Breaking the (Benford) Law
Statistical Fraud Detection in Campaign Finance

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Abstract

Benford's law is seeing increasing use as a diagnostic tool for isolating pockets of large data sets having irregularities that deserve closer inspection. Popular and academic accounts of campaign finance are rife with tales of corruption, but the complete data set of transactions for federal campaigns is enormous. Performing a systematic sweep is extremely arduous; hence, these data are a good candidate for initial screening by comparison to Benford's distributions.

Key Words: Benford's Law; Campaign Finance.

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Benford's Law is a fine example of a deeply nonintuitive and intriguing mathematical result, simple enough to be described (if not fully explained) even to those without any formal training in math. The law pertains to the first digits of a collection of numbers. Most people's intuition is that, in "ordinary" large sets of numbers, each integer from 1 through 9 should appear as the leading digit with roughly equal probability. By contrast, Benford's Law reports that the digit 1 leads approximately 30% of the time and each successive digit is less common, with 9 occurring less than 5% of the time. Strikingly, this pattern holds for a diverse set of numbers that have no apparent connection to one another.

Although the law now sports Benford's name, the astronomer and mathematician Simon Newcomb was the first to note, in an 1881 *American Journal of Mathematics* article, that not all possible first digits appear with equal frequency in large sets of "natural numbers."[1] Newcomb never proffered a theoretical explanation for this phenomena, but his observation, "the law of probability of the occurrence of numbers is such that all mantissæof their logarithms are equally probable," (40) suggests a convenient expression for the empirical distribution of first digits.

$$P(d) = \log_{10}\left(\frac{1+d}{d}\right) \quad \text{for } d \in \{1, ..., 9\}.$$

Benford, in turn, set out empirically to test Newcomb's hypothesis. He collected data from a wide variety of data sets, including areas of rivers, population figures, addresses, American league baseball statistics, atomic weights of elements, and numbers appearing in *Reader's Digest* articles, among others (Benford, 1938). In his analysis of this varied and large set of numbers (consisting of 20,229 individual set of numbers), there was a surprisingly good fit to the distribution of leading digits first laid out by Newcomb (1881). Thus, as so often happens, the law was named not for its discoverer, but for its first popularizer. Others followed up by confirming the (approximate) fit of still more sources of numbers, including stock market data, census statistics, some accounting data, stock market prices, and ebaY bids (Hill, 1995; Giles, 2006; Ley, 1996). About a century after Newcomb's discovery, rigorous proof of the law (and derivation of when and why it holds) were finally developed (Hill, 1995).

1 Fraud and Irregularity Detection By Benford's Law

An interesting application of Benford's Law has emerged in recent decades. Whenever first digits should follow Benford's Law, it follows that deviations from the known distribution in data expected to conform signal some type of irregularity, possibly deliberate fraud. Accordingly, Benford's Law has been put to use as a simple and effective way to test for fraudulent manipulation of data, as might exist in accounts when embezzlement has occurred (Nigrini, 1999; Durtschi, Hillison and Pacini, 2004). If a data source generally

[1] The term "natural numbers" is usually reserved for the positive (or, sometimes, non-negative) integers, but Newcomb was contrasting logarithms read from a prepared table and their anti-logarithms, which are rational numbers.

conforms to the law, random deletion would not induce a worse fit, but if entries are being falsified or there are accidental systematic omissions, violations can follow. Experimental research has shown that people do a poor job of replicating known data-generating processes, for instance by over-supplying modes or under-supplying long runs (Camerer, 2003, 134–138). Benford's law is widely applicable but not widely known, so it seems very unlikely that those manipulating numbers would seek to preserve fit to the Benford distribution. In that sense, it could be an unusually good diagnostic.

An immediate, important caveat is that not all numbers follow the law. In accounting, for example, the first-digit distribution can become skewed when receipts include a very large number of identical transactions, reflecting sales of an especially popular item whose price is constant. In another context, election returns are unlikely to follow the law in many typical situations, where districts are of nearly equal size and the range of competition conspires to fix most vote totals in a limited range. Taking the top 3 vote getters in all 2002 US House elections, almost 38% of the vote totals had 1 as the leading digit, while 4 was next most common, at about 12%. On the other hand, vote totals in pre-existing geographic units that are not artificially constructed subject to an equal-size constraint (such as counties) conform to Benford's Law much better (Cho, Gaines and Gimpel, 2006).

