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**Review of Literature**

**Foreign Aid**

There are currently no papers detailing an analytical approach to identify foreign projects linked to corruption. Most papers deal with the subject in anecdotal manner. Most analytical papers dealing with the subject of foreign aid and international development focus on the transparency of foreign aid amounts and the effect of foreign aid on corruption in the recipient country. Ghosh and Kharas detail in their paper, *The Money Trail: Ranking Donor Transparency in Foreign Aid*, one of the main themes of analytics in foreign aid.

In their paper, Ghosh and Kharas detail how transparency of aid activity is recognized as one of the key areas so that aid effectiveness can be improved. In the paper they propose an index to measure and rank donors on transparency of their aid activities. The authors used the Transparency Index and rates 31 bilateral and multilateral donor agencies on six measure of transparency. They found that being a member of the International Aid Transparency Initiative (IATI) is a powerful signal of a donor being more transparency across other dimensions not measured in the Transparency Index. The authors also did not find any relationship between transparency and donor aid volume values. Overall, the World Bank’s International Development Association (IDA) and Australia are identified as the most transparency donors, while Korea and Inter-American Development Bank Special Fund are the least transparent (Ghosh & Kharas, 2011).

One of the major topics that Ghosh and Kharas describe in their paper is the fragmentation of aid activities. Figure 1 below from Ghosh and Kharas shows the increase in the number of commitments and the decrease in the mean of the commitment size (Ghosh & Kharas, 2011). This might be an advantage in trying to discern possible commitments (foreign aid projects) that are meant for corruption. Collins, Zubairi, Nielson, and Barder estimate that at least $18 billion of aid a year is susceptible to corruption (Collins, Zubairi, Nielson, & Barder, 2009). 

Okada and Samreth in their paper investigate the effect of foreign on corruption using a quantile regression method. The authors in their paper describe that foreign aid reduces corruption and its reduction effect is greater in less corrupt countries. Though the authors acknowledge that this effect is different by different donor countries. What distinguishes their paper from other papers in the international development field is that they focus on the effect of foreign aid on corruption in recipient countries. Their conclusion is that foreign aid generally decreases corruption level. Their methodology and variables that they include in their study are not robust enough to make this claim. Okada and Samreth look at Aid (Total), GPP per Capita, Democracy, and English Legal origin as three variables that are tied to corruption. The authors do not account for other indicators which have been shown to have a large impact on corruption in countries (Okada & Samreth, 2011). These indicators include, but are not limited to health levels, education levels, and government institution strength (Kimura & Todo, 2010). Even though Okada and Samreth do not take these variables into account, their paper is important because of analytical approach they take to answering a problem in the international development field.

**Benford’s Law**

Benford’s law is a law of mathematics that describes a numerical regularity in real-world numbers expressed in the decimal system. According to Benford, various digits do not occur with the same frequencies. For example, the formula for the first digit is P(d1) = log(1+(1/d1)) with d1 being one of the numerals 1,…,9. The joint distribution of the first and all later digits adhere to the following probabilities: P(D1 = d1,…,Dk = dk) = log[1+ with D1, D2 signifying the first, second, etc. significant digit and di the numerals 0,1,…,9 (j=2,…,k) (Benford, 1938). Benford’s law was then further investigated to study two-digit distribution and Mebane in 2006 argues that the frequencies of the numerals of election counts at precinct level approximate a Benford distribution of the second digit (Mebane, 2006). Breunig and Goerres then used Mebane’s methodology to look at electoral irregularities in Germany. The authors were able to replicate Mebane’s methodology and found irregularities in different levels of the Bundestag elections in Unified Germany (Breunig & Goerres, 2011).

Apart from elections, Benford’s Law has been used extensively in detecting fraud in financial records. In Durtshi, Hillison, and Pacini, the authors describe Benford’s Law and how it can be used to in auditing. The authors show that a digital analysis of records can be effectively used and show where auditors should exercise caution when using Benford’s Law. Finally, the authors identify data sets that can be expected to follow Benford’s distribution, discuss the power of statistical tests, types of frauds that would be detected and not be detected by such analysis, the potential problems that arise when account contains too few observations, as well as issues related to base rate of fraud. Overall, this paper has an in-depth and practical explanation of the analytical technique and explains how to be successful when using it (Durtschi, Hillison, & Pacini, 2004).

Benford’s law has also been applied to drug discovery data. Orita, Moritomo, Niimi, and Ohno demonstrate that several data sets in the field of drug discovery follow Benford’s distribution, whereas ‘doctored’ data do not. Their findings indicate the applicability of Benford’s law in assessing data quality in the field of drug discovery. We also propose a useful index of evaluating data quality based on Benford’s law (Orita, Moritomo, Niimi, & Ohno, 2010). Finally, Kraus and Valverde describe in their paper, *A Data Warehouse Design for the Detection of Fraud in the Supply Chain by Using the Benford’s Law*, how to develop a data warehouse solution that supports forensic analytics to use Benford’s Law to detect fraud. Their application primarily focuses on supply chain management processes such as procurement and inventory management. They used parameterized stored procedures with Dynamic SQL to analyze their supply chain data (Kraus & Valverde, 2014).

Based on the literature review, Benford’s Law and its variation of examining second digit distributions will work for attempting to detect fraud in foreign aid transactions. The importance of this paper is that no other authors have used this analytical technique, nor any other analytical techniques, to attempt to pinpoint fraud in foreign aid.

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