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Benford's law for collusion detection: An experimental validation

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Abstract

Benford's Law has been widely used to detect anomalies in numerical data, including applications aimed at uncovering price manipulation and collusion, yet most applications rely on observational data in which market competitiveness is not directly controlled. This paper provides an experimental validation of Benford-based tests by exploiting exogenous variation in competition generated by a field entry experiment in rural Kenyan agricultural markets. Using transaction-level price data from Bergquist and Dinerstein (2020), we examine whether deviations from Benford's Law respond systematically to experimentally induced changes in market structure. We find that prices deviate substantially from Benford's Law in low-competition environments, and that conformity improves as competition increases. Importantly, this improvement is driven by entry of traders without prior connections to incumbents, while entry per se produces only modest changes.

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1. Introduction

Benford's Law (Newcomb (1881); Benford (1938)) is a well-established mathematical phenomenon, which postulates that the first few digits in many natural data sets adhere to a logarithmic distribution. This empirical law has been widely used to uncover irregularities and anomalies in various domains, including financial, accounting, and election data, which may be indicative of fraudulent behavior.[1]

In the context of market structure, the law has been used to screen price data for potential manipulation and collusive behavior. For example, Abrantes-Metz et al. (2011) applied Benford's Law to examine the dynamic integrity of daily Libor, ultimately raising suspicions of manipulation and collusion among banks. In the context of agricultural markets, Martínez-Sánchez (2021) used Benford's Law to detect signs of price manipulation in the Spanish almond industry. These analyzes assume that Benford's Law is fulfilled when there is perfect competition in the markets because economic agents cannot influence prices, and it is not fulfilled when they can influence prices through collusive behavior between them.

This paper extends this application, testing the assumption that Benford's Law aligns with market competition levels. To this end, we use the data set from the third field experiment implemented by Bergquist and Dinerstein (2020) in Kenya,[2] which encourages traders to enter randomly selected markets. So, we can check if Benford's Law is fulfilled, or is close to being fulfilled, when the entry of traders is encouraged (treatment), and if it is not fulfilled when the entry of traders is not encouraged (control). Our findings validate Benford's Law as a tool to detect collusion in markets.

The remainder of the paper is organized as follows. Section 2 describes the third experiment implemented by Bergquist and Dinerstein (2020) and outlines the empirical methodology. Section 3 presents and discusses the results. Section 4 concludes.

2. Methodology

2.1. Bergquist and Dinerstein (2020)

Bergquist and Dinerstein (2020) conduct a comprehensive investigation into the competitive structure of rural agricultural markets in Africa. The authors employ a series of field experiments to identify the level of cost pass-through, the curvature of demand, and the effects of market entry on prices. Their experimental design, which manipulates the competitive structure of the markets, provides a natural setting to observe how deviations from Benford's Law vary with the level of competition. Benford's Law is expected to hold in competitive markets where prices are determined by a multitude of independent factors, while deviations from the law may occur in less competitive markets where prices can be influenced by collusive behavior.

In our study, we utilize data from their "Experiment 3: Entry Experiment," which focuses on market transactions in small street markets where traders purchase agricultural products from local producers. In the experiment, traders who typically did not participate in a particular market were offered subsidies to enter and sell in that market on a specific day. This design was explicitly intended to induce additional competition: days in which subsidized external traders entered a market therefore featured a higher level of competitive pressure relative to the benchmark days in which no externally incentivized participants were present. These

[1] See Barabesi et al. (2022) for recent results on Benford's Law.

[2] The high market power of traders in African agricultural markets is one reason for their technological stagnation in agriculture (Suri and Udry (2022)).

conditions represent different levels of competition in the market and were designed to stimulate competition and observe the impact of new market entrants on price-setting behavior. The original dataset includes information on transaction prices in each market and information on when entrants did not have colleagues who were original traders in that market. Bergquist and Dinerstein find that markets in which entrants have no prior connections increase competition to a level that is statistically indistinguishable from Cournot competition. However, markets in which entrants have pre-existing connections continue to display collusive behavior.

We use final transaction prices provided by Bergquist and Dinerstein, together with information on the number of participants and information on whether participants have contact with incumbents in the market. In the original data, the total number of entrants is recorded for each market session and ranges from 0 to 3. By contrast, the information needed to identify entrants without prior contacts is available only at the four-week block level. To make the comparison between overall entry and entry without prior contacts fully consistent, we therefore aggregate the total number of entrants to the same four-week block level. Since each block includes four market sessions, the total number of entrants in our analysis can exceed 3 and ranges from 0 to 9. Accordingly, our analysis compares transaction prices across blocks with no entrants and blocks with positive entry, both for total entrants and for entrants without prior contacts.

