Temperature and the work of bureaucrats: evidence from auditing reports in Brazil

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Abstract

A growing body of literature shows evidence that high temperatures negatively impact performance. Less studied is the impact on the work performance of government bureaucrats. Our paper estimates the impact of temperature on auditors' work performance, measured by the likelihood with which auditors report corruption. We use data on hundreds of municipalities randomly audited in an anti-corruption program in Brazil. We find that auditors are more likely to report corruption if their fieldwork is conducted under higher temperatures. We discuss the potential mechanisms underlying our findings, which highlight important avenues for further research. Our results have implications for understanding the influence of external factors on essential government functions that impact social welfare.

Keywords: temperature, work performance, corruption, government audit
JEL Codes: H83, J81, Q54

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1 Introduction

Bureaucratic efficiency is essential in developing countries, where the public sector's effectiveness is crucial for successful development activities (Ashraf et al., 2020; Banuri et al., 2018; Dal Bó et al., 2013; Duflo et al., 2012; Glewwe et al., 2010; Kahn et al., 2001; Muralidharan and Sundararaman, 2011; World Bank, 2008). In particular, auditors play a critical role in developing economies, where corruption tends to be prevalent (Olken and Pande, 2012), and audit results impact electoral outcomes and future corrupt behavior (Avis et al., 2018; Bobonis et al., 2016; Ferraz and Finan, 2008; Olken, 2007; Zamboni and Litschig, 2018).

Our paper estimates the effect of temperature shocks on auditors' work performance. Performance is measured by written audit reports from a federal anti-corruption program in Brazil.[1] Across several months, auditors were assigned to inspect the use of federal funds at randomly selected municipalities. Our empirical strategy exploits temperature shocks at the time municipalities are audited. Local weather conditions can affect auditors' ability to interview local community members or oversee development projects, potentially impacting their ability to report more or less corruption. The random nature of the audit program guarantees that the municipality assignment and the audit timing are unrelated to weather conditions.

We find that temperature has a statistically and economically significant effect on auditors' work performance. A one standard deviation increase in temperature during the audit period increases auditors' likelihood of reporting corruption by 17 percent. Results are robust to different specifications, alternative performance measurements, and falsification test using lag and lead temperature measurements.

[1] Previous findings highlighting the economic importance of this anti-corruption program for political outcomes and social welfare (Avis et al., 2018; Bobonis et al., 2016; Ferraz and Finan, 2008; Olken, 2007; Zamboni and Litschig, 2018).

Our paper provides evidence that temperature can affect bureaucratic efficiency in a high-stakes context: public spending audits in a developing country. Our findings contribute to the emerging literature on the effects of external factors on workers' productivity (Adhvaryu et al., 2022; Custers et al., 2021; LoPalo, 2023; Somanathan et al., 2021). Closer to ours are Heyes and Saberian (2019) and Obradovich et al. (2018) on the temperature effects on public servants' work performance, both in the US context. We contribute by showing that temperature can affect the work of bureaucrats with consequence to corruption reporting.

2 Context and Data

In 2003, the Brazilian federal government started a national anti-corruption program to investigate local corruption at the municipality level. Municipalities were randomly selected by a public lottery, and municipal governments' expenditures of federal transfers are audited. In each round, 50 or 60 municipalities were randomly drawn, with replacement, from all municipalities with fewer than 450,000 residents. After the lottery, the Controladoria Geral da União (CGU), a branch of the federal government in charge of transparency policies, sends around 10 to 15 auditors to each selected municipality.

Audits typically take five days, Monday to Friday. Afterward, auditors write a report about irregularities and evidence of corruption found during the fieldwork. Auditors receive extensive training and guidelines on how to produce reports, with standardized rules about formatting and content. Reports often contain photo images taken during the fieldwork or tables made based on collected information. The municipality administration can respond to reported irregularities, and the audit team revises the report based on justifications. The final report is made public on the CGU website, which is the information we analyze.

2.1 Data

Weather-related measures: we use the Princeton Global Meteorological Forcing Dataset, a gridded, three-hourly dataset, with information on rainfall, air pressure, specific humidity, and dry-bulb temperature (Appendix A.). We use average temperature between 9 am to 5 pm, roughly corresponding to the time auditors work in the field (Figure D.1).

Corruption information from audit reports: we use data manually compiled by Brollo (2011) and Brollo et al. (2013), made available online by the researcher. The authors coded information contained in the publicly available audit reports. Broad corruption includes "irregularities that could also be interpreted as bad administration rather than overt corruption." Therefore, all reported irregularities are classified as broad corruption, which includes mismanagement of public resources. A subset of these irregularities is classified as narrow corruption, defined as "only severe irregularities that are also more likely to be visible to voters." As outcome variables, we use the indicators of whether auditors reported any broad and narrow corruption for audited municipalities. We also collect additional information from the audit reports: fieldwork dates, total number of figures and tables in each report.

Municipality characteristics are from the Population Census in 2000: urban population share, income per capita, log of population, and population share below the poverty line.

The final data contains 966 audits conducted from the 2nd to 19th audit rounds, from 2003 to 2005. Summary statistics are shown in Table 1, by type of irregularity. Auditors reported broad corruption in 711 audits, of which 424 were also classified as narrow corruption. The table indicates that audits resulting in reported corruption are more likely to be conducted on hotter days. Additionally, more images and tables are used in audit reports in which corruption is reported. This suggests that auditors use images and tables as evidence of corruption and mismanagement.

Table 1: Summary Statistics (by corruption definitions)

