FRAUD DETECTION IN MEDICARE

CREATING FRAUD INDICATORS

Introduction

- Medicare stands as a federal health insurance program for: people who are 65 or older, certain younger people with disabilities and people with end-stage renal disease.
- Corruption and inefficient public spending in healthcare systems can degrade the system, which increase the cost for the population, reduce accessibility to treatments, in simple words: negative health impacts.
- To combat misuse of public resource, with aid of forensic accounting tools based on Benford's Law we can leverage information from Medicare dataset to create fraud indicators.
- This project is inspired by Nigrini, M. J. (2011). *Forensic analytics: Methods and techniques for forensic accounting investigations*. Wiley.

Research Questions

- 1. How real-world data behave when analyzed with forensic accounting tools Benford’s Law?
- 2. In case we have discrepancies between real-world data and expected Benford’s Law, how can we leverage this information to flag transactions as suspicious?

DATASETS

- Medicare Part B
- List of Excluded Individuals/Entities (LEIE)
- Order And Referring
- State Medicaid Exclusion List

Medicare dataset

- Medicare Physician & Other Practitioners - by Provider and Service with information on services and procedures provided to Original Medicare (fee-for-service) Part B (Medical Insurance) beneficiaries by physicians and other healthcare professionals; aggregated by provider and service.
- Medicare dataset has 29 columns with National Provider Identifier (NPI) and FFS data.
- NPI will be our key to match with the other datasets when creating target variable and FFS will give numbers to identify possible frauds or improper payments.

Medicare dataset

	Rndrng_NPI	Rndrng_Prvdr_Last_Org_Name	Rndrng_Prvdr_First_Name	HCPCS_Cd	HCPCS_Desc	Avg_Mdcr_Pymt_Amt
0	1003000126	Enkeshafi	Ardalan	99213	Established patient outpatient visit, total ti...	83.908220
1	1003000126	Enkeshafi	Ardalan	99214	Established patient outpatient visit, total ti...	118.570638
2	1003000126	Enkeshafi	Ardalan	99217	Hospital observation care on day of discharge	61.066923
3	1003000126	Enkeshafi	Ardalan	99220	Hospital observation care, typically 70 minutes	141.442857
4	1003000126	Enkeshafi	Ardalan	99222	Initial hospital inpatient care, typically 50 ...	105.700833
5	1003000126	Enkeshafi	Ardalan	99223	Initial hospital inpatient care, typically 70 ...	170.388889
6	1003000126	Enkeshafi	Ardalan	99226	Subsequent observation care, typically 35 minu...	84.338125
7	1003000126	Enkeshafi	Ardalan	99231	Subsequent hospital inpatient care, typically ...	31.255862
8	1003000126	Enkeshafi	Ardalan	99232	Subsequent hospital inpatient care, typically ...	58.462108
9	1003000126	Enkeshafi	Ardalan	99233	Subsequent hospital inpatient care, typically ...	84.875327
10	1003000126	Enkeshafi	Ardalan	99238	Hospital discharge day management, 30 minutes ...	59.603478
11	1003000126	Enkeshafi	Ardalan	99239	Hospital discharge day management, more than 3...	86.786378
12	1003000126	Enkeshafi	Ardalan	99454	Remote monitoring of physiologic parameters, i...	63.303729
13	1003000126	Enkeshafi	Ardalan	99457	Remote physiologic monitoring treatment manage...	48.005374
14	1003000126	Enkeshafi	Ardalan	99458	Remote physiologic monitoring treatment manage...	38.270000

Dataset shape: 9.886.177 rows, 29 columns

Medicare dataset

- Dataset is highly detailed, showing each and every service by the provider, thus we will simplify the dataset grouping the columns.
- A provider can have the same name as another, therefore we will be grouping as per NPI, since it is unique and will be used as our primary key to link with the other datasets.
- For Categorical features it will keep unique values, i.e., if HCPCS_Cd is more than one is present, it will join the unique entries creating a new entry.
- For Numerical features, Tot_Benes, Tot_Srvcs and Tot_Bene_Day_Srvcs we will sum and for the other numerical features, we are using weighted average with Tot_Bene_Day_Srvcs as weight.

