



JASP for Audit User Manual

Statistical Auditing Group

“The best things in life are free.”

Contents

Preface	5
Getting Started	7
Downloading JASP	7
Enabling the Audit module	8
Accessibility	8
I Audit Sampling	11
1 Sampling Workflow	13
1.1 The four stages of the sampling workflow	13
1.2 A practical example in JASP	14
2 Planning	23
3 Selection	25
4 Evaluation	27
5 True Value Estimation	29
II Data Auditing	31
6 Benford's Law	33
6.1 Main settings	33
6.2 Main output	35
6.3 Report	35
6.4 Advanced	38
7 Repeated Values	39
7.1 Main settings	40
7.2 Main output	40
7.3 Report	41
7.4 Advanced	42

Contents

III Algorithm Auditing	43
8 Fairness	45
References	47

Preface

The **JASP for Audit User Manual** provides detailed instructions and best practices for working with the Audit module in the free and open-source software JASP. It covers various aspects, including data import, analysis techniques, and interpretation of results. The manual is curated by the Statistical Auditing Group at Nyenrode Business University, ensuring that users have access to reliable and up-to-date information.

Getting Started

Statistical theory is fundamental to many auditing procedures. To perform these procedures effectively, auditors need user-friendly software for statistical analyses and the knowledge to interpret the results. JASP (JASP Team, 2025) is an open-source, free-of-charge, cross-platform statistical software program that supports statistical auditing through its Audit module (Derks et al., 2021).

The Audit module (i.e., JASP for Audit) allows auditors to plan, execute, and interpret a wide range of statistical auditing procedures using state-of-the-art statistical methods, thereby reducing programming errors and simplifying the process. Tailored for auditors, the module features an intuitive interface that aligns with audit processes and international standards on auditing. In addition to standard frequentist methods, the Audit module incorporates Bayesian methods to enhance audit transparency and efficiency by utilizing existing information.

In summary, the Audit module takes care of the complex statistical work, allowing you to concentrate on interpreting the results of your analysis. The remaining paragraphs in this chapter discuss how to get started using JASP for Audit.

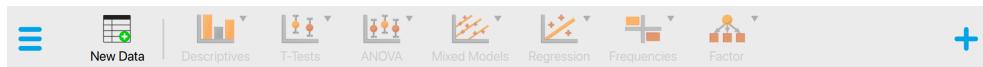
Downloading JASP

JASP for Audit is part of JASP, which can be freely downloaded from www.jasp-stats.org. Click the ‘Download JASP’ button on the homepage to access the download page and choose your preferred installation. JASP is available for Windows, MacOS, Linux, and Chrome OS.



Enabling the Audit module

After opening JASP, you will see the following main menu bar at the top of the screen.



To find the Audit module, click the '+' icon on the right of this menu bar. A different menu will appear on the right side which shows all available modules. Check the box next to 'Audit' to make the module visible in the main menu bar. You can now access the Audit module and its analyses by clicking its module icon in the menu bar (see image below).

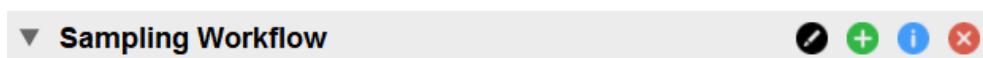


Accessibility

The Audit module is a robust tool for statistical auditing. The following paragraphs detail its accessibility features, including where to locate help files and how to ensure the reliability of the statistical results is ensured.

Help files

Once you open an analysis in the Audit module, you can click the blue 'i' icon next to the analysis title to access a help file that explains its functionality. Additional help files for certain settings can be accessed by clicking the blue 'i' icon next to those settings.



Validation of statistical results

The statistical results generated by the Audit module are based on the R package jfa (Derks, 2025). For comprehensive documentation and information on the benchmarks used for validation, please visit the package website at <https://koenderks.github.io/jfa/>.

Part I

Audit Sampling

Chapter 1

Sampling Workflow

The goal of statistical audit sampling is to infer the misstatement in a population based on a representative sample. This can be challenging, but the Audit module simplifies the process into four stages: planning, selection, execution, and evaluation.



More detailed information about the individual stages in the audit sampling workflow is provided below.

1.1 The four stages of the sampling workflow

In the planning stage, you determine the sample size needed to support the assertion that the population's misstatement is below the performance materiality. This involves using prior audit outcomes and information about inherent risk and control risk. Expectations about error rates also influence the sample size required to maintain statistical confidence.

Using the sample size from the planning stage, you select a statistically representative sample. Each sampling unit receives an inclusion probability, and units are selected based on these probabilities. Monetary unit sampling assigns probabilities to individual monetary units, making higher-value items more likely to be selected. Record sampling assigns equal probabilities to all items.

In the execution stage, you assess the correctness of selected items. The simplest method categorizes items as correct or incorrect, while a more accurate method considers the true value (audit value) of items. Annotating samples with audit values provides a more precise estimate of misstatement. If book values are unavailable, use the correct/incorrect method.

In the evaluation stage, you use the annotated sample to infer the total misstatement

in the population. Statistical techniques calculate a projected maximum misstatement, and the population is approved if this is below the performance materiality.

