Global variation in GHG emissions disclosure quality:

Evidence from irregularities in reported emission numbers

Emma-Riikka Myllymäki

Audencia Business School

ermyllymaki@audencia.com

Ly Pham

University of Vaasa

ly.pham@uwasa.fi

Jukka Sihvonen

Aalto University

jukka.sihvonen@aalto.fi

March 2026

Acknowledgements: We appreciate the comments from Sadok El Ghoul and Juha Kinnunen.

Global variation in GHG emissions disclosure quality:

Evidence from irregularities in reported emission numbers

Abstract

As corporate climate performance gains importance, the reliability of greenhouse gas (GHG) emissions disclosures has come under scrutiny. This paper investigates how national-level characteristics—rule of law, transparency, climate awareness, and environmental performance—shape the quality of corporate GHG emissions reporting across 42 countries. Using these factors, we classify countries into LOW, MIDDLE, and HIGH institutional clusters and assess reporting irregularities through three techniques: Benford's Law conformity, small year-to-year reductions, and base-ten threshold effects.

Our analysis shows that Benford's Law deviations are similar across all clusters while the other two methods show distinct cross-country patterns. Firms in high-engagement institutional environments (HIGH) are more likely to report small year-to-year reductions in emissions and exhibit stronger base-ten threshold behavior, consistent with stronger pressure to signal continuous climate improvement. Firm-level characteristics—including emission targets, sensitive industries, and external assurance—help explain these irregularities, with Big 4 assurance linked to higher reporting quality. These findings contribute to the literature on sustainability reporting by providing large-sample quantitative evidence on the reliability of global GHG disclosures. The findings highlight how stronger institutional environments can both enhance transparency and create pressure that encourages strategic reporting, thus offering insights for regulators, standard setters, and assurance providers.

Keywords: *climate; GHG emissions; reporting errors; irregularities; reporting manipulation; Benford's Law*

1. Introduction

As stakeholders become increasingly concerned about companies' climate performance (e.g., Eccles and Klimenko, 2019; Krueger et al., 2020), the reliability of corporate greenhouse gas (GHG) emissions disclosures becomes even more important (e.g., Berg et al., 2024; Busch et al., 2023; Talbot and Boiral, 2018). GHG emissions are widely regarded as a key indicator of corporate climate performance, and their disclosure plays a critical role in enabling informed decision-making by both stakeholders and reporting entities. Prior research has shown that GHG emissions disclosures are considered by capital markets in firm valuation decisions (Griffin et al., 2017; Matsumura et al., 2014) and by lenders when assessing credit risk and making lending decisions (Jung et al., 2018). For such disclosures to be meaningful, their reporting should be of high quality.

GHG reporting has become more standardized over time, particularly with the adoption of the GHG Protocol by many firms. Still, significant challenges continue to compromise the quality of reported data. These include, for example, the use of subjective judgment, reliance on estimates, and challenges in data collection, all of which may result in reporting errors or even be exploited for intentional misreporting (e.g., Kolk et al., 2008; Depoers et al. 2016; Talbot and Boiral, 2018; Berg et al., 2024). More research is needed on the accuracy of reported GHG emissions (e.g., Busch et al., 2023). Our first objective is to introduce a quantitative framework for evaluating the quality of reported emissions data by applying multiple irregularity detection techniques. In addition to assessing conformity with Benford's Law (Benford, 1938)—which provides expected digit distributions under randomness and thus signals potential manipulations—we also examine patterns such as small year-to-year reductions in emissions and base-ten threshold effects. Together, these methods allow us to generate broader and more robust evidence on the reliability of corporate GHG emissions disclosures.

The second objective of this paper is to examine international differences in the quality of corporate GHG emissions reporting across 42 countries. Drawing on prior literature on the role of institutional environments in shaping corporate disclosure (e.g., Ball et al., 2000; Leuz et al., 2003; Srinivasan et al., 2015; Cahan et al., 2016; Marquis et al., 2016), we posit that countries' governance quality and climate-related engagement shape firms' incentives and capabilities to produce reliable emission numbers, and hence, affect the accuracy of reported GHG emissions.

Leuz et al. (2003) use cluster analysis to group countries with similar legal and institutional characteristics to examine differences in earnings management across institutional clusters. In a similar vein, we apply cluster analysis to classify 42 countries into three groups based on four key dimensions: (i) *rule of law*, capturing respect for and enforcement of laws (e.g., Pinnuck et al., 2021; Cahan et al., 2016); (ii*) transparency*, capturing corruption perceptions (e.g., Ioannou and Serafeim, 2012; Leuz et al., 2003)[1]; (iii) *climate awareness*, reflecting public knowledge and beliefs about climate change (e.g., Dhaliwal et al.,2012)[2]; and (iv) *environmental performance*, a comprehensive indicator that assesses a country's performance in climate change mitigation, environmental health and ecosystem vitality, and also incorporates the strength of environmental policy framework (e.g., Choi and Luo, 2021; Cahan et al., 2016).[3] The first two dimensions are used to proxy for a country's governance quality, whereas the latter two serve as proxies for its climate-related engagement. The clustering reveals distinct institutional environments that may shape corporate climate reporting behavior:

---

[1] Both rule of law index and transparency index are obtained from the World Bank database.

[2] Climate perception index: https://www.socialprogress.org/thematic-webpages/climate-perceptions-index

[3] The Environmental Performance Index is developed by the Yale Center for Environmental Law and Policy: https://epi.yale.edu/.