2.2. Benford's Law

The Benford's Law was first reported by Newcomb (1881) and later independently by Benford (1938). Benford's Law posits that in natural and diverse datasets, the leading digit follows a specific logarithmic distribution. In the context of market prices, this law applies under conditions such as a broad range of prices and multiple independent factors influencing their formation. In rural agricultural markets, where prices result from numerous independent transactions and are influenced by a variety of factors (weather, supply and demand, transportation costs), Benford's Law is expected to hold.

This law describes the distribution of the first digit of a set of numbers. The first digit (D1) is highly skewed toward low values, with digit 1 appearing with probability of 30.1%, digit 2 with 17.6%, and subsequent digits occurring with monotonically decreasing frequencies. In our data, however, the distribution of the first digit cannot conform to Benford's Law by construction. Due to the institutional and economic environment of the Kenyan maize markets during the experimental period, transaction prices lie in a narrow range, such that the first digit is always either 2 or 3. As a result, deviations of D1 from the Benford distribution would be mechanically driven by price levels rather than by pricing behavior, rendering the first digit uninformative for our purposes. For this reason, and following Martínez-Sánchez (2021), we rely on extensions of Benford's Law that characterize the expected distributions of the second and third digits (Berger and Hill, 2011), which are the focus of our analysis. Expected distributions of first (D1), second (D2) and third (D3) digit are given by

$$P(D1 = d_1) = \log_{10}\left(1 + \frac{1}{d_1}\right), d_1 = 1,2 \ldots 9, \tag{1}$$

$$P(D2 = d_2) = \sum_{i=1}^{9} \log_{10}\left(1 + \frac{1}{10 \cdot i + d_2}\right), d_2 = 0,1,2 \ldots 9, \tag{2}$$

$$P(D3 = d_3) = \sum_{j=1}^{9}\sum_{i=0}^{9} \log_{10}\left(1 + \frac{1}{100 \cdot j + 10 \cdot i + d_3}\right), d_3 = 0,1,2 \dots 9, \qquad (3)$$

In our analysis, given the characteristics of our data, we focus on D2 and D3. The distribution of D2 is substantially more homogeneous than the distribution of D1, and for the third digit D3 the distribution is close to uniform, as can be seen in Figure 1.
To check whether the maize price follows Benford's Law, we use the Pearson's Chi-square test, Kuiper test, M-statistic (M), D-statistic (D) test and Mean Absolute Deviation (MAD).[3] These statistics increase as the deviations of the data from Benford's Law are greater. According to Nigrini (2012), MAD values below 0.006 indicate close conformity with Benford's Law, 0.006-0.012 indicate acceptable conformity, 0.012-0.015 indicate marginally acceptable conformity, and values above 0.015 indicate nonconformity with Benford's Law.

3. Results

Table I reports descriptive statistics and Benford's Law test statistics for prices. The first panel aggregates markets into four-week blocks and classifies observations by the total number of entrants observed over each block. The second panel applies the same block aggregation but restricts attention to entrants without prior links to incumbent traders. For each classification, the table reports mean and median prices, together with several measures of deviation from Benford's Law based on the second and third digits of prices.
It is important to note that, in this setting, traders act as buyers purchasing from local producers. As a result, increased competition among traders leads to higher prices paid to producers. Accordingly, the higher average prices observed in markets with entrants—particularly those without prior contacts—are consistent with more competitive outcomes rather than with increased collusion.
As shown in Table I, conformity of the price data to Benford's Law is poor: according to Nigrini's (2012) thresholds, mean absolute deviation (MAD) values above 0.015 indicate nonconformity, and every cell in our sample exceeds that threshold by a substantial margin. In the data where prior connections are not taken into account, (Entrant number per block, 0 entrants vs. 1–9 entrants), MAD(D2) declines from 0.0633 (N = 4,208) to 0.0498 (N = 4,357). Similarly, chi-square and Kuiper statistics decrease with entry. These reductions are meaningful in magnitude even though they do not bring MAD values near the conventional conformity range: entry moves the distributions closer to Benford's pattern, but full conformity is not achieved. The D3 statistics show a very small reduction (MAD D3 from 0,0447 to 0,0430). The empirical implication is therefore directional—but the absolute fit remains low. Visually (Figure 1), the departure is evident: many empirical bars lie well above or below the Benford reference line across several digits, leading to wide and systematic gaps rather than small, random fluctuations.