	(1)	(2)	(3)	(4)	(5)	(6)
	Broad = 1	Broad = 0	Broad Diff. ((1) - (2))	Narrow = 1	Narrow = 0	Narrow Diff. ((4) - (5))
Wet bulb temp. (°C)	23.30	22.15	1.15***	23.57	22.56	1.01***
	(3.31)	(4.04)	(0.26)	(3.19)	(3.75)	(0.23)
Dry bulb temp. (°C)	27.97	26.44	1.53***	28.18	27.08	1.10***
	(3.96)	(4.89)	(0.31)	(3.80)	(4.56)	(0.28)
Number of images	19.81	18.14	1.67	22.60	16.84	5.76***
	(22.38)	(24.56)	(1.68)	(24.08)	(21.75)	(1.48)
Number of tables	27.84	19.08	8.76***	32.66	19.95	12.71***
	(23.42)	(13.62)	(1.55)	(26.50)	(14.60)	(1.34)
Rainfall (mm/day)	2.74	3.26	-0.52*	2.70	3.02	-0.32
	(3.48)	(4.59)	(0.28)	(3.46)	(4.06)	(0.25)
Long-run average wet bulb temp.	24.26	23.56	0.71***	24.45	23.79	0.66***
	(2.32)	(2.71)	(0.18)	(2.24)	(2.56)	(0.16)
Long-run average dry bulb temp.	28.30	27.28	1.01***	28.49	27.67	0.81***
	(2.84)	(3.31)	(0.22)	(2.72)	(3.16)	(0.19)
Long-run average rainfall	3.81	4.33	-0.52***	3.72	4.13	-0.41***
	(1.39)	(1.29)	(0.10)	(1.47)	(1.29)	(0.09)
Share of pop urban (%)	59.23	59.55	-0.32	57.78	60.52	-2.74*
	(22.10)	(24.86)	(1.67)	(21.94)	(23.49)	(1.48)
Log pop.	9.50	9.47	0.04	9.55	9.45	0.10
	(0.98)	(1.12)	(0.07)	(0.99)	(1.04)	(0.07)
Share of pop poor (%)	44.80	37.41	7.39***	48.51	38.43	10.09***
	(22.50)	(22.00)	(1.63)	(22.31)	(21.84)	(1.43)
Second-time audit	0.01	0.01	0.00	0.01	0.01	-0.01
	(0.11)	(0.09)	(0.01)	(0.08)	(0.12)	(0.01)
Observations	711	255	966	424	542	966

Notes: In columns (1), (2), (4), and (5), means (and standard deviations) are shown. In columns (3) and (6), differences in variable means between municipalities with and without corruption detected (and their standard errors) are shown. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

3 Empirical Strategy

We exploit the exogenous variation in temperature when audits are conducted to identify the causal effect of temperature on the probability of reporting corruption. In equations (1) and (2), the outcome variable, C_{ijt}, is an indicator for any corruption (broad and narrow separately) reported for a municipality i in a mesoregion j that is audited in the t'th round of the audit program.[2] The effect of wet-bulb temperature (T_{ijt}) on reported corruption is assumed to affect the outcome linearly (Equation 1), or non-linearly (Equation 2) using

[2]Mesoregion is an administrative unit smaller than state, and there are 137 mesoregions in Brazil.

binned wet-bulb temperature (T^b_{ijt}) with 2°C-intervals.

$$C_{ijt} = \alpha T_{ijt} + \beta P_{ijt} + X'_{ij}\gamma + \mu_j + \nu_t + \epsilon_{ijt} \tag{1}$$

$$C_{ijt} = \sum_b \alpha_b T^b_{ijt} + \beta P_{ijt} + X'_{ij}\gamma + \mu_j + \nu_t + \epsilon_{ijt}. \tag{2}$$

The inclusion of municipality-level long-run temperature in X_{ij}[3] controls for the potential municipality-level confounding factors, such as long-term climate affecting institutions in municipalities (Dell et al., 2012). Mesoregion fixed effects (μ_j) account for mesoregion-level climate characteristics such as variance in the long-run temperature, rulling out the possibility that a potentially complex mesoregion-level relationship between climate and institution biases our estimates, and accounting for differences across states, such as state-based audit teams. As a robustness check, we use state fixed effects instead of mesoregion fixed effects. The possibility that mesoregion fixed effects do not control for municipality-level climate characteristics is discussed in a falsification test. Audit wave fixed effects (ν_t) control for seasonality. The error term is denoted by ϵ_{ijt} and inferences are based on the clustered wild-bootstrap method at the state level (Cameron et al., 2008).

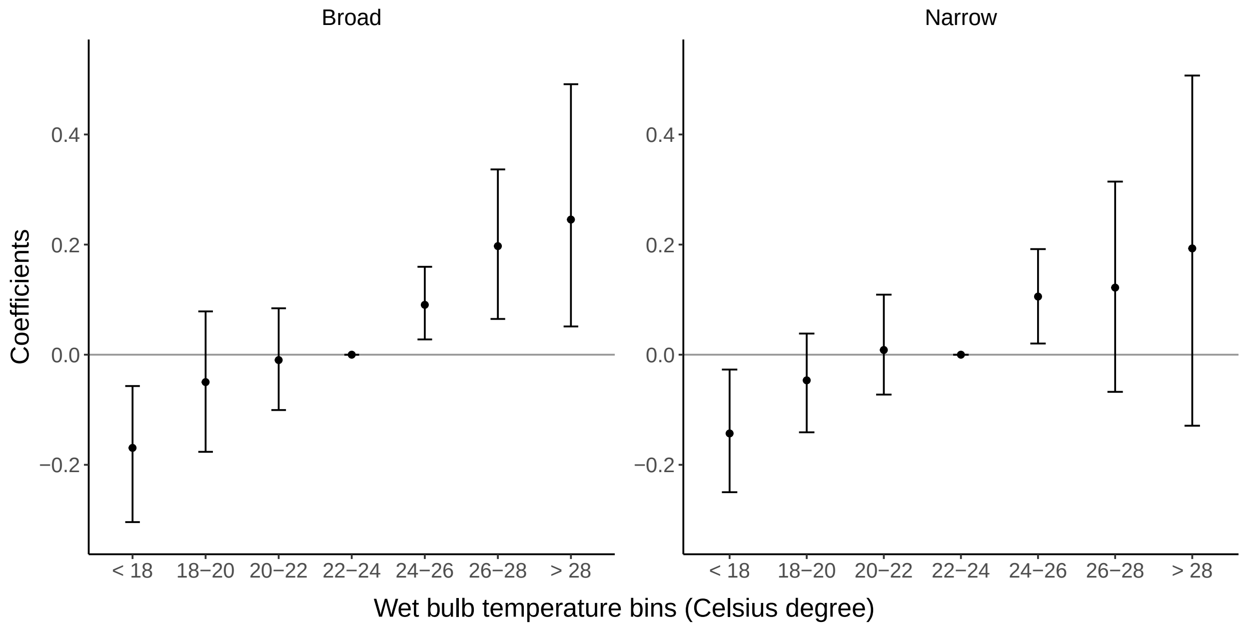
4 Results

We find that auditors are more likely to report corruption if the temperature is higher during audit fieldwork. Table 2 reports results from the linear specification. The point estimates are statistically significant and economically meaningful: a one standard deviation increase in wet-bulb temperature increases the probability of reporting narrow corruption by 7.5 percentage points (or 17 percent). Note that since municipalities have the chance to revise, explain, and correct any irregularities wrongfully flagged before the public release of