This manual emphasizes the practical application of the audit sampling workflow in JASP. For a deeper understanding of the statistical theory behind the four stages of the audit sampling workflow, read the free online book *Statistical Audit Sampling with R*.

1.2 A practical example in JASP

The Audit module in JASP offers two ways to navigate the audit sampling workflow: the Sampling Workflow analysis, which guides you through all four stages, and individual analyses for Planning, Selection, and Evaluation. This chapter uses the classical sampling workflow analysis to explain the Audit module's core functionality. Note that a Bayesian variant of the sampling workflow is also available.

Let's explore an example of the audit sampling workflow. To follow along, open the 'Testing for Overstatements' dataset from the Data Library. Navigate to the top-left menu, click 'Open', then 'Data Library', select '7. Audit', and finally click on the text 'Testing for Overstatements' (not the green JASP-icon button).



This will open a dataset with three columns: 'ID', 'bookValue', and 'auditValue'. The 'ID' column represents the identification number of the items in the population. The 'bookValue' column shows the recorded values of the items, while the 'auditValue' column displays the true values. The 'auditValue' column is included for illustrative purposes, as auditors typically know the true values only for the audited sample, not for all items in the population.



	ID	bookValue	auditValue
1	82884	242.61	242.61
2	25064	642.99	642.99
3	81235	628.53	628.53
4	77769	431.87	431.87
5	55080	620.88	620.88
6	93224	501.76	501.76
7	24331	466.01	466.01
8	81460	295.2	295.2
9	14608	216.48	216.48
10	79064	243.43	243.43
11	6227	296.26	296.26
12	59109	341.64	341.64
13	81527	203.02	203.02
14	27240	520.5	520.5
15	76073	469.93	469.93
16	83056	543.04	543.04
17	46163	511.62	511.62
18	85963	364.09	364.09
19	92464	76.76	76.76
20	15611	450.56	450.56
21	76619	582.6	582.6
22	91370	232.67	232.67
23	56015	268.26	268.26
24	91470	307.29	122.92

1.2.1 Stage 1: Planning

To start the sampling workflow, click on the Audit module icon and select ‘Sampling Workflow’. This will open the following interface, where you need to specify the settings for the statistical analysis.



The screenshot shows the Sampling Workflow interface with several sections highlighted:

- 1. Item ID (required)**: Contains fields for **ID** and **Book Value (optional)**.
- 2. Sampling Objectives**: Includes options for **Performance materiality** (Relative 3.000 %), **Absolute**, and **Minimum precision**. Confidence is set at 95.0 %.
- 3. Expected Misstatements**: Shows **Absolute** misstatement as 1.
- 4. Audit Risk Model**: Displays risk levels for **Inherent risk** (High, 100 %), **Control risk** (High, 100 %), and **Analytical risk** (High, 100 %).
- 5. Display**: Contains **Explanatory text** and **Report** buttons.
- Advanced**: Contains **Download Report** and **To Selection** buttons.

The following five settings are required:

1. **Indicate the variables:** First, enter the variable indicating the identification numbers of the items in the corresponding box. Optionally, if you have access to the book values of the items, you can enter this variable as well.
2. **Sampling objectives:** Next, formulate your sampling objectives. Enable the ‘Performance materiality’ objective if you want to test whether the total misstatement in the population exceeds a certain limit (i.e., the performance materiality). This approach allows you to plan a sample such that, when the sample meets your expectations, the maximum error is said to be below performance materiality. Enable the ‘Minimum precision’ objective if you want to obtain a required minimum precision when estimating the total misstatement in the population. This approach allows you to plan a sample such that, when the sample meets expectations, the uncertainty of your estimate is within a tolerable percentage. In the example, we choose a performance materiality of 3.5%.
3. **Expected misstatement:** Then, indicate how many misstatements are tolerable in the sample. In the example, we choose to tolerate one full misstatement in the sample.
4. **Prior information:** Additionally, indicate the risks of material misstatement via the audit risk model. According to the Audit Risk Model, audit risk can be divided into three constituents: inherent risk, control risk, and detection risk. Inherent risk is the risk posed by an error in a financial statement due to a factor other than a failure of internal controls. Control risk is the probability that a material misstatement is not prevented or detected by the internal control systems of the company (e.g., computer-managed databases). Both these risks are commonly assessed by the auditor on a 3-point scale consisting of low, medium, and high. Detection risk is the probability that an auditor will fail to find material misstatements in an organization’s financial statements. For a given level of audit risk, the tolerable level of detection risk bears an inverse relationship to the other two assessed risks. Intuitively, a greater risk of material misstatement should require a lower tolerable detection risk and, accordingly, more persuasive audit evidence. In this example, we choose to set all risks to ‘High’ and solely rely on evidence from substantive testing.

The primary output from the planning stage, shown below, indicates that a minimum sample size of 134 sampling units is required to achieve 95% assurance that the misstatement in the population is below 3.5%, while allowing for one misstatement in the sample.