[3] See Balashov et al. (2021) for a brief description of the Pearson's Chi-square test, the Kuiper test, M-statistic and the D-statistic. See Nigrini (2012) for a brief description of the MAD test, which is size-independent.

Table I: Descriptive Statistics and Test Statistics

		N	Price		Chi-Square		Kuiper		M		D		MAD	
			Mean	median	D2	D3	D2	D3	D2	D3	D2	D3	D2	D3
Entrant number per block	**0**	4208	28.86	28.32	1897.7	1032.6	18.8000	10.0301	0.0988	0.0804	0.2102	0.1564	0.0633	0.0447
	1 to 9	4357	29.53	28.89	1459.5	1019.9	13.6670	9.8361	0.1024	0.0788	0.1779	0.1526	0.0498	0.0430
Entrant number without contacts	**0**	5495	28.74	27.96	3077.8	1655.9	23.6849	14.3253	0.1278	0.0797	0.2322	0.1732	0.0673	0.0495
	1 to 9	3070	30.04	30.00	527.89	542.83	8.2496	4.7451	0.0606	0.0794	0.1313	0.1328	0.0371	0.0337

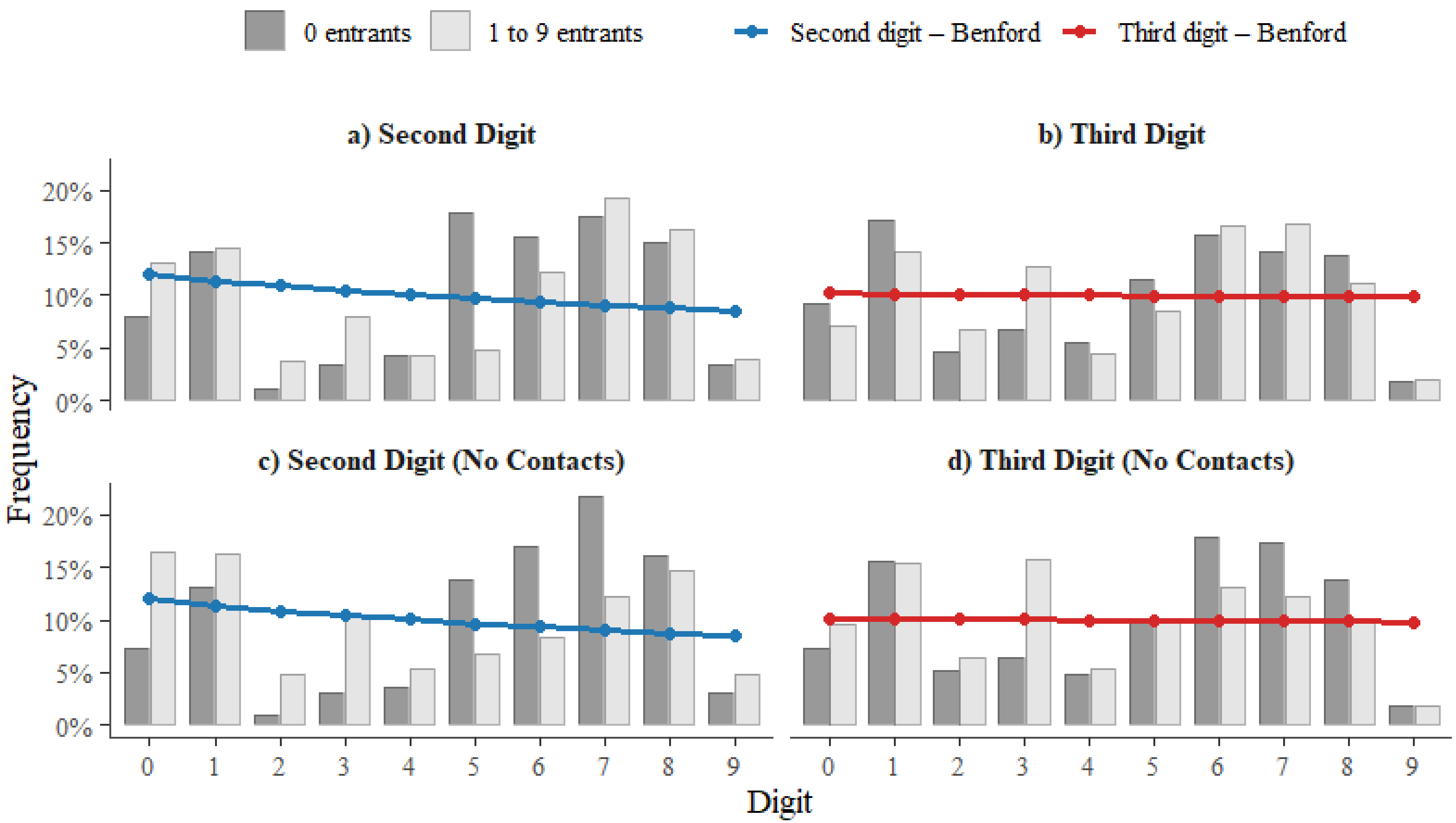
Note: The table reports descriptive statistics and Benford's Law test statistics for prices (per kilogram) at the transaction level. N is the number of transactions with observed prices. Panels present results under two alternative classifications of market entry: Entrant number per block aggregates the total number of entrants over each four-week block. Entrant number without contacts is defined at the same level of aggregation because information on prior contacts is only available at the block level. D2 and D3 refer to the second and third digits of prices, respectively. Test statistics measure deviation from Benford's Law, with higher values indicating greater deviation. Chi-Square is Pearson's chi-square test statistic. Kuiper is a distribution-free goodness-of-fit test. M is the maximum absolute deviation (Kolmogorov-Smirnov statistic). D is the Euclidean distance between observed and expected distributions. MAD is the Mean Absolute Deviation. According to Nigrini (2012), MAD values below 0.006 indicate close conformity with Benford's Law, 0.006-0.012 indicate acceptable conformity, 0.012-0.015 indicate marginally acceptable conformity, and values above 0.015 indicate nonconformity with Benford's Law.

