Assessing Data Integrity in Voluntary Carbon Offsets Using Benford's Law

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Abstract

High-profile scandals have fueled growing doubts about the credibility of claimed emission reductions in the voluntary carbon market. Numerous studies have highlighted issues such as inflated baselines, lack of additionality, and questionable data integrity in carbon offset projects. This study uses Benford's Law to assess the reliability of emission reduction data in the voluntary carbon market, focusing on both ex ante Estimated Emission Reductions (EERs) and the Verified Emission Reductions (VERs)—ex post credit issuances. It compares patterns across crediting programs, countries, and project types to identify potential irregularities. Nonconformity was found to be prevalent across crediting programs, project types, and countries. The findings provide insights to improve transparency and credibility in carbon offset practices.

1 Introduction

Carbon offsetting is a mechanism that allows entities—such as companies or individuals—to compensate for their own greenhouse gas (GHG) emissions by purchasing credits generated from emission reduction or removal projects developed elsewhere. These projects are typically implemented by specialized developers and follow a multi-stage project cycle. Developers begin by estimating potential emissions reductions using approved methodologies and submitting this information in project design documents at the time of registration; this stage produces the "Estimated Emission Reductions" (EERs), which are ex ante projections. Once a project is implemented, it undergoes monitoring and third-party verification to determine the actual reductions achieved during a given crediting period, resulting in the issuance of "Verified Emission Reductions" (VERs). Each issued credit typically represents one metric ton of CO_2-equivalent reduction or removal. The term "voluntary carbon offsets" generally refers to credits used issued by non-state crediting

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programs—regardless of their eventual use in voluntary or compliance settings—so long as they originate outside of government-backed mechanisms such as the Clean Development Mechanism (CDM), China's Certified Emission Reduction (CCER) program, emerging Article 6 frameworks, etc.

Voluntary carbon offsets have gained prominence following the Paris Agreement but faced unresolved governance and integrity challenges (Kreibich, 2024). In January 2023, an investigation revealed that more than 90% of rainforest carbon offsets certified by Verra, a leading carbon credit certifier, did not represent genuine carbon reductions and may have exacerbated global warming (Greenfield, 2023). In October 2024, former executives of C-Quest Capital, a carbon credit project developer, were charged with fraud. They allegedly manipulated data to secure fraudulent carbon credits and misled investors into committing over $100 million (Smagalla, 2024). This case underscores the potential for misconduct in the carbon credit market. As a result, the voluntary carbon market has recently seen a significant contraction in transaction volumes, with a 56% year-on-year decline in 2023. The market has placed greater attention on higher-quality carbon credits and a stronger focus on carbon removals rather than reductions (Procton, 2024), but there is still a lack of consensus and transparency in defining quality criteria for offsets (Huber, Bach, & Finkbeiner, 2024).

Numerous academic studies have also pointed out that carbon offsetting may not represent real emission reductions. A recent systematic evaluation estimates that less than 16 percent of the carbon credits constitute real emission reductions (Probst et al., 2024). Additional research has documented various structural weaknesses in offset programs, including the use of optimistic baseline assumptions (e.g., overstating deforestation rates), methodological inconsistencies, and adverse selection, all of which undermine the credibility (Cames et al., 2016; Coffield et al., 2022; Gill-Wiehl, Kammen, & Haya, 2024; Haya et al., 2023; Kollmuss, Schneider, & Zhezherin, 2022; Stapp et al., 2023; West, Börner, Sills, & Kontoleon, 2020; West et al., 2023). While some of these concerns stem from broader methodological uncertainties—such as inflated baselines and doubts about additionality—others involve potential misreporting or fraud in the numerical data itself. Our analysis focuses on the latter category: data integrity issues in reported emission reductions that may signal manipulation and are amenable to detection using Benford's Law. Fraudulent claims could lead to substantial financial gains for project developers while weakening the effectiveness of carbon markets as a climate mitigation tool (Civillini, 2023; Schülke, 2024; Smagalla, 2024).

Against this backdrop, this paper provides the first systematic statistical assessment of data irregularities in the voluntary carbon market using Benford's Law, a mathematical principle widely used in forensic analysis. We draw from the v2024-10 version of the Voluntary Registry Offsets Database (VROD), developed by the Berkeley Carbon Trading Project (Haya, Abayo, Rong, So, & Elias, 2024). The database contains detailed project-level data from four major crediting programs: the American Carbon Registry (ACR), the Climate Action Reserve (CAR), Verra, and Gold Standard (GS). These programs act as private standard-setters: they establish methodologies, oversee project validation and verification, and issue tradable credits.

In our analysis, we examine the "estimated emission reductions" (EERs) which refers to the ex ante emission reduction quantities reported in project documents, and the "verified emission reductions" (VERs), representing the emission reductions certified by the programs for each crediting period. We also further organize our analysis in three dimensions: crediting programs, project types, and country of origin.

We found nonconformity to be widespread across crediting programs, project types, and countries. While the extent of deviation varies, estimated emission reductions exhibit greater inconsistencies than verified data, suggesting potential manipulation of ex ante claims. Despite some improvements in verified data, irregularities remain across various categories and contexts. Although Benford's Law does not directly identify fraudulent activity, it serves as a diagnostic tool for detecting statistical anomalies. Deviations from the expected distribution may indicate areas where further scrutiny is warranted. Since this mathematical property is scale-invariant, it does not capture issues rooted in systemic practices, such as inflated baselines or lack of additionality, as long as the data is naturally generated.

The remainder of this paper is structured as follows. Section 2 introduces Benford's Law and its applications. Section 3 describes the data and method. Section 4 presents the empirical findings, while Section 5 concludes.

2 Benford's Law and Its Application

Benford's Law is a statistical principle that describes the expected distribution of first digits in many naturally occurring datasets. First observed by Simon Newcomb in 1881 and later formalized by Frank Benford in 1938, the law states that smaller digits are more likely to appear as the first digit of a number (Benford, 1938). Formally, the probability $\mathrm{P}(d_1)$ of a given first digit d_1 occurring is:

$$p(d_1) = \log_{10}\left(1 + \frac{1}{d_1}\right), \text{where } d_1 \in \{1, 2, \ldots, 9\}. \tag{1}$$

This results in a monotonically decreasing distribution, where the digit 1 appears as the first digit approximately 30% of the time, while the digit 9 appears only about 4.6% of the time. The same principle applies to the second digit, where each digit occurs between about 8.5% and 12%. This logarithmic distribution is observed in datasets that span multiple orders of magnitude and are unconstrained by artificial limits. The law is scale-invariant, meaning it applies regardless of measurement units or data magnitude, making it useful for assessing whether datasets follow expected patterns or show signs of irregularities.

Benford's Law has been widely applied in forensic analysis, particularly in fraud detection and data integrity assessments. Prior research has leveraged Benford's Law to identify anomalies in diverse fields, including COVID-19 case reporting (Campolieti, 2022; Koch & Okamura, 2020; Kolias, 2022), financial accounting data (Alali & Romero, 2013), and international macroeconomic statistics (Nye & Moul, 2007). It has also been applied to detect irregularities in self-reported survey data (Judge & Schechter, 2009; Kaiser, 2019), where it helps assess data reliability.