- LOW cluster: This group includes countries that score low on all four dimensions. These countries often have weaker legal enforcement, higher levels of corruption, lower societal engagement with climate issues, and poorer overall environmental outcomes. Firms in this cluster may lack the necessary regulatory oversight, technical capacity, and stakeholder pressure to prioritize high-quality emissions reporting. Moreover, given the lower salience of climate concerns in the national discourse, firms are unlikely to face reputational consequences for poor reporting, reducing both their motivation and capacity to improve data accuracy. Brazil, China, and Russia are examples of countries found to belong to the LOW cluster.
- HIGH cluster: Countries that fall into this group are characterized by strong legal enforcement, low levels of corruption, high societal engagement with climate issues, and better overall environmental outcomes. Countries with stronger institutions may shape companies' incentives and capacity for accurate reporting. However, because these countries have adopted stronger climate engagement, companies may face substantial reputational pressure to show continuous improvement, increasing the risk of opportunistic behavior and GHG emissions manipulation. Sweden, Finland, Germany, and the Netherlands are examples of countries found to belong to the HIGH cluster.
- MIDDLE cluster: This cluster includes countries that exhibit mid-range governance and environmental indicators. Firms in these countries typically operate in environments with moderate regulatory enforcement, stakeholder pressure and alignment with climate goals. Examples of countries in this cluster are the United States, Spain, and Italy.

Benford's Law has been used in prior accounting research to detect irregularities in financial statement data, often interpreted as potential errors or manipulation (e.g., Amiram et al., 2015). We apply Benford's Law to the reported Scope 1 and Scope 2 emission (location-based) numbers within each institutional cluster to assess the quality of GHG emissions data.

The results show that all three clusters have substantial deviations from Benford's Law expected distribution.

Our second approach for identifying irregularities in reported emissions is to examine whether firms strategically report small reductions in emissions (year-to-year changes just below zero). Prior studies show that firms manage performance to meet or narrowly beat benchmarks—such as reporting small positive earnings to avoid losses (Burgstahler & Dichev, 1997; Beatty et al., 2002). We posit that similar incentives may drive strategically reported small reductions in emissions. The results show that this behavior is most pronounced in HIGH cluster, where both Scope 1 and Scope 2 emissions exhibit clear discontinuities at zero, consistent with firms facing strong pressure to demonstrate climate progress. The MIDDLE group also shows signs of such behavior, though more moderately and primarily in relative Scope 2 emissions. In contrast, firms in LOW-governance environments display only weak evidence of small-reduction clustering. Together, these patterns suggest that incentives to signal incremental emissions improvements differ across institutional settings and may contribute to reporting irregularities.

Our third approach is to examine whether firms manage reported emissions around salient base-ten thresholds—for example, values just below 10,000 or 1,000,000 tons. Prior research documents that firms strategically bunch reported numbers around psychologically salient round-number thresholds—for example, revenues just above base-ten cutoffs (Stice et al., 2022) or gross margins at highly accessible round values (Cedergren & Li, 2024). We apply similar logic for reported emissions. The analysis reveals systematic bunching below these thresholds, particularly for Scope 1 emissions across all institutional clusters, indicating that firms may intentionally report figures just below psychologically meaningful round numbers. This behavior is strongest in the HIGH cluster, moderate in the MIDDLE cluster, and weaker but still present in LOW cluster. For Scope 2 emissions, threshold effects appear mainly in

HIGH-governance countries, where firms have greater market flexibility to adjust purchased-energy footprints. Together, these patterns suggest that firms may fine-tune emissions to avoid round-number thresholds, consistent with subtle forms of reporting management.

Overall, these findings suggest that stronger institutional environments do not necessarily prevent GHG misreporting. One possible explanation is that firms operating in countries with ambitious climate agendas face heightened pressure to demonstrate progress, which may encourage selective, strategic, or otherwise overly optimistic reporting practices.

To further examine firm-level characteristics that could affect reporting quality, such as the existence of emissions targets, the industry classification, the existence of CSR external auditors, and whether the CSR auditor is a Big4 firm, we divide firms within each cluster based on these indicators and apply Benford's Law analysis and base-ten threshold analysis to the subsamples. We also conduct logit regression of those indicators on the likelihood of reporting small emissions reductions. The results are consistent for Benford's law analysis and small reduction analysis: firms with emission target, firms belonging to environmentally sensitive industries, and firms with external CSR auditors exhibit higher deviations from Benford's Law and more likely to report small emissions reductions. The findings suggest that those firms may be under additional pressure, increasing the likelihood of emissions manipulation, or that their complex operations and structure complicate the emission calculation. Nevertheless, among firms with CSR external assurance, clients of Big4 firms show fewer deviations from Benford's Law and are less likely to report small reductions. This is consistent with the common view in the accounting literature that Big4 firms is associated with higher audit quality.

This study makes two key contributions to the literature. First, it offers large-sample quantitative approaches to evaluating the reliability of climate disclosures by statistically analyzing reported GHG emission numbers. This complements prior research that has primarily relied on content analysis of GHG emission reports or disclosure indicators from various databases, such as CDP datasets (e.g., Kolk et al., 2008; Comyns and Figge, 2015; Liesen et al. 2015; Talbot & Boiral, 2018; Dragomir, 2012; Ding et al., 2023; Döring et al., 2023). These studies explore, for example, the extent and completeness of GHG disclosures, their adherence to reporting standards or frameworks, and the presence of external assurance. However, there is limited prior research examining whether the underlying numbers are free from error or manipulation. Our approach addresses this gap by enabling us to detect irregularities, thereby examining the plausibility of reported numbers.