Aggregated Medicare dataset

	NPI	Last_Org_Name	First_Name	HCPCS_Cd	HCPCS_Desc	Avg_Mdcr_Pymt_Amt
0	1003000126	Enkeshafi	Ardalan	99213, 99214, 99217, 99220, 99222, 99223, 9922...	Established patient outpatient visit, total ti...	61.441327
1	1003000134	Cibull	Thomas	88304, 88305, 88312, 88313, 88321, 88341, 8834...	Pathology examination of tissue using a micros...	27.620868
2	1003000142	Khalil	Rashid	62323, 64483, 64484, 64490, 64491, 64493, 6449...	Injection of substance into spinal canal of lo...	71.649996
3	1003000423	Velotta	Jennifer	81002, G0101, Q0091	Urinalysis, manual test, Cervical or vaginal c...	31.303448
4	1003000480	Rothchild	Kevin	99202, 99203, 99212, 99213	New patient outpatient visit, total time 15-29...	48.870698
5	1003000530	Semonche	Amanda	81002, 90662, 90670, 90732, 93000, 99213, 9921...	Urinalysis, manual test, Vaccine for influenza...	96.499037
6	1003000597	Kim	Dae	50590, 51102, 51700, 51702, 51705, 51798, 5200...	Shock wave crushing of kidney stones, Aspirati...	73.625755
7	1003000639	Benharash	Peyman	99205	New patient outpatient visit, total time 60-74...	161.090000
8	1003000704	Gatton	Zachary	00142	Anesthesia for lens surgery	118.130500
9	1003000720	Hernandez	Otniel	81003, 99203, 99204, 99205, 99213	Automated urinalysis test, New patient outpati...	68.720287
10	1003000738	Zumwalt	Juliette	20610, 20611, 29823, 29827, 73030, 73562, 9920...	Aspiration and/or injection of large joint or ...	40.744730
11	1003000795	O'neill	Michael	90832	Psychotherapy, 30 minutes	40.528673
12	1003000829	Kochanek	Michelle	97110, 97112, 97140, 97161	Therapeutic exercise to develop strength, endu...	25.300159
13	1003000902	Lohano	Jaivanti	81003, 90662, 90732, 99204, 99213, 99214, 9949...	Automated urinalysis test, Vaccine for influen...	75.950196
14	1003000936	Stellingworth	Mark	36415, 85610, 93000, 93010, 93228, 93270, 9327...	Insertion of needle into vein for collection o...	46.623078

- Aggregated dataset shape: 1.123.589 rows, 29 columns

How real-world data behave when analyzed with forensic accounting tools from Benford's Law?

Benford's Law Tests

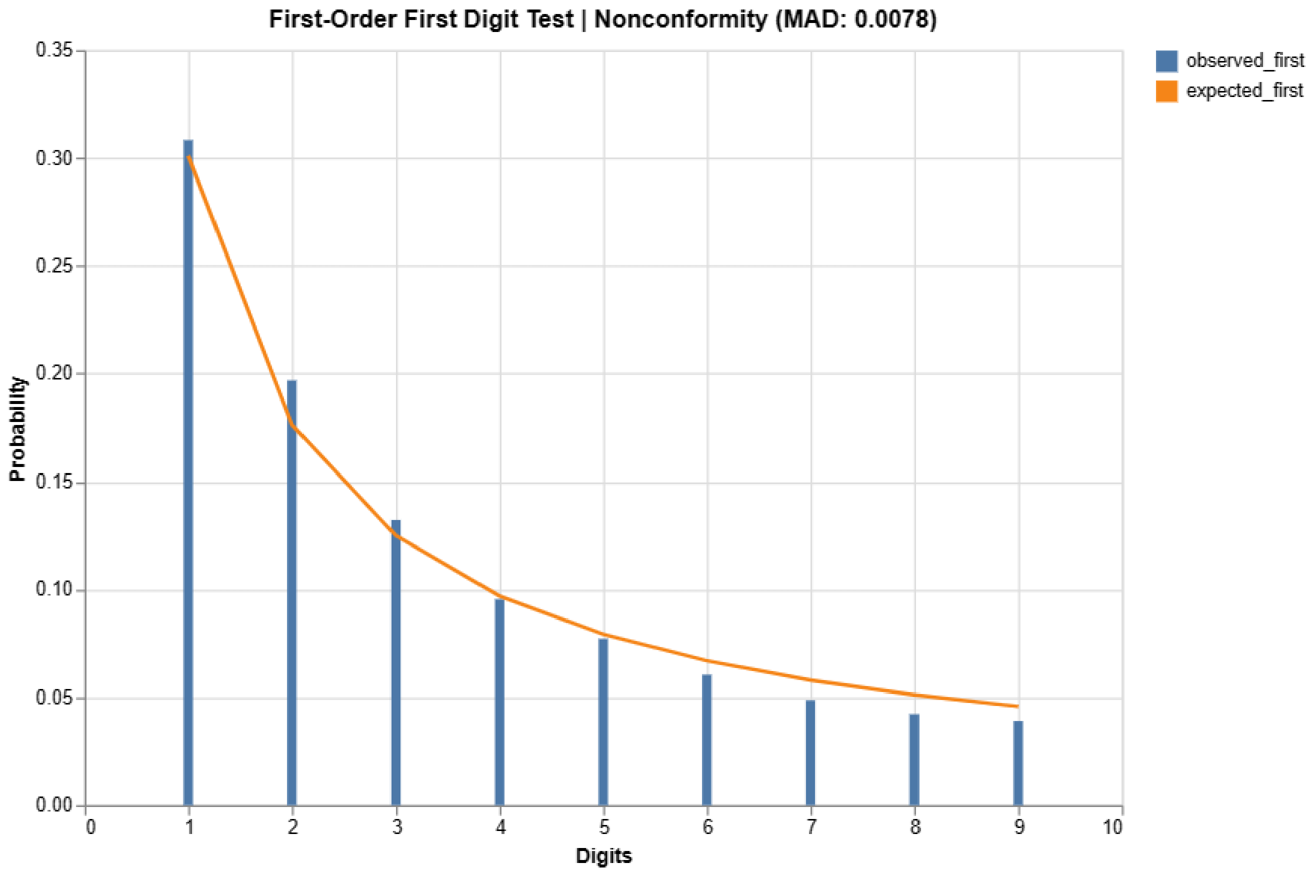
- First Order First Digit Test
- First Order Second Digit Test
- First Order First-Two Digit Test
- First Order Last Two Digit
- Second Order First-Two Digits Test
- Summation Test
- Largest Growth Test
- Relative Size Factor Test