Benford's Law has also been used to evaluate the integrity of self-reported environmental data, particularly in pollution monitoring. For example, studies on pollution monitoring have applied Benford's Law to assess the reliability of self-reported emissions data. Marchi and Hamilton (2006) examined the U.S. Toxics Release Inventory (TRI), showing that significant reductions in self-reported emissions were not always matched by similar decreases in monitored concentrations. Similarly, Zahran, Iverson, Weiler, and Underwood (2014) analyzed self-reported lead emissions data and found that reporting accuracy improved over time despite the relaxation of regulations. Beiglou, Gibbs, Rivers, Adhikari, and Mitchell (2017) investigated wastewater treatment plant discharge data and demonstrated that Benford's Law could serve as an effective tool for compliance assessment. Another study Wang, Chen, Mao, Liu, and Rong (2022) applied the method to China's coal statistics, finding that the data significantly deviated from the expected distribution, with inconsistencies and spatial heterogeneity across provinces and industries.

In climate research, Benford's Law has been used to examine the credibility of emission reduction claims under the Clean Development Mechanism (CDM) administered under the UNFCCC (Cole, Maddison, & Zhang, 2020). The researchers applied Benford's Law to test the integrity of CDM emission reduction data, conducting digital frequency analysis on both estimated emission reductions (EERs) and certified emission reductions (CERs). Their findings indicated that while EERs reported in project design documents did not conform to Benford's Law—suggesting potential misreporting—CERs, which had undergone third-party verification, largely conformed to the expected distribution. The result suggests that the CDM's auditing process improves the reliability of reported emission reductions by verifying and adjusting early projections before credit issuance.

Building on prior research, this study extends the use of Benford's Law to the voluntary carbon market, which has become the main arena for offset crediting after the CDM largely became dormant. In our analysis, we first compare patterns across four major crediting programs: ACR, CAR, Verra, and Gold Standard. Unlike CDM, which operates under the centralized oversight of the United Nations, the voluntary carbon market lacks unified governance. Instead, it relies on multiple private crediting programs. These programs, typically non-profit entities, act as registries for carbon offset projects, issuing credits and establishing methodologies, standards, and verification protocols to validate emission reductions. Research has also shown that these private authorities have become key stakeholders in climate governance (Green, 2013; Andonova & Sun, 2019; Renckens, Pue, & Janzwood, 2022). However, this fragmented structure increases the potential for inconsistencies and irregularities in the reported data between programs, since each operates under its own methodologies, verification processes, and enforcement mechanisms.

Second, we compare data conformity across different countries, as country-specific factors play a significant role in shaping the reliability and integrity of emission reduction data. Project developers often establish baselines for emissions reductions based on local conditions such as deforestation rates, economic factors, and energy profiles. This flexibility means countries with less robust data systems or higher variability in baseline assumptions may inadvertently inflate or distort reported emissions reductions. Additionally, the capacity of local institutions to monitor, validate, and verify projects significantly influences data reliability. In countries with weaker governance structures or limited technical expertise, project data may be less consistent or prone to errors.

Finally, we compare results among project types, as different project categories—such as forestry, renewable energy, agriculture, and waste management—operate under distinct methodologies, assumptions, and challenges. For instance, forestry projects often rely on estimated deforestation avoidance, which can be subject to inflated baseline assumptions, whereas renewable energy projects may face fewer uncertainties but still pose additionality concerns in regions with pre-existing renewable energy policies. Agricultural projects, including soil carbon sequestration, involve complex biophysical processes and long-term monitoring requirements that can affect data reliability. Research has shown the effectiveness of carbon crediting programs varies significantly by project type (Probst et al., 2024). We seek to understand whether data irregularities show distinct patterns.

This study makes several contributions to the literature on carbon market integrity. First, it extends the application of Benford's Law from a centralized, UN-supervised compliance mechanism (CDM) to the more fragmented and privately governed voluntary market. This shift in institutional context allows for an empirical assessment of whether patterns of data irregularities found in the CDM persist under very different governance arrangements. Second, it introduces a systematic comparison across crediting programs, project types, and national contexts, offering insights into how governance structures influence data reliability. Finally, by comparing estimated and verified emission reductions, the study sheds light on the extent to which verification processes mitigate potential reporting distortions. The above contributions offer important input for policy discussions on improving transparency in voluntary carbon markets.

3 Data and Method

The study utilizes the Voluntary Registry Offsets Database (VROD) developed by the Berkeley Carbon Trading Project. Many previous research has used this database (Haya et al., 2023; Fujii et al., 2024; Trencher, Nick, Carlson, & Johnson, 2024). Our study uses the recently released version v2024-10. The database compiles carbon offset project data from four major crediting programs: Verra, Gold Standard, the American Carbon Registry (ACR), and the Climate Action Reserve (CAR), including database with detailed information on project names, registries (e.g., Verra, Gold Standard, ACR, CAR), project types (e.g., forestry, renewable energy, agriculture), methodologies, geographic locations, emission reduction claims, credit vintage, credit issuances, etc. While minor inconsistencies may exist, VROD is compiled from official registries and is widely regarded as a reliable source for carbon market research.

For Benford's Law to be applicable, the dataset must meet specific criteria to ensure reliability and meaningful results. The established guidelines point out that the dataset must span multiple orders of magnitude without artificial minimum or maximum thresholds that could distort the distribution (Goodman, 2016; Li et al., 2019; Singleton, 2011). Variables must be continuous, numerical, and derived from processes that naturally generate data. Additionally, the dataset should be sufficiently large to minimize random error and enhance the robustness of statistical analysis.

In this study, carbon offset emission reduction data is well-suited for analysis under Benford's Law, as it is naturally generated through diverse project activities and spans multiple orders of magnitude. We extend the approach of a previous study (Cole et al., 2020) that applied Benford's Law to analyze emission reduction claims under the Clean Development Mechanism (CDM) to assess the integrity of reported data in the voluntary carbon market.

The same reasoning applies to the voluntary carbon offset market. Both estimated emission reductions (ex-ante) and verified emission reductions (ex-post) are expected to follow Benford's Law for several reasons. First, emission reduction data describes a single physical phenomenon—CO_2 emissions—where reported values are derived from standardized scientific formulas used in approved methodologies. Unlike datasets that are artificially constrained by predetermined upper or lower bounds, emission reductions do not have theoretical maximum or minimum values (except for zero). In our data, the emission reduction spread across multiple orders of magnitude, from 1 to 5,250,000. There is no inherent reason why either estimated or verified reductions should be constrained by specific numerical patterns. Although crediting programs have thresholds to differentiate large-scale and small-scale projects, the calculation and certification of emission reductions should be based solely on the assigned scientific formulas, independent of these labels.

Furthermore, emissions data—like many economic, financial, and environmental datasets—can often be modeled as a growing process, where numbers are generated based on incremental accumulation or proportional changes rather than arbitrary reporting. Since such processes tend to follow a geometric distribution, their first-digit frequencies should align with Benford's expected distribution.