Second, we contribute to the literature on cross-national differences in corporate reporting quality (e.g., Cahan et al., 2016; Marquis et al., 2016; Srinivasan et al., 2015; Leuz et al., 2003; Ball et al. 2000) by examining specifically GHG emissions reporting accuracy and how it is shaped by the institutional environment. Our findings show that the relationship is not straightforward. We posit that even with strong governance, a country's higher climate engagement may induce pressure to signal better climate performance without fully achieving it, especially when actual reductions are costly or difficult. High-governance environments also entail greater scrutiny by regulators, NGOs, and the media, which raises reputational risks. To manage this risk, firms may employ more sophisticated forms of misreporting (e.g., rounding emissions downward). Given the still early stage of climate reporting, the focus may be on whether GHG emissions are disclosed, and not on the precision and accuracy of the reported figures.

The second section discusses the background literature. The third section describes our data and research design, while the fourth section presents the empirical results. The last section concludes our study.

2. Background

2.1. GHG emissions reporting quality

The transition toward a low-carbon economy has intensified the demand for reliable information on corporate climate performance, with GHG emissions serving as a central indicator. The 2015 Paris Agreement underscored the urgency of addressing climate change and reinforced the need for reliable GHG emissions data to support decision-making by both stakeholders and reporting entities. In response, several disclosure initiatives have been developed, for example, the Task Force on Climate-Related Financial Disclosure (TCFD, 2017). Investors increasingly integrate climate risk exposure into their capital allocation decisions, and demand greater transparency regarding climate risk (Krueger et al., 2020).

Although many firms have undertaken efforts to measure, manage, and reduce their GHG emissions, the production of accurate and decision-useful emissions data remains challenging. GHG data frequently rely on estimates, managerial judgment, and complex data collection processes, introducing potential for both unintentional error and deliberate misstatement (Kolk et al., 2008; Depoers et al., 2016; Talbot & Boiral, 2018; Berg et al., 2024). Concerns about the quality of corporate GHG emissions reporting have been raised for a long time (e.g., UNEP FI, 2013), and reporting quality— even for Scope 1 emissions—may not have significantly improved (Busch et al., 2023) despite harmonization efforts through standards such as the GHG Protocol.

The extant literature using content analysis provides evidence of the lack of quality in GHG emissions disclosures. Talbot and Boiral (2018), for example, analyze sustainability reports of energy-sector firms applying GRI standards and identify impression management strategies as well as shortcomings in the assurance process. Comyns and Figge (2015) evaluate the quality of GHG reporting in the oil and gas sector across seven dimensions and document only modest improvements over time. Liesen et al. (2015) assess disclosures against GHG Protocol, GRI, and CDP guidelines, reporting that only 15% of disclosing firms provide what the authors classify as complete information. Dragomir (2012) highlights that the major European oil and gas companies examined have reports containing unexplained figures and methodological inconsistencies.

More recent work has applied textual analysis to climate-related disclosures (Ding et al., 2023) or used CDP data to determine the level of detail and external verification of GHG disclosures (Döring et al., 2023). A smaller stream of research has examined the consistency of reported GHG emissions across disclosure channels. Depoers et al. (2016) compare emissions reported in corporate reports with those submitted to the CDP and find systematically lower amounts in the former. The authors attribute this discrepancy to the exclusion of certain emission categories from sustainability reports, where firms use their own standards to disclose their climate performance.

2.2. Institutional environment affecting GHG emissions reporting

Firms are embedded within broader social and institutional contexts, and their decision-making is shaped by the characteristics of these institutional environments (e.g., Ioannou and Serafeim, 2012; Campbell, 2007). Consequently, institutional characteristics can be expected to influence both the incentives and capabilities of firms to accurately report their GHG emissions.

We first consider the role of a country's governance quality. Prior research on financial accounting suggests that the extent of country-specific enforcement mechanisms and compliance with laws and regulations can shape firms' financial reporting behavior (e.g., Srinivasan et al. 2015; Leuz et al. 2003). In the sustainability reporting domain, evidence suggests that firms domiciled in jurisdictions with stronger rule of law exhibit higher levels of CSR disclosure (Cahan et al., 2016) and are more likely to restate sustainability reports when errors are discovered, likely due to higher litigation risk (Pinnuck et al., 2021).

Second, given the focus on GHG emissions reporting, we consider countries' environmental orientation, particularly with respect to climate change. Countries vary significantly in their climate ambition and stakeholder expectations (e.g., Choi and Luo, 2021). Firms operating in countries with stronger climate commitments are more likely to experience pressure to report on GHG emissions (e.g., Liesen et al., 2015). Choi and Luo (2021), for example, find that the negative association between carbon emissions and firm value is more pronounced in countries with carbon pricing mechanisms and stringent environmental regulations.

Based on the prior literature, GHG reporting quality may vary systematically across institutional contexts. In countries with *weak governance structures and low climate salience,* enforcement mechanisms are often limited, and firms face little reputational risk for poor reporting. In such settings, incentives to invest in robust GHG measurement and reporting systems may be low, and technical capacity may be underdeveloped, leading to a higher likelihood of reporting errors. These errors may arise unintentionally, due to a lack of expertise or inadequate infrastructure, or may reflect opportunistic misreporting when consequences are minimal.