Benford’s Law conformity

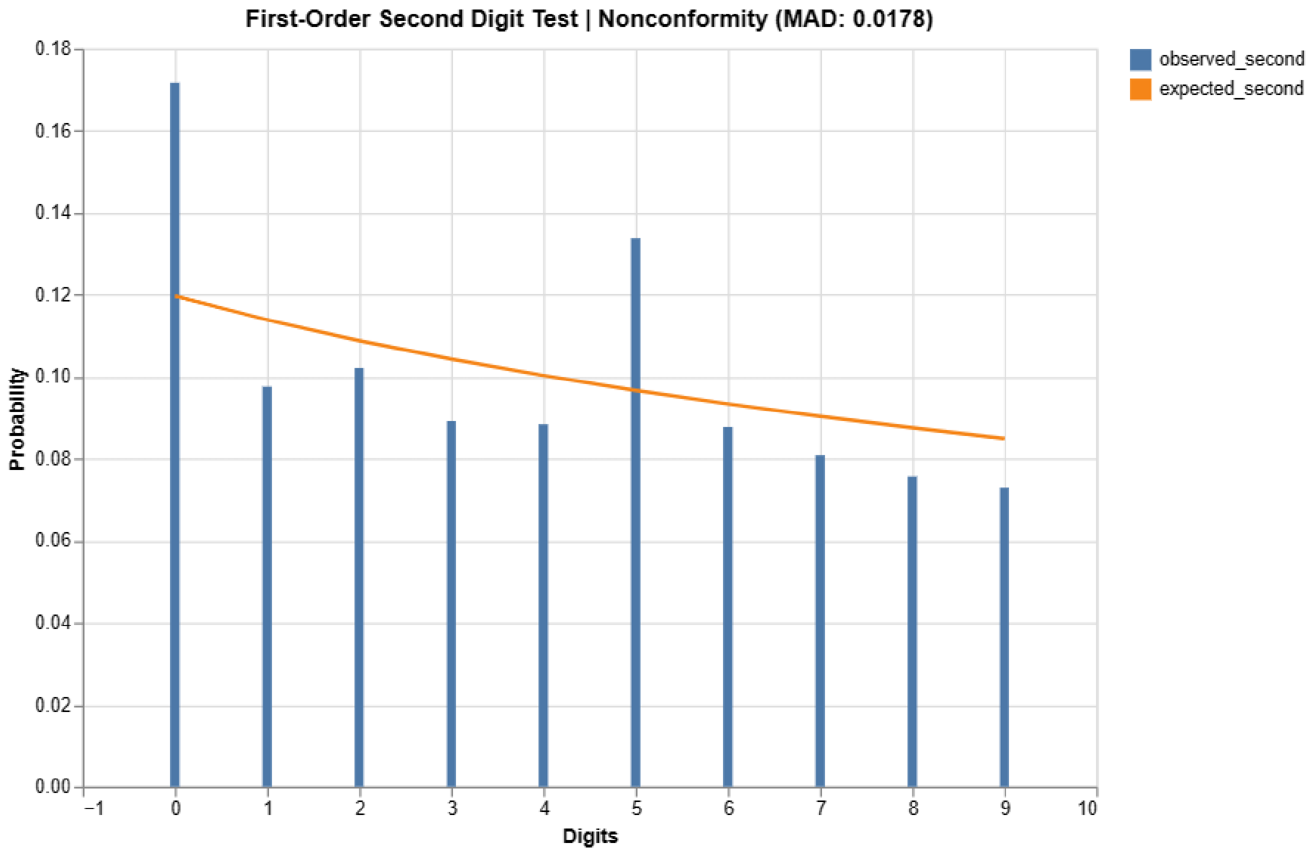
First-Two Digits MAD Range	Conclusion
0.0000 to 0.0012	Close conformity
0.0012 to 0.0018	Acceptable conformity
0.0018 to 0.0022	Marginally acceptable conformity
Above 0.0022	Nonconformity