Finally, based on the Generalized Significant Digit Law (Hill, 1995), which suggests that random samples from a random collection of distributions tend to follow Benford's Law, it is plausible to assume that emissions data, if unbiased and generated by diverse of factors (such as different facilities, types of emissions, etc.) would conform Benford's distribution. Therefore, any significant deviation from this expected distribution might indicate data manipulation or non-compliance.

For our analysis, we use the variables "Total Number of Credits Registered" (ACR), "Total Number of Offset Credits Registered" (CAR), "Estimated Annual Emission Reductions" (Verra), "Estimated Annual Emission Reductions" (Gold Standard) to calculate Estimated Emission Reductions (EERs), and "Credits Issued to Project" (ACR), "Total Offset Credits Issued" (CAR), "Quantity Issued" (Verra), "Quantity" (Gold Standard) for Verified Emission Reductions (VERs). The unit of analysis is the unique incidence of credit registration and issuance. There are sometimes multiple entries for the same batch of issued credit, we then aggregate them by vintage years and issue dates.

To analyze the Benford conformity between different project types, we dropped categories with fewer than 100 samples, leaving those that cover at least 90% of the projects under the crediting programs. For example, under Verra, we excluded chemical, construction, fugitive, livestock, mining, and transportation projects, as they each have fewer than 100 registered projects. We then analyzed and categorized the remaining projects into four groups: AFOLU (Agriculture, Forestry, and Other Land Use), Energy Demand, Energy Industries, and Waste Handling and Disposal, accounting for around 92% of the total registered projects. For the Gold Standard, we categorized projects into four types: Energy Efficiency, Biogas, Solar Thermal, and Wind Power. Other project types, such as A/R, Biomass, Liquid Biofuel, and Small, Low-Impact Hydro, have been excluded due to their lower frequency of occurrence—each has fewer than 200 projects. These project types, while still valid, represent a smaller portion of the total data set (less than 15%) and will not be included in the final analysis.

We use five statistical tests to evaluate how well the data conforms to Benford's Law: the m, d^*, Chi-Square Test, Likelihood Ratio Test, and Kolmogorov-Smirnov Test. Each test provides a unique perspective on data conformity. The m-statistic calculates the maximum absolute deviation between observed and expected frequencies, which is defined as $m = \max_{i=1,2,3,\ldots,9}\left(|b_i - e_i|\right)$, where b_i is the observed frequency of the digit i (the first digit in the data); e_i is the expected frequency of the digit i based on Benford's distribution. The d statistics is calculated based on the Euclidean distance between the two distributions, so it is calculated as $d = \sqrt{\sum_{i=1}^{9}(b_i - e_i)^2}$.. Based on the literature, we then divide d by the maximum possible distance between the two distributions to get d^* (Judge & Schechter, 2009; Tam Cho & Gaines, 2007). That is, when all the leading digits are 9. For m and d^*, we used Monte Carlo simulations for generating the relevant critical values taking into account their sample size.

The Chi-Square Test evaluates the overall fit between observed and expected frequencies, with larger values indicating worse conformity. The Likelihood Ratio Test compares the fit of the observed data to Benford's Law against an alternative model, and the Kolmogorov-Smirnov Test examines the largest discrepancy in cumulative distributions. Together, these tests ensure a comprehensive analysis of the dataset's alignment with Benford's distribution. For all these tests, a larger statistic means a worse fit to Benford's First Significant Digit (FSD). There are no theoretical reasons to prefer one statistic over the other among our measures. We chose m and d^* as they were recommended as preferable distance measures (Judge & Schechter, 2009). Other statistical tests were all very common tests to test the conformity of two distributions.

4 Result

Figure 1 provides descriptive information on carbon offset projects by crediting programs. The bar chart shows the growth in the number of carbon offset projects from 1998 to 2023. There are 4130 projects in the database, with Verra having the largest number (1,941), a steep increase in project numbers starting around 2015 and peaking in 2023. Gold Standard shows steady growth (891) and has overtaken Verra in the number of projects in 2023. The database contains a large number of issuance data, which we aggregate at the vintage year and unique issue date for further analysis. The projects have led to more than 2 billion tons of carbon credits issued. To put this into perspective, this number is about 6 percent of one year's global carbon emissions, or less than half of the US's annual emissions. Among the crediting programs, Verra leads by a significant margin, with over 1.3 billion credits issued, far surpassing Gold Standard (380 million), ACR (300 million), and CAR (220 million).

ACR and CAR play important but niche roles in the carbon offset market, primarily focusing on projects tailored to the U.S. policy environment. Both programs emphasize alignment with compliance markets, such as California's cap-and-trade system, and often develop methodologies specifically suited to North American contexts. Given their specialized scope and smaller scale compared to Verra and Gold Standard, we exclude ACR and CAR when comparing countries and project types.

Figure 2 presents the results of the five statistical measures: mean absolute deviation (m), Euclidean distance (d^*), Chi-Square (χ^2) Test, likelihood ratio (LR), Kolmogorov-Smirnov (KS) to quantify the deviation of each program's data from Benford's Law, with significance levels denoted for 95% (*) and 99% (**) (See details in the method section). The red line in the figures represents the theoretical distribution predicted by Benford's Law, while the bar charts depict the actual distribution of the first significant digits (FSD) from the emission reduction data. Comparing the two allows us to visually assess the degree of conformity to Benford's Law.

Our findings show that, except for estimated emission reductions for the CAR, we reject the null hypothesis that the data conforms to Benford's Law. While most programs exhibit deviations from the expected Benford distribution, Verra and Gold Standard—the two largest—display relatively larger discrepancies. When we compare their estimated emission reductions (EERs) and verified emission reductions (VERs), EERs generally exhibit larger deviations from Benford's Law, as reflected in higher test statistics. For example, in Verra, estimated reductions have a d-statistic of 0.077**, compared with 0.015* for verified reductions. Gold Standard shows a similar pattern. This pattern suggests that discrepancies are more pronounced at the registration stage, where ex ante estimates may be inflated or overly optimistic. The verification process appears to reduce these deviations.

It is important to note that estimated emission reductions (EERs) are ex-ante projections that are often rounded to convenient figures, while verified emission reductions (VERs) represent ex-post quantified outcomes reported with higher numerical precision. Although such differences in reporting practice are unlikely to substantially affect first-digit conformity, they may contribute modestly to the observed gap between EERs and VERs.

For ACR and CAR, both programs show smaller deviations, with some tests failing to reject the null hypothesis, and the verified emission reductions show slightly worse conformity. As a robustness check, we also conducted second-digit Benford tests (See Table S1), and the results are largely consistent with the first-digit analysis.

