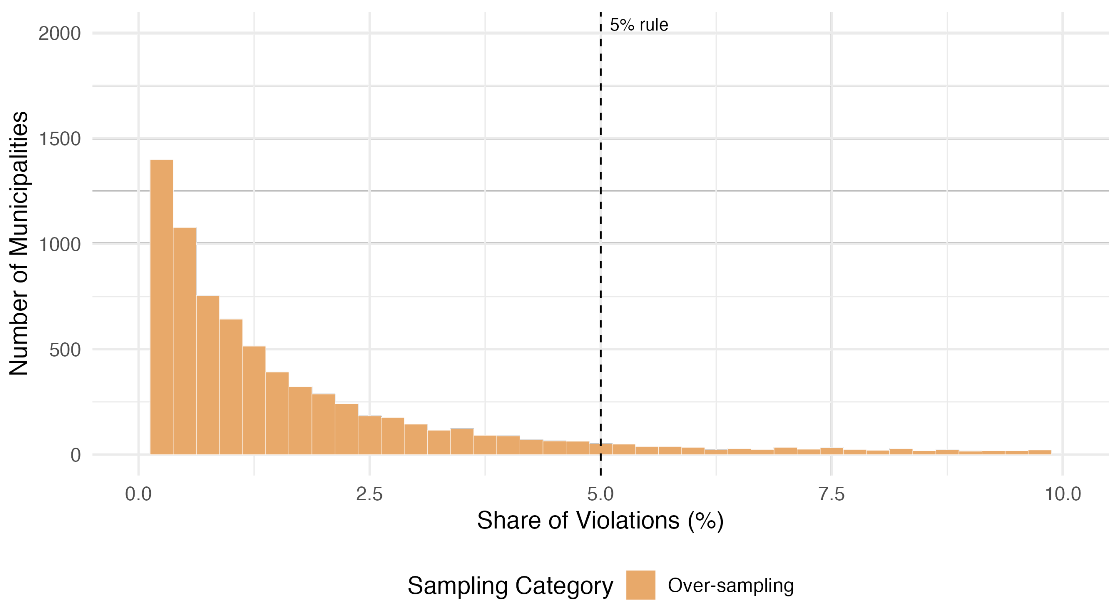
Notes: Standard errors in parentheses. Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

share of positive results by expanding the denominator, reducing the measured violation rate below what a minimum-compliant regime would have recorded. Third, municipalities that detected a violation and complied with Brazil's mandatory resampling protocol would mechanically appear as over-samplers, meaning the lower reported violation rate partly reflects remediation activity already embedded in both the numerator and denominator of the share. The administrative data alone cannot separate these mechanisms, which is why we turn to the distribution of violation shares around the regulatory threshold as a more direct test of strategic behavior.

For under-samplers, the null result is itself informative. The municipal characteristics in column 2 — capturing socioeconomic conditions, infrastructure quality, and institutional capacity — are likely correlated with both the propensity to under-sample and the underlying rate of water quality violations. If under-sampling reflects operational and financial constraints rather than strategic concealment, conditioning on observables that proxy for those same constraints would absorb most of the relevant variation, leaving the under-sampling indicator without residual explanatory power. The null result is consistent with this reading: among municipalities of comparable capacity, under-sampling is not associated with systematically higher violation rates, suggesting capacity constraints rather than deliberate evasion as the primary driver of incomplete monitoring.

As over-samplers systematically report a lower share of violations than the other two groups, we further investigate whether there is evidence of active threshold manipulation by examining the distribution of reported violations around the cutoff. Figure 10 plots this distribution for over-sampling municipalities subject to the five percent rule. The distribution exhibits no detectable excess mass just below the threshold, providing suggestive evidence against active manipulation.