[3] municipality long-run temperature, the share of the urban population, income per capita, the log of population, population share below the poverty line, and an indicator for the second-time audit

the reports, the positive effects of temperature on corruption reporting are unlikely to be due to corruption over-reporting. Figure 1 shows the regression coefficients allowing non-linear effects of wet-bulb temperature[4]

Figure 1: Wet-bulb temperature effects on reported corruption



Notes: The figure shows the regression coefficients of an indicator for corruption (left: broad, right: narrow) reported on the wet-bulb temperature bins. Each temperature interval does not include the right end. The 90% confidence intervals are shown. Control variables include the share of the urban population, income per capita, log of population, the population share below the poverty line, an indicator for second-time audit, and long-run (1980-2016) temperature and rainfall measures. Audit wave fixed effects and mesoregion fixed effects are included in the regressions. Confidence intervals are calculated with clustered wild-bootstrap at the state level.

As a falsification test, we add, to Equation (1), temperature measures on the same days one year before and one year after the actual fieldwork. This allows us to test whether results in columns (1) and (2) in Table 2 are spurious correlations caused by the relationship between the long-run weather and actual corruption levels. If the relationship is not spurious, we would observe a statistically insignificant relationship between corruption reports and the

[4]WB temperature takes into account the air temperature and humidity simultaneously, extensively used in climate science and biology to represent heat stress danger and thermal comfort (Budd, 2008; Liljegren et al., 2008), and in economics studies (Adhvaryu et al., 2020; Geruso and Spears, 2018). Results using dry-bulb temperatures are reported in the appendix.

lead and lag variables. In columns (3) and (4) in Table 2, results show negligible effects of past and future temperature and unchanged point estimates of temperature measures during the actual fieldwork. These reinforce our argument that we identify the contemporaneous temperature effects on the probability of reporting corruption.[5]

Table 2: Regression: Corruption reports and temperature

	(1)	(2)	(3)	(4)
	Broad	Narrow	Broad	Narrow
Wet bulb temp. (°C)	0.017	0.021	0.021	0.023
	[0.001, 0.031]*	[0.002, 0.037]*	[0.002, 0.039]*	[0.003, 0.040]*
WB temp. ($t-1$) (°C)			-0.011	-0.004
			[-0.028, 0.008]	[-0.021, 0.016]
WB temp. ($t+1$) (°C)			-0.001	-0.001
			[-0.023, 0.016]	[-0.029, 0.023]
Rainfall (mm/day)	0.000	0.001	0.001	0.001
	[-0.010, 0.011]	[-0.007, 0.011]	[-0.010, 0.013]	[-0.006, 0.011]
Observations	966	966	966	966
R-squared	0.27	0.32	0.27	0.32
Mesoregion FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Mean of outcome	0.736	0.439	0.736	0.439
SD of temperature in year t	3.550	3.550	3.550	3.550

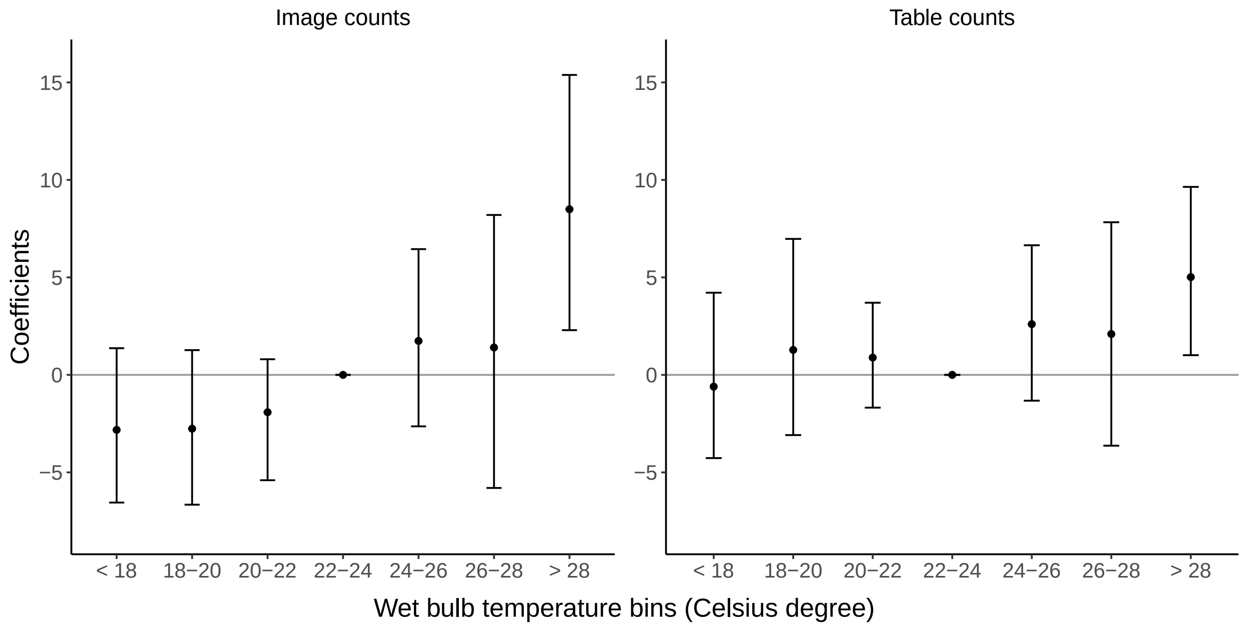
Notes: The dependent variable in columns (1) and (3) is an indicator for broad corruption reported, and the dependent variable in columns (2) and (4) is an indicator for narrow corruption reported. Control variables include the share of the population that is urban, income per capita, log of population, population share below the poverty line, an indicator for second-time audit, and long-run (1980-2016) temperature and rainfall measures. Numbers in square brackets are 90% confidence intervals, calculated with clustered wild-bootstrap at the state level. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$ Results using state-fixed effects are reported in Table C.5 and Figures D.4 and D.5. State-level clustered standard errors reported on Table C.1.