After further examination, we found that one important source of deviation may come from smaller-scale projects. In Figure 3, we limited the analysis to projects under 100,000 tons of carbon emission reductions (note that the reduced sample size and narrower range of magnitudes mean that lower conformity with Benford's Law is expected). Projects at the registration stage show bunching at several thresholds. For example, Verra projects tend to bunch right below or at 60,000 tons of estimated carbon reduction; GS projects bunch around or at 10,000 and 60,000 tons of estimated carbon reduction, particularly evident in household projects employing the methodology for Reduced Emissions from Cooking and Heating (TPDDTEC). This bunching pattern is no longer as evident in the lower graphs of Figure 3, which show the frequency distribution for verified emission reduction. This pattern is most likely due to the standards established by carbon crediting programs. Verra projects typically qualify as "small-scale" projects under 60,000 tons. For the Gold Standard, projects under 10,000 tons are classified as "micro" scale, and those under 60,000 tons as "small" scale, with other thresholds for various project types. Projects classified as smaller scale are often subject to simplified monitoring, reporting, and verification processes to make them economically viable. This classification likely creates incentives for project developers to structure their projects exactly at or just below the thresholds when registering their estimated emission reductions. This incentive has less influence at the verification stage as project developers have limited control over the process.

This pattern is consistent with known cases in the voluntary carbon market. For example, in 2023, Climate Home News revealed that rice cultivation projects in China, developed under the AMS-III.AU methodology (*Methane emission reduction by adjusted water management practice in rice cultivation*), were deliberately structured to qualify as "small-scale"(Civillini, 2023). Developers segmented these projects into smaller units, ensuring that annual emission reductions remained just below the 60,000 tons threshold. This strategy enabled them to benefit from simplified procedures and reduced scrutiny. In response, Verra permanently inactivated the AMS-III.AU methodology in 2023 and subsequently rejected 37 rice cultivation projects. For the first time, Verra also imposed significant sanctions on the project developers and validation/verification bodies (VVBs) involved. This case is analogous to what the Clean Development Mechanism (CDM) refers to as "debundling"—the artificial splitting of a large project into multiple smaller-scale activities to qualify for simplified rules—as addressed in UNFCCC guidance (UNFCCC, 2015). Overall, this example highlights how thresholds for regulatory categorization may create incentives for manipulation.

Figure 4 presents Benford's Law statistics and visualization of first-digit distribution for the major project types. To facilitate analysis, we aggregate all subcategories into broader project types, such as Agriculture, Forestry, and Other Land Use (AFOLU), Energy Demand (e.g., cookstoves, lighting), Energy Industries (e.g., biogas, solar, methane recovery), and Waste Handling and Disposal for Verra, as well as Energy Efficiency (e.g., cookstoves, water purification), Biogas, Solar Thermal (e.g., solar cookers and heaters), and Wind Power for Gold Standard. It is important to note that under Verra's classification system, a single project may belong to multiple categories. For a detailed distribution of project types, please refer to Tables S2 and S3 in the supplementary information. The figure also compares EERs with VERs for each project type.

A notable pattern emerges in Verra's Agriculture, Forestry, and Other Land Use (AFOLU) projects. Both estimated and verified emission reductions show significant deviations from Benford's Law in the full dataset. However, when we exclude the 285 projects associated with the scandal-plagued AMS-III.AU methodology, the statistics improve considerably and align closely with Benford's Law expectations. The results highlight that when crediting programs strengthen oversight of project methodologies and verification processes, we observe improved conformity in reported emission reductions.

For Verra's projects outside AFOLU, Energy Demand and Waste Handling and Disposal projects show consistent deviations from Benford's Law, with limited improvement in verified reductions. In contrast, Energy Industries exhibit smaller deviations. For Gold Standard, deviations are most pronounced in Energy Efficiency and Biogas projects. Both categories show large discrepancies in estimated reductions, with only partial improvement in verified data. In contrast, Wind Power projects perform better, with verified reductions more closely conforming to Benford's Law. These results highlight the need for greater scrutiny in project types where irregularities persist despite verification.

The project distribution across countries reveals distinct patterns between Gold Standard and Verra, reflecting their differing geographic focuses and market strategies. We provide the detailed frequencies and percentages of country participation in the Verra and Gold Standard in Tables S4 and S5 of the supplementary information. Verra projects are dominated by contributions from China (27.66%) and India (24.94%), as the program focuses on large-scale renewable energy and forestry projects in high-emission countries. In contrast, Gold Standard projects are more evenly distributed across smaller countries, with significant contributions from India (16.9%), Turkey (8.7%), and several African nations. This distribution reflects Gold Standard's emphasis on smaller-scale, community-driven initiatives, often in regions with high development needs. To compare variation across countries, we focus on China and India due to their dominance in the market, as well as Turkey, which is the only country besides these two with more than 200 projects in both programs.

Figure 5 presents Benford's Law statistics and visualizations of the FSD distributions for China, India, and Turkey, covering both estimated and verified emission reductions across Verra and Gold Standard. For China, two sets of statistics are included: one using the full dataset and another excluding projects that applied the AMS-III.AU methodology. We only include projects that have generated reductions, thus the number is slightly lower than in Tables S4 and S5.

The findings reveal significant variation in conformity across countries. For China, the FSD distributions deviate substantially from the expected monotonic decreases. Verra projects exhibit a noticeable clustering around the digit 5 in the estimated emission reductions, largely tied to the AMS-III.AU methodology, where many projects intentionally registered just under the 60,000 tons threshold. Excluding projects that used this methodology significantly improves conformity, with verified emission reductions showing only mild deviations from the expected distribution. On the other hand, Gold Standard projects in China also display anomalies, with unusually high frequencies of the digits 4, 8, and 9. Further examination suggests that this pattern, at least partially, arises from the Program of Activities—a framework that groups smaller projects under one umbrella—being subdivided into smaller projects of identical sizes. While this paper does not attempt to adjudicate the motivation behind this practice, it is a subject worthy of further investigation.

In contrast, India and Turkey exhibit different patterns. India's data shows a closer alignment with Benford's Law compared to China. For Verra, the EERs align closely with Benford's Law expectations, yet deviations emerged in the verified emission reductions. This is a less common pattern. India's Gold Standard projects show significant deviation and have improved after verification. As for Turkey, all data from Verra and Gold Standard aligns well with Benford's Law. These contrasting results point out the influence of national institutions and governance structures on the voluntary carbon market, even within a system that predominantly operates between private entities. The variation highlights the importance of understanding how country-specific factors shape program implementation and reporting practices.

5 Conclusion

This study provides the first statistical examination of data irregularities in the voluntary carbon market using Benford's Law. Our analysis reveals several key patterns across crediting programs, countries, and project types. Among crediting programs, Verra and Gold Standard exhibit larger discrepancies compared to the American Carbon Registry (ACR) and the Climate Action Reserve (CAR), which are tailored to the U.S. compliance context. Project-type comparisons show that nonconformity is prevalent across categories but with notable variations. For Verra, deviations in Agriculture, Forestry, and Other Land Use (AFOLU) projects are largely driven by the AMS-III.AU methodology, which has since been inactivated. For Gold Standard, wind power projects show greater conformity, especially after verification, compared to energy efficiency and biogas projects. The country-level analysis highlights notable anomalies in China, especially in projects linked to problematic methodologies like AMS-III.AU, while India and Turkey generally show closer alignment with Benford's expectations.