Table 1. Planning Summary

	Value
Performance materiality	0.035
Inherent risk	1.000
Control risk	1.000
Analytical risk	1.000
Detection risk	0.050
Tolerable misstatements	1.000
Minimum sample size ^a	134

Note. The minimum sample size is based on the binomial distribution ($p = 0.035$)

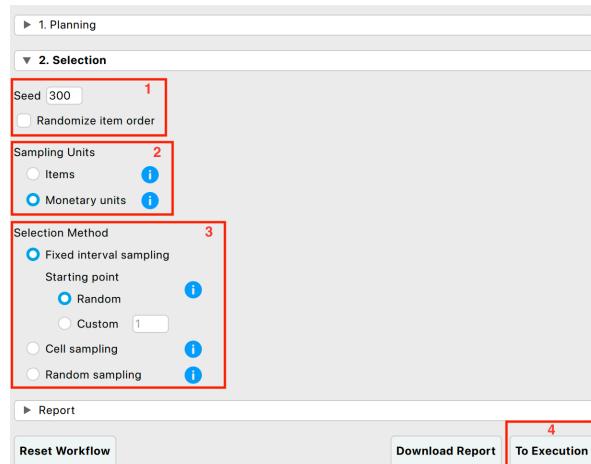
^a Based on this sample size, the selection interval spans 10471.8 units.

5. **Next stage:** Finally, progress to the selection stage by clicking the ‘To Selection’ button.

For a more detailed explanation of the settings and output in the planning stage, see Chapter 2.

1.2.2 Stage 2: Selection

In the selection stage, you must select the 134 sampling units from the population. Once the ‘To Selection’ button is pressed, the interface from the selection stage opens.



The following four settings are required:

1. **Randomness:** Begin by selecting the settings related to randomness in the selection procedure. The seed setting is important as it ensures that random procedures are reproducible, allowing for consistent results across multiple runs. A random number will be chosen each time you start the analysis. Additionally, the ‘Randomize item order’ setting is available to randomly shuffle the rows in the dataset, which can help mitigate any biases that might arise from the original order of the data.
2. **Sampling units:** Next, specify the sampling units for the selection process. These units can either be items or monetary units. If no book value variable

is provided, the sampling units default to ‘Items’, enabling attribute sampling. Conversely, if a book value variable was indicated during the planning stage, the sampling units default to ‘Monetary units’, facilitating monetary unit sampling (MUS). MUS is particularly useful for auditing financial data as it considers the monetary value of each unit.

3. **Sampling method:** Then, choose the selection method to be used in the sampling process. The available algorithms include:

- **Fixed interval sampling:** This method selects units at regular intervals from the dataset, ensuring a systematic sampling approach.
- **Cell sampling:** This technique involves dividing the dataset into cells and randomly selecting units from each cell, promoting a systematic sampling approach with a bit of randomness.
- **Random sampling:** This approach randomly selects units from the entire dataset, providing a simple yet effective method for ensuring randomness.

The primary output from the selection stage, as shown in the first table below, reveals that 134 sampling units were selected from 134 items. The sample’s total value amounts to €67,821.22, representing 4.8% of the total population value. The second table provides details specific to interval selection using monetary unit sampling. It indicates the number of items selected in the ‘Top stratum’, which includes all items larger than a single interval (for fixed interval selection). In this instance, there were 0 items in the top stratum.

Table 3. Selection Summary ▾

No. units	No. items	Selection value	% of population value
134	134	€67,821.22	4.8%

Note. From each of the intervals of size 10471.8, unit 9584 is selected using seed 300.

Table 4. Information about Monetary Interval Selection

	Items	Value	Selected items	Selected units	Selection value	% of total value
Total	3,500	€1,403,220.82	134	134	€67,821.22	4.8%
Top stratum	0	€0	0	0	€0	0%
Bottom stratum	3,500	€1,403,220.82	134	134	€67,821.22	4.8%

Note. The top stratum consists of all items with a book value larger than a single interval.

4. **Next stage:** Finally, progress to the execution stage by clicking the ‘To Execution’ button.

1.2.3 Stage 3: Execution

In the execution stage, you must judge the fairness of the 134 sampled items. Once the ‘To Execution’ button is pressed, the interface from the execution stage opens.

The screenshot shows the 'Sampling Workflow' interface in the 'Execution' stage. At the top, there are three tabs: '1. Planning', '2. Selection', and '3. Execution'. The '3. Execution' tab is active. Below it, there are two sections: 'Annotation' and 'Column name selection result'. The 'Annotation' section has three radio button options: 'Audit value' (selected), 'Correct / Incorrect', and 'Audit / Incorrect'. The 'Column name selection result' section shows 'selected' in a red box and 'auditResult' in another red box. A 'Continue' button is at the bottom right of this section. Below this, a 'Sample List' section titled 'Annotate your selected items with their audit (true) values.' contains a table with columns: Row #, ID, bookValue, selected, and auditResult. Row 25 is highlighted in red. A 'Reset Workflow' button is at the bottom left, and a 'To Evaluation' button is at the bottom right, also in a red box.