As a robutsness check, we use the contents of audit reports (tables and figures) as proxy of reported corruption and analyze how they are affected by temperature during fieldwork. Positive correlations between reported corruption and the number of figures and tables support this view (Table 2). Appendix E shows examples of images and tables in audit reports

[5] As an alternative falsification test, we also test whether only lag and lead temperatures, added one at a time, affect reported corruption. Table C.3 in the appendix shows statistically and economically insignificant effects of these temperatures, which is aligned to our preferred test.

and how they are used as evidence of corruption and mismanagement. The objectivity of figures and tables as a measure of corruption is an advantage over the corruption measures used in our main analysis.

Figure 2: Wet-bulb temperature effects on number of images and tables



Notes: The figure shows the regression coefficients of the number of images (left) and the number of tables (right) on the wet-bulb temperature bins. Each temperature interval does not include the right end. The 90% confidence intervals are shown. Control variables include the urban population share, income per capita, log of population, the population share below the poverty line, an indicator for second-time audit, and long-run (1980-2016) temperature and rainfall measures. Audit wave fixed effects and mesoregion fixed effects are included in the regressions. Confidence intervals are calculated with clustered wild-bootstrap at the state level.

Figure 2 shows the positive effect of high wet-bulb temperature on the numbers of images (left panel) and tables (right panel), suggesting that when the temperature during fieldwork is higher, auditors report more corruption using visual evidence (e.g., figures and tables).[6] It should be noted that the results using figures and tables do not necessarily reflect an effect of temperature on how auditors conduct fieldwork. While images and tables

[6]Results with a linear specification in Table C.4 show imprecise and statistically insignificant estimates. This can be because a linear specification did not fully capture the non-linear nature of the relationship between temperature and reported figures/tables. Figure D.3 shows overall positive but weaker effects of dry-bulb temperature, which is consistent with the discussion in Section ??.

are more likely to be included in reports if there is corruption or mismanagement involved, auditors may not use collected evidence if no issue is found. We rely on the consistent results across different reported corruption measures to support the robustness of our findings.

5 Discussion of potential mechanisms

We cannot test for mechanisms behind the relationship between temperature and corruption reporting due to data limitations. Based on the literature, we discuss different potential drivers of our findings, providing several suggestive topics for future research.

First, the temperature can change how auditors conduct fieldwork through a change in mood and a change in productivity. For mood, Baylis (2020) and Baylis et al. (2018) find that extreme temperature worsens the expressed sentiment and increases the frequency of aggressively profane phrases in social media. Heyes and Saberian (2019) find that judges are more likely to make decisions unfavorable to applicants when temperatures are high, attributing part of the mechanism to mood. A productivity channel could explain our results if auditors under-report corruption when the temperature is lower. Whereas Adhvaryu et al. (2020); Custers et al. (2021); LoPalo (2023); Somanathan et al. (2021) find lower productivity under higher temperature, Stevens (2017) finds that lower temperature decreases labor productivity. This could explain our findings if *lower* temperature decreases auditors' productivity and, as a result, they collect less evidence of corruption.

Second, the temperature during fieldwork can change how auditors write reports. If auditors write reports at the audited municipalities during or after their fieldwork, the temperature while writing the reports can affect the mood (Baylis, 2020; Baylis et al., 2018; Heyes and Saberian, 2019) and cognitive performance (Graff Zivin et al., 2020; Melo and Suzuki, 2023; Park, 2020) of auditors, altering the reports' contents. If high temperature induces stress during their fieldwork, this could affect what auditors remember when writing reports. For instance, Hoscheidt et al. (2014) experimentally find that negative memories encoded under stress retain for more extended periods. Therefore, the temperature during fieldwork can still affect report writing even if auditors write reports elsewhere.

6 Conclusion

In this study, we investigate the effects of temperature on the productivity of bureaucrats and corruption reporting. Our findings suggest that work conditions might influence high-stakes audits conducted at specific times. Improved work conditions (Adhvaryu et al., 2020; Custers et al., 2021), work flexibility (Adhvaryu et al., 2022; LoPalo, 2023), or even training to raise awareness of these potential external factors could mitigate the identified effects. However, understanding the mechanisms through which temperature affects auditors' work performance can provide accurate guidance on the most effective type of intervention, and is our recommendation for future research.

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A Construction of weather-related variables

Weather information in this study comes from the Princeton Meteorological Forcing Dataset. This reanalysis dataset combines the climate model information and observational data from various sources such as weather stations and satellite observations. It provides weather information even in places where observational data is scarce. The Princeton Meteorological Forcing Dataset is a 3-hourly dataset: weather variables are recorded at 0 am, 3 am, . . . , 9 pm at Greenwich time zone. Also, this is a gridded dataset at a resolution of 0.25×0.25 degrees. For details on the dataset, see Sheffield et al. (2006).

We use dry-bulb temperature, specific humidity, air pressure, and rainfall information in the dataset. To obtain each of these variables at each municipality, we use weather measures at four grid points surrounding municipality centroids and take the average of them, weighted by the inverse distance between the centroids and each of the four grid points. As daily weather measures, for variables other than the rainfall measure, we take the average values recorded between 9 am and 5 pm at the local time, accounting for the time zones and the daylight saving time. For instance, in a municipality in a state Acre, whose time zone is UTC−05:00, we use variables at 10 am, 1 pm, and 4 pm since they correspond to 3 pm, 6 pm, and 9 pm at Greenwich time zone, at which times weather information is recorded in the Princeton Meteorological Forcing Dataset. We take the average of these values and use it in our analyses as the temperature measurement on a particular day. Given these numbers, we take the average of them during fieldwork, which we use in the analyses. Since rainfall is recorded only daily, we take the average rainfall during the audit fieldwork as a rainfall measure in the regressions.

In the analyses, we use two different measures for temperature: dry-bulb temperature and wet-bulb temperature. Dry-bulb temperature is directly obtained from the Princeton Meteorological Forcing Dataset, and the wet-bulb temperature is calculated based on dry-bulb temperature, specific humidity, and air pressure, using the following formula (Geruso and Spears, 2018):

$$
\begin{aligned}
T_{wb} = T_{db} * \left[atan(0.151977 * (R + 8.313658)^{1/2}\right] + atan(T_{db} + R) \\
- atan(R - 1.676331) + 0.00391838R^{3/2} * atan(0.023101R) - 4.686035 \\
R = 0.263 * p * s * \left[\exp\left(\frac{17.67T_{db}}{T_{db} + 243.5}\right)\right]^{-1},
\end{aligned}
$$

where T_{wb} is wet-bulb temperature (°C), T_{db} is dry-bulb temperature (°C), R is relative humidity (%), p is air pressure (Pa), and s is specific humidity.