Our study extends the discussion on data integrity from the Clean Development Mechanism (CDM) to the voluntary carbon market, which now constitutes most of the global carbon offset activities. There are notable similarities and differences between the findings. Earlier research found that certified emission reductions (CERs) under the CDM generally conformed to Benford's Law after auditing. Our findings show that, indeed in some circumstances, estimated emission reductions (EERs) display greater irregularities from Benford's Law than in verified emission reductions (VERs). However, the pattern is not universal and VERs rarely achieve the level of conformity in the voluntary carbon market as observed in the CDM. Additionally, while earlier analyses highlighted greater nonconformity in wind projects in specific countries, our study reveals that nonconformity spans most project types in the voluntary market for both estimated and verified reductions. Notably, wind projects in the voluntary market show less deviation after verification, in contrast to the CDM findings.

Our key finding suggests that thresholds set by crediting programs to define project scales influence the distribution of reported emission reductions, with certain numbers appearing more frequently. Designing projects to align with these thresholds is not inherently problematic, but these limits create incentives for structuring or dividing projects to meet easier requirements. This issue is corroborated by the case of rice cultivation projects using AMS-III.AU, where irregularities were again identified through our Benford's Law analysis. Further scrutiny is warranted for projects that report values right at or just below the thresholds.

Overall, our findings show data irregularities are prevalent in the voluntary carbon market. While this nonconformity does not prove fraudulent practices, recent news suggests significant challenges persist in ensuring the transparency and integrity of carbon offsets. Within this context, we concur that Benford's Law can be a valuable diagnostic tool (Cole et al. 2020), flagging suspicious patterns that might otherwise remain unnoticed and guiding subsequent investigations with complementary methods.

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Figure 1: Descriptive Information by Crediting Program

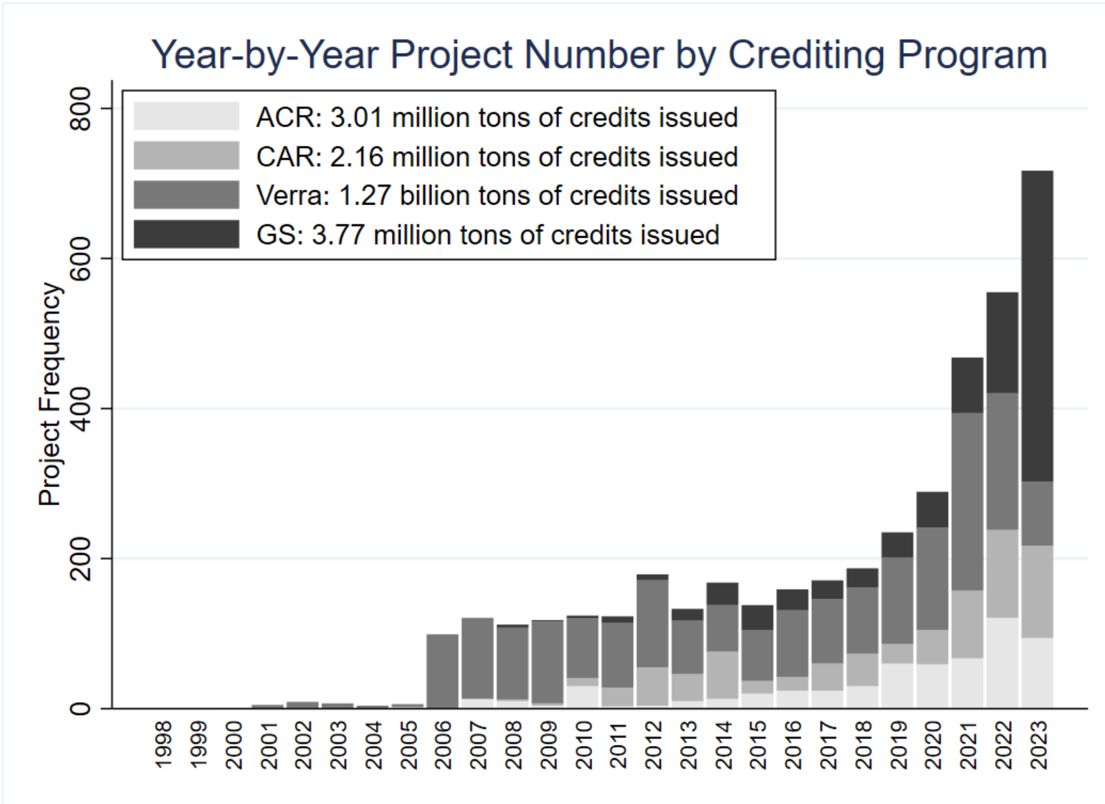
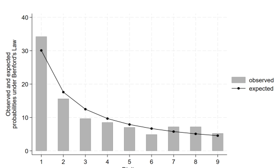


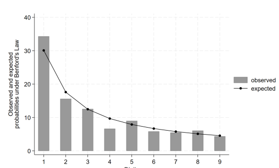
Figure 2: Benford's Law Statistics and FSD Visualization by Crediting Program

Program	N	m	d*	χ^2	LR	KS
Overall	37455	0.014**	0.027**	380.038**	357.893**	0.031**
American Carbon Registry (ACR)						
Estimated Emission Reduction	607	0.042*	0.062**	20.909**	20.637**	0.043
Verified Emission Reduction	1710	0.042**	0.056**	38.064**	39.579**	0.042**
Climate Action Reserve (CAR)						
Estimated Emission Reduction	717	0.017	0.025	5.192	5.039	0.025
Verified Emission Reduction	2489	0.027**	0.033**	17.737*	17.673*	0.027*
Verra						
Estimated Emission Reduction	4417	0.068**	0.077**	303.546**	253.658**	0.055**
Verified Emission Reduction	10514	0.012**	0.015*	19.697*	19.778*	0.009
Gold Standard						
Estimated Emission Reduction	3407	0.081**	0.118**	650.743**	545.453***	0.122**
Verified Emission Reduction	13594	0.038**	0.051**	408.958**	370.847**	0.050**

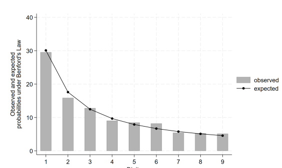
* indicates 95% and ** indicates 99% significance level.



