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Number Generation Patterns Associated with Innate Characteristics

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Credited to Frank Benford and based on work with logarithmic number tables, Benford's Law states that the frequency of individual digits from zero to nine follows a pattern, with one being the most frequently and nine being the least frequently found (Benford, 1938). Benford's Law has been studied across a host of disciplines, ranging from physics and the hard sciences to financial records for a variety of businesses across several industries (e.g., Sambridge, Tkalčić, and Jackson, 2010; Alali and Romero, 2013b; Ley, 1996; Wallace, 2002), finding support for the natural occurrence of Benford's Law. For example, Nigrini and Miller (2007) detail evidence of Benford's Law being successfully applied to a large data set for surface hydrology and some evidence supporting a similar pattern with a wetlands and lake data set.

Within the auditing and forensic accounting professions, studies detail when and how Benford's Law may be applied from academic and practitioner perspectives with a focus on data analytic methods including tools (e.g., Moore and Benjamin, 2004; Nigrini, 2012; Nigrini and Mittermaier, 1997; Kumar and Bhattacharya, 2003; Wang and Yang, 2009; Durtschi, Hillison, and Pacini, 2004; Lanza, 2000; Cleary and Thibodeau, 2005). In the majority of cases, the practitioner begins by determining if the number pattern in the detail records examined deviates from Benford's Law. Specifically, Nigrini (1999) proposes that the existence of a potential anomaly results in a situation requiring further investigation, not clear evidence of wrongdoing or fraudulent/fictitious numbers. However, if an individual is modifying transactions, he or she may add invoice numbers and associated dollar amounts with those invoices. These generated transactions may cause the data set to deviate from the frequency of digit patterns represented by Benford's Law and may allow the professional to conclude that this is evidence of fraudulent transactions after the completion of an investigation.

Prior research establishes that people do not follow Benford's Law or a uniform distribution when creating, or generating, numbers (see Hassan, 2003; Mosimann, Wiseman, and Edelman, 1995; Hsu, 1948). However, these generated number patterns have not been analyzed for biases based on underlying characteristics of the person generating them for current society. We explore if select personal characteristics can be associated with variances in number generation patterns.

Individuals have studied the relationship amongst personal characteristics, such as gender and cultural identification, for associations with fraudulent behavior/crimes with mixed results (e.g., Albrecht, Turnbull, Zhang, and Skousen, 2010; Bierstaker, 2009; Watson, 2003; Cumming, Leung, and Rui 2015; Daly 1989). Due to these mixed results, we delve into the neuroscience and psychology literatures to determine if there are physical reasons for systematic differences in processing between the genders or among various cultures for individuals. Waymire (2014) argues that accounting can directly influence the physical processing of information within the human brain. In a similar vein, we argue that research does support the possibility that cultural and gender influences may result in different processing, ultimately affecting the output. For our purposes, the output is a number generation exercise. Therefore, we examine if specific individual characteristics influence number generation patterns.

From two Midwestern schools during Fall 2015, we distributed a survey, using Qualtrics, that results in 1,335 observations. Our results fail to provide convincing evidence that gender impacts the number generation process. However, the results do provide evidence supporting an association between cultural identification and variations in number generation patterns for the first digit.

The participants' responses are consistent with individual characteristics manifesting themselves in reliable patterns with large samples. Our results suggest that identification with a culture outside the United States (U.S.) might influence number patterns. These results should be of interest to auditors and fraud investigators utilizing Benford's Law as a tool

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to identify anomalies (e.g., Bolton and Hand, 2002; Nigrini, 1999). A forensic accountant could use these results to potentially construct a profile of a potential perpetrator. Allan (2002) highlights the importance of the profiling step for the potential recovery of assets.

The remainder of the article outlines the prior literature specifically related to forensics and fraud, hypotheses development, the survey process, and the methodology. Next, the result section follows. The final section concludes.

Prior Literature

A focus of forensic research pertains to gender differences and associations with various fraudulent schemes (e.g., Lenard, Yu, York, and Wu 2016; Baird and Zelin, 2016; Baird, Zelin, and Robert, 2009). The 2016 Association of Certified Fraud Examiners (ACFE) Report to the Nations supports a consistent seventy/thirty percent split between males and females for reported perpetrators (ACFE 2016). Further supporting differences between the genders, Hilliard (2016) finds that females are more likely than males to commit asset misappropriation crimes when controlling for the compensation, education, position, and age of the perpetrator. However, Holtfreter (2005) finds that amongst corruption, asset misappropriation, and fraudulent financial statements, only one pairing, asset misappropriation and fraudulent financial statements, is statistically significant for gender differences. Moderating the impact of gender, Shawver, Bancroft, and Sennetti (2006) find that socialization amongst participants can negate the gender effect. These mixed results allow us to explore if gender has any association with different number patterns.