Figure 10: Distribution of Violation Shares Around the 5% Threshold



Two caveats qualify the interpretation of Figure 10. First, our data record reported violations at the annual level, whereas the five percent rule applies monthly. The figure is therefore informative about the distribution of annual reported violation rates, but analyzing bunching requires reported violations to be distributed roughly uniformly across months, an assumption unlikely to hold given well-documented seasonal patterns in Brazilian water quality driven by tourism demand shocks and climatic variation.[8] This temporal aggregation also interacts with the mandatory resampling protocol triggered by each positive coliform result. Given that a single monthly violation initiates a

[8]Studies of Brazilian coastal beaches document sharp increases in fecal contamination during peak tourism months, when temporary population surges overwhelm local sanitation infrastructure (Pessoa et al., 2016; de Sousa et al., 2013; REGO, 2010). On the climatic side, rainfall has been linked to coliform contamination in drinking-water systems (Nascimento Santos et al., 2023), and higher rates of inadequate drinking water have been documented at the onset of the rainy season in the semi-arid Northeast (Dias et al., 2018). If violations concentrate in specific months, annual shares will understate the frequency of monthly threshold exceedances.

sequence of follow-up tests within the same or subsequent months, the annual violation share reflects not only the underlying contamination rate but also the intensity of the remediation response. Second, we do not observe how sampling strategies are implemented at the utility level. Brazil's federal regulations establish minimum sampling frequencies and require representative distribution-system coverage, but leave utilities considerable discretion over specific site selection— that could either attenuate or generate bunching around compliance thresholds.[9]

The negative association between over-sampling and reported violations admits multiple interpretations that cannot be adjudicated with the administrative data alone. Over-samplers may face lower underlying contamination rates and choose to document this through additional testing. They may dilute the share of positive results by expanding the denominator of routine samples beyond the regulatory minimum. They may also appear as over-samplers mechanically, as a consequence of the mandatory follow-up protocol that any positive coliform detection triggers under Portaria GM/MS No. 888/2021, which would mean that the lower reported violation rate partly reflects remediation activity already counted in the numerator and denominator of the share. Each of these mechanisms produces the same empirical pattern, a lower reported violation share conditional on observable municipal characteristics, yet each carries different welfare implications. The null result for under-samplers admits a more straightforward reading.

The regression evidence and the bunching analysis point in different directions and should be read as such. The absence of detectable mass just below the five percent threshold provides no support for active manipulation by over-samplers, at least as far as the annual record allows us to see. The regression result, a lower reported violation share among over-samplers conditional on observables, is consistent with manipulation but also with genuinely better water quality and with the mechanical effect of mandatory resampling following positive detections. Neither piece of evidence settles the question on its own, and the administrative data assembled here cannot separate the three mechanisms. What both results do establish, jointly, is that the reported violation share

[9] Under Portaria MS nº 2.914/2011 (governing monitoring requirements until its 2017 consolidation) and the current Portaria GM/MS nº 888/2021, water suppliers must follow state-approved sampling plans and routinely monitor microbiological indicators such as total coliforms and *E. coli* at representative points in the distribution system. However, utilities retain discretion in defining specific sites, conditional on justification to the surveillance authority. Utilities anticipating regulatory scrutiny could allocate samples disproportionately to low-risk locations, mechanically reducing observed violation shares and attenuating bunching. Conversely, if utilities intensify sampling after initial results suggest non-compliance—permitted insofar as the regulations mandate follow-up investigations after positive findings but do not prohibit additional discretionary sampling—then bunching becomes plausible: expanding the denominator of monthly tests could pull the final violation proportion just below binding limits.

is not a sufficient statistic for water quality. It is the outcome of decisions taken at the sampling stage, and those decisions are themselves correlated with the municipal characteristics that predict contamination risk. Any assessment of compliance that conditions on the violation share alone inherits whatever selection operated in the stages that produced it.