Table II: Descriptive Statistics for the second and third digit

Entrant number		N	D2			D3		
			Median	Mean	SD	Median	Mean	SD
per block	**0**	4208	6.00	4.98	2.70	5.00	4.45	2.78
	1 to 9	4357	6.00	4.61	3.02	5.00	4.50	2.66
without contacts	**0**	5495	6.00	5.19	2.67	6.00	4.70	2.72
	1 to 9	3070	4.00	4.08	3.07	4.00	4.09	2.67

D2 and D3 are discrete variables taking values from 0 to 9. SD denotes standard deviation.

Figure 1: Digit Distribution by Entrant Number and Benford's Law



Panels (a) and (c) show the distribution of the second and third digits, respectively, by entrant number per block (no entrants vs. 1–9 entrants). Panels (b) and (d) report the corresponding distributions when distinguishing markets by entrant number without prior contacts (no entrants vs. 1–9 entrants without contacts). Bars represent the empirical frequency of each digit (0–9), while the solid line depicts the theoretical distribution implied by Benford's Law. Dark bars correspond to markets with no entrants, and light bars to markets with entry. The figure illustrates a systematic convergence toward Benford's Law as competition increases in markets where new entrants have no prior connections with incumbent traders. See Table 1 for sample sizes and formal goodness-of-fit statistics.

The clearest improvement in absolute conformity occurs in markets where entrants lack prior contacts with incumbent traders. For blocks with no independent entrants the MAD(D2) equals 0.0673 (N = 5,495) and the chi-square is 3,077.8; for blocks with 1–9 entrants without contacts MAD(D2) drops to 0.0371 (N = 3,070) and chi-square to 527.9. The D3 statistics show a parallel decline (MAD D3 from 0.0495 to 0.0337). These changes are large both relatively and in absolute terms: while MAD = 0.0371 still lies above the strict conformity threshold, it represents a materially closer match to Benford's distribution than the control and is close to the marginally acceptable range identified in the literature. Thus, independent entry produces the largest absolute improvement in fit across all measured statistics. This pattern coincides with higher average prices, consistent with stronger competition among buyers. As shown in Table A.I (see Appendix), which disaggregates the information reported in Table I by the number of entrants, this effect appears to be driven primarily by the presence of independent competitors rather than by their number: conformity improves sharply once at least one independent entrant is present, but does not increase monotonically with the number of entrants without prior contacts.
To further characterize the distribution of digits, we report descriptive statistics in Table II. The second digit exhibits substantial dispersion across its support (0–9), with means ranging from 4.08 to 5.19 and standard deviations between 2.67 and 3.07 across subsamples. Similar patterns are observed for the third digit. These results indicate that digit realizations are not concentrated around a narrow central value, but instead spread widely over the admissible range.
Figure 1 shows the full distribution of second (D2) and third digit (D3). It also clarifies that the visual convergence toward Benford's Law depends on the composition of entry rather than on entry per se. When all additional entrants are pooled together (Panels (a) and (c), "entrant number per block"), the graphical evidence does not show a clear or systematic improvement in the fit relative to the no-entry case. The empirical digit frequencies for markets with 1–9 entrants remain visibly distant from the Benford reference line for several digits, and the overall shape of the distribution is broadly similar to that observed in control markets. This visual impression is fully consistent with the modest changes observed in the corresponding goodness-of-fit statistics reported in Table I, where MAD, chi-square, and Kuiper statistics decline only slightly when moving from zero to 1–9 entrants per block.
In contrast, Panels (b) and (d), which restrict attention to markets where additional entrants have no prior contacts with incumbent traders, reveal a much clearer visual convergence toward Benford's distribution. In these panels, the empirical bars align more closely with the Benford reference line across a wider range of digits, and the large pointwise gaps evident in the no-entry case are substantially reduced. This visual improvement mirrors the pronounced declines in the statistical measures of deviation shown in Table I for the "without contacts" subsample. Taken together, the graphical and statistical evidence suggests that Benford's Law is not merely responding to mechanical increases in the number of traders, but rather to the nature of competition in the market, capturing the presence of effective, independent competition.