Table 5 MAD range

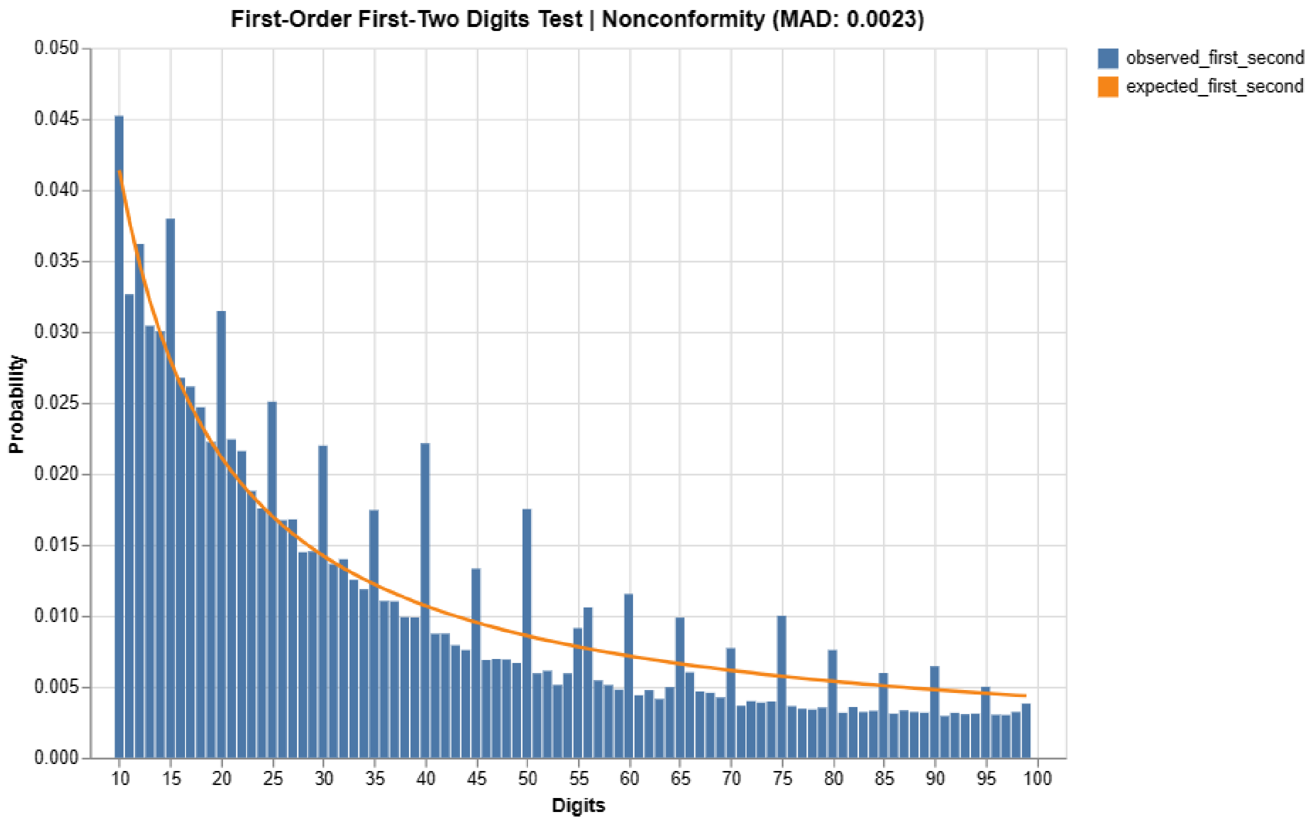
$$\text{Mean Absolute Deviation} = \frac{\sum_{i=1}^{K} |AP - EP|}{K}$$