From a different perspective, broad cultural differences have been proposed to impact attitudes and actions towards fraud and corruption (Bierstaker, 2009). Watson (2003) administers ethical vignettes and finds evidence that culture affects attitudes towards fraud in general but not specific fraud schemes. Albretch, Turnbull, Zhang, and Skousen (2010) explore the culture of one country, South Korea, to interpret specific cultural artifacts through the lens of the fraud triangle. These researchers conclude that there is a specific cultural impact on corruption. These studies allude to a potential impact from culture identification on individual actions, which we leverage in our hypothesis development.

Hypotheses Development

Using the forensic literature as a base, we explore the neuroscience and psychology literatures to focus on research addressing why individual characteristics might result in different task outcomes. We target two individual characteristics, gender and birth culture identification, and their interaction with a number generation task.

Gender Hypothesis

We leverage neuroscience and psychology literatures detailing differences between the genders (Kimura, 1992; Cahill, 2006) to hypothesize that there is a gender impact on number generation. However, the existence of gender differences remains a debated area within neuroscience as multiple studies fail to find differences for the actual completion of tasks, e.g., measured along dimensions of time or accuracy, irrespective of the different physiological brain activation patterns (Bell, Willson, Wilman, Dave, and Silverstone, 2006; McRae, Ochsner, Mauss, Gabrieli, and Gross, 2008; Piefke, Weiss, Markowitsch, and Fink, 2005).

Brain scientists study people’s reactions to different tasks using functional magnetic resonance imaging (fMRI) to examine the brain activation patterns (e.g., Formisano et al., 2002). The scientists measure the blood oxygen levels (BOLD response) to record how the different parts of the brain are activated when doing a particular task. Gender is a variable often examined when evaluating the results of studies.

Specific gender differences in brain activity, measured using fMRI, have been documented but remain controversial (e.g., Cahill, 2006; for a summary paper, see Kaiser, Haller, Schmitz, and Nitsch, 2009). Supporting differences in task accomplishment, Speck, Ernst, Braun, Koch, Miller, and Chang (2000) detail a significant difference between the genders for their working memory study. Marchewka, Jednorog, Falkiewicz, Szeszkowski, Grabowska, and Szatkowska (2012) examine the fMRI images of subjects when instructing subjects to tell the truth or lie. These authors provide evidence that the left middle frontal gyrus responds differently for males compared with females when disclosing personal information. When the subjects were disclosing non-personal information, no gender difference is identified. This result is robust to controlling for the subjects’ perceived gender identification.

Interestingly, while the brain appears to be activated differently between the genders (e.g., Piefke et al., 2005; Grabowski, Damasio, Eichhorn, and Tranel, 2003), Bell et al., (2006) do not find a consistent significant gender difference in the resulting outcome from the performance of the assigned activities. In a similar vein, Schienle, Schäfer, Stark, Walter, and Vaitl (2005) center their experiment on discovering variations between the genders using various visual cues. Overall, they conclude that the genders are more similar than different when responding to negative emotional cues, for example, fear and disgust. Thus, the neurological literature does not clearly support a gender effect.

Similar mixed results can be found in the psychology literature. Males and females appear to have differential information processing strengths: females are better at language related tasks, while males are superior with tasks involving spatial considerations (Kimura, 1992). But, these results are not consistently robust for numeric processing. Specifically, Hines, Herman-Meglińska, Bednarek, and Grabowska (1996) examine the difference in processing speeds for classification of numbers as even or odd relative to the presentation format (e.g., digits, words, or dot patterns) between the genders. These researchers do not discuss any differences between the genders as it relates to the processing speed relative to the digit presentation. In contrast, they find a gender advantage with the word or dot representations. Beyond task-based comparisons, Halpern (2013) argues that there are cognitive differences between the genders, but she recommends that studies need to be interpreted with caution. The researcher posits that differences found in neuroscience images may not translate into differential behavior.

Therefore, we state our first hypothesis in the null:

H1: There are no differences between the genders for number generation.