B Results using dry-bulb temperature

Table C.2 shows positive but statistically insignificant effects of dry-bulb temperature on corruption reports. Furthermore, Figure D.2 shows the *negative* impact of high dry-bulb temperature (higher than 32°C) on reporting broad corruption. The difference from regression results with wet-bulb temperature suggests the importance of taking humidity into account in this context. In particular, the negative impact of high dry-bulb temperature found in Figure D.2 might be capturing the effect of lower humidity. Indeed, due to the low humidity level, the average wet-bulb temperature for municipalities in the highest dry-bulb temperature bin (> 32) is 25.4°C, which is lower than that of the second-highest dry-bulb temperature bin ($30 - 32$), which is 26.1°C. This resonates with the role of humidity affecting individual comfort found in previous studies (Jing et al., 2013; Li et al., 2019). Moreover, the results are consistent with findings in economics studies such as Geruso and Spears (2018) and LoPalo (2023), which find an important interactive effect between temperature and humidity on health and labor outcomes.

C Appendix tables

Table C.1: Regression: Corruption reports and temperature (standard errors not wild bootstrapped)

VARIABLES	(1) Broad	(2) Narrow	(3) Broad	(4) Narrow
Wet bulb temp. (°C)	0.017*	0.021**	0.021**	0.023**
	(0.008)	(0.010)	(0.010)	(0.010)
Wet bulb temp. (one-year lag) (°C)			-0.011	-0.004
			(0.009)	(0.010)
Wet bulb temp. (one-year lead) (°C)			-0.001	-0.001
			(0.010)	(0.014)
Rainfall (mm/day)	0.000	0.001	0.001	0.001
	(0.005)	(0.005)	(0.005)	(0.005)
Observations	966	966	966	966
R-squared	0.27	0.32	0.27	0.32
Mesoregion FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Mean of outcome	0.736	0.439	0.736	0.439
SD of temperature in year t	3.550	3.550	3.550	3.550

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable in columns (1) and (3) is an indicator for broad corruption reported, and the dependent variable in columns (2) and (4) is an indicator for narrow corruption reported. Control variables include the share of the urban population, income per capita, log of population, population share below the poverty line, an indicator for second-time audit, and long-run (1980-2016) temperature and rainfall measures. Numbers in parentheses are the state-level clustered standard errors. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

Table C.2: Regression: corruption reports and dry-bulb temperature

	(1) Broad	(2) Narrow	(3) Broad	(4) Narrow
Dry bulb temp. (°C)	0.008	0.012	0.008	0.014
	[-0.007, 0.021]	[-0.002, 0.025]	[-0.009, 0.024]	[0.001, 0.027]*
Dry bulb temp. (one-year lag) (°C)			-0.003	-0.002
			[-0.016, 0.011]	[-0.018, 0.015]
Dry bulb temp. (one-year lead) (°C)			0.001	-0.003
			[-0.019, 0.022]	[-0.024, 0.017]
Rainfall (mm/day)	0.003	0.005	0.003	0.005
	[-0.006, 0.014]	[-0.003, 0.015]	[-0.007, 0.014]	[-0.003, 0.015]
Observations	966	966	966	966
R-squared	0.26	0.32	0.26	0.32
Mesoregion FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Mean of outcome	0.736	0.439	0.736	0.439
SD of temperature in year t	4.275	4.275	4.275	4.275

Notes: The dependent variable in columns (1) and (3) is an indicator for broad corruption reported, and the dependent variable in columns (2) and (4) is an indicator for narrow corruption reported. Control variables include the share of the urban population, income per capita, log of population, the population share below the poverty line, an indicator for second-time audit, and long-run (1980-2016) temperature and rainfall measures. Numbers in square brackets are 90% confidence intervals, which are calculated with clustered wild-bootstrap at the state level. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

Table C.3: Regression: corruption reports (falsification tests)

	(1) Broad	(2) Broad	(3) Narrow	(4) Narrow
Wet bulb temp. (one-year lag) (°C)	-0.006		0.002	
	[-0.020, 0.009]		[-0.013, 0.018]	
Wet bulb temp. (one-year lead) (°C)		0.002		0.006
		[-0.012, 0.014]		[-0.017, 0.027]
Observations	966	966	966	966
R-squared	0.26	0.26	0.32	0.32
Mesoregion FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Mean of outcome	0.736	0.736	0.439	0.439
SD of temperature	3.387	3.722	3.387	3.722

Notes: The dependent variable in columns (1) and (2) is an indicator for broad corruption reported, and the dependent variable in columns (3) and (4) is an indicator for narrow reported corruption. Control variables include the share of the urban population, income per capita, log of population, the population share below the poverty line, an indicator for second-time audit, and long-run (1980-2016) temperature and rainfall measures. Numbers in square brackets are 90% confidence intervals, which are calculated with clustered wild-bootstrap at the state level. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

Table C.4: Regression: numbers of images and tables and temperature

	(1) Images	(2) Tables	(3) Images	(4) Tables
Wet bulb temp. (°C)	0.092	-0.305	0.144	-0.597
	[-0.679, 0.706]	[-1.179, 0.354]	[-0.600, 0.725]	[-1.533, 0.150]
Wet bulb temp. (one-year lag) (°C)			0.265	0.306
			[-0.508, 1.273]	[-0.231, 0.906]
Wet bulb temp. (one-year lead) (°C)			-0.273	0.391
			[-1.215, 0.412]	[-0.396, 1.097]
Rainfall (mm/day)	0.061	0.144	0.066	0.119
	[-0.262, 0.409]	[-0.177, 0.477]	[-0.255, 0.427]	[-0.212, 0.462]
Observations	966	966	966	966
R-squared	0.48	0.50	0.48	0.50
Mesoregion FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Mean of outcome	19.366	25.526	19.366	25.526
SD of temperature in year t	3.550	3.550	3.550	3.550

Notes: The dependent variable in columns (1) and (3) is the number of images in reports, and the dependent variable in columns (2) and (4) is the number of tables in the reports. Control variables include the share of the urban population, income per capita, log of population, the population share below the poverty line, an indicator for second-time audit, and long-run (1980-2016) temperature and rainfall measures. Numbers in square brackets are 90% confidence intervals, calculated with clustered wild-bootstrap at the state level. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