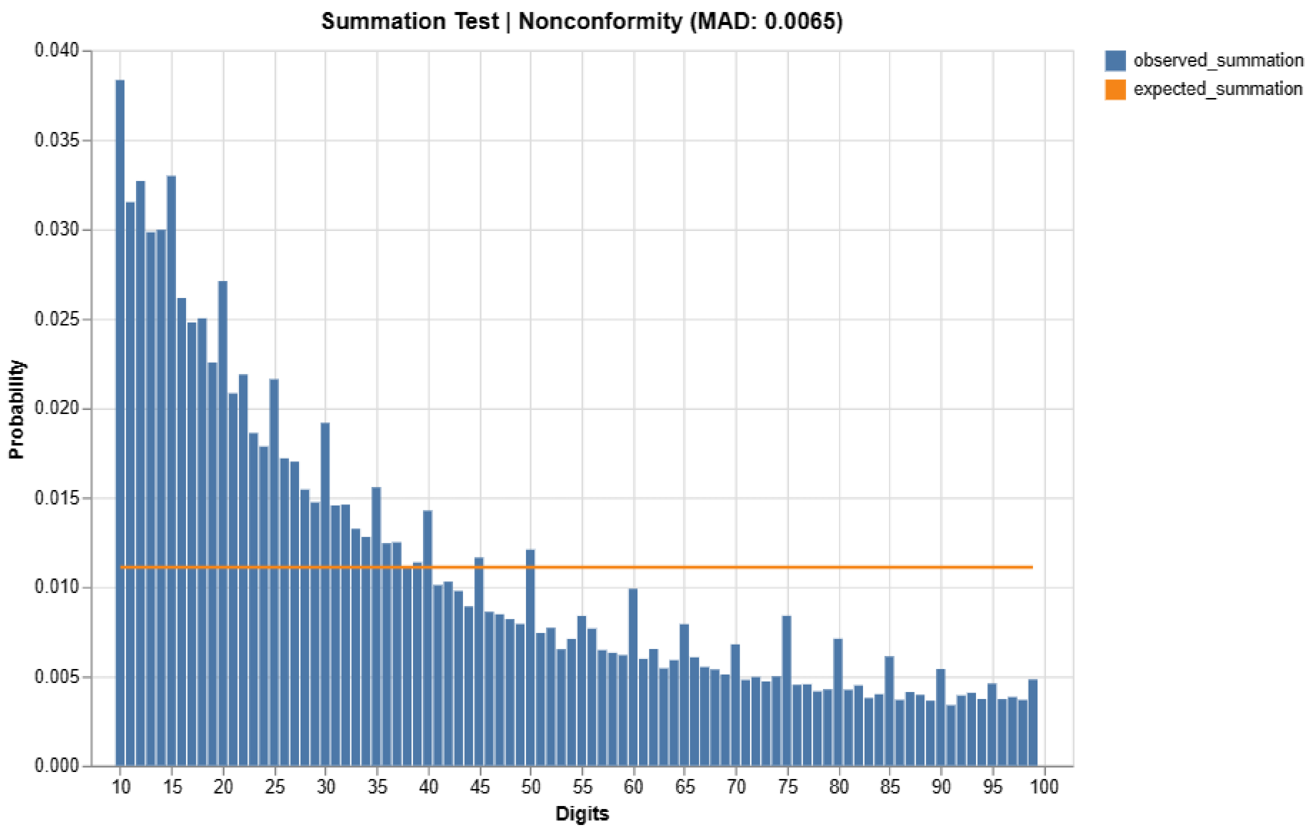
First Order First Digit



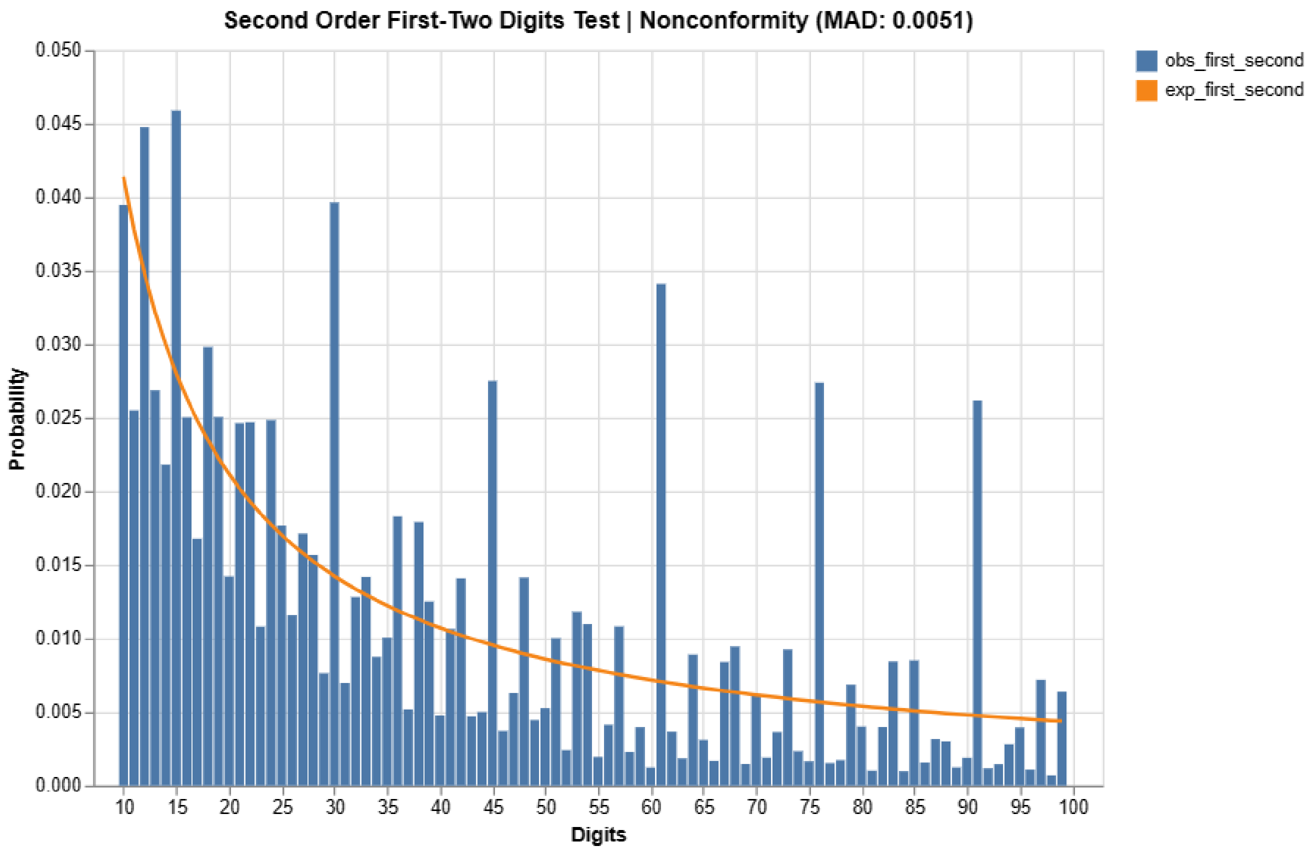
First Order Second Digit



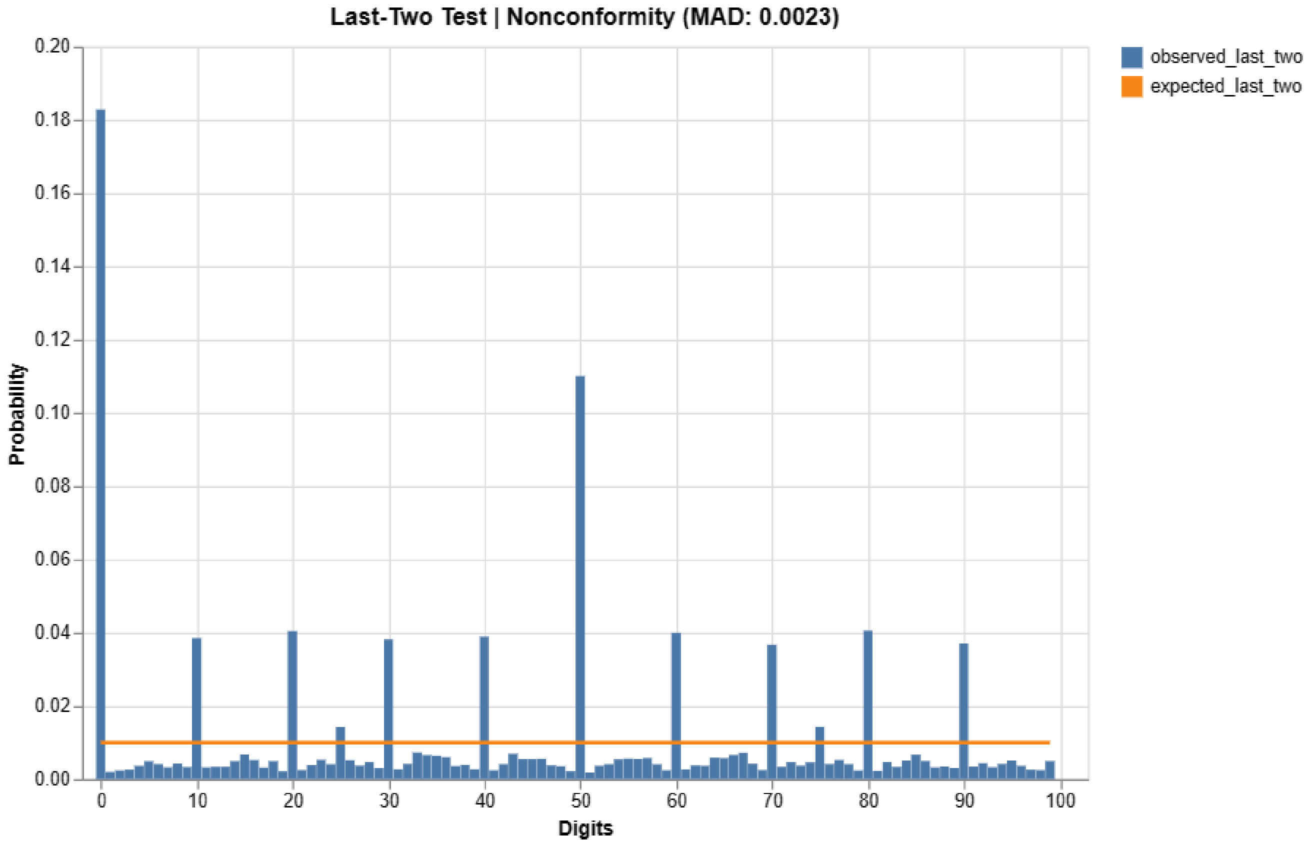
First Order First-Two Digit



Summation Test



Second Order First-Two Digits



Last-two digits

Benford's Law test results

- Benford’s law set a preposition that natural data follow a pattern.
- Few spikes in certain values due to intrinsic characteristic of the data. For example, it is expected that bills charges have higher amounts of values ending in 0, such as 10, 50 and 90.
- All tests results in nonconformity, thus indicate that we should explore more our data.

Tests	Conclusion
First Order First Digit Test	Nonconformity
First Order Second Digit Test	Nonconformity
First Order First-Two Digit Test	Nonconformity
First Order Last Two Digit	Nonconformity
Second Order First-Two Digits Test	Nonconformity
Summation Test	Nonconformity