Row #	ID	bookValue	selected	auditResult
25	50,826	331.03	1	200
54	81,087	379.26	1	379.26
79	69,335	394.16	1	394.16
106	88,261	266.66	1	266.66
134	27,117	914.95	1	914.95
160	97,972	709.76	1	709.76
187	29,395	349	1	349

The following four settings are required:

1. **Annotation method:** First, decide how to annotate the selected items. You have two choices:
 - Audit value: Annotate the items with their audit (true) values. This method is recommended (and automatically selected) when the items have a monetary value.
 - Correct / Incorrect: Annotate the items as correct (0) or incorrect (1). This method is recommended (and automatically selected) when the items do not have a monetary value.
2. **Column names:** Next, specify the names of the two columns that will be added to the dataset. The first column name will indicate the result of the selection, while the second column name will contain the annotation of the items. Click the 'Continue' button to confirm the settings and open the data viewer.
3. **Annotating items:** Then, use the data viewer to annotate the selected items with their book value. For example, in this case, item 50826 (row 25, highlighted in red) had a book value of €333.03 but a true value of €200. The remaining items have correctly reported book values.
4. **Next stage:** Finally, progress to the evaluation stage by clicking the 'To Evaluation' button.

1.2.4 Stage 4: Evaluation

In the evaluation stage, you assess the misstatement in the sample and extrapolate it to the entire population. Once you press the 'To Evaluation' button, the interface for the evaluation stage will open.



The following setting is required:

- Annotation variable:** Specify the variable that contains the annotation of the items in the corresponding box.

The following setting is optional:

- Additional tables:** It is recommended to request the 'Misstated items' table from the 'Report' section. This table displays the items in the sample where the book value did not match the true value. Additional tables and figures to clarify the output, which will be discussed in Chapter 4, can be requested here as well.

The primary output from the evaluation stage, as shown in the first table below, indicates that the most likely misstatement in the population is estimated to be 0.003, or 0.3%. The 95% upper bound for this estimate is 0.027, or 2.7%. This upper bound is lower than the performance materiality of 3.5%, meaning the auditor has achieved at least 95% assurance that the population misstatement is below the performance materiality.

Table 4. Evaluation Summary

	Value
Performance materiality	0.035
Sample size	134
Misstatements	1
Taint	0.396
Most likely misstatement	0.003
95% Upper bound	0.027
Precision	0.025
p-value	0.019

Note. The results are computed using the binomial distribution.

Table 5. Misstated Items

ID	Book value	Audit value	Difference	Taint	Counted
50,826	€331.03	€200	€131.03	0.396	x1
Total			€131.03	0.396	

Based on the results of this statistical analysis, the auditor concludes that the population is free of material misstatement.

Chapter 2

Planning

i This page is currently under construction.

Chapter 3

Selection

i This page is currently under construction.

Chapter 4

Evaluation

i This page is currently under construction.

Chapter 5

Ture Value Estimation

i This page is currently under construction.

Part II

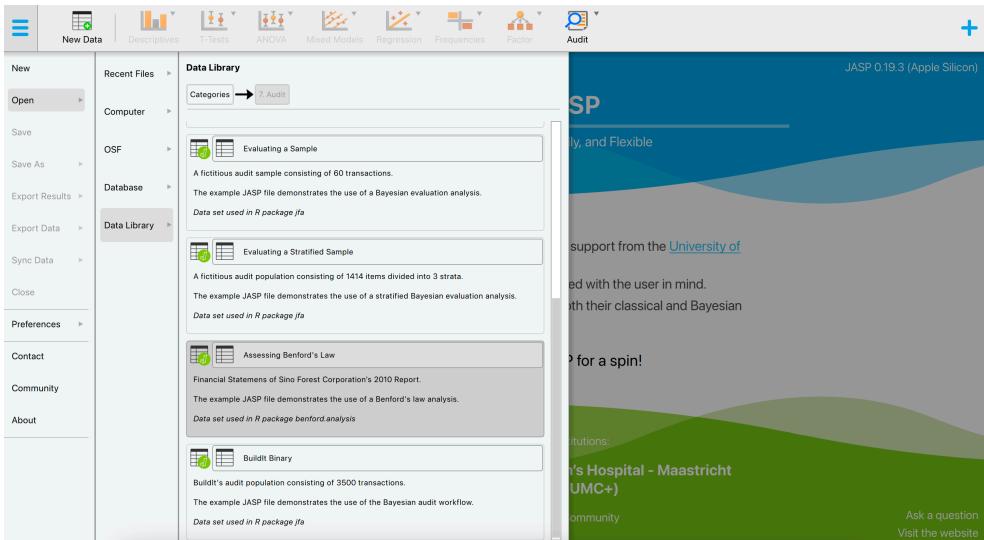
Data Auditing

Chapter 6

Benford's Law

Benford's law states that the distribution of leading digits in a population naturally follows a certain distribution. In auditing, assessing whether a distribution of digits in the population conforms to Benford's law may provide additional evidence that the items or transactions in a population might need further investigation.