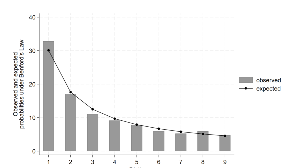
ACR EERs



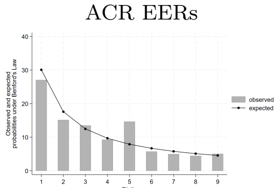
ACR VERs



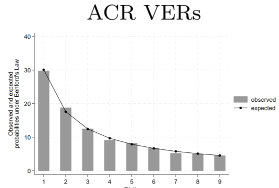
CAR EERs



CAR VERs



Verra EERs



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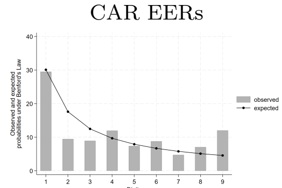
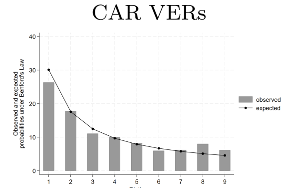
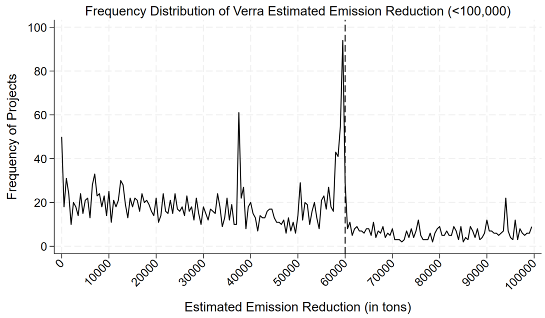


GS EERs

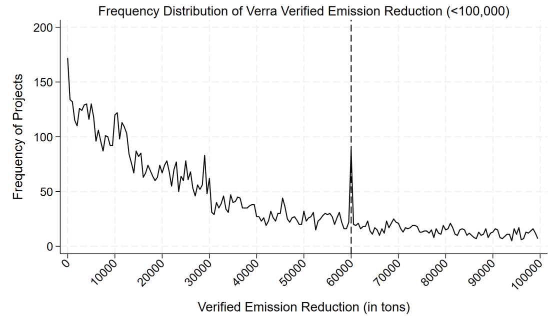


GS VERs

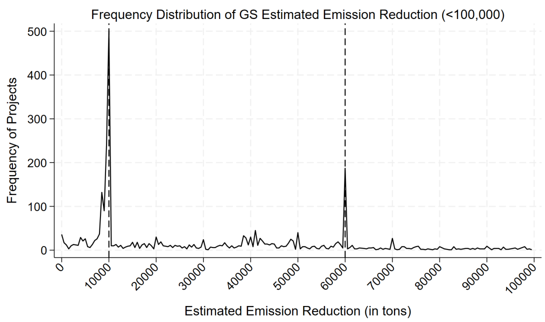
Figure 3: Frequency Distribution of Estimated and Verified Emission Reductions (EERs and VERs) under 100,000 Tons for Verra and Gold Standard



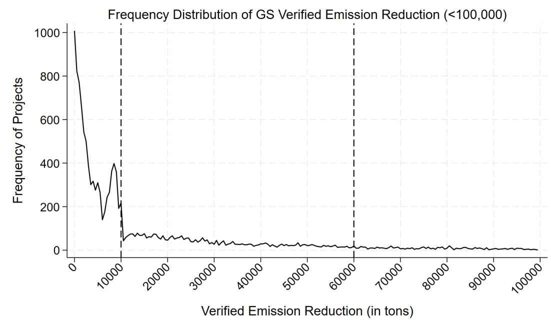
Verra EERs (N=2,836)



Verra VERs (N=8,269)



GS EERs (N=2,864)



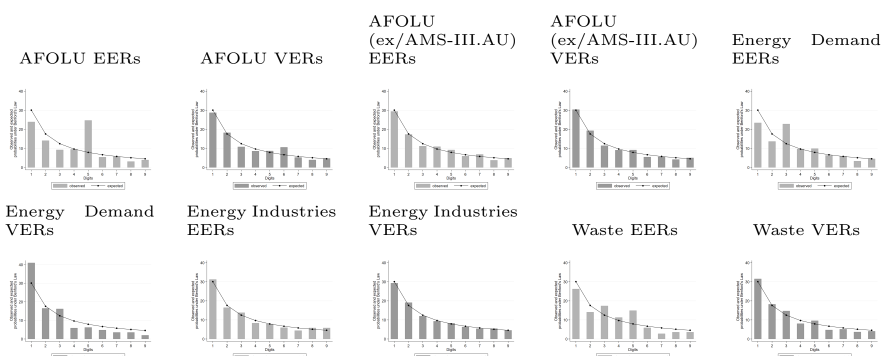
GS VERs (N=12,801)

Figure 4: Benford's Law Statistics and FSD Visualization by Project Type

Program	N	m	d*	χ^2	LR	KS
Verra						
Agriculture Forestry and Other Land Use Projects						
Estimated Emission Reduction	1486	0.168**	0.180**	589.434**	400.803**	0.130**
Verified Emission Reduction	1400	0.039**	0.047**	43.654**	39.122**	0.033*
Estimated Emission Reduction (w/o AMS-III.AU)	1201	0.013	0.029	14.063	14.141	0.021
Verified Emission Reduction (w/o AMS-III.AU)	1324	0.017	0.028	12.174	12.286	0.021
Energy Demand						
Estimated Emission Reduction	503	0.104**	0.127**	60.654**	53.223**	0.105**
Verified Emission Reduction	641	0.109**	0.125**	65.352**	67.799**	0.136**
Energy Industries						
Estimated Emission Reduction	1936	0.014	0.032*	24.927**	24.987**	0.020
Verified Emission Reduction	7558	0.015**	0.019**	20.113**	19.873*	0.008
Waste Handling and Disposal						
Estimated Emission Reduction	609	0.070**	0.104**	72.555**	66.394**	0.073**
Verified Emission Reduction	1051	0.023	0.043*	23.168**	23.992**	0.045**
Gold Standard						
Energy Efficiency						
Estimated Emission Reduction	1943	0.121**	0.171**	768.619**	645.778**	0.179**
Verified Emission Reduction	7011	0.039**	0.050**	107.828**	108.742**	0.039**
Biogas						
Estimated Emission Reduction	365	0.075**	0.113**	73.190**	61.193**	0.109**
Verified Emission Reduction	1859	0.180**	0.246**	1806.515**	1152.276**	0.303**
Solar Thermal						
Estimated Emission Reduction	227	0.075*	0.098*	25.316**	24.539**	0.085*
Verified Emission Reduction	785	0.046**	0.072**	55.861**	48.311**	0.088**
Wind Power						
Estimated Emission Reduction	394	0.047	0.095**	40.515**	37.714**	0.089**
Verified Emission Reduction	1792	0.018	0.029	15.004	14.878	0.040**

* indicates 95% and ** indicates 99% significance level.

