Appendix - Potential COVID-19 potential test fraud detection: Findings from a pilot study comparing conventional and statistical approaches

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Zitieren
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The methods and results of the publication “COVID-19 test fraud detection: Findings from a pilot study comparing conventional and statistical approaches” are described in more detail in this appendix. The R-syntax for the calculation is provided, as well as a pseudo data set with which the syntax can also be tested.

Organisational and administrative information

The publicaton “COVID-19 potential test fraud detection: Findings from a pilot study comparing conventional and statistical approaches”, is a joined projekt of the Department for Psychological Research Methods - Trier University, Department 2 | Epidemiology and Health Monitoring - Robert Koch Institute, the Department Infectious and Environmental Hygieneare - Health Authority of the City of Cologne and the Department Digital Global Public Health - Hasso Plattner Institute. The appendix presented here provides additional results and data for the publication and was currated by Department 2 | Epidemiology and Health Monitoring of the Robert Koch Institute. Questions regarding the content of the data can be addressed directly to the correspondending author Michael Bosnjak (bosnjak@uni-trier.de).
The publication of the data as well as the quality management of the (meta-)data is done by the department MF 4 | Research Data and Infromation Management. Questions regarding data management and the publication infrastructure can be directed to the Open Data Team of the Department MF4 at OpenData@rki.de.

> Bosnjak M, Dahm S, Kuhnert R, Weihrauch D, Schaffrath Rosario A, Hurraß J, Schmich P, Wieler L und Nießen J (2024): COVID-19 test fraud detection: Findings from a pilot study comparing conventional and statistical approaches.

Data

We used data on claims for COVID-19 antigen tests submitted for reimbursement by 907 test centers operating in a German city with approximately one million residents for the timespan April 8, 2021 through August 28, 2022.
The data were transmitted on a daily basis via an online portal provided for this purpose by the ministry of a federal German state. Transmission was mandatory by law for the test centers by “CoronaTeststrukturVO” from 2021-03-09, regulated in §5.
For each claim, the following information was provided: test center category (pharmacy, doctor’s or dentist’s office, private test center), date of testing, number of tests performed per day, number of positive tests per day.
The detailed data schmea of the analysed data can be found in section data schema of the simulated data, as we provide simuleted data in the same format.

Methods and Results

We used four statistical methods to detect fraud, which are described in the following sections. All results shown are based on the original data.

- Outlier identification from the mean number of tests per day invoiced (high number of tests)
- Low positive rates identified by Poisson regression (low positive rate)
- Deviations from Benford’s Law
- Deviations from the assumption of equally distributed last digits

Outlier identification from the mean number of tests per day invoiced (high number of tests)

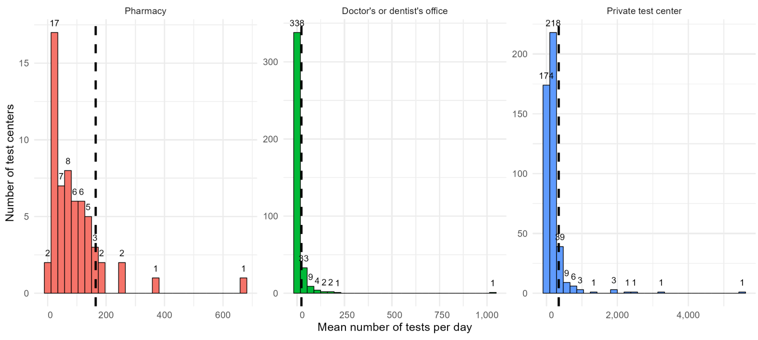
In our first statistical approach aimed at identifying disproportionately high test volumes invoiced, the numbers of tests invoiced per day are classified as conspicuous if they fall outside the 90% percentile in terms of the mean number of tests performed per day within a test center category.

Analysis script
The analysis on outlier identification from the mean number of tests per day invoiced was performed using an R script. The content of the script is provided as R file:

> supporting_material/scripts/Fraud_Methods_Description.r

Figure 1 shows the corresponding distributions resulting form the analysis.