Table C.5: Regression: corruption reports and temperature (with state fixed effects)

	(1) Broad	(2) Narrow	(3) Broad	(4) Narrow
Wet bulb temp. (°C)	0.021	0.022	0.023	0.022
	[0.005, 0.034]**	[0.008, 0.036]**	[0.005, 0.039]**	[0.010, 0.036]***
Wet bulb temp. (one-year lag) (°C)			-0.010	-0.005
			[-0.025, 0.004]	[-0.017, 0.006]
Wet bulb temp. (one-year lead) (°C)			0.002	0.002
			[-0.012, 0.016]	[-0.020, 0.023]
Rainfall (mm/day)	0.000	0.002	0.000	0.002
	[-0.010, 0.012]	[-0.005, 0.012]	[-0.010, 0.013]	[-0.005, 0.012]
Observations	966	966	966	966
R-squared	0.15	0.21	0.15	0.21
State FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Mean of outcome	0.736	0.439	0.736	0.439
SD of temperature in year t	3.550	3.550	3.550	3.550

Notes: The dependent variable in columns (1) and (3) is an indicator for broad corruption reported, and the dependent variable in columns (2) and (4) is an indicator for narrow corruption reported. Control variables include the share of the urban population, income per capita, log of population, the population share below the poverty line, an indicator for second-time audit, and long-run (1980-2016) temperature and rainfall measures. Numbers in square brackets are 90% confidence intervals, calculated with clustered wild-bootstrap at the state level. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

D Appendix figures

Figure D.1: Distributions of temperature during fieldwork

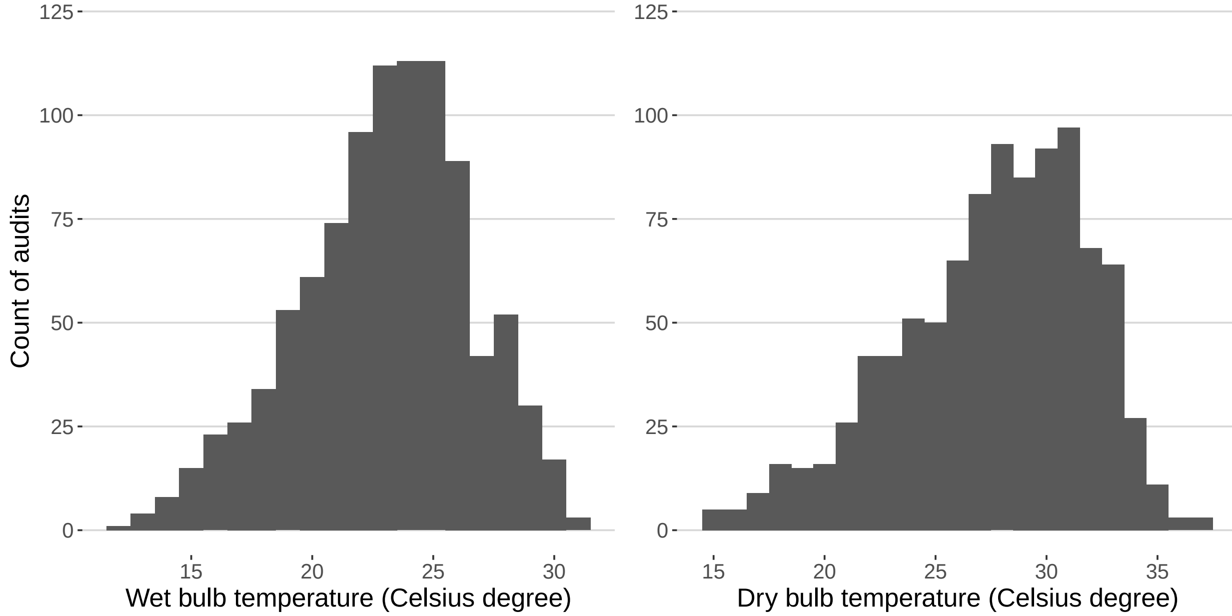
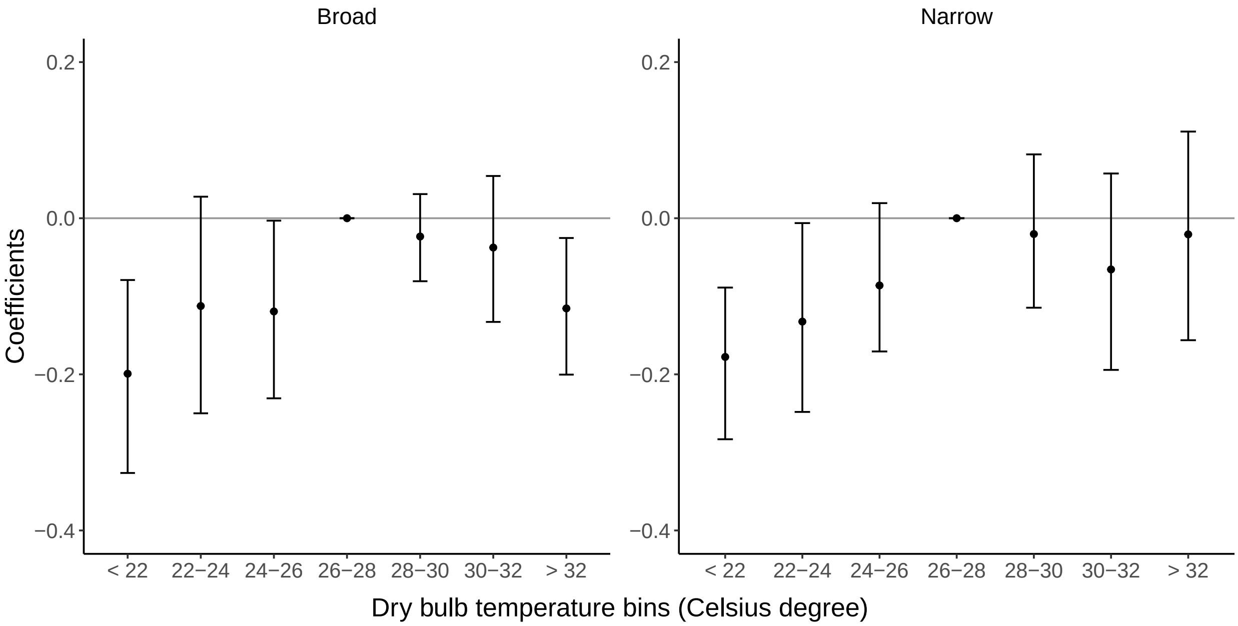
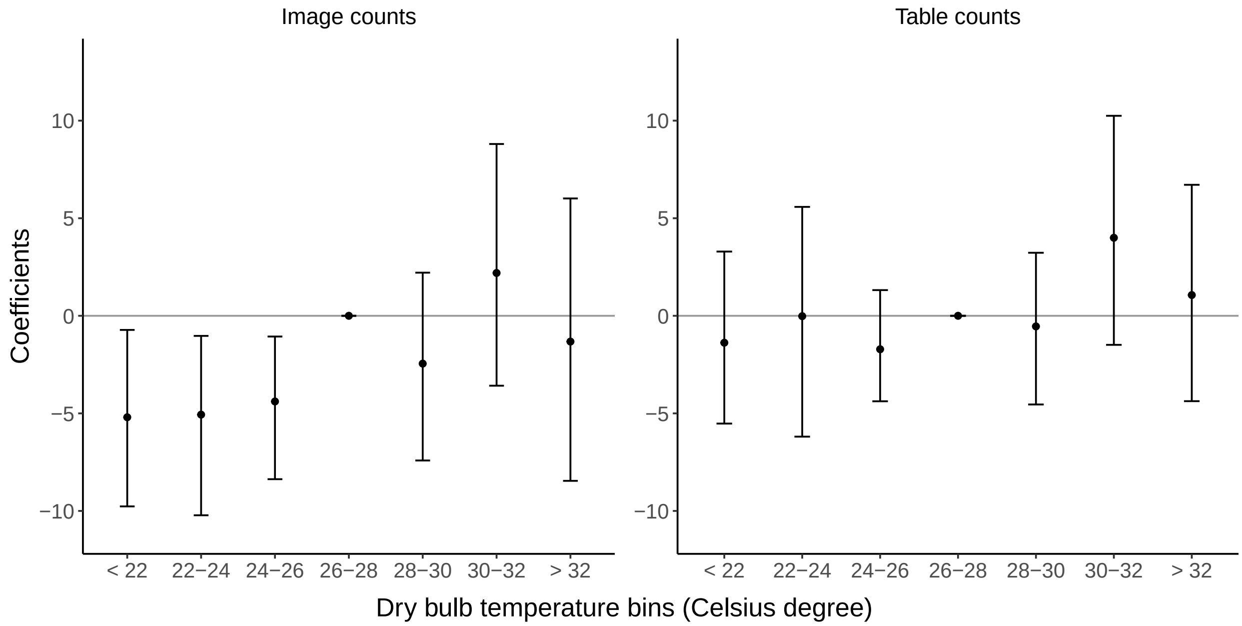