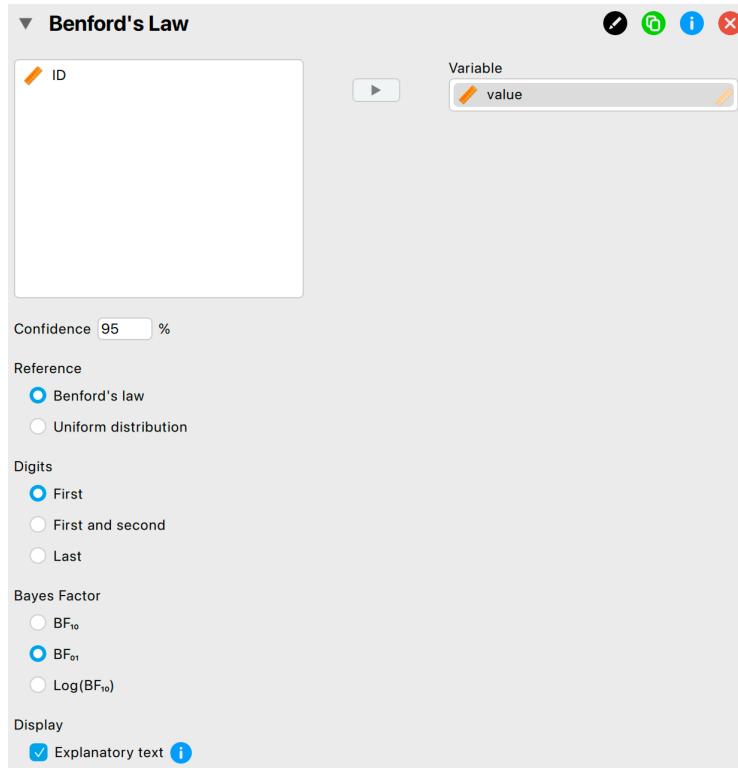
Let's explore an example analysis of Benford's law. To follow along, open the 'Assessing Benford's Law' dataset from the Data Library. Navigate to the top-left menu, click 'Open', then 'Data Library', select '7. Audit', and finally click on the text 'Assessing Benford's Law' (not the green JASP-icon button).



6.1 Main settings

The interface of the Benford's law analysis in JASP is shown below. We will investigate whether the distribution of first digits in the variable 'value', which represents

the recorded values of transactions in a financial population, adheres to Benford's law. That is, the null hypothesis, H_0 , states that the distribution of first digits follows Benford's law, while the alternative hypothesis, H_1 , states that it does not.



These are the main settings for the analysis.

- **Variable:** Begin by entering the variable whose digit distribution you wish to test in the designated box. In the example, this is the variable 'value', so we drag this variable to the field on the right.
- **Confidence:** Indicate the confidence level for your analysis. This level, which complements the significance level, determines when to reject the null hypothesis. In the example, we use a confidence level of 95%.
- **Reference:** Select a reference distribution to compare the chosen digits against. By default, this is set to 'Benford's law,' but you can also opt for a uniform distribution. In the example, we select 'Benford's law'.
- **Digits:** Choose which digits to compare against the reference distribution. You can select the first digits (default), the first two digits, or the last digits. Benford's law typically applies to the first or first two digits, while the uniform distribution is usually applied to the last digits. In the example, we choose to test the first digits against Benford's law.
- **Bayes factor:** Select which Bayes factor is displayed in the main output table. ' BF_{10} ' represents the Bayes factor in favor of the alternative hypothesis over the null hypothesis, ' BF_{01} ' represents the Bayes factor in favor of the null hypothesis over the alternative hypothesis, and 'Log(BF_{10})' represents the logarithm of

- BF_{10} .
- **Explanatory text:** Finally, select whether to show explanatory text in the output.

6.2 Main output

The main table in the output, shown below, shows the sample size (n), the mean absolute deviation (MAD), the chi-square value (X^2) and its degrees of freedom (df). The table shows a p-value of 0.478, indicating that H_0 should not be rejected at a significance level of 5%. Furthermore, the table presents the Bayes factor in favor of the null hypothesis, BF_{01} , which is 6.9×10^6 . This suggests that the data provide very strong evidence supporting H_0 over H_1 .

Table 1. Omnibus Test – Benford's Law ▾

n	MAD	X^2	df	p	BF_{01}^a
value	772	0.007	7.652	8	0.468 $6.900 \times 10^{+6}$

Note. The null hypothesis specifies that the first digits (1 – 9) in the data set are distributed according to Benford's law.

^a The Bayes factor is computed using a Dirichlet($\alpha_1, \dots, \alpha_9$) prior with $\alpha = 1$.

Note that non-conformity to Benford's law does not necessarily indicate fraud. A Benford's law analysis should therefore only be used to acquire insight into whether a population might need further investigation.

6.3 Report

These following settings enable you to expand the report with additional output, such as tables and figures.



6.3.1 Tables

The following tables can be requested in the ‘Report’ section of the interface.

- **Frequency table:** Check this box to display a table of the observed and expected frequencies of the digits. Clicking the ‘Confidence interval’ option shows confidence intervals for the observed relative frequencies in the table.

The frequency table displays the observed count for each leading digit in the second column. Adjacent to this, it shows the expected relative frequency under Benford's law alongside the observed relative frequency in the data. Additionally, p-values and Bayes factors are provided to test whether the observed relative frequencies differ from the expected ones. In this case, only the digit

8 has a p-value smaller than 0.05, indicating a significant deviation from the expected relative frequency under Benford's law.