Figure 1: Histograms of the mean number of tests performed per day (x-axis) by test center type (pharmacies, doctor’s or dentist’s offices, private test centers). The dashed vertical line indicates the 90% percentile of each distribution. Test centers falling on the right sides of these lines are considered statistically conspicuous. The numbers above the bars indicate the number of test centers within each bar.



A total of 91 testing centers (6 pharmacies, 39 physician practices/dentists, and 46 private testing sites) were classified as suspicious using this approach. Table 1 shows the basic statistics of the tests performed per day, divided into conspicuous and non-conspicuous test centers according to the statistical method.

Table 1: Basic statistics of the mean number of tests per day and test centers by facility type, statistically conspicuous and statistically not conspicuous of fraud

Facility type	Statistically conspicuous			Statistically not conspicuous			Total		
	N	Median	Max	N	Median	Max	N	Median	Max
Pharmacy	6	252.2	679.3	54	64.1	161.5	60	71.0	679.3
Doctor's or dentist's office	39	51.7	1,032.0	351	3.5	23.0	390	3.8	1,032.0
Private test center	46	515.4	5,520.0	411	106.6	342.2	457	116.3	5,520.0

Low positive rates identified by Poisson regression (low positive rate)

The positive rates were modeled by a Poisson regression model with random effects using the logarithms of the number of positive tests per day and per test center as dependent variable and the logarithms of the respective total number of tests as offset. The variability between the test centers were modeled by random intercepts for test centers. In addition, to account for changes in the positive rates over time for example induced by changing incidence, calendar week specific random intercepts were introduced in the model. Differences in positive rates between the facility types were controlled by fixed effects.

$$\log(pos_{ijkl}) = \log(test_{ijkl}) + A + \beta_j + \gamma_k + x_l \cdot typ_l + \varepsilon_{ijkl}$$

pos_{ijkl} : Number of positive tests at day i in test center $j(j = 1, \dots, 907)$ the week $k(k = 1, \dots, 73$ and in facility type $l(l = 1, 2, 3)$
$test_{ijkl}$: Number of tests at day i in test center j in week k in facility type l
A : Global intercept (fixed effect)
β_j : Test center-specific deviation from the global intercept (random effect)
γ_k : Calendar week specific deviation from the global intercept (random effect)
typ_l : Facility type: Pharmacy, doctor’s or dentist’s office or private test center (fixed effect)
x_l: Factor accounting for differences in positive rates by facility type (fixed)
ε_{ijkl} : Residual at day i in test center j in week k and facility type l not explained by the regression.

Analysis script

The analysis to identify low positive rates by Poisson regression was performed with an R script. The content of the script is provided as R file:

> supporting_material/scripts/Fraud_Methods_Poisson_Regression.r

Corona tests were performed in the time span April 8, 2021 through August 28, 2022 on 73 weeks respective 508 days in 907 test centers, but not all centers operated for the entire period. This resulted in a total of N = 118,908 positive rates.

Table 2: Statistics of estimated fixed effects

Variable	Estimate	Standard Error	P-value
A **(global intercept)**	-5.004	0.257	< 0.0001
typ_2**(Facility type: doctor’s or dentist’s office)**	0.149	0.192	0.45
typ_3**(Facility type: private test center)**	-0.477	0.182	0.0086

The differences between the mean positive rates by facility type (Table 2) were significant in the regression at P = 0.009. In particular, the rate of positive tests was lower for the private test centers than for the pharmacies or the physicians’ practices. The estimated random intercepts for the 907 test centers (β_j) were centered by 0 and had a variance of 1.65. The variance of the 73 week specific random intercepts (γ_k) was estimated to be 2.67. Both variables (β and γ) were significant with P < 0.0001

A low center specific random intercept j indicates a low mean positive rate for the tests in resp. center. Therefore, the reporting of tests conducted by a test center was considered conspicuous if its estimated random intercept was significantly low. The estimated test center intercepts (β_j) and their standard deviations sd(β_j) were used to generate test values comparable to the t-values of the t-test:

$$r_j = \frac{\beta_j}{sd(\beta_j)}, j = 1, \dots, 907$$

The test values r_j ranged from -23.0 to 49.0 corresponding to positive rates of 0.5% resp. 10.6%. A value of r_j < -6 was regarded as significant. According to this criterion, the 907 test centers could be classified to 88 conspicuous and 819 not conspicuous test centers (s. Table 3), where the mean positive rate in conspicuous test centers amounted to 0.6% and the not conspicuous test centers had a mean positive rate of 2.3%.