Figure D.2: Dry-bulb temperature effects on reported corruption



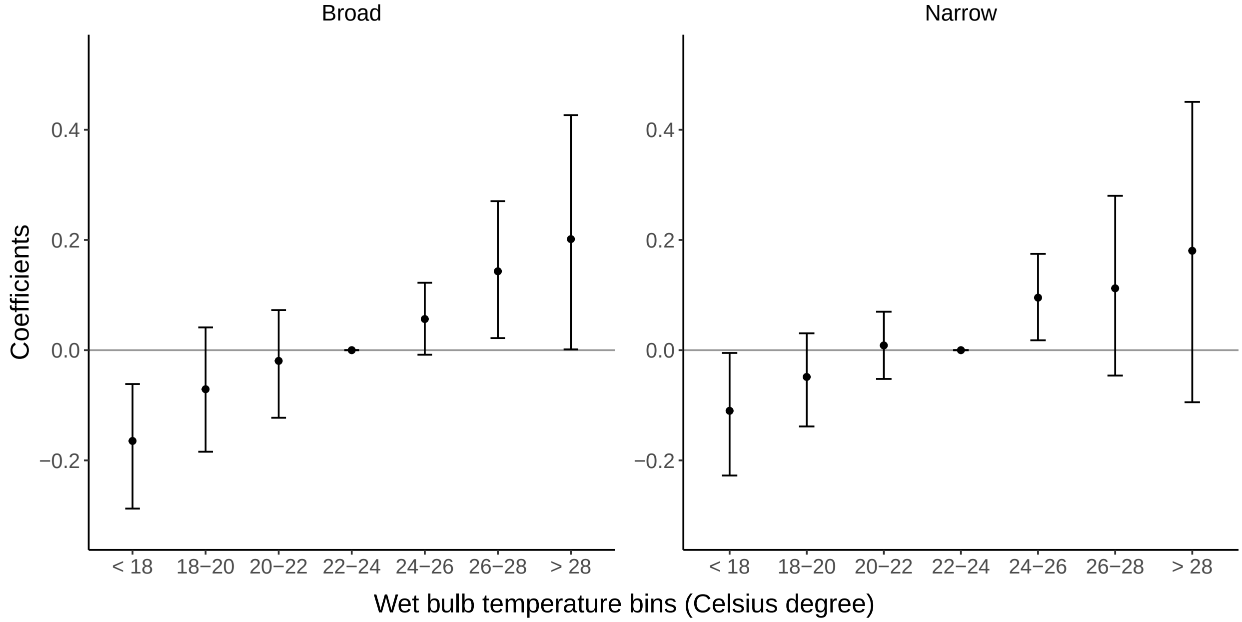
Notes: The figure shows the regression coefficients of an indicator for corruption (left: broad, right: narrow) reported on the dry-bulb temperature bins. Each temperature interval does not include the right end. The 90% confidence intervals are shown. Control variables include the share of the urban population, income per capita, log of population, the population share below the poverty line, an indicator for second-time audit, and long-run (1980-2016) temperature and rainfall measures. Confidence intervals are calculated with clustered wild-bootstrap at the state level.