4.3.2 Characterizing Water Quality Among Reporting Municipalities

Figure 11: Share of Positive Samples Above Regulatory Limit — SNIS 2022

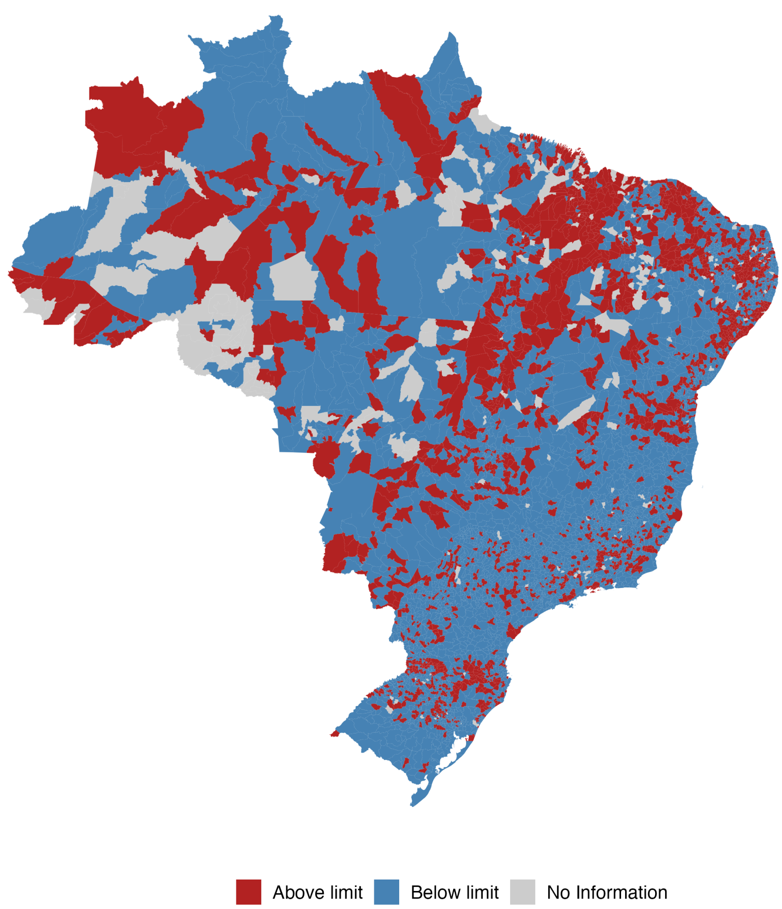


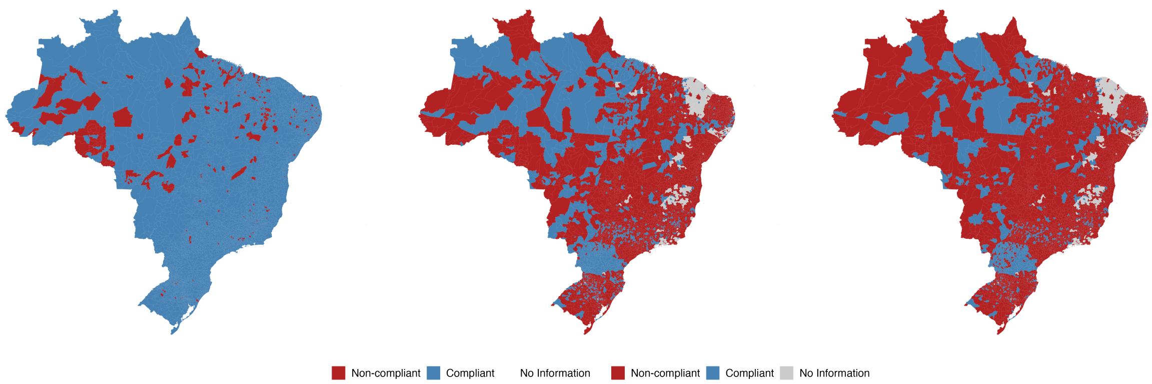
Figure 11 maps the geographic distribution of reported water quality violations, defined as exceeding the maximum allowable share of reported samples with positive results for total coliforms under Brazilian legislation, across Brazilian municipalities in 2022. For municipalities serving more than 20,000 inhabitants, the threshold is 5% of samples; for municipalities serving 19,999 inhabitants or fewer, the applicable standard is a presence-absence rule, under which any positive result constitutes a violation. Grey municipalities are those that did not report water quality data to SNIS in 2022, for whom compliance status cannot be determined. Reported violations are heavily concentrated in the North and Northeast, where large contiguous areas appear in red, suggesting systemic water quality problems in these regions. The Center-West also displays a notable share of non-compliant municipalities, particularly in its eastern portion. By contrast, the South and Southeast are predominantly blue, indicating that most municipalities in these regions satisfy the applicable regulatory threshold. The geographic pattern mirrors the broader inequalities in water infrastructure and institutional capacity across Brazilian regions, with the poorest and most remote areas displaying both the highest rates of non-reporting and, among those that do report, the highest rates of violations.