Table 2. Frequency Table

Leading digit	Count	Benford's law	Relative frequency	95% Confidence Interval		p ^a	BF ₀₁ ^b
				Lower	Upper		
1	231	0.301	0.299	0.267	0.333	0.937	24.083
2	124	0.176	0.161	0.135	0.188	0.277	15.737
3	97	0.125	0.126	0.103	0.151	0.957	33.397
4	70	0.097	0.091	0.071	0.113	0.626	32.411
5	64	0.079	0.083	0.064	0.105	0.689	37.398
6	54	0.067	0.070	0.053	0.090	0.719	41.126
7	40	0.058	0.052	0.037	0.070	0.537	37.795
8	54	0.051	0.070	0.053	0.090	0.022	3.449
9	38	0.046	0.049	0.035	0.067	0.606	46.150

Note. The null hypothesis specifies that the relative frequency of a digit is equal to its expected relative frequency under Benford's law.

^a Confidence intervals and p-values are based on independent binomial distributions.

^b Bayes factors are computed using a beta(1, 1) prior.

- **Matched rows:** Check this box to display a table showing the rows that have a certain number as their leading/last digit(s).

In the example, we request a table of rows that match the digit 8. The first column displays the row number where the digit is found, and the second column shows the matched value. Using this table, you can identify the transactions that may warrant further investigation.

Table 3. Rows Matched to Leading Digit 8 ▼

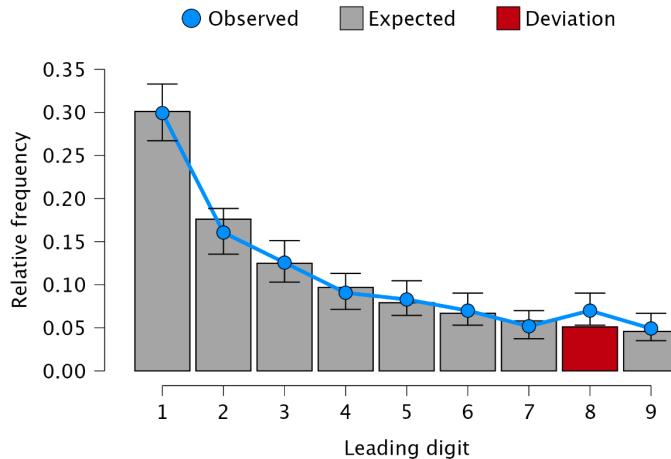
Row	Value
5	89,712.000
21	8,179.000
33	8,498.000
34	8,756.000
59	87,670.000
84	8,179.000
103	826.000
125	8,555.000
138	82,447.000
192	845.000
199	8,000.000
210	837.000
215	8,000.000
218	8,340.000
225	826.000

6.3.2 Plots

The following tables can be requested in the ‘Report’ section of the interface.

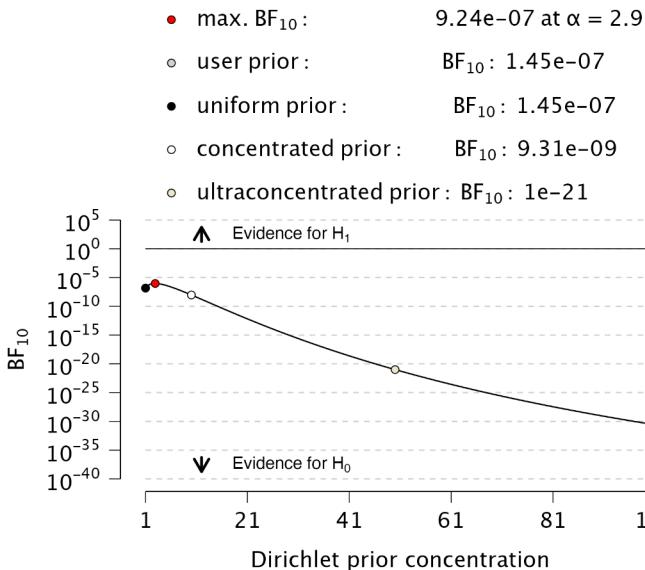
- **Observed vs. expected:** Check this box to display a figure that illustrates the observed frequencies compared to the expected frequencies.

The figure in the output visualizes the observed relative frequencies compared to the expected ones, with the digit 8 highlighted in red. From this figure, it is immediately clear that the transactions starting with the digit 8 may warrant further inspection.



- **Bayes factor robustness check:** Check this box to display a figure that shows the Bayes factor under different specifications of the prior concentration parameter.