Table 3: Summary of classifications into statistical conspicuous versus not conspicuous test centers according to the Poisson regression model used

Facility type	Statistically conspicuous		Statistically not conspicuous		Total	
	Number	Positive rate	Number	Positive rate	Number	Positive rate
Pharmacy	11	0.88	49	2.82	60	2.44
Doctor's or dentist's office	16	0.59	374	3.95	390	2.75
Private test center	61	0.54	396	2.24	457	1.95
Total	88	0.58	819	2.33	907	2.02

Deviations from Benford’s Law

Requirements for Benford Analysis:

For data to undergo Benford analysis, it must exhibit a specific range and be reported over a certain number of days. The Benford principle may be compromised if test centers frequently operate at maximum capacity, leading to the reporting of similar test numbers. This can lead to a false positive result for a test center according to Benford’s Law. Test centers reporting tests on only a few days are ineligible for Benford analysis because the distribution of the first digit lacks the necessary variability for evaluation. To address this, we stipulate that the number of tests must be reported over a minimum of 30 days.

Analysis script

The analysis for deviations from Benford’s Law was performed using an R script. The content of the script is provided as R file:

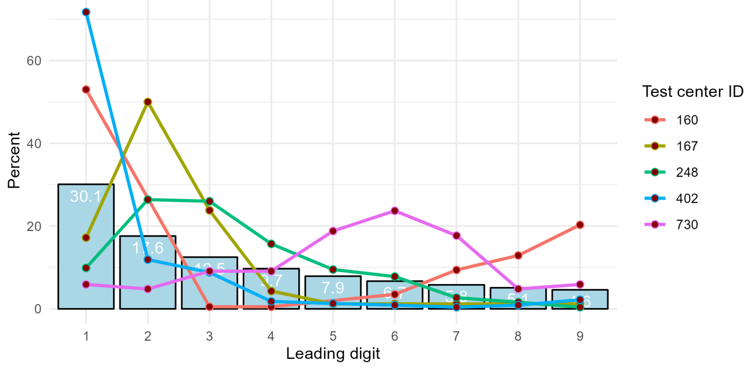
> supporting_material/scripts/Fraud_Methods_Benford.r

Figure 2 shows the distribution of the leading digit according to Benford’s law and the distribution over all data available for the observation period. Overall, there is good agreement. The leading 1 as well as the 2 occur slightly disproportionately according to Benford’s law.

Figure 2: Distribution of leading digit of total reporting numbers (line) versus expected values of Benford’s law (bars).

A chi-square test is calculated for each of these 665 test centers. The chi-square test value determines the degree of deviation.

Figure 3: Illustration of the distribution of the leading digit of the five test centers (lines) with the largest deviations from Benford’s law.



In table 4, we have summarized the number of test centers classified by conventional methods and Benford´s Law. The threshold for test centers considered to be conspicuous according to Benford´s Law was set to those 10% with the largest chi-square test value.

Table 4: Number of test centers by facility type, (non) suspected of fraud by the conventional approach, and (non) suspected of fraud by the statistical approach focusing on the deviation from Benford´s law.

Facility type	Suspected of fraud by the health authorities (conventional approach)			Not suspected of fraud by the health authorities (conventional approach)		
	Statistically conspicuous	Statistically not conspicuous	Total	Statistically conspicuous	Statistically not conspicuous	Total
Pharmacy	0	0	0	5	55	60
Doctor's or dentist's office	0	4	4	8	197	205
Private test center	10	65	75	44	227	321
Total	10	69	79	57	529	586

Based on table 4, the percentage of positive overlap between the traditional and Benford's law-based methods amounts to 12.7% (10/79), the percentage of negative overlap 90.3% (529/586), and the share of incrementally identified potentially fraudulent test centers identified by Benford's law which were undetected by traditional approaches amounts to 9.7% (57/586) related to all test centers.