Birth Culture Identification Hypothesis

Building on the neuroscience literature that explores the real number line (Dehaene, 2001), we incorporate the cultural impact that counting different ways (e.g., left hand to right hand or right hand to left hand) has on the processing of numbers (Tschentscher, Hauk, Fischer, and Pulvermüller, 2012). The final building block includes research that describes different cultural interpretations of specific numerals (Göbel, Shaki, and Fischer, 2011). Taken as a whole, the individual Arabic digits' processing varies by culture, leading to our second hypotheses positing an impact of culture on number generation.

Neuroscience researchers have examined processing of Arabic numbers as part of different tasks to understand how the brain processes numbers (Dehaene, 2011). Tschenstscher et al., (2012) perform an event study using fMRI to examine which parts of the brain are activated when people are shown the digits or words for the numbers zero through nine. Their study found evidence that brain activity differed between those who finger counted starting with their left hand, as opposed to those who count beginning with their right hand, most pronounced for the numbers one through five. Lindemann, Alipour, and Fischer (2011) provide survey evidence that Western and Eastern cultures do use their hands for counting in different ways.

Number cognition and processing cannot be entirely separated from the language processing that an individual performs. As such, cultural pressures can influence the numerical study results using fMRI as a measurement tool. Han and Northoff (2008) summarize several studies providing evidence of differences in brain function, as measured by BOLD responses, between Eastern and Western cultures, covering a variety of tasks, including ones related to processing Arabic numerals. Gobel et al., (2011) state that all numbers greater than four are influenced by the cultural environment and detail several studies supporting various number and counting patterns beyond a single Western and Eastern orientation that form the basis for several fMRI studies.

From the numerology literature, cultures differ with their use of numbers within their language and the meaning assigned to any particular number, especially those numbers comprised of a single digit. Specifically, Dossymbekova, Daulet, Kenzhebaeva, and Zeinolla (2015) explain the differences between the Chinese and Kazakhstani languages as they relate to numbers. The authors describe the special meanings ascribed to specific numbers for the Chinese language, including one and five as lucky numbers. According to these authors, key revered numbers in both cultures include one, three, seven, eight, and nine.

Taken as a whole, the number processing performed by all individuals can be influenced by culture that may have specific meanings attached to individual numbers. Possibly birth culture may influence a person's number generation patterns. However, as this factor requires linkages between the generation of number patterns in an individual and the resulting influence of a broader cultural construct, so possibly no affect will be detected.

In addition, the surrounding American culture may influence any non-U.S. born person, resulting in acculturalization, negating influences from the birth culture. Specifically, Ryder, Alden, and Paulhus (2000) study the competing hypothesis that the birth culture can be completely subsumed over time, as opposed to maintaining aspects of both the birth and current surrounding culture, if different. These researchers document support that university students can maintain cultural identification across multiple platforms. Since individuals may identify with multiple cultures with different levels of identification, we state our second hypothesis in the null:

H2: There are no differences related to cultural identification for number generation.

Survey and Methodology

To test the hypotheses, we deploy a survey requiring participants to enter a four-digit number followed by several demographic questions.[1] The full survey instrument is detailed in Appendix A and is adapted from Hsu (1948). Prior research has required participants to generate a four- or six-digit number, but not with identical demographic questions (Diekmann, 2007; Hsu, 1948). Also, Benford (1938) used four digit numbers and larger to determine his formulas for the distribution of the digits of large numbers and developed a separate analysis for fewer digit numbers. As such, we require a four-digit number and exclude leading zeros from our population as this effectively results in a three-digit number.

Qualtrics was used to distribute the survey instrument to the university populations (faculty, staff, and students) for two Midwestern, public universities during the Fall 2015 semester. Prior to starting the survey, each participant's consent was obtained, but they retained complete confidentiality, except for those who voluntarily elected to participate in a random drawing for two gift cards based on a connection with one of the universities.[2]

We contend that the university affiliations, resulting in extensive inclusion of students, are consistent with prior studies (e.g., Baird, Zellin, and Robert 2009) and appropriate for the research. Shulz (1999) and Chan, Landry, and Troy (2011) conclude that students can be a cost-effective and appropriate population if the skill and knowledge needed to perform the task are appropriate to that age group. We assert that the generation of a four-digit number is appropriate for a university student. Our study does not specifically focus on identified fraudsters, which would be a difficult population to identify and survey, but on general tendencies for individuals.