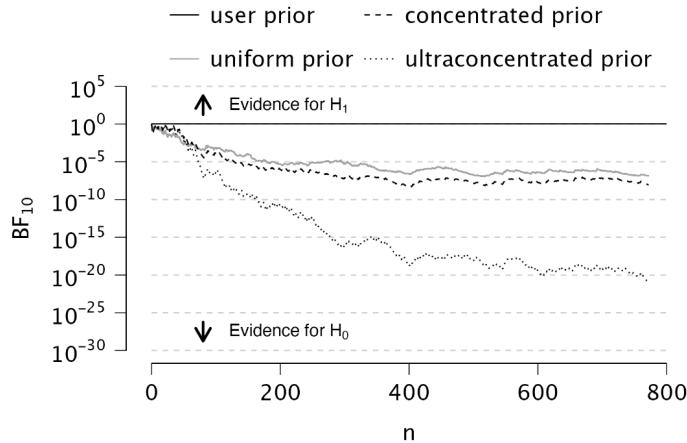
The figure below is referred to as a robustness check. If the Bayes factor supports a particular hypothesis across all reasonable values of the prior concentration parameter, the result is considered robust regarding the choice of prior distribution. In this instance, the figure demonstrates that the Bayes factor consistently provides evidence in favor of the null hypothesis, regardless of the prior concentration parameter values.



- **Sequential analysis:** Select this box to display a figure illustrating the Bayes factor as a function of sample size, across various prior specifications.

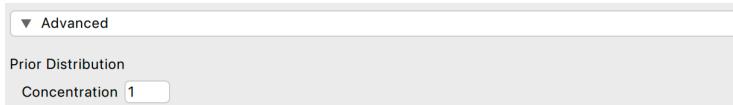
In the example analysis, the sequential analysis plot demonstrates that the

Bayes factor provides increasing evidence in favor of H_0 as the sample size grows. Additionally, this evidence is more pronounced when using a more concentrated prior distribution.



6.4 Advanced

The following advanced settings allow you to customize the statistical computations according to your preferences.



- **Concentration:** Specify the concentration parameter for the Dirichlet prior distribution. Adjusting this value will alter the Bayes factor in the main output table. A larger concentration parameter indicates a more concentrated prior distribution, suggesting that the population proportions are more similar. When testing against the uniform distribution, this implies a stronger belief in H_0 . Conversely, when testing against Benford's law, it indicates a stronger belief in H_1 .

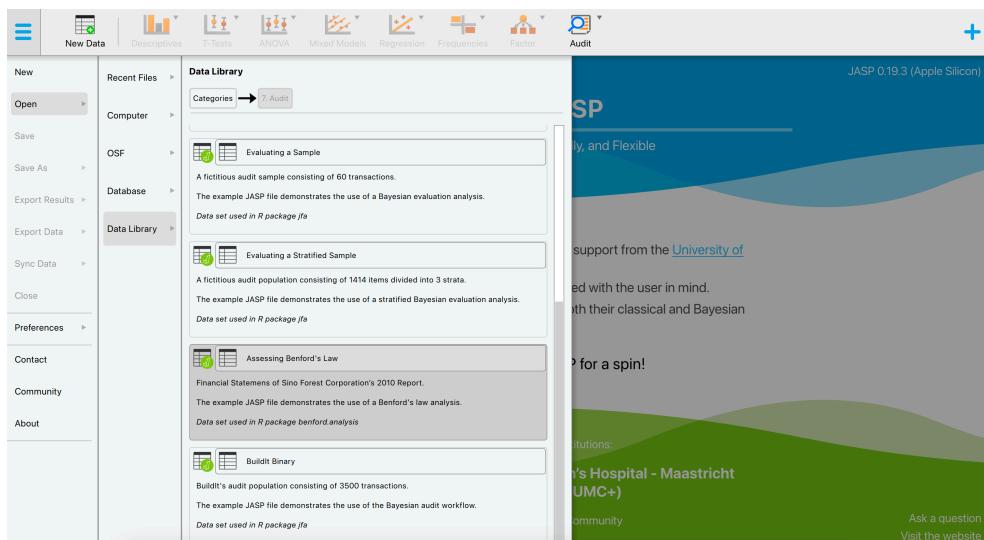
Chapter 7

Repeated Values

The repeated values analysis analyzes the frequency with which values get repeated within a dataset (called “number-bunching”) to statistically identify whether the data were likely tampered with. Unlike Benford’s law this approach examines the entire number at once, not only the first or last digit (Simohnsohn, 2019).

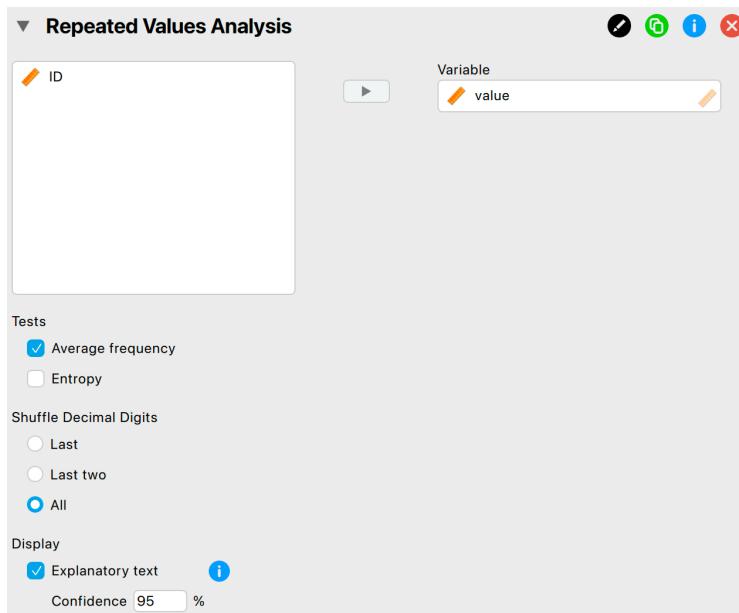
To determine whether the data show an excessive amount of bunching, the null hypothesis that the data do not contain an unexpected amount of repeated values is tested. To quantify what is expected, this test requires the assumption that the integer portions of the numbers are not associated with their decimal portions.