By contrast, in countries with *strong governance quality and high levels of climate engagement*, firms are likely to subject to more rigorous oversight by regulators, investors, and civil society. This institutional environment fosters accountability through mechanisms such as legal liability, investor activism, and media scrutiny, which can incentivize firms to invest in accounting systems for emissions and align with best reporting practices. However, the heightened pressure to demonstrate progress can also create incentives for misreporting, such as selectively disclosing favorable data or adjusting figures within discretion available. This aligns with earlier findings in the sustainability reporting literature, which show that firms under scrutiny often engage in impression management or provide poor quality disclosures to preserve legitimacy (e.g., Prado-Lorenzo and Garcia-Sanchez, 2010; Dragomir, 2012; Liesen et al., 2015; Talbot and Boiral, 2018). Therefore, firms operating in highly engaged institutional environments may face dual pressures: greater accountability that encourages accuracy, but also reputational incentives that may increase the risk of opportunistic reporting behavior. Consequently, we examine whether and how the accuracy of reported GHG emissions varies across institutional environments characterized by rule of law, transparency, climate awareness, and environmental performance.

3. Research Design and Sample Selection

3.1. Cluster analysis for grouping countries

We use cluster analysis to classify 42 countries into three different clusters based on the four variables that were discussed in section 2.2: Yale EPI, Rule of law, Climate change awareness, and Country transparency index. Rule of law and Country transparency index (corruption index) belong to the country's governance quality aspect that we consider affecting the quality of emissions disclosures. Both Rule of law and Country transparency index (Corruption index) have been shown to be important institutional characteristics that affect the disclosure quality (Choi & Luo, 2021; Leuz et al, 2003), while low corruption is associated with better corporate social performance (Ioannou & Serafeim, 2012, Lee et al., 2026). Climate change awareness and Yale EPI capture the aspect of countries' environmental orientation. Dhaliwal et al (2012) found that the level of public awareness of CSR plays an important role in the functioning of CSR disclosures in financial markets. In countries with strong stakeholder orientation, characterized by high awareness of climate change and high environmental performance, societal expectations for corporate social responsibility are higher, thus firms are expected to provide more CSR disclosures (Tsang et al., 2024).

Clustering is a technique used to classify objects into groups so that within each group, objects are similar (Chen, 2009). Clustering has been used in accounting research to classify firms (Jensen, 1971), municipalities (Johansson & Siverbo, 2011), and countries (Leuz et al., 2003). Two widely used methods for clustering are k-median and k-means. In this paper, we use k-median for the clustering process as recent studies have shown that k-median outperforms other clustering methods (Brusco et al., 2017). Nevertheless, when we follow Leuz et al. (2003) and use k-mean clustering for standardized variables, the inferences from the findings remain similar.

3.2. Finding irregularities in reported emissions

3.2.1. Benford's Law method

To study the quality of reported GHG emissions data, we utilize Benford's Law (Benford, 1938). According to Benford's Law, the distribution of leading digits in many naturally occurring datasets follows a predictable pattern. For example, the first digit of the number has expected frequencies as follows: [4]

$$Probability(D_1 = d_1) = \log\left(1 + \frac{1}{d_1}\right);\ d_1 = (1, 2, 3 \dots 9)$$

And the first two digits have expected frequencies as:

[4] Following this formula, the expected frequencies for the first digit from 1 to 9 are: 1: 30.103%, 2: 17.609%, 3: 12.494%, 4: 9.691%, 5: 7.918%, 6: 6.695%, 7: 5.799%, 8: 5.115%, 9: 4.576%

$$Probability(D_1D_2 = d_1d_2) = \log\left(1 + \frac{1}{d_1d_2}\right);\ d_1 = (1, 2, 3 \ldots 9), d_2 = (0, 1, 2 \ldots 9)$$

Originally, Benford (1938) does not specify which type of data beyond natural events should or should not follow the expected frequencies. However, some rule-of thumb criteria were later developed to provide guidance on what kinds of data could follow Benford's Law. These include: (1) data should represent the sizes of facts or events, (2) there should be no built-in minimum or maximum values except for a minimum of 0 in some cases, (3) data should not consists of identification numbers or labels such as personal identifiers, bank accounts, and (4) datasets should contain more small values than large ones (Nigrini, 2012).

Accounting data such as market values or revenues have been shown to follow Benford's Law (Nigrini, 2012) and accounting research has utilized this method. For example, Amiram et al. (2015) used Benford's Law to study financial statement errors, while Kinnunen and Koskela (2003) used it to detect cosmetic earnings management. Qu et al. (2020) apply Benford's law to examine the financial reports of nonprofit organizations. Le and Lobo (2022) studied how audit quality is related to the conformity of financial statement numbers to Benford's law and found that conformity increases with audit quality, especially for income statement items. However, most of the studies suggest that the deviation from Benford's Law is not a definitive evidence of fraud but rather a signal that warrants further investigation.

Similar to accounting data, the GHG emissions data should also follow Benford's law for the several reasons. First, they occur naturally rather than being artificially bounded by human conventions, and they span over a large range of magnitudes. Second, GHG emissions are calculated from different sources; they are results of mathematical process and this type of data usually follows Benford's law (Durtschi et al., 2004). In addition, GHG emissions data have more small values than large ones, and the ratio of mean to median is quite large (Scope1 has mean of 1 477 774, median of 11 232, and skewness of 118). As Wallace (2002) suggests, if a dataset has a high mean-to-median ratio and high skewness, it is more likely to follow Benford's Law.

Empirically, GHG emissions have been tested for Benford conformity in several studies. Dumas and Devine (2000) used North Carolina air pollution data to provide empirical evidence that the digital frequency analysis can detect pollution-data irregularities. Coracioni (2020) examines whether emissions follow Benford's Law as a basis for environmental policy decisions. Balakrishnan and Beemamol (2023) tested daily emissions data and found that this data conforms to Benford's Law in 2020 but not in 2021.