4. Conclusion

We investigate the validity of Benford's Law to detect collusive behavior through a novel approach, which is based on the use of a data set from the field experiment analyzed by Bergquist and Dinerstein (2020). This field experiment, specifically designed to test the competition model in rural agricultural markets, has provided a unique context for our study.
Our results demonstrate fewer deviations from Benford's Law in markets characterized by enhanced competition, especially where new entrants had no prior contacts within the market. This aligns with Bergquist and Dinerstein (2020) findings, which showed that markets without prior connections among entrants tend to exhibit competition levels akin to those predicted by Cournot competition models. In contrast, markets with entrants who have pre-existing relationships displayed persistent collusion. Consequently, the significance of this study lies in its innovative experimental validation of Benford's Law as a valuable tool for detecting collusion in various market contexts. This insight is particularly beneficial for policymakers, providing a means to identify markets with suboptimal

competition where interventions might be necessary to ensure fairer and more equitable conditions. Moreover, our research opens up new avenues for testing other empirical laws in diverse economic scenarios, extending beyond the primary focus on collusion detection.

Disclosure of interest

The authors report there are no competing interests to declare.

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6. Appendix

Table A.I: Descriptive Statistics and Test Statistics by Number of Independent Entrants

		N	Price		Chi-Square		Kuiper		M		D		MAD	
			Mean	median	D2	D3	D2	D3	D2	D3	D2	D3	D2	D3
Entrant number per block	**0**	4208	28,86	28,32	1897,70	1032,60	18,80	10,03	0,099	0,080	0,210	0,156	0,063	0,045
	1 or 2	1242	28,85	28,28	493,26	448,83	7,810	6,289	0,096	0,107	0,198	0,190	0,056	0,050
	3 or 4	1532	30,32	30,30	397,430	275,00	7,065	4,040	0,076	0,073	0,157	0,134	0,046	0,035
	5 or more	1583	29,31	28,89	1094,40	541,36	12,08	8,27	0,157	0,102	0,255	0,184	0,072	0,048
Entrant number without contacts	**0**	5495	28,74	27,96	3077,80	1655,90	23,68	14,33	0,128	0,080	0,232	0,173	0,067	0,049
	1 or 2	1722	29,50	29,63	404,49	316,59	6,51	4,45	0,070	0,036	0,152	0,135	0,044	0,036
	3 or 4	989	30,56	30,35	290,38	249,12	5,83	4,26	0,081	0,116	0,172	0,159	0,047	0,038
	5 or more	359	31,17	31,11	120,70	126,43	4,16	2,04	0,102	0,105	0,180	0,188	0,049	0,047

Note: The table reports descriptive statistics and Benford's Law test statistics for prices (per kilogram) at the transaction level, disaggregated by the number of entrants in each four-week block. N is the number of transactions with observed prices. Panels present results under two alternative classifications of market entry: Entrant number per block aggregates the total number of entrants over each four-week block. Entrant number without contacts is defined at the same level of aggregation because information on prior contacts is only available at the block level. D2 and D3 refer to the second and third digits of prices, respectively. Test statistics measure deviation from Benford's Law, with higher values indicating greater deviation. Chi-Square is Pearson's chi-square test statistic. Kuiper is a distribution-free goodness-of-fit test. M is the maximum absolute deviation (Kolmogorov-Smirnov statistic). D is the Euclidean distance between observed and expected distributions. MAD is the Mean Absolute Deviation. According to Nigrini (2012), MAD values below 0.006 indicate close conformity with Benford's Law, 0.006-0.012 indicate acceptable conformity, 0.012-0.015 indicate marginally acceptable conformity, and values above 0.015 indicate nonconformity with Benford's Law.