In case we have discrepancies between real-world data and expected Benford's Law, how can we leverage this information to flag transactions as suspicious?

In case we have discrepancies between real-world data and expected Benford's Law, how can we leverage this information to flag transactions as suspicious?

- Leveraging the information diverted from Benford's Law tests, we figured that we could create our own flags to signalize if something seems abnormal. That being sad, we created three criteria to define if an average submitted charge should be flagged as suspicious.
- The first one, we need historical data to confront with the last data available. In this case, we compared 2021 and 2020 data. If the charges growth rate in the period is too high, not being justifiable by the increase of new beneficiaries, we would raise a flag, but please notice that price adjustment, for example due to inflation could occur, hence this information alone won't define as fraud, but a flag to keep an eye on it.
- RSF test is used to raise flags in possible errors, in this case, if a max value is way to high in contrast to the second max value, this might raise an alert that an error is occurring. For example, if a person usually pays 700-900 for credit card bill, but for this month the bill is 3000$ is due to a flight ticket bought for vacation, the bank should emit an alert to the customer identifying an anormal value. The same logic can be applied for our dataset, hence we set a criterion that in case RSF ratio is high, we should investigate to understand the reason.
- Our last test was a simple test to compare the median values charged for each HCPCS code used to identify the specific medical service furnished by the provider. Hence if a provider charges more than double of the median price of the specific HCPCS code, we should investigate why is occurring overcharging for the same services provided by others.