Overall, both theoretical reasoning and empirical evidence indicate that emissions data should follow Benford's Law, and deviations from the expected digit frequencies may reveal irregularities or other meaningful features of the data.

We begin the analysis by comparing the first-digit frequency of Scope 1 and Scope 2 (location-based) emissions with the expected distribution according to Benford's Law for the full sample. The distributions for Scope 1 and Scope 2 are presented in Figures 1A and 1B, respectively, with the supporting data is shown in Figure 1C. These figures indicate that the first digits of the reported emissions generally follow Benford's Law.

The objective of this study is to compare the quality of GHG emissions data across different institutional clusters. However, the results of Benford's Law analysis are greatly affected by sample size. In larger samples, the digit distribution is expected to align more closely with Benford's Law, and thus even small deviations can be statistically significant. In contrast, smaller samples tolerate higher deviations. As a result, it is difficult to compare results across clusters of different sizes.

To overcome this issue, we utilize a random sampling approach and perform the analysis on equal-sized subsamples. Specifically, from each cluster, we randomly draw 300 observations and perform Benford's Law analysis. We repeat this process (random sampling and analysis) 1 000 times to ensure that our results do not occur by chance.

To assess conformity with Benford's Law, several measures can be used. The most widely used measure according to prior literature (Amiram et al., 2015; Cleary & Thibodeau, 2005; Nigrini, 2012) is the mean absolute deviation (MAD), which is the average of the absolute differences between the actual and expected distributions. We report the average MAD value over 1000 trials, as well as the minimum and maximum MAD values observed. In addition, we apply the Kolmogorov–Smirnov test and report its statistic (the maximum absolute deviation MAX). [5] Originally, Kolmogorov-Smirnov test accounts for sample size, and thus differences in sample size could bias cross-cluster comparison. However, this should not be a problem in our case, because we apply the tests for equal random samples of 300 observations each.

3.2.2. Small reduction in reported emissions

Prior studies in accounting research document that firms often engage in earnings management by reporting small, positive increases in earnings just above key benchmarks such as zero earnings or prior-year performance (Burgstahler & Dichev, 1997). Studies have found unusually high frequencies of observations just above these cutoffs, consistent with managers using discretion to avoid reporting losses or earnings declines (e.g., Beatty et al, 2002; Byzalov & Basu, 2019).

Following the same logic, we examine whether firms strategically report small reductions in emissions compared to previous years. If firms do so, we should observe a comparable excess mass just below the zero-change thresholds, mirroring the well-documented

[5] Another common method is using the Z-statistic; however, it can only evaluate one digit at a time. We do not apply this method.

pattern found around earnings benchmarks. To test for this discontinuity in distribution around zero emission change, we utilize the local polynomial density estimators proposed by Cattaneo et al. (2020), building on the original McCrary (2008) test. In addition, to examine how firm and country characteristics affect this behavior, we run a logit regression on the indicators of reporting small reductions in emissions.

3.2.3. Base-Ten threshold effects in reported emissions

Prior research in accounting has documented the behavior of bunching around certain thresholds. Cedergren & Li (2024) found significant bunching around salient thresholds of gross margins, such as highly round numbers (10%, 30%, 40%), or neatly divisible numbers (25% or 75%). Similarly, Stice et al. (2022) document that firms tend to report revenues just above the base-ten thresholds, such as 10 million, 20 million, 1 billion. These papers contributed beyond the typical meet-and-beat earnings management literature, as they show that the pressure to beat targets is only one explanation for the phenomenon. Stice et al. (2022) found that the bunching above base-ten threshold exists even when there is no explicit target. Cedergren & Li (2024) argue that these round numbers are more accessible and easier to remember, thus the cognitive accessibility makes them intrinsic reference points. In similar notion, Christoffersen et al. (2026) found that the intrinsic motivations which are based on psychological and non-economic factors play a significant role in explaining earnings benchmark beating, even when controlling for extrinsic motivations or in the absence of those motivations.

Following this logic, we examine whether firms intentionally avoid certain thresholds when reporting emissions, even when there is no explicit target. We follow Stice et al. (2022) to build a list of thresholds which is presented in Panel A of Table 6. For each threshold, we count the number of observations just below and just above the threshold with chosen bins widths (0.025, 0.05, 0.1, and 0.15). We calculate the ratio of observations just below to those just above, and test the discontinuity with binomial tests and the local polynomial density estimators proposed by Cattaneo et al. (2020), building on the original test by McCrary (2008).

3.3. Data

We begin our data collection process with the Trucost Environmental dataset. Trucost dataset provides data on Greenhouse gas (GHG) emissions for over 20,000 companies around the world.[6] Trucost data come from different sources, including companies' publicly available reports or Trucost's own estimations based on an environmental profiling model (Azar et al., 2021). In this paper, we want to investigate the quality of firms' reported emissions, therefore we take only observations where emissions (Scope 1 and Scope 2) are reported by the firms. We begin with 27,905 firm-year observations with available data on reported Scope 1 emissions, covering 10,663 unique firms of 85 countries from 2020 to 2024. The sample without missing values for reported Scope 2 has 25,883 observations.

To reduce noise in clustering and data analysis, we exclude countries with fewer than 50 observations in the sample, reducing 355 observations. We further delete 4,474 duplicate observations. Moreover, we exclude countries without necessary data on country-level characteristics, reducing the sample by 70 firm-year observations. As a result, our final sample contains 23,000 observations, covering 10,448 unique firms from 42 countries. Panel A of Table 1 presents the sample composition by year, showing a general increase in the number of observations over time and a notable jump in year 2023.