Benford's Law is more "robust" than one might imagine. For instance, while not all numbers will conform to the Benford distribution, if distributions are randomly selected and random samples are taken from each of the distributions, then the frequency of digits of this combined set will converge to Benford's distribution even if the separate distributions deviate from Benford's distribution (Hill, 1995, 1998).

Durtschi, Hillison and Pacini (2004) provide guidelines on the type of numbers that one can expect to follow Benford's Law.

1. Numbers that result from mathematical combination of numbers (e.g., quantity * price)
2. Transaction-level data (e.g., disbursements, sales)
3. Large Data Sets
4. Mean is greater than median and skew is positive

On the flip side, numbers that would not follow Benford's Law have the following characteristics.

1. Numbers are assigned (e.g., check numbers, invoice numbers)
2. Numbers influenced by human thought (e.g. prices set a psychological thresholds ($1.99))
3. Accounts with a large number of firm-specific numbers (e.g., accounts set up to record $100 refunds)
4. Accounts with a built in minimum or maximum
5. Where no transaction is recorded.

These restrictions apply to a great many number sources, and clearly comparison to Benford's proportions is not always warranted. While some interesting applications of Benford's Law have recently emerged, few have ventured in to the world of politics where corruption of various kinds is commonly alleged. If history is any guide, there must be myriad instances where one will be astonished by the applicability of Benford's Law in the political realm. Here, we explore data on campaign finance, a field rife with allegations of fraud, cheating, and corruption.

2 FEC filings

Campaign finance regulations are nearly a century old, and the long history of ever-changing laws and scandals, large and small, suggests that incentives to slip through loopholes and twist (or ignore) restrictions are a persistent feature of competitive politics. The data describing most financial transaction undertaken by candidates seeking federal office have, in recent years, become fairly easy to access, as the Federal Election Commission has made a practice of posting all reports to public electronic databases. A simple method of examining FEC data for signs of fraud is appealing partly because the very reason the FEC provides these data to the public is to guard against abuses of the system. By its very existence, the FEC archive enlists all interested parties in the task of monitoring the flow of money in federal elections.

In general, however, the FEC's campaign finance data archive would not seem to be a good prospect for data that follow Benford's Law, because of the existence of numerous laws regulating political contributions. For instance, individuals have historically been limited to donating a maximum of $2,000 to federal candidates per election cycle ($1,000 designated for the primary campaign and $1,000 for the general campaign, without regard for actual timing of the donations or disbursements).[2] A large proportion of all donors give the maximum amount, making the number 1 even more modal than usual in the donation records. The data, in other words, violate item 3 in the checklist above.

2.1 In-Kind Contributions and Joint Fundraising Committees

One variety of transaction that might escape this tendency to cluster is the in-kind contribution. In general, individuals are permitted to donate services to candidates without fixing a dollar amount on their efforts. Thus, volunteers can work as many hours as they please for a congressional campaign without running afoul of FEC regulations. However, under some circumstances, donors must declare a cash value for services or goods donated to a campaign. When a third party pays the bills on behalf of a campaign committee (whether the recipient is a celebrity performing for a fee, a commercial landlord collecting rent, etc.), the individual footing the bill is making an in-kind donation to the campaign. If an organization puts paid workers at the service of a campaign, the total wage bill represents an in-kind donation. All such donations are subject to the same limits as cash contributions. The key aspect of in-kind donations for present purposes is that they seem comparatively unlikely to cluster at the maximum permitted value, since they are

[2] The Bipartisan Campaign Reform Act increased this amount, effective immediately after the 2002 general election.

often computed according to retail prices or pre-set wages and hours worked. In addition, the limits mentioned above apply to donations to candidate committees, but not to donations of so-called "soft" money to party committees. Candidates generally accept donations through campaign committees, however, they can also set up "Joint Fundraising" committees (JFC) that raise both regulated ("hard money") contributions and soft money simultaneously. The JFCs, in turn, re-distribute the money, generally by passing on the maximum permitted amount to the candidate committee as hard money, and then channeling the balance to a party committee as soft money. Hence, the category of in-kind contributions to joint fundraising committees represents an unusual subset of the FEC domain, since neither contribution limits nor round-value focal points constrain the data strongly.