When analyzing the data, we examine each of the four digits separately based on the literature detailing different patterns for first digits versus subsequent digits (Diekmann, 2007; Hill, 1988; Skousen, Guan, and Wetzel, 2004). To determine if there is a statistically significant difference between the genders and cultural identities, we use the Kolmogorov-Smirnov goodness of fit test, like prior research (Judge and Schechter, 2009; Hill, 1988). If we find a statistically significant result, we can reject the null hypothesis as stated and conclude that our results support an association between the factor of interest and the number generation pattern.

Data and Results

The survey results in our final sample of 1,335 responses. From our initial population of responses, we exclude those responses with leading zeros, removing eighty observations. Next, we exclude those responses where the respondent failed to complete all the demographic information, reducing the sample by twenty-one responses.

Table I reflects the top ten four-digit numbers that were received from the survey respondents. Not surprisingly, the top number was 1234, consistent with prior research on passwords (Malone and Maher, 2012). However, besides this single number, there was a wide distribution of unique numbers provided. [see Table I, pg 824]

Table II and Table III reflect the survey results by gender and by cultural identification. The most common first digit is one, while the least common first digit is nine. [see Table II and III, pg 824–825]

The results are tabulated in Table IV. For H1, the Kolmogorov-Smirnov test results do not support any difference in the number generation patterns between males and females. Our result is consistent with Hsu (1948). For H2, the test

[1] One demographic question asked about the dominant hand. However, much of the fMRI literature referenced in this article solely use right-handed subjects, so there was not a detailed basis for hypothesis motivation. In addition, age was not a demographic question specifically asked so we are unable to test for any differences across age groups.

[2] Upon analysis of the results, we note there is a significant school difference. However, when we examine the demographics for responses between the two institutions, cultural identification is statistically different between the two institutions (χ^2=170.6398, ρ-value <.0001).

statistics do support a difference between U.S. vs. non-U.S. cultural identity in the number generation patterns for the first digit (z-statistic = 0.058226, ρ-value= 0.0009). These results suggest there may be a linkage to the way numbers are processed in the brain and number generation patterns. [see Table IV, pg 825]

We perform a robustness test by examining the difference between developed countries (comprised of the U.S., Australia, and Europe) and the remainder of the world with similar inferences.[3] To be consistent with prior studies (e.g., Judge and Schechter, 2009; Hill, 1988), we report the chi-square test results in Table V. The inferences remain consistent with the cultural identity results above. In addition, we find limited support for a gender difference on the fourth digit (χ^2= 20.3827, ρ-value= 0.0628). This limited support suggests that there may be times when gender differences might have some influence on the number patterns. [see Table V, pg 826]

Overall, we conclude that the evidence appears to support the birth cultural identification hypothesis but fails to support the gender hypothesis.

Conclusion

Benford's Law is used to assist auditors and forensic accountants with the potential identification of issues by highlighting potentially unusual deviations from expected number patterns, especially as they relate to financial data. The identification of issues results when deviations from Benford's Law are documented and substantiated as being fabricated data. Since the perpetrator of an act can fabricate data, we administer a survey to investigate if purposely generated number patterns can be associated with innate, individual characteristics. Our results provide insight into potential perpetrator characteristics that may have real world implications for fraud investigation.

We find consistent support for a cultural, but not gender, bias being associated with specific number generation patterns. Importantly, for the traditional application of Benford's Law, we find the significance using the first digit. With financial data, the application of Benford's Law usually tests the first digit of the number for compliance with the expected frequencies (Hassan, 2003; Alali and Romero, 2013a). This fact provides exploratory evidence suggesting specific innate factors may influence the human generation of numbers, as suggested by Hill (1996). However, as neuroscience continues to uncover the exact mechanisms within the brain responsible for digit formation and usage, future research may be able to identify those non-random patterns more specifically that humans use for processing information.

Within the domain of fraud investigations, forensic accountants use a variety of techniques for investigations. Clements and Knudstup (2016) survey practitioners to reveal the most common procedures performed during investigations. They find that the most common procedures include looking for individuals with "unusual behavior" or "extravagant lifestyles" (p. 173). These individual related procedures are important to narrow the pool of potential perpetrators. Our results, showing an association between birth culture identification and number generation patterns, can be used in a similar way. This result is important as Benford's Law relies on the identification of number generation patterns deviating from an expected pattern to highlight potential areas for further investigation. Thus, we presume that if deviations from Benford's Law have been validated, then a forensic accountant could potentially narrow the potential perpetrator pool using our results. Thus, our research is helpful to shed light on the potential characteristics of individuals who might be reflected in the evidence when performing fraud or audit investigations.

[3] The distribution of non-U.S. identification within the survey results contained the most responses for East Asia, Southwest Asia, and South Asia.