Let’s explore an example analysis of repeated values. To follow along, open the ‘Assessing Benford’s Law’ dataset from the Data Library. Navigate to the top-left menu, click ‘Open’, then ‘Data Library’, select ‘7. Audit’, and finally click on the text ‘Assessing Benford’s Law’ (not the green JASP-icon button).



7.1 Main settings

The interface ...



These are the main settings for the analysis.

- **Variable:** ...
- **Tests:** ...
- **Shuffle decimal digits:** ...
- **Explanatory text:** ...
 - Confidence: ...

7.2 Main output

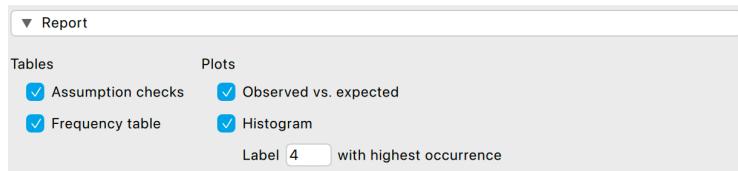
Table 1. Repeated Values Test

n	Frequency		
	Average	p	
value	772	1.324	0.024

Note. The displayed p-value is one-sided and is computed on the basis of 500 samples.

7.3 Report

These following settings enable you to expand the report with additional output, such as tables and figures.



7.3.1 Tables

The following tables can be requested in the ‘Report’ section of the interface.

- **Assumption checks:** ...

Table 2. Assumption Checks

	n	r	t	df	p
Integer values – Decimal values	772	-0.027	-0.738	770	0.461

Note. The displayed p-value is for a two-sided test against $H_0: r = 0$.

- **Frequency table:** ...

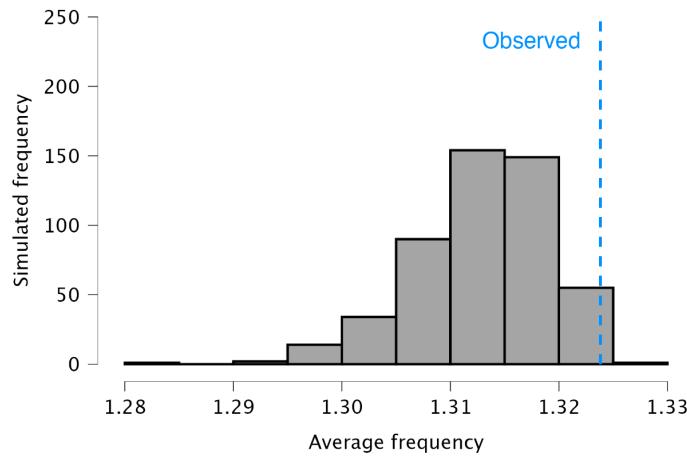
Table 3. Frequency Table ▾

Value	Count	Percentage
87,670	5	0.6 %
1,670	4	0.5 %
17,008	4	0.5 %
636	3	0.4 %
1,403	3	0.4 %
8,756	3	0.4 %
50,000	3	0.4 %
150,000	3	0.4 %
1,473,353	3	0.4 %

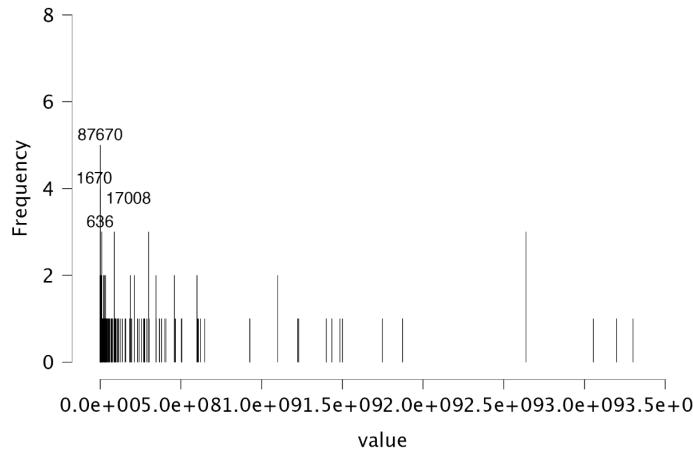
7.3.2 Plots

The following figures can be requested in the ‘Report’ section of the interface.

- **Observed vs. expected:** ...



- **Histogram:** ...



Part III

Algorithm Auditing

Chapter 8

Fairness

i This page is currently under construction.

This is the user manual for **JASP for Audit**, which is a module for the free and open-source statistical software program **JASP** that integrates the functionality of the **jfa** package and offers a user-friendly graphical interface that caters specifically to statistical auditing (<https://jasp-stats.org>).