One high profile scandal involving alleged fraud in accounting for campaign contributions and expenses involved Hillary Clinton, and revolved around in-kind donations to a JFC. In January 2005, David Rosen, the Director of Finance for Clinton's 2000 Senatorial campaign, was indicted on four counts of causing false campaign finance reports to be filed with the FEC. Prosecutors alleged that Rosen repeatedly and knowingly under-reported in-kind contributions to New York Senate 2000, Clinton's JFC (Tonken, 2004). The main incentive for such obfuscation would have been that FEC rules at the time allowed candidates to pay for fundraising events with soft money provided that the costs were no more than 40% of the total hard money raised. Thus, minimizing costs allowed the Clinton campaign to preserve precious hard money, which could be used for direct campaign advertisements in the bruising and expensive air war that lay ahead. Rosen faced up to five years in prison, but was acquitted. The defense, accepted by the jury, did not deny fraud and shoddy accounting, but blamed others, claiming that Rosen was unaware of the shenanigans (Ryan, 2005).

Unfortunately, although the FEC is diligent about collecting and posting candidate reports, the data are not coded in such a way that one can easily identify in-kind donations, let alone in-kind donations to JFCs. For obscure reasons, the only in-kinds that are distinctly marked are those made from one committee (as opposed to an individual) to another committee. The reasons money is shuffled between committees are, again, somewhat arcane, and related to the fact that campaign finance regulations are: (a) ever-changing, as they seem almost without exception to produce some unintended consequences; (b) constrained in several manners by a tangled jurisprudence incorporating, for instance, first-amendment protection of political speech; and, (c) created by plainly not disinterested actors, namely incumbent politicians.

3 Analysis of In-Kind Contributions

The data reported in Table 1 are the first digit relative frequencies (as percentages) for all committee-to-committee, in-kind contributions catalogued by the FEC for each of the last 6 election cycles. To provide

Table 1: **Committee-to-Committee In-Kind Contributions (First Digits), 1994–2004**

	Newcomb	Benford data	1994	1996	1998	2000	2002	2004
1	30.1	28.9	32.9	24.4	27.4	26.4	24.9	23.3
2	17.6	19.5	18.7	21.7	18.5	21.1	22.6	21.1
3	12.5	12.7	13.6	15.8	15.3	11.1	10.7	8.5
4	9.7	9.1	7.9	9.6	10.3	10.7	11.6	11.7
5	7.9	7.5	8.9	10.2	11.8	10.1	10.5	9.5
6	6.7	6.4	8.3	6.3	5.9	4.3	4.3	4.2
7	5.8	5.4	4.1	4.8	3.7	6.4	3.4	3.7
8	5.1	5.5	2.4	3.2	3.9	2.4	3.0	4.0
9	4.6	5.1	3.2	4.0	3.3	7.5	9.0	14.1
N		20,229	9,632	11,108	9,694	10,771	10,348	8,396
χ^2		85.1	349	507	431	4,823	1,111	2,181
V_N^*		2.9	5.7	10.1	8.1	5.5	7.8	8.7
d^*		0.024	0.052	0.081	0.061	0.071	0.097	0.131

a comparison baseline, the second column shows the values for the 20 diverse data sets Benford collected and discussed in his 1938 paper.