In contrast to the publication, only the test sites that could also be evaluated by the method are considered here. This means that the positive, negative overlap and the proportion of undetected by traditional approaches are higher than in the results in the publication.

Deviations from the assumption of equally distributed last digits

Requirements for Last Digit Analysis:

Similar to the Benford approach, the last digit method requires data with a sufficient range for evaluating the distribution of the last digit. A minimum number of daily reports (≥30) is essential for this evaluation. Unlike Benford’s law, the distribution of the last digit includes zero. However, in the single-digit range 0-9, testing centers were not obligated to report “0” on days without testing, leading to a systematic underrepresentation of zero. To mitigate this bias, only test reports with more than 9 tests per day are considered for the distribution. In summary, for the last digit method evaluation, a test center must have reported more than 9 tests per day for at least 30 days. This method could only be applied to 512 of the 907 test sites.

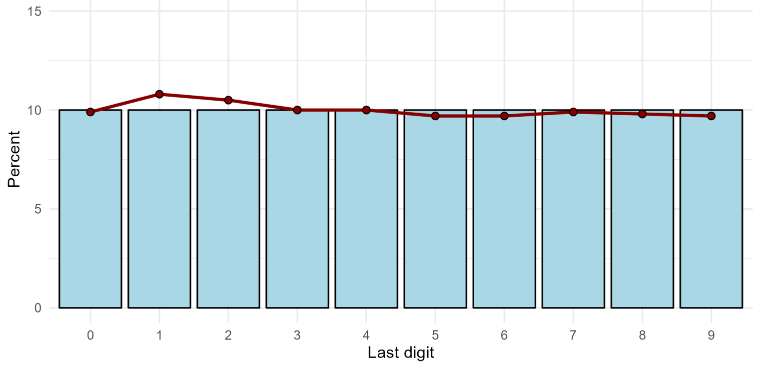
Analysis script

The analysis on deviations from the assumption of equally distributed last digits was performed using an R script. The content of the script is provided as R file:

> supporting_material/scripts/Fraud_Methods_Last_Digit.r

Figure 4 shows the distribution of the last digit comparing the expected distribution versus all reported data in the observation period. Overall, there is good agreement. The last digits 1 and 2 seem to be slightly overrepresented.

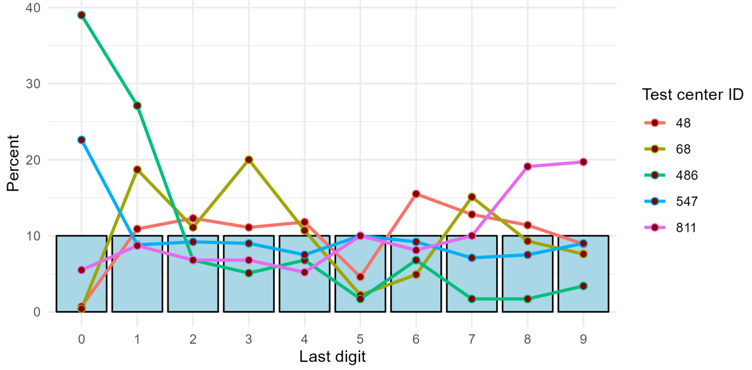
Figure 4: Distribution of the last digit of the total number of reports (line) versus the expected distribution (bar).



A chi-square test is calculated for each of the 512 test centers. The chi-square test value determines the degree of deviation.

The five test centers with the greatest deviation from the expected distribution can be seen in Figure 5. It seems that the zero and the number 5 were deliberately avoided as the last digit in the test center 48 and 68. Test center 486 reported only an average of 11 tests per day and all numbers below 10 are not considered. Therefore, the distribution has only limited informative value.

Figure 5: Distribution of the last digit of the five test centes (line) with greatest deviation from the expected distribution (bar).



The threshold for test centers considered to be conspicuous according to the assumption about the last digit distribution was set to those 10% with the largest chi-square test value, yielding 52 test centers. In Table 5, we have summarized the number of test centers classified by traditional approach and the Last Digit method.