[Table 1 HERE]

Panel B of Table 1 displays the number of firm-year observations per country, along with descriptive statistics for four country-level variables used in the cluster analysis. The United

[6] https://www.marketplace.spglobal.com/en/datasets/trucost-environmental-(46)

States and Japan have the highest number of observations, with each country accounting for more than 13% of the sample.

Transparency is highest in Denmark and New Zealand and lowest in Russia and Mexico. The rule of law scores highest in Finland and Norway and lowest in Russia and the Philippines. Finland and Germany show the highest levels of climate awareness and environmental performance. In contrast, Indonesia and Saudi Arabia report the lowest climate awareness, while India and the Philippines have the lowest environmental performance scores.

4. Empirical results

4.1. Cluster analysis

Table 2 reports the results of the clustering process. Panel A presents the classification of countries into each cluster. Panel B presents the cluster profiles with the average values of the four variables used in the clustering analysis. Cluster 1 includes Brazil, China, Colombia, India, Indonesia, Malaysia, Mexico, Nigeria, Pakistan, Peru, Philippines, Russia, Saudi Arabia, South Africa, Thailand, and Turkey. This cluster is referred to as "LOW", as it is characterized by low rule-of-law scores, low transparency, and low environmental performance and awareness.

The second cluster, referred to as "MIDDLE", has better rule of law, higher transparency, environmental performance, and greater climate awareness compared to the LOW cluster. It consists of 13 countries: Chile, Hungary, Hong Kong, Greece, Israel, Italy, Poland, Portugal, Korea Republic (South Korea), Spain, Taiwan, United Arab Emirates, and the United States of America. The third group, referred to as "HIGH", has the highest scores for all variables and includes Australia, New Zealand, Canada, Japan, Singapore, and other countries in Europe.

Panel C reports the number of observations and descriptive statistics by cluster. The HIGH cluster contains the largest share of observations (39.18%), followed by the MIDDLE cluster with roughly one-third of the sample, and the LOW cluster with 27.72%. On average, firms in the LOW cluster exhibit the highest levels of both Scope 1 and Scope 2 emissions. However, the emissions are highly skewed, and the median values of Scope 1 is are lowest in the LOW cluster, while the MIDDLE and HIGH clusters have similar values. The median of Scope 2 is highest in the MIDDLE cluster, followed by the LOW cluster, and lowest in the HIGH cluster.

The prevalence of emission targets is highest in the HIGH cluster (64%), followed by the MIDDLE cluster (50%) and the LOW cluster (36%). The existence of CSR audit and the use of Big 4 as CSR auditors follow the same patterns. The MIDDLE cluster has the lowest proportion of observations in sensitive industries (38%), while LOW and HIGH clusters have similar values (43% and 45%, respectively).

[TABLE 2 HERE]

To illustrate how institutional characteristics define the clusters, we map the countries in Figure 2, which visually highlights the resulting groupings.

4.2. Irregularities in reported emissions

4.2.1. Benford's Law method

Table 3 presents the results of the Benford's Law analysis for the three clusters. Panel A presents the guidance from Drake and Nigrini (2000) for non-conformity of the dataset based on MAD values. Panel B reports the analysis results for the first digit, Panel C for the first two digits, and Panel D for the second digit.

All three Panels reveal that all three clusters have similar levels of deviation, both for Scope 1 and Scope 2. Over 1,000 random samplings, the average MAD value for the first digit for all clusters is 0.014 (Panel B), which is considered to violate Benford's Law for the first digit. When considering the distribution of MAD over 1,000 random samples, we cannot find support for non-conformity (comparing with 0.012), but the test against marginal conformity (0.008) is significant. One exception is the Scope 2 (location-based) for HIGH cluster, it is not significantly higher than 0.008, indicating conforming with Benford's Law.

Similarly, the MAD value for the first two digits in Panel C is 0.003, higher than the non-conformity threshold of 0.0018. MAD values of the second digits are around 0.014, at the borderline of violating conformity. For brevity, we do not report the Chi-square statistics and results of the Kolmogorov–Smirnov tests, but they are consistent with the results using MAD values. Second digit analysis reveals no sign of non-conformity.

[TABLE 3 + 4 HERE]

Table 4 provides evidence of Benford's Law conformity in first digit distribution across different subsamples.

Emission targets (Panels A and B). Firms with targets exhibit slightly higher first-digit deviations than firms without targets, particularly in LOW jurisdictions (Scope 1: MAD increases from 0.013 to 0.015; Scope 2: MAD increases from 0.014 to 0.016). In MIDDLE cluster, deviations are broadly unchanged; in HIGH cluster, they increase slightly (Scope 1: MAD increases from 0.014 to 0.015; Scope 2: MAD increases from 0.013 to 0.014). MAX values show the same pattern as MAD.

Sensitive industry (Panels C and D): When industries are not classified as sensitive, the digit frequency is relatively stable across clusters, with no cluster exhibiting systematically higher irregularities. This suggests that non-sensitive industries follow similar reporting patterns regardless of cluster membership. Within sensitive industries, Scope 1 deviations increase modestly across all clusters. The increase is larger for LOW and HIGH clusters, where firms in sensitive sectors exhibit the greatest irregularity in first-digit patterns. This can be explained by the fact that the HIGH cluster faces intense stakeholder oversight (investors, rating agencies, NGOs, regulators). For sensitive sectors, firms face incremental financial and reputational penalties for abrupt emission spikes. Therefore, the combination of complex measurement and strong external pressure can create adjustments that affect the first digit distribution of Benford's Law. Scope 2 is less affected by industry sensitivity and remains stable, with only minor changes. Purchased electricity often has tariff structures and grid-emission factors, which give firms less discretion than Scope 1 emissions. Therefore, the sensitive vs. non-sensitive effect is much smaller in Scope 2. The MAX values show the same pattern as MAD. Panel D shows that Scope 2 (location-based) of HIGH cluster is conformed to Benford's Law.