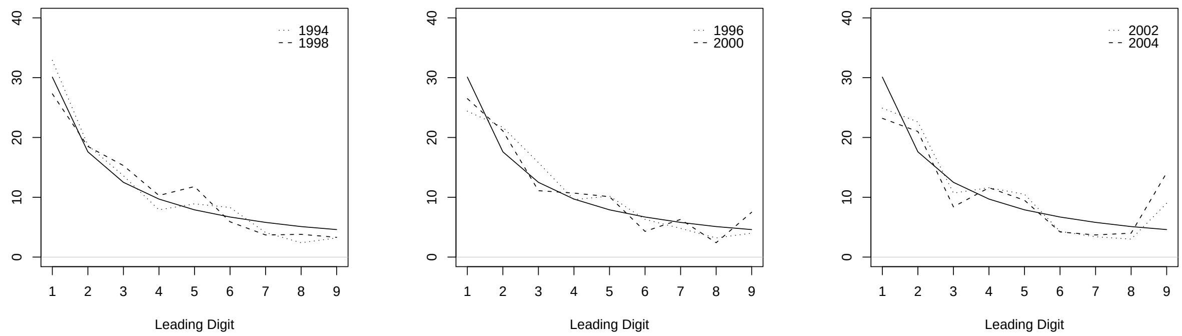
A casual perusal reveals that fit to the Newcomb-Benford theoretical distribution for the FEC data seems to have gotten worse over time. Figure 1 is a graphical depiction of the data's conformity. In each plot, the expected "Benford's law" values are plotted by the solid line. The first plot covers the two oldest midterm elections in this set, 1994 and 1998, and shows that while the fit is not perfect, it is quite close. The second plot pertains to contributions for the two presidential-election years of 1996 and 2000. This fit is not quite as tight as for the corresponding prior midterms, but there is still a strong resemblance to the expected Benford values. The third plot covers the most recent cases, 2002 and 2004, and shows the greatest deviation from theory. The lack of fit most evident on the ends, with an over-representation of leading 9s and under-representation of leading 1s.

To make these comparisons more precise, one can compute formal test statistics. One alternative is to conduct a χ^2 goodness-of-fit test. The null hypothesis is that the data follow the Benford distribution, shown in the column labelled "Newcomb" in Table 1. The test statistic is

$$\chi^2 = \sum_{i=1}^{k} \frac{(O_i - E_i)^2}{E_i}$$

where O_i and E_i are the observed and expected frequencies for digit i, respectively. The test statistic follows a χ^2 distribution with 8 degrees of freedom; accordingly, the null hypothesis is rejected if $\chi^2 > \chi^2_{\alpha,8}$, where

Figure 1: **In-Kind Contributions and Benford's Law**



α is the level of significance. As the table shows, for every year we analyze, the χ^2 test produces huge values that lead one to reject the null hypothesis at any conceivable significance level (the critical value for the 0.001-level here is 26). Indeed, one can reject the null hypothesis for the very data that Benford used to demonstrate the accuracy of Newcomb's law. As is well known, χ^2 tests are very sensitive to sample size having enormous power for large N, so that even quite small differences will be statistically significant. As others have found, this test appears to be too rigid to assess goodness-of-fit well, especially since the Benford proportions do not represent a true distribution that one would expect to occur in the limit (Ley, 1996; Giles, 2006).

A second alternative, used, for instance, by Giles (2006) is a modified Kolmogorov-Smirnov test, Kuiper's test statistic (Kuiper, 1962),

$$V_N = D_N^+ + D_N^-$$

where

$$D_N^+ = \sup_{-\infty<x<\infty} \left[F_N(x) - F_0(x)\right]$$

and

$$D_N^- = \sup_{-\infty<x<\infty} \left[F_0(x) - F_N(x)\right].$$

Giles, citing Stephens (1970), favors a modified form of the V_N test statistic, V_N^*, which is independent of sample size and has critical value of 2.001 for $\alpha = 0.001$. The table shows that our values for V_N^*, like the χ^2 values, lead us to reject conformity with Benford's law for all of our FEC data sets. Again, though, we would also reject the null hypothesis for Benford's data on the basis of this test, suggesting that perhaps it is also too rigid. The very naming of the "law" after Benford reflects the common understanding that he demonstrated that Newcomb's idea is widely applicable to real-world data, not the contrary. Since no one has suggested that Benford's Law holds asymptotically, a more ideal statistic would be invariant—or perhaps less sensitive to—the sample size than, say, the χ^2 statistic. For the same reason, we need not feel compelled to compute p-values or at least to be strongly attached to them.