Figure D.3: Dry-bulb temperature effects on numbers of images and tables



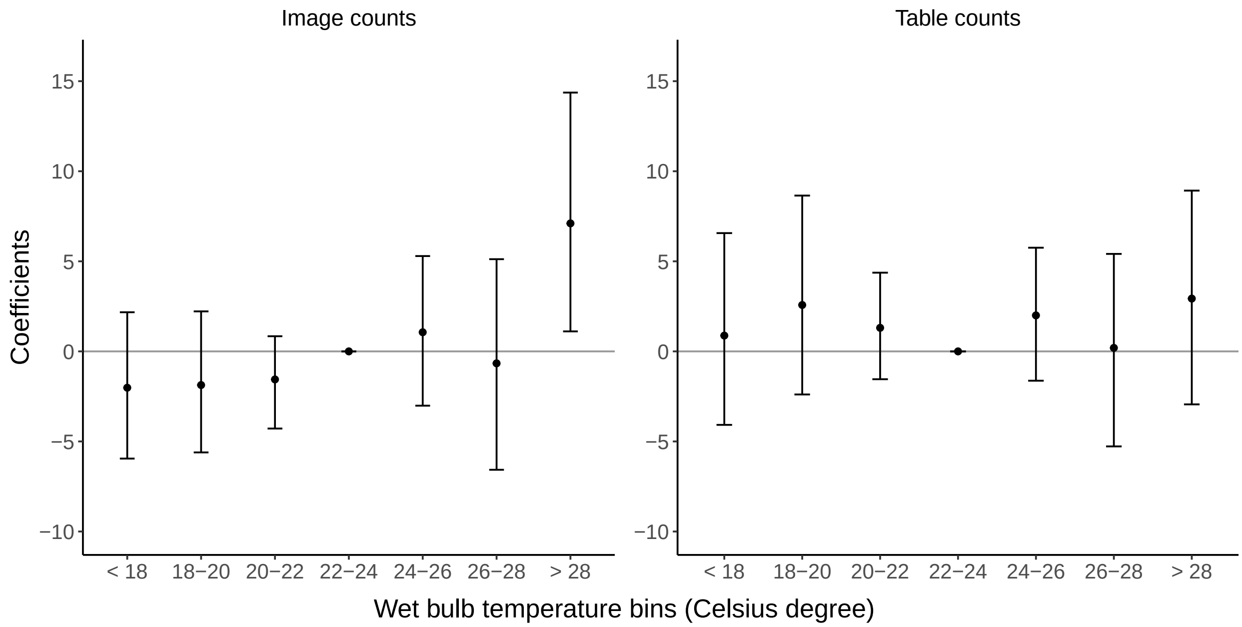
Notes: The figure shows the regression coefficients of the number of images (left) and the number of tables (right) on the dry-bulb temperature bins. Each temperature interval does not include the right end. The 90% confidence intervals are shown. Control variables include the share of the urban population, income per capita, log of population, the population share below the poverty line, an indicator for second-time audit, and long-run (1980-2016) temperature and rainfall measures. Confidence intervals are calculated with clustered wild-bootstrap at the state level.

Figure D.4: Wet-bulb temperature effects on reported corruption (with state fixed effects)



Notes: The figure shows the regression coefficients of an indicator for corruption (left: broad, right: narrow) reported on the wet-bulb temperature bins. Each temperature interval does not include the right end. The 90% confidence intervals are shown. Control variables include the share of the urban population, income per capita, log of population, the population share below the poverty line, an indicator for second-time audit, and long-run (1980-2016) temperature and rainfall measures. Audit wave and state fixed effects are included in the regressions. Confidence intervals are calculated with clustered wild-bootstrap at the state level.

Figure D.5: Wet-bulb temperature effects on number of images and tables (with state fixed effects)



Notes: The figure shows the regression coefficients of the number of images (left) and the number of tables (right) on the wet-bulb temperature bins. Each temperature interval does not include the right end. The 90% confidence intervals are shown. Control variables include the share of the urban population, income per capita, log of population, the population share below the poverty line, an indicator for second-time audit, and long-run (1980-2016) temperature and rainfall measures. Audit wave and state fixed effects are included in the regressions. Confidence intervals are calculated with clustered wild-bootstrap at the state level.

E Example of images and tables from the reports

To show that figures and tables are used in reports as evidence of corruption, we present examples of figures and tables in audit reports. Although only a few illustrations are provided, most figures and tables in other reports are similarly used. All reports are public and available at the CGU website. As supporting evidence of corruption, Figure E.1 reports information on companies involved in a bid. Figures and tables are also used to provide evidence of mismanagement, besides severe corruption. Figure E.2 shows the photos in which equipment and insecticides are stored improperly.

Figure E.1: Example table from an audit report

N.	Empresa	Data de constituição	CNPJ	Quadro Societário
1	[redacted]	23/01/2004 (*)	[redacted]	[redacted]
2	[redacted]	14/06/1996	[redacted]	[redacted]
3	[redacted]	30/10/2000	[redacted]	[redacted]

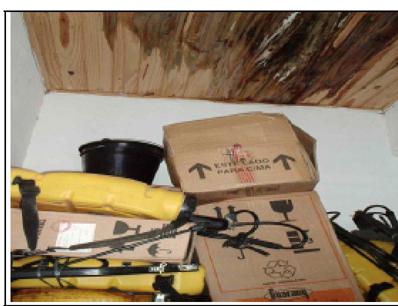
(*) Observe-se que a empresa [redacted] – empresa vencedora – foi constituída cerca de 1 mês antes da abertura das propostas.

Notes: The table from an audit report a municipality audited at the 10th lottery wave. The table shows the names, dates of establishment, identification numbers of firms (CNPJ), and structures of companies invited for the bidding. The table footnote emphasizes that the winning company was established one month before the bidding opening. Identifiable information is hidden, although, in the original report, the information is public and available at the CGU website.

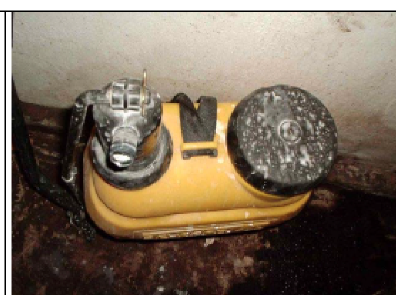
Figure E.2: Example figures from an audit report

Armazenamento de equipamentos do combate à dengue em local inadequado, tomado pela umidade.

Detalhe do chão do depósito, ao lado da estante, completamente molhado.



Equipamentos de uso individual empilhados; teto do depósito encharcado.



Equipamento de uso individual guardado sujo.

Notes: Figures from an audit report of a municipality audited at the 10th lottery wave. The left-top figure shows the storage of equipment for dengue, which is inappropriately placed in a humid environment. The right-top figure shows the wet floor next to the shelf in the left-top figure. The left-bottom figure shows the stocked equipment, where the near roof is wet. The right-bottom figure shows equipment that is not maintained correctly.