Table 5: Number of test centers by facility type, (non) suspected of fraud by the conventional approach, and (non) suspected of fraud by the statistical approach focusing on the deviation from the law of equally distributed last digits.

Facility type	Suspected of fraud by the health authorities (conventional approach)			Not suspected of fraud by the health authorities (conventional approach)		
	Statistically conspicuous	Statistically not conspicuous	Total	Statistically conspicuous	Statistically not conspicuous	Total
Pharmacy	0	0	0	1	58	59
Doctor's or dentist's office	1	3	4	14	48	62
Private test center	7	68	75	29	283	312
Total	8	71	79	44	389	433

Based on table 5, the percentage of positive overlap between the traditional and Last-Digit-assumption-based methods amounts to 10.1% (8/79), the percentage of negative overlap 89.8% (389/433), and the share of incrementally identified potentially fraudulent test centers identified by the last digit assumption which were undetected by traditional approaches amounts to 10.2% (44/433).

As with Benford, only the test sites that could also be assessed by the method are considered here. This means that the positive, negative overlap and the proportion of undetected by traditional approaches are higher than in the results in the publication.

Comparison and combination of the four statistical methods used

The positive and negative overlap give the ratio betweet the number of identified test centers by our analysis and the number given by health authorities.
If all test sites that are conspicuous by at least one statistical method are considered, the positive overlap also increases by 50.5% (47 test centers of the 93 test centers conspicuous by health authorities were classified also as conspicuous by at least one of the statistical methods). The negative overlap decreases to 78.1% (table 6). If test sites are considered to be conspicuous in the combination of at least 2 methods, the positive and negative overlap is comparable to that of the individual methods.
A more detailed descrition of the comparison can be found in the “Outcomes” section of our corsponding publication:

> Bosnjak M, Dahm S, Kuhnert R, Weihrauch D, Schaffrath Rosario A, Hurraß J, Schmich P, Wieler L und Nießen J (2024): COVID-19 test fraud detection: Findings from a pilot study comparing conventional and statistical approaches.

Table 6: Positive and negative overlap and share of incrementally identified potentially fraudulent test centers by statistical approaches

Statistical approach	Positive overlap	Negative overlap	Share of incrementally identified potentially fraudulent test centers
At least identified by one method	50.5%	78.1%	21.9%
At least identified by two methods	9.7%	93.6%	6.4%

Simulated data

Based on the data schema of the analysed data, we have simulated data for overall 807 test centers for which we assumed that they operated within the time period 2021-03-01 till 2021-12-31, containing 136,192 observations. Furthermore, we assumed that 15% of the test centers invoiced for fraudulent test results. For these ‘criminal’ test centers are simulated high numbers of tests, low positive rates, deviations from Benford’s Law and deviations from the assumption of equally distributed last digits.
The resulting characteristics of simulated data are shown in table 7. The simulated data does not contain any information from the original data and can be used to test the R-scripts we provided for the analysis.

Table 7: Characteristic of simulated data

Facility type	test centers [N]	test centers suspected of fraud [N]	Tests [N]	Tests per day			Positive tests [%]
				Mean	Max	median	
Pharmacy	290	4	6,795,707	137.5	1,387	98	1.42
Doctor's or dentist's office	357	6	8,312,270	141.4	1,663	110	1.75
Private test center	160	3	4,457,176	159.3	2,019	113	1.16
Total	807	13	19,565,153	143.7	2,019	106	1.50

Content and structure of the appendix data

The tables, figures and their data, R-scripts and simulated data described in the section Methods and Results are made available in the appendix as open data. The following section describes the structure of the dataset in more detail.

Data Tables

The results of the analyses conducted are provided as data tables. The files are named as the corresponding tables in the Methods and Results sextion as `Table_1.tsv`, etc.