One other possible measure of fit, then, not connected to a hypothesis-testing framework and insensitive to sample size, is based on Euclidean distance from Benford's distribution in the 9-dimensional space occupied by any first-digit vector. Here, let

$$d = \sqrt{\sum_{i=1}^{9}(p_i - b_i)^2},$$

where p_i and b_i are the proportions of observations having i as the leading digit in the data and expected by Benford's distribution, respectively. Because these vectors are compositional, we can compute the maximum possible distance, associated with a distribution where the first digit expected to occur least often (9) is the only one actually observed. Division by this maximum value converts the distance-from-Benford value, d, for any given empirical distribution to a score bounded between 0 and 1. The bottom row of the table shows these scores (labelled "d^*") Again, the last two elections stand out as exhibiting somewhat worse fit than their earlier counterparts, and the Benford data provide a rough sense for what constitutes a realistic, small value.

None of these figures, of course, pinpoint why the data describing in-kind contributions for the last two elections have departed from the prior pattern of loose fit to Benford's law. This analysis merely identifies an anomaly worthy of further inspection: the origin of the poor fit to Benford's law could be bad record keeping, new practices in donations that correspond to the checklist of Benford inapplicability, changes associated with the "McCain-Feingold" Bipartisan Campaign Reform Act, or actual fraud or other irregularity in financial transactions.

To explore further when and how discrepancies between actual data and the theory occur, one might examine subsets of the data. Indeed, there is an especially strong rationale for re-examining the data by size of contribution. Thus far we have followed common practice by neglecting a point Benford emphasized in his 1938 article, that the Newcomb distribution is a "law for large numbers" (554). Benford derived alternative distributions for numbers having only one-, two-, or three- digits, since the "limiting order" routinely described as "Benford's distribution" turns out to be a crude approximation for such small numbers.

In Table 2 we disaggregate the FEC data according to the size of the contribution, and we report Benford's theoretical distributions for one-, two-, and three- digit numbers, to which the FEC data can be compared. (For each of these distributions, we also report their standardized distance from the familiar, large-N Benford distribution in the d^* column.) It is evident, and not terribly surprising, that fit is always worse in subsets (as compared with the totals in Table 1). Aggregation plays no small part in the Benford tendency. The other main pattern is that fit is generally poor for the one-digit numbers and the four-digit numbers, and better for the intermediate categories. A striking oddity is that 2000 looks very little like the