Figure 12 maps regulatory compliance across the three layers for 2022. The compliance layers are cumulative: the first layer captures reporting, and a municipality is compliant if it submitted any water quality data to SNIS; the second layer additionally requires sampling adequacy, and a municipality is compliant only if it both reported and collected exactly the number of samples prescribed by Portaria GM/MS No. 888/2021; the third layer further requires that the share of samples testing positive for total coliforms does not exceed the 5% threshold for municipalities serving more than 20,000 inhabitants, or that no more than one sample returns a positive result for municipalities with fewer than 20,000 inhabitants.

Because the layers are cumulative, municipalities that fail at the first layer, by not reporting, are classified as non-compliant in all subsequent layers as well, even though their sampling adequacy and violation rates cannot be directly observed. Grey municipalities, which appear only in the second and third panels, are those served by more than one water provider; as discussed in Section 3, the minimum required sample is defined at the provider level and cannot be aggregated to the municipal level when multiple providers operate within the same municipality, making it impossible to assess whether these municipalities satisfy the sampling adequacy criterion.

In the first layer, the large majority of municipalities report water quality data in 2022, with noncompliance concentrated predominantly in the North. Isolated pockets of non-reporting are also visible in parts of the Northeast and Center-West, though these represent a small share of

Figure 12: Cumulative Regulatory Compliance Across Three Layers – SNIS 2022



municipalities overall. Compliance falls sharply in the second layer, and the geographic distribution of noncompliance broadens considerably, extending across large portions of both the North and the South. Notably, the South and Southeast, which were largely compliant at the first layer, display widespread noncompliance at the second layer, suggesting that reporting and sampling adequacy are distinct dimensions of regulatory behavior that do not necessarily move together.

It is worth noting that the sources of noncompliance likely differ systematically across regions. In wealthier, more densely populated southern municipalities, deviations from prescribed sampling rates may predominantly reflect over-sampling, a form of noncompliance with different welfare implications than the under-sampling more likely to characterize poorer, more rural municipalities in the North, where resource and capacity constraints are binding, as discussed in Section 4.

The transition from the second to the third layer, which additionally requires that violation rates remain below the applicable threshold, produces comparatively little additional noncompliance. The two maps are strikingly similar in both the overall share of non-compliant municipalities and their geographic distribution, indicating that most municipalities that report and sample correctly also satisfy the violation-rate criterion. This suggests that the binding constraint in the compliance hierarchy is sampling adequacy rather than violation rates. The incremental noncompliance introduced at this final stage remains geographically concentrated in the North, consistent with the capacity constraints noted above, and is largely invisible in the South and Southeast, where municipalities that clear the second layer almost universally satisfy the third.

Figures 11 and 12 reveal a striking contrast. Figure 11, which conditions solely on whether reported samples exceed the applicable violation threshold, is predominantly blue, suggesting that most reporting municipalities satisfy the water quality standard. Figure 12, however, reveals considerably more noncompliance, particularly in the second and third panels. This difference is almost entirely attributable to sampling adequacy: once compliance is conditioned on whether municipalities collect the prescribed number of samples, a large share of previously blue municipalities turn red. In other words, the apparent compliance suggested by violation rates alone is partly an artifact of insufficient sampling; municipalities that collect too few samples are less likely to detect violations, and thus may appear compliant when they are not.

5 Conclusions and policy recommendations

This paper develops a three-layer framework for understanding compliance with drinking water quality regulation in systems that rely on provider self-monitoring. Rather than treating reported violations as a direct measure of regulatory performance, the framework organizes compliance as a sequential process: providers must first report monitoring information, then collect the required number of samples, and only then can sampled water quality be evaluated against regulatory thresholds. Because each layer is a necessary condition for the next, failures in reporting and sampling shape the set of violations that become visible in official statistics. Reported violations, therefore, reflect not only underlying water quality conditions, but also the reporting and sampling processes through which contamination becomes visible in the administrative record.