Benford's Law Tests

- • Largest Growth test
- • Relative Size Factor test
- • HCPCS test

Largest Growth Test

- We compared 2021 and 2020 data.
- If the charges growth rate in the period is above a threshold, taking into consideration the increase of new beneficiaries, we would raise a flag.

	Rndrng_NPI	Sum_2021	Tot_Benes_2021	Sum_2020	Tot_Benes_2020	Sum_growth	Tot_bene_growth	Sum_bene_ratio	ratio_flag
0	1538144910	98401.906275	10948038.0	97027.700598	10342594.0	1.014163	1.058539	0.958078	0
1	1891731626	108890.330026	5586675.0	110824.887552	5467219.0	0.982544	1.021849	0.961535	0
2	1932145778	105890.329231	5296381.0	97742.967041	4111244.0	1.083355	1.288267	0.840940	0
3	1063497451	98077.502440	6877772.0	95401.872824	6108559.0	1.028046	1.125924	0.913069	0
4	1366479099	100922.779814	4854261.0	96616.018640	4414351.0	1.044576	1.099655	0.949913	0
...	...	...	...	...	...	...	...	...	...
1123582	1215033550	333.286385	17.0	350.000000	41.0	0.952247	0.414634	2.296595	1
1123583	1902162688	191.000000	37.0	332.000000	41.0	0.575301	0.902439	0.637496	0
1123584	1528180171	295.000000	82.0	295.000000	36.0	1.000000	2.277778	0.439024	0
1123585	1528180197	993.750000	16.0	1671.250000	12.0	0.594615	1.333333	0.445961	0
1123587	1528180361	256.000000	16.0	320.000000	25.0	0.800000	0.640000	1.250000	0

996091 rows × 9 columns

Relative size factor test

- RSF is the ratio between the highest value and the second highest value.
- If the RSF ratio is above a threshold we should raise a flag and investigate.

	max_1	max_2	rsf	rsf_flag
0	1165.704744	1122.043654	1.038912	0
1	2762.000000	2504.675000	1.102738	0
2	3082.260278	2762.000000	1.115952	0
3	1160.750857	1122.000000	1.034537	0
4	3050.000000	2990.000000	1.020067	0
...	...	...	...	...
1123582	333.286385	0.000000	0.000000	0
1123583	191.000000	0.000000	0.000000	0
1123584	295.000000	0.000000	0.000000	0
1123585	993.750000	0.000000	0.000000	0
1123587	256.000000	0.000000	0.000000	0

996091 rows × 4 columns

HCPCS Test

- ▶Calculate the median values charged for each HCPCS code used to identify the specific medical service furnished by the provider.
- ▶Hence if a provider charges more than double of the median price of the specific HCPCS code, we should investigate why is occurring overcharging for the same services provided by others.

	Rndrng_NPI	HCPCS_Cd	Avg_Sbmtd_Chrg	Avg_Sbmtd_Chrg_HCPCS	HCPCS_ratio	HCPCS_flag
0	1003000126	99213	125.000000	150.000000	0.833333	0
1	1003000126	99214	173.829787	220.173102	0.789514	0
2	1003000126	99217	257.620513	187.363636	1.374976	0
3	1003000126	99220	1192.656191	471.000000	2.532179	0
4	1003000126	99222	319.666667	309.000000	1.034520	0
...	...	...	...	...	...	...
9886172	1992999825	99214	291.000000	220.173102	1.321687	0
9886173	1992999874	99223	699.117647	465.050000	1.503317	0
9886174	1992999874	99232	249.467181	172.000000	1.450391	0
9886175	1992999874	99233	355.699670	253.000000	1.405928	0
9886176	1992999874	99239	368.638554	269.000000	1.370404	0

9886177 rows × 6 columns

Conclusion

- Insightful Vision with Forensic Accounting Tools:

  Forensic accounting tools enhanced our understanding of the data, allowing us to gain deeper insights creating Anomaly Detection and Fraud Flagging.

thank you!