Table 2: **In-Kind Contributions by Contribution Size**

		1	2	3	4	5	6	7	8	9	N	d^*
Benford ($i < 10$)		0.393	0.258	0.133	0.082	0.053	0.036	0.024	0.015	0.007		
Benford ($9 < i < 100$)		0.318	0.179	0.124	0.095	0.076	0.064	0.054	0.047	0.042		0.018
Benford ($99 < i < 1000$)		0.303	0.176	0.125	0.097	0.079	0.067	0.058	0.051	0.045		0.002
Newcomb-Benford ($i > 999$)		0.301	0.176	0.125	0.097	0.079	0.067	0.058	0.051	0.046		0.002
1994												
	$1 – $ 9	0.090	0.067	0.073	0.060	0.062	0.502	0.054	0.034	0.058	536	0.535
	$10 – $ 99	0.349	0.206	0.126	0.083	0.083	0.047	0.051	0.027	0.027	3,493	0.051
	$100 – $ 999	0.305	0.187	0.153	0.077	0.104	0.075	0.038	0.023	0.038	4,902	0.055
	$1000+	0.579	0.190	0.108	0.081	0.027	0.000	0.001	0.011	0.001	701	0.294
1996												
	$1 – $ 9	0.057	0.116	0.210	0.099	0.080	0.080	0.080	0.077	0.202	352	0.389
	$10 – $ 99	0.159	0.218	0.154	0.096	0.109	0.088	0.085	0.048	0.043	3,875	0.166
	$100 – $ 999	0.259	0.226	0.172	0.090	0.108	0.056	0.028	0.024	0.036	5,925	0.093
	$1000+	0.558	0.191	0.073	0.127	0.044	0.002	0.005	0.000	0.000	956	0.278
1998												
	$1 – $ 9	0.101	0.084	0.054	0.027	0.104	0.191	0.054	0.289	0.097	298	0.437
	$10 – $ 99	0.188	0.144	0.192	0.105	0.110	0.100	0.060	0.046	0.054	3,305	0.153
	$100 – $ 999	0.282	0.192	0.158	0.113	0.141	0.037	0.029	0.027	0.022	5,017	0.090
	$1000+	0.548	0.306	0.039	0.065	0.039	0.001	0.001	0.000	0.000	1074	0.305
2000												
	$1 – $ 9	0.427	0.036	0.056	0.021	0.053	0.167	0.062	0.058	0.120	468	0.274
	$10 – $ 99	0.184	0.213	0.101	0.077	0.105	0.045	0.101	0.031	0.144	4,297	0.176
	$100 – $ 999	0.249	0.203	0.142	0.154	0.117	0.040	0.047	0.021	0.027	4,855	0.100
	$1000+	0.560	0.308	0.045	0.050	0.036	0.000	0.001	0.000	0.000	1151	0.316
2002												
	$1 – $ 9	0.034	0.073	0.069	0.019	0.203	0.165	0.119	0.111	0.207	261	0.466
	$10 – $ 99	0.195	0.206	0.124	0.078	0.097	0.051	0.038	0.030	0.181	4,356	0.183
	$100 – $ 999	0.250	0.234	0.107	0.172	0.118	0.038	0.032	0.031	0.018	4,760	0.123
	$1000+	0.543	0.316	0.040	0.041	0.057	0.000	0.000	0.001	0.002	971	0.307
2004												
	$1 – $ 9	0.035	0.031	0.040	0.035	0.256	0.172	0.154	0.181	0.097	227	0.495
	$10 – $ 99	0.165	0.155	0.089	0.071	0.055	0.052	0.041	0.055	0.316	3,345	0.305
	$100 – $ 999	0.238	0.231	0.095	0.180	0.129	0.035	0.037	0.027	0.028	3,836	0.136
	$1000+	0.490	0.359	0.040	0.043	0.064	0.002	0.000	0.002	0.000	988	0.292

other 5 election years in regard to the smallest contributions—it has by far the best fit to the one-digit theory because of a large number of (inherently suspicious) \$1 transactions. Although how best to generalize the distance score to acknowledge the fact that the predicted values are now a 9×4 matrix rather than a 9-tuple is not obvious, if one simply computes weighted averages of the distance for each subset, then, once again, the 2004 data seem to offer markedly worse conformity to Benford's distributions (the values are, in order, from 1994 to 2004: 0.097; 0.144; 0.146; 0.161; 0.174; 0.231).

4 Conclusion

Benford's Law is a simple yet powerful tool allowing quick screening of data for anomalies. Comparison of empirical data to these theoretical distributions will not usually locate a "smoking gun," but it can be a very good initial diagnostic to select where to go looking and sniffing for that gun in any area where fraud is an ongoing possibility, and comprehensive checking is problematic. Indeed, this is how Benford's Law is currently utilized in other contexts. Tax returns whose first digits do not follow Benford's Law are flagged for closer scrutiny and possible audit, but the filers of these tax returns are not automatically charged with fraud (Nigrini, 1996). The ability to ferret through millions of tax returns quickly to identify a suspicious set is an accomplishment to be hailed. Similarly, in campaign finance, the suspicion of fraud is rampant and the number of contributions and campaign committees is very large. An objective, simple, and effective fraud alarm is invaluable whenever there are large quantities of numerical information on an activity prone to cheating.

One could easily broaden the scope of Benford searches in the FEC data archive, for instance, by testing contributions by committees and flagging those whose contributions deviate most drastically from theory. Benford also derived a non-uniform distribution for second digits, and the first- and second- digit distributions are not independent, so comparison of data to their joint distribution might prove fruitful in some contexts. As we suggested here, possibly the most suitable subset of the FEC archive is in-kind contribution to JFCs, a large class of transactions that, unfortunately, is not presently identifiable. We look forward to better data collection and processing practices by the FEC to facilitate more careful scrutiny of these important data.

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