Using data from Brazilian municipalities between 2010 and 2022, we show that failures at each compliance layer are widespread, non-random, and systematically associated with municipal characteristics. At the first layer, non-reporting is concentrated among poorer, smaller, and less-developed municipalities, precisely the locations where underlying contamination risks are likely greatest. At the second layer, both under- and over-sampling are widespread, while exact compliance with prescribed sample counts is relatively uncommon. At the third layer, reported violations are shaped by sampling behavior in systematic ways. Under-samplers exhibit persistently higher raw violation rates, though this association weakens substantially once municipal characteristics are held constant, a pattern more consistent with operational and capacity constraints than with deliberate concealment. Over-samplers report fewer violations than exact-samplers conditional on observables, a result that admits several interpretations, including genuinely better water quality, dilution of positive results through excess testing, and the mechanical effect of mandatory resampling following contamination events. The administrative data alone cannot distinguish among these mechanisms. What the evidence does establish, however, is that reported violations are shaped by sampling behavior and therefore do not fully capture underlying water quality conditions.

These patterns have implications beyond Brazil. Across LAC and in middle-income countries more broadly, regulatory systems for drinking water quality share the key structural features highlighted by our framework: reliance on provider self-monitoring, heterogeneity in institutional capacity, and a near-exclusive focus on threshold-reported violations as the published compliance metric. To the extent that selection into reporting and sampling is correlated with underlying water quality risk in those settings as well, official violation rates will tend to understate non-compliance where it is most consequential. Strengthening water quality governance, therefore, requires attention to all three layers of the compliance hierarchy, not only the one that is routinely measured.

First, enforcement efforts should expand beyond threshold violations to encompass reporting adequacy and, critically, sampling adequacy, including the possibility that providers strategically select low-risk sampling locations or collect excess samples in ways that reduce measured violation rates. Our results suggest that gaps in the first two layers have measurable consequences for the reliability of the official record, and that the municipalities where these gaps are largest are also those where the consequences for public health are likely to be most severe.

Second, horizontal coordination between information systems and systematic cross-validation against health surveillance data would allow regulators to identify municipalities where administrative compliance records and population health outcomes diverge in ways that are difficult to explain by drinking water quality alone, providing a practical tool for targeting oversight. The absence of such coordination reflects a broader pattern that the Organization for Economic Co-operation and Development (OECD) has documented as an information gap in multi-level water governance: the multiplicity of institutions involved in the sector generates asymmetries in data availability that make it impossible for any single agency to construct a reliable picture of compliance (OECD, 2011;

Akhmouch, 2012). SISAGUA already embeds a form of triangulation by collecting water quality data separately from both providers and health authorities within the same system. However, low regional coverage and the absence of a variable recording the minimum number of samples required make it difficult to use SISAGUA for policy studies of the kind developed here. This last limitation is precisely why the present study relies on SNIS rather than SISAGUA: assessing sampling adequacy, the second compliance layer, requires knowing both the number of samples collected and the regulatory minimum each provider was obligated to collect

Third, improving compliance in poorer and more rural municipalities requires addressing the capacity constraints that may drive under-sampling, not only the regulatory incentives. The appropriate modality is context-dependent: centralized laboratory testing is most cost-effective where proximity to infrastructure permits it (Trimmer et al., 2024), while portable or community-based approaches may be preferable in more remote settings. Ramesh et al. (2024) demonstrates that minimally trained community members can reliably conduct water quality monitoring using integrated sensor kits, and Marks and Shrestha (2019) documents compliance improvements from 7 to 50 percent following the introduction of solar-powered field laboratories in rural Nepal. A differentiated testing strategy, calibrated to local logistical constraints, could meaningfully close the monitoring gap in the municipalities where it matters most.

Fourth, and specific to the Brazilian context, the informativeness of administrative drinking water quality data could be improved by extending reporting requirements to include finer detail on sampling timing, intra-system sampling locations, and the identity of the testing entity. SISAGUA is already a regional model for regulatory transparency, and these additions would strengthen its capacity to detect anomalous sampling patterns and provide a richer basis for enforcement.