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Appendix A

This survey is about a study on numbers, which consists of four questions, and should only take about two minutes of your time. Your answers will be completely anonymous.

1. Please write a four-digit number in the box below. The four-digit number must be original, i.e., created in your mind; and it must not represent an event, a fact or a datum, such as a telephone number, a house number, etc.

2. Please select your sex:
   - A. Male
   - B. Female

3. Please indicate which hand you use when signing your name.
   - A. Right hand
   - B. Left hand

4. Please select the region where you come from.
   - A. North America (i.e., USA, Canada, Mexico)
   - B. Latin America, South America (i.e., Argentina, Brazil, Chile)
   - C. Sub-Saharan Africa (i.e., Kenya, Nigeria, South Africa)
   - D. Middle East, North Africa, and Greater Arabia (i.e., Egypt, Afghanistan, Saudi Arabia)
   - E. East Asia, Southwest Asia (i.e., China, Japan, North Korean, Malaysia, Singapore)
   - F. South Asia (i.e., India, Pakistan)
   - G. Australia and Oceania (i.e., Australia, New Zealand)
   - H. Europe (i.e., UK, Germany, Russia)
   - I. Not Sure.

Thanks so much for your participation!

Table I: Most Frequent Four-Digit Numbers

Number	Observations
1234	42
1738	13
1357	6
7777	6
1111	5
4444	5
6666	5
8888	5
9999	5
1212	4

This table details the top ten most frequently provided four-digit numbers from the survey.

Table II: Distribution of Digits Derived from a Four-Digit Number Based on Gender

	First Digit Frequency		Second Digit Frequency		Third Digit Frequency		Fourth Digit Frequency	
Arabic Numeral	Male	Female	Male	Female	Male	Female	Male	Female
0			41	28	30	39	41	32
1	137	135	45	25	58	67	58	29
2	86	79	92	109	93	86	75	96
3	63	63	73	86	93	97	65	72
4	74	75	70	86	67	68	80	105
5	60	65	81	78	69	83	69	68
6	53	69	62	70	59	64	57	73
7	76	87	79	89	47	59	69	81
8	64	67	59	71	81	61	69	80
9	41	41	52	39	57	57	71	65

This table details the results from the survey with each four-digit response decomposed into the individual digits along gender lines.

Table III: Distribution of Digits Derived from a Four-Digit Number Based on Cultural Identity

	First Digit Frequency		Second Digit Frequency		Third Digit Frequency		Fourth Digit Frequency	
Arabic Numeral	US	Non-US	US	Non-US	US	Non-US	US	Non-US
0			53	16	58	11	57	16
1	193	79	59	11	108	17	75	12
2	137	28	148	53	141	38	145	26
3	107	19	137	22	145	45	117	20
4	121	28	125	31	119	16	144	41
5	109	16	133	26	123	29	115	22
6	105	17	108	24	97	26	102	28
7	137	26	141	27	88	18	123	27
8	113	18	113	17	114	28	104	25
9	72	10	77	14	101	13	112	24

This table details the results from the survey with each four-digit response decomposed into the individual digits reported for those that identify with the U.S. and all other nations comprise the non-U.S. category.

Table IV: Kolmorgorov-Smirnoff Test Results

	Gender			US		
	KS z statistic	KSa statistic	ρ value	KS z statistic	KSa statistic	ρ value
First Digit	0.0168	0.6132	1.0000	0.0582	2.1274	0.0009
Second Digit	0.0268	0.9803	1.0000	0.0363	1.3251	0.2388
Third Digit	0.0189	0.6892	1.0000	0.0182	0.6664	1.0000
Fourth Digit	0.0309	1.1288	0.6253	0.0204	0.7461	1.0000

This table details the Kolmogorov-Smirnov test results for each of the digit frequencies for both the gender and cultural results. We apply a Bonferroni adjustment to calculate the significance of the results.

Table V: Chi-Squared Test Results

	Gender			US		
	Df Freedom	Test Statistic	ρ value	Df Freedom	Test Statistic	ρ value
First Digit	8	2.8829	1.0000	8	30.9170	0.0006
Second Digit	9	15.8672	0.2788	9	16.5151	0.2275
Third Digit	9	7.3123	1.0000	9	15.3412	0.3279
Fourth Digit	9	20.3827	0.0628	9	7.5637	1.0000

This table details the Chi-Square test results for each of the digit frequencies for both the gender and cultural results. We apply a Bonferroni adjustment to calculate the significance of the results.