FSD Visualization by Project Type: Verra



FSD Visualization by Project Type: GS

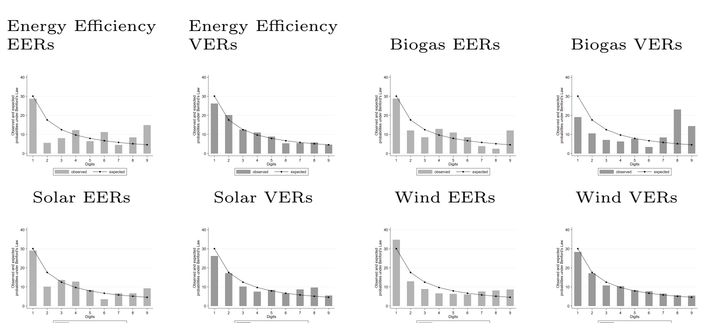


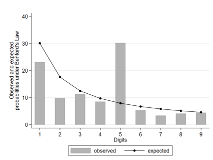
Figure 5: Benford's Law Statistics and FSD Distribution by Country

Program	N	m	d*	χ^2	LR	KS
China						
Verra Estimated Emission Reduction	1222	0.223**	0.240**	850.089**	540.234**	0.173**
Verra Verified Emission Reduction	2074	0.031**	0.045**	48.963**	45.199**	0.049**
Verra Estimated Emission Reduction (w/o AMS-III.AU)	951	0.050**	0.071**	48.967**	46.922**	0.054**
Verra Verified Emission Reduction (w/o AMS-III.AU)	1998	0.020	0.028	18.216*	17.514*	0.024
GS Estimated Emission Reduction	269	0.140**	0.194**	162.050**	122.155**	0.152**
GS Verified Emission Reduction	1757	0.198**	0.286**	2286.944**	1432.875**	0.356**
India						
Verra Estimated Emission Reduction	1102	0.014	0.022	5.070	5.015	0.013
Verra Verified Emission Reduction	3419	0.018*	0.026**	17.944*	18.233*	0.033**
GS Estimated Emission Reduction	569	0.057**	0.104**	56.862**	54.543**	0.105**
GS Verified Emission Reduction	1871	0.017	0.027	18.372*	17.130*	0.031*
Turkey						
Verra Estimated Emission Reduction	241	0.019	0.033	3.085	3.080	0.019
Verra Verified Emission Reduction	843	0.031	0.038	7.258	7.275	0.031
GS Estimated Emission Reduction	305	0.040	0.064	12.585	12.588	0.038
GS Verified Emission Reduction	1190	0.014	0.025	8.353	8.188	0.022

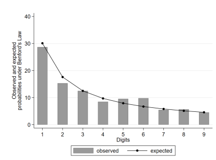
* indicates 95% and ** indicates 99% significance level.

FSD Visualization: China

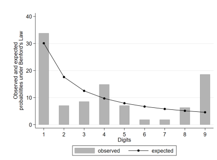
Verra EERs



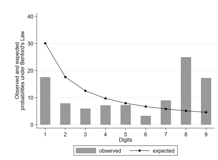
Verra VERs



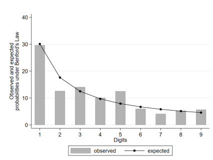
GS EERs



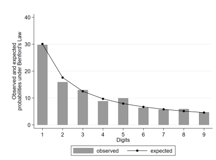
GS VERs



Verra EERs (w/o AMS-III.AU)

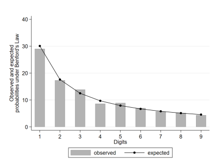


Verra VERs (w/o AMS-III.AU)

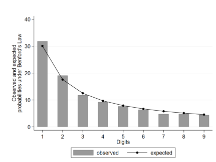


FSD Visualization: India

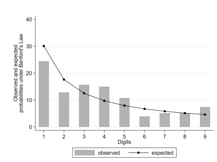
Verra EERs



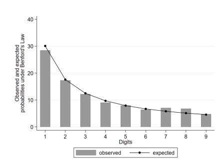
Verra VERs



GS EERs

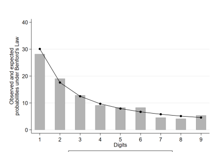


GS VERs

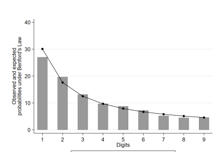


FSD Visualization: Turkey

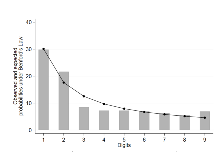
Verra EERs



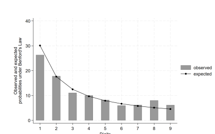
Verra VERs



GS EERs



GS VERs



6 Appendix: Supplementary Tables

Table S1: BL Statistics By Crediting Programs (based on second digit)

Program	N	m	d*	χ^2	LR	KS
Overall	37407	0.025**	0.029**	262.702**	252.017**	0.025**
American Carbon Registry (ACR)						
Estimated Emission Reduction	606	0.020	0.040	8.591	8.591	0.051*
Verified Emission Reduction	1703	0.013	0.023	8.140	8.098*	0.022
Climate Action Reserve (CAR)						
Estimated Emission Reduction	716	0.015	0.032	7.063	7.179	0.041
Verified Emission Reduction	2488	0.017	0.030*	20.178**	20.062**	0.038**
Verra						
Estimated Emission Reduction	4412	0.018**	0.029**	33.550**	32.652**	0.032**
Verified Emission Reduction	10505	0.014**	0.019**	13.574	13.539	0.008
Gold Standard						
Estimated Emission Reduction	3401	0.206**	0.236**	200.676**	175.098***	0.096**
Verified Emission Reduction	13576	0.014**	0.023**	64.353**	64.323**	0.025**

* indicates 95% and ** indicates 99% significance level.

Table S2: Project Type Frequencies and Percentages (Verra)