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A Appendix Results

Figure 13: Reporting vs Non-Reporting Municipalities in 2022 — SISAGUA and SNIS

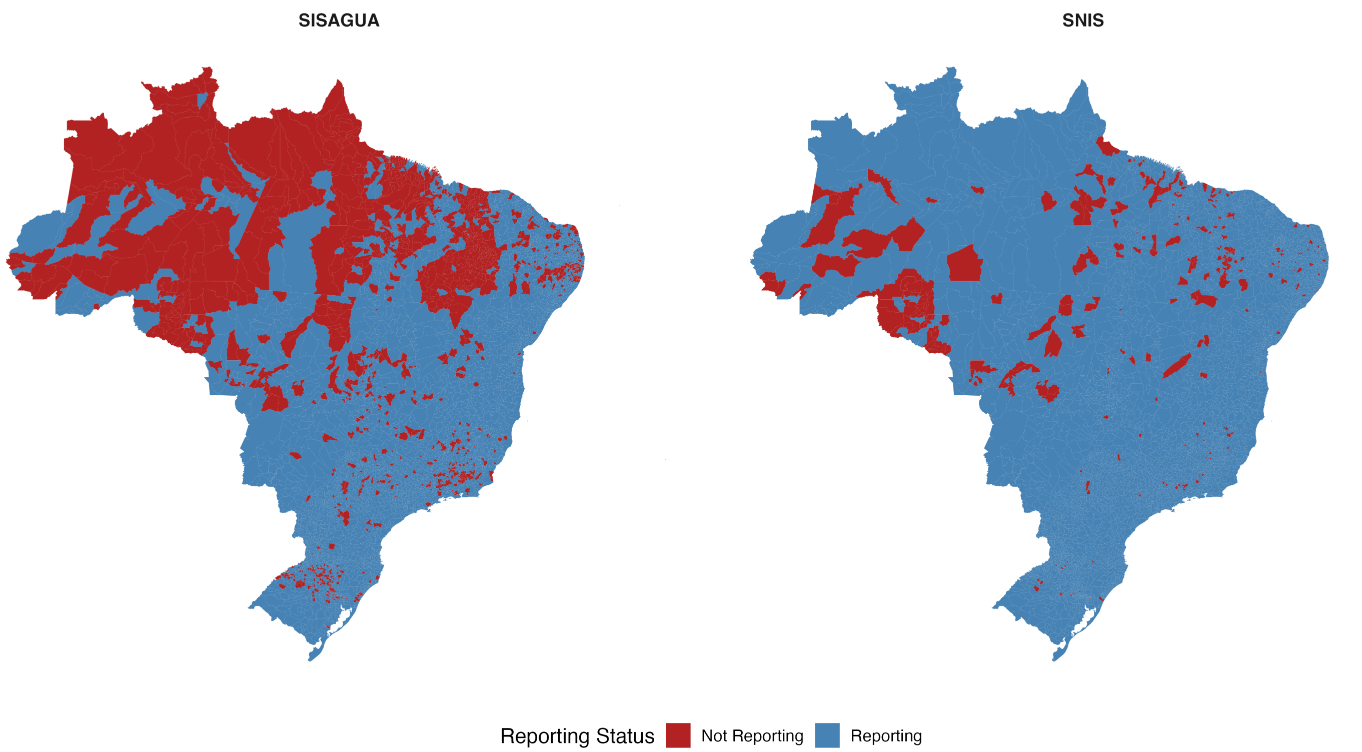

Table 4: Persistence in Sampling Behavior

	Under-sampling			Exact reporting			Over-sampling		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Under-sampling $_{t-1}$	0.584***	0.432***	0.388***						
	(96.206)	(77.411)	(62.006)						
Under-sampling $_{t-2}$		0.256***	0.182***						
		(45.104)	(27.753)						
Under-sampling $_{t-3}$			0.169***						
			(30.137)						
Exact reporting $_{t-1}$				0.757***	0.598***	0.578***			
				(156.505)	(85.429)	(75.156)			
Exact reporting $_{t-2}$					0.211***	0.161***			
					(32.423)	(20.335)			
Exact reporting $_{t-3}$						0.089***			
						(14.275)			
Over-sampling $_{t-1}$							0.606***	0.469***	0.439***
							(117.111)	(89.857)	(76.048)
Over-sampling $_{t-2}$								0.227***	0.169***
								(43.569)	(27.969)
Over-sampling $_{t-3}$									0.126***
									(23.999)
R^2	0.345	0.389	0.407	0.569	0.588	0.591	0.367	0.399	0.409
N					47,388				

t statistics in parentheses, clustered by municipality.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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