CSR assurance (Panels E and F). For Scope 1, assured firms exhibit higher first-digit deviations in all clusters. This trend might be due to the fact that firms with external audits are larger, more complex reporters (especially in HIGH cluster), but also under greater pressure for performing well in environmental aspects. Without external audit, first-digit conformity is borderline for all clusters, but all clusters exhibit clear non-conformity when emissions are externally assured. The deviation is highest in HIGH cluster. For Scope 2 (location-based), the effect is heterogeneous: deviations rise in LOW cluster but fall slightly in HIGH cluster, with MIDDLE remains unchanged. This could be explained by greater supplier standardization in more advanced markets. In all subsamples, MAX results indicate larger single-digit gaps when CSR auditors are involved, especially for Scope 1.

Big 4 assurance (Panel G and H). The presence of a Big 4 auditor appears to enhance reporting quality. It is linked to lower Scope 1 first-digit deviations among LOW and MIDDLE clusters, and to lower Scope 2 deviations among MIDDLE and HIGH clusters. A small Scope 2 increase in LOW cluster likely reflects transitional effects from methodology upgrades and boundary redefinitions introduced by audit firms. In all subsamples, MAX results indicate fewer large single-digit gaps when Big 4 is involved.

For brevity we do not report the results of the analysis for the first two digits and for the second digits of Scopes 1 and 2. The untabulated results of these two analyses are consistent with the results from the first digit analysis.

4.2.2. Small reduction in reported emissions

Figure 3 presents the histogram of emission changes by cluster, scope, and emission type (absolute or relative). While the LOW and MIDDLE clusters show a relatively balanced bell shape for absolute emissions, the HIGH cluster shows a spike right at 0 for both Scope 1 and Scope 2. For relative emissions, the bell shape is no longer balanced for all three clusters, as more reductions are reported than increases.

Figure 4 shows the plots and p-values from the discontinuity tests (Cattaneo et al., 2020; McCrary, 2008). The tests confirm our observations in Figure 3, as we reject the null that there is no manipulation in the density around zero for the HIGH cluster. This means the HIGH cluster has a greater mass of small reductions in emissions relative to small increases, in both Scope 1 and Scope 2, and in both absolute and relative forms. For the MIDDLE cluster, we observe a discontinuity around zero only for changes in relative Scope 2 emissions (significant at the 5% level). For the LOW cluster, the result is significant at the 10% level only for the change in absolute Scope 2 emissions.

Table 5 reports the results of the small-reduction analysis for both absolute and relative emissions. *DSMALL_S1* and *DSMALL_S2* are the binary variables for small reductions in absolute Scope 1 and Scope 2 emissions, respectively. Since firms usually want to show that their relative emissions (emissions scaled by revenues) decrease, we also report statistics and regression results for *DSMALL_S1REL* and *DSMALL_S2REL*. These variables equal one if the ratio of emissions to revenues is reduced by less than 2% compared to the previous year.

[TABLE 5 HERE]

Panel A shows the percentage of firms reporting a reduction of less than 2% compared to the previous year, while Panels B and C show the Firth logit regression results. Panel A indicates that the LOW cluster has fewer firms reporting small reductions in both absolute and relative emissions (about 2% for absolute values and 1.2%–1.4% for relative values). The HIGH cluster has the most firms reporting small reductions in Scope 1 (4.2% for absolute values and 2.4% for relative values), while the MIDDLE cluster has the most firms reporting small reductions in Scope 2 (4% for absolute values and 2.4% for relative values). These results are consistent with Figures 3 and 4.

On one hand, this pattern reflects the emissions-target patterns reported in Table 2, where the HIGH cluster has the highest proportion of firms with emission targets (64%) and the LOW cluster has only 36% of firms setting such targets. On the other hand, the high proportion of small reductions in the HIGH cluster reflects strong pressure to signal progress in emissions-reduction efforts. In contrast, countries in the LOW cluster have less incentive to report small reductions due to low target adoption and weaker external pressure. The countries in the MIDDLE cluster represent a transitional context, where they face moderate pressure and possess moderate governance quality, resulting in moderate incentives to report small reductions.

The Firth logit regression results in Panels B and C reveal that firms in sensitive industries, firms with emission targets, and firms with external CSR auditors are more likely to report small reductions—consistent with the hypothesis that high pressure increases incentives to meet or narrowly beat targets. The BIG4_CSR coefficient is negative and strongly significant, indicating that Big 4 auditors, as a proxy for higher audit quality, reduce the likelihood of reporting small reductions in emissions. These results hold when we control for cluster fixed effects or country fixed effects (Columns 2–3 and 5–6), and are consistent with the Benford's law analysis we observed in section 4.2.1.

Even though a single piece of evidence cannot establish intentional emissions management and small reductions may reflect genuine abatement efforts, the combined results tell a more consistent story. The distribution of changes, descriptive statistics, logit regression results, and prior literature on "meet-or-beat" behavior collectively point toward a systematic pattern that aligns more closely with managerial incentives to strategically report or finely adjust emissions rather than purely reflecting operational improvements. When multiple indicators converge, the overall weight of the evidence suggests that at least part of the observed emission reductions may be driven by reporting incentives rather than genuine environmental performance.