Project Type	Full		China		India	
	Freq.	Percent (%)	Freq.	Percent (%)	Freq.	Percent (%)
Agriculture Forestry and Other Land Use	1,476	0.33	533	0.44	175	0.16
Agriculture Forestry and Other Land Use; Energy industries (renewable/non-renewable sources)	1	0.00	-	-	-	-
Agriculture Forestry and Other Land Use; Energy industries (renewable/non-renewable sources); Livestock, enteric fermentation, and manure management; Transport; Waste handling and disposal	1	0.00	-	-	1	0.00
Agriculture Forestry and Other Land Use; Energy industries (renewable/non-renewable sources); Waste handling and disposal	2	0.00	-	-	-	-
Agriculture Forestry and Other Land Use; Livestock, enteric fermentation, and manure management	4	0.00	-	-	-	-
Agriculture Forestry and Other Land Use; Waste handling and disposal	2	0.00	1	0.00	-	-
Chemical industry	15	0.00	1	0.00	4	0.00
Chemical industry; Energy demand; Energy industries (renewable/non-renewable sources)	1	0.00	-	-	1	0.00
Chemical industry; Energy industries (renewable/non-renewable sources)	2	0.00	1	0.00	1	0.00
Chemical industry; Transport	2	0.00	1	0.00	1	0.00
Construction	6	0.00	-	-	-	-
Construction; Energy industries (renewable/non-renewable sources)	1	0.00	-	-	-	-
Construction; Manufacturing industries	7	0.00	-	-	-	-
Energy demand	481	0.11	-	-	192	0.17
Energy demand; Energy distribution; Energy industries (renewable/non-renewable sources)	1	0.00	-	-	-	-
Energy demand; Energy industries (renewable/non-renewable sources)	17	0.00	2	0.00	2	0.00
Energy demand; Energy industries (renewable/non-renewable sources); Waste handling and disposal	1	0.00	-	-	-	-
Energy demand; Waste handling and disposal	2	0.00	-	-	-	-
Energy distribution	8	0.00	1	0.00	-	-
Energy distribution; Energy industries (renewable/non-renewable sources); Transport	1	0.00	-	-	1	0.00
Energy distribution; Transport	1	0.00	-	-	-	-
Energy industries (renewable/non-renewable sources)	1,524	0.34	351	0.29	635	0.58
Energy industries (renewable/non-renewable sources); Fugitive emissions from fuels (solid, oil and gas)	2	0.00	1	0.00	-	-
Energy industries (renewable/non-renewable sources); Fugitive emissions from fuels (solid, oil and gas); Mining/mineral production	1	0.00	1	0.00	-	-
Energy industries (renewable/non-renewable sources); Livestock, enteric fermentation, and manure management	9	0.00	3	0.00	2	0.00
Energy industries (renewable/non-renewable sources); Livestock, enteric fermentation, and manure management; Transport	1	0.00	1	0.00	-	-
Energy industries (renewable/non-renewable sources); Livestock, enteric fermentation, and manure management; Waste handling and disposal	78	0.02	67	0.05	-	-
Energy industries (renewable/non-renewable sources); Manufacturing industries	19	0.00	5	0.00	3	0.00
Energy industries (renewable/non-renewable sources); Mining/mineral production	23	0.01	23	0.02	-	-
Energy industries (renewable/non-renewable sources); Transport	15	0.00	-	-	6	0.01
Energy industries (renewable/non-renewable sources); Waste handling and disposal	237	0.05	113	0.09	19	0.02
Fugitive emissions from fuels (solid, oil and gas)	24	0.01	1	0.00	-	-
Fugitive emissions from fuels (solid, oil and gas); Mining/mineral production	9	0.00	6	0.00	-	-
Fugitive emissions from production and consumption of halocarbons and sulphur hexafluoride	7	0.00	1	0.00	-	-
Fugitive emissions from production and consumption of halocarbons and sulphur hexafluoride; Manufacturing industries	1	0.00	-	-	-	-
Livestock, enteric fermentation, and manure management	40	0.01	3	0.00	-	-
Livestock, enteric fermentation, and manure management; Waste handling and disposal	57	0.01	52	0.04	3	0.00
Manufacturing industries	35	0.01	1	0.00	19	0.02
Manufacturing industries; Waste handling and disposal	2	0.00	1	0.00	1	0.00
Metal production	2	0.00	-	-	1	0.00
Metal production; Mining/mineral production	1	0.00	-	-	-	-
Mining/mineral production	31	0.01	1	0.00	-	-
Transport	41	0.01	3	0.00	9	0.01
Transport; Waste handling and disposal	5	0.00	-	-	5	0.00
Waste handling and disposal	222	0.05	48	0.04	21	0.02
Total	**4,418**		**1,222**		**1,102**	

Table S3: Project Type Frequencies and Percentages (GS)

Project Type	Full		China		India	
	Freq.	Percent (%)	Freq.	Percent (%)	Freq.	Percent (%)
A/R	63	1.77	3	1.1	6	1
Biogas - Cogeneration	29	0.82			1	0.17
Biogas - Electricity	114	3.2	33	12.13	7	1.17
Biogas - Heat	236	6.63	117	43.01	61	10.18
Biomass, or Liquid Biofuel - Cogeneration	8	0.22			5	0.83
Biomass, or Liquid Biofuel - Electricity	38	1.07	5	1.84	17	2.84
Biomass, or Liquid Biofuel - Heat	31	0.87	2	0.74	5	0.83
Energy Efficiency - Agriculture Sector	2	0.06			1	0.17
Energy Efficiency - Commercial Sector	11	0.31	1	0.37	1	0.17
Energy Efficiency - Domestic	1,973	55.45	9	3.31	214	35.73
Energy Efficiency - Industrial	21	0.59	8	2.94	3	0.5
Energy Efficiency - Public Sector	8	0.22			2	0.33
Energy Efficiency - Transport Sector	26	0.73			4	0.67
Geothermal	22	0.62	5	1.84		
Other	175	4.92	2	0.74	40	6.68
PV	27	0.76			2	0.33
Small, Low - Impact Hydro	166	4.67	19	6.99	12	2
Solar Thermal - Electricity	180	5.06	24	8.82	86	14.36
Solar Thermal - Heat	33	0.93	12	4.41	12	2
Wind	395	11.1	32	11.76	120	20.03
Total	3,558	100	272	100	599	100

Table S4: Country/Area Frequencies and Percentages (Verra)

Country/Area	Freq.	Percent (%)
China	1,222	27.66
India	1,102	24.94
Brazil	280	6.34
Turkey	241	5.45
United States	175	3.96
Madagascar	91	2.06
Colombia	88	1.99
South Africa	63	1.43
Kenya	57	1.29
Vietnam	56	1.27
Thailand	55	1.24
Germany	45	1.02
Peru	42	0.95
Mexico	40	0.91
Indonesia	38	0.86
Uganda	38	0.86
Argentina	36	0.81
Chile	30	0.68
Zambia	30	0.68
Canada	28	0.63
Uruguay	26	0.59
Malawi	24	0.54
DR Congo	20	0.45
Cambodia	19	0.43
Bangladesh	18	0.41
Malaysia	18	0.41
Paraguay	18	0.41
Tanzania	18	0.41
Ghana	17	0.38
Laos	17	0.38
Guatemala	16	0.36
Australia	15	0.34
Pakistan	15	0.34
Rwanda	15	0.34
South Korea	15	0.34
Nepal	14	0.32
Philippines	14	0.32
Senegal	14	0.32
Italy	13	0.29
Myanmar	13	0.29
Congo	10	0.23
Mozambique	10	0.23
Nigeria	9	0.20
Sri Lanka	9	0.20
Honduras	8	0.18
Morocco	8	0.18
Papua New Guinea	8	0.18
Belize	7	0.16
Bolivia	7	0.16
Ethiopia	7	0.16

Table S5: Country Frequencies and Percentages (GS)

Country	Freq.	Percent (%)
India	599	16.87
Turkey	308	8.68
China	272	7.66
Kenya	243	6.85
Uganda	218	6.14
Rwanda	192	5.41
Bangladesh	131	3.69
Nepal	118	3.32
Malawi	109	3.07
Nigeria	102	2.87
Burkina Faso	99	2.79
Mozambique	79	2.23
Vietnam	72	2.03
Ethiopia	66	1.86
Eritrea	46	1.30
South Africa	46	1.30
Tanzania	46	1.30
Zambia	45	1.27
Thailand	36	1.01
Honduras	34	0.96
Myanmar	33	0.93
Ghana	31	0.87
Brazil	29	0.82
Madagascar	29	0.82
DR Congo	28	0.79
Togo	28	0.79
Dominican Republic	25	0.70
Indonesia	23	0.65
Sierra Leone	21	0.59
Zimbabwe	21	0.59
Mongolia	20	0.56
Colombia	19	0.54
Peru	19	0.54
Laos	18	0.51
Switzerland	17	0.48
Guatemala	15	0.42
Cambodia	14	0.39
Nicaragua	12	0.34
Pakistan	12	0.34
Egypt	11	0.31
International	11	0.31
Senegal	11	0.31
Mali	10	0.28
Mexico	10	0.28
Benin	9	0.25
Cameroon	9	0.25
Gambia	9	0.25
Haiti	9	0.25
Philippines	9	0.25
Sri Lanka	9	0.25