File	Description	Download
Table_1.tsv	Basic statistics of the mean number of tests per day and test centers by facility type, statistically conspicuous and statistically not conspicuous of fraud	💾
Table_2.tsv	Statistics of estimated fixed effects	💾
Table_3.tsv	Summary of classifications into statistical conspicuous versus not conspicuous test centers according to the Poisson regression model used	💾
Table_4.tsv	Number of test centers by facility type, (non) suspected of fraud by the conventional approach, and (non) suspected of fraud by the statistical approach focusing on the deviation from Benford´s law.	💾
Table_5.tsv	Number of test centers by facility type, (non) suspected of fraud by the conventional approach, and (non) suspected of fraud by the statistical approach focusing on the deviation from the law of equally distributed last digits.	💾
Table_6.tsv	Positive and negative overlap and share of incrementally identified potentially fraudulent test centers by statistical approaches	💾
Table_7.tsv	Characteristic of simulated data	💾

Supporting Materials

The Supporting Materials folder contains

- All figures used in the appendix
- The underlying data for the figures
- The R-scripts used for the analysis
- Sample data for testing the analysis scripts

Figures and Figure Data

The figures listed in the appendix and their underlying data are provided in the “Figures” subfolder as .png and .tsv files.

> supporting_material/figures

The figures are named according to the numbering in the appendix as `figure_1.png`, etc. The underlying data for the figures are provided following the naming of the figures as `figure_1_data.tsv`, etc. The variables and values of the figure data are explained below.

Variables and valuests of the figure data

Variable	Type	Variations	Description
testcenter_id / tnr	integer	`1` … `807`	ID of test center
typ_l	string	`Pharmacy`, `Doctors or dentists office`, `Private test center`	Facility type
mean	float	`≥0`	mean number of tests per day
p90	float	`≥0`	90% percentil
leading_figure	integer	`1` … `9`	first digit
last_figure	integer	`0` … `9`	last digit
theoretical_percent	float	`≥0`	theoretical percentage of digit
observed_percent	float	`≥0`	observed percentage of digit
suspicious_des	integer	`0`, `1`	suspicious yes or no (`1` = yes, `0` = no)

R Scripts

The analysis scripts for the individual methods are provided as .r-files in the following subfolder:

> supporting_material/scripts

The naming of the scripts is based on the methods used and is linked in the “Analysis script” sections.

Simulated data

Simulated data for testing the evaluation R-scripts are provided. These correspond to the data schema described below.

Data schema of the simulated data

Variable	Type	Values	Description
typ	string	`Pharmacy`, `Doctors or dentists office`, `Private test center`	Facility type (pharmacy, doctor’s or dentist’s office or private test center)
tnr	interger	`1` … `999`	Testcenter identification number
date	date	`yyyy-mm-dd`	Date of the tests in ISO 8601 format
week_yr	string	`ww_yyyy`	Identifer for the calendar week (ww) of the Year (yyyy)
getestet	interger	`≥0`	Number of tests per day
positiv	interger	`≥0`	Number of positiv tests per day
investigation	interger	`0`, `1`	Indicator for investigation by the health authorities (`1` = yes, `0` = no)

The simulated data are available in the folder supporting_material in the file

> simulated_data.csv

Further information on the simulated data can be found in the corresponding section.

Metadata

To increase findability, the provided data are described with metadata. The Metadata are distributed to the relevant platforms via GitHub Actions. There is a specific metadata file for each platform; these are stored in the metadata folder:

> Metadata/

Versioning and DOI assignment are performed via Zenodo.org. The metadata prepared for import into Zenodo are stored in the zenodo.json. Documentation of the individual metadata variables can be found at https://developers.zenodo.org/representation.

> Metadata/zenodo.json

The zenodo.json includes the publication date (`"publication_date"`) and the date of the data status:

```
"dates": [
  {
    "start": "2023-09-11T15:00:21+02:00",
    "end": "2023-09-11T15:00:21+02:00",
    "type": "Collected",
    "description": "Date when the Dataset was created"
  }
],
```

Guidelines for Reuse of the Data

Open data from the RKI are available on Zenodo.org, GitHub.com, OpenCoDE, and Edoc.rki.de:

- https://zenodo.org/communities/robertkochinstitut
- https://github.com/robert-koch-institut
- https://gitlab.opencode.de/robert-koch-institut
- https://edoc.rki.de/

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