4.2.3. Base-Ten threshold effects in reported emissions

The results of the base-ten threshold analysis are reported in Table 6 and Figures 5 and 6.

Panel A of Table 6 lists all thresholds used in the analysis. For each threshold, we count the number of observations just below and just above the relevant threshold using selected bin widths (0.025, 0.05, 0.1, and 0.15). We then calculate the ratio of observations just below to those just above the threshold and test the discontinuity using binomial tests and the local polynomial density estimators proposed by Cattaneo et al. (2020), based on the original test by McCrary (2008).

In Panel B, across the two narrowest bin widths (0.025 and 0.05), all three clusters exhibit ratios greater than 1, indicating a larger concentration of observations just below the cutoff compared to just above. These imbalances are statistically significant at conventional levels: p-values are all below 0.05. As the bin width increases (0.1 and 0.15), the magnitude of the discontinuity diminishes, and p-values rise, consistent with the expectation that wider bins dilute localized threshold effects. Across the narrowest bins, the LOW and HIGH clusters show the largest discontinuities, whereas the MIDDLE cluster exhibits the weakest bunching.

In Panel C, significant discontinuities appear mainly in the MIDDLE and the HIGH cluster, whereas the LOW cluster shows no statistically meaningful bunching at any bin width. The magnitude of the discontinuity is most pronounced in the narrower bins. Overall, the HIGH cluster displays the strongest and most consistent bunching, followed by moderate effects in the MIDDLE cluster and negligible effects in the LOW cluster.

In Panel D, the subsample results for both Scope 1 and Scope 2 do not show a consistent or interpretable pattern across CSR-audit status, auditor type, emission targets, or industry sensitivity. Although some ratios appear higher in certain cells, the variation is irregular across clusters and scopes; thus, no robust conclusions can be drawn. This aligns with the notion of intrinsic motivation in the literature (Cedergren & Li, 2024; Christoffersen et al., 2026)—that is, threshold behavior may arise from psychological reference points rather than external pressure.

Taken together, the results highlight two distinct forms of threshold behavior. Scope 1 manipulation is concentrated among firms in both weaker-institution settings—consistent with lower regulatory scrutiny and higher managerial discretion—and stronger-institution settings, where reputational pressure is high. This is consistent with the Benford's Law findings in Section 4.2.1. Scope 2 manipulation, by contrast, emerges more clearly in high-governance environments, where firms have greater flexibility to adjust purchased-energy footprints. These markets typically offer more developed renewable-energy options, regulated certificate-trading systems, and clearer reporting standards, enabling quick adjustments without major operational changes. Renewable energy certificate markets are often underdeveloped or nonexistent, electricity markets are less liberalized, and firms have fewer options to switch suppliers or purchase verified green power. As a result, even if firms want to finetune their reported Scope 2 emissions to avoid crossing thresholds, they simply do not have the same accessible, low-cost mechanisms available to them.

Figure 5 and Figure 6 complement the findings above. Figure 5 shows that the distribution of threshold effects varies systematically with the magnitude of reported emissions, and these patterns differ across institutional clusters. In the LOW cluster, the ratio of observations just below versus above the base-ten threshold peaks at $k = 6$, corresponding to emissions in the six-digit range (1,000,000–9,999,999), and is relatively high at $k = 4$ (values ranging from 10,000 to 99,999), which is also where most firms in these countries tend to report their Scope 1 and Scope 2 emissions. Figure 5, Panel B shows that the LOW cluster has a balanced ratio of "just-below/just-above" in nearly all Scope 2 magnitudes except for very large emitters (k = 6).

By contrast, firms in the MIDDLE cluster display only modest below/above ratios at the lower k values (3–4) but exhibit a pronounced and exceptional peak at $k = 6$. This indicates that firms in countries with intermediate institutional quality—such as the United States, South Korea, Spain, and Italy—tend to engage in threshold management primarily at larger emission magnitudes.

In the HIGH cluster, the phenomenon of reporting below thresholds is almost nonexistent at small magnitudes (k = 1 and 2). The distribution peaks at k = 5 for both Scope 1 and Scope 2. Overall, the differing positions of the peak across clusters indicate that institutional quality influences not only whether firms manage emissions around salient thresholds but also the emission scales at which such behavior is most likely to occur.

Figure 6 presents the discontinuity tests around the reporting thresholds, and the results are consistent with the findings discussed above. In this test, we compute the distance between each firm's emissions value and the relevant threshold, scaled by the threshold itself, so that the distance is expressed relative to the threshold. The goal is to assess whether there is a discontinuity at the cutoff value (0), using the local polynomial density estimators proposed by Cattaneo et al. (2020), building on the original McCrary (2008) test. The figures show clear statistical evidence of discontinuity at zero for all three clusters in Scope 1 emissions, indicating that firms are more likely to report values just below the threshold than just above. For Scope 2 emissions, however, the discontinuity is not statistically significant in the LOW and MIDDLE clusters and appears only in the HIGH cluster. This result is fully consistent with Panels B and C of Table 6.

5. Conclusions

This paper investigates international differences in the quality of corporate GHG emissions reporting by applying a set of complementary irregularity-detection techniques across a large global sample. Using country-level characteristics such as rule of law, transparency, climate awareness, and environmental performance, we classify 42 countries into three institutional clusters. Our analyses reveal clear and systematic variation in emissions-reporting quality across these clusters.

Using the first approach, we find that all three institutional clusters display very similar levels of deviation from Benford's Law. The results indicate that Benford non-conformity does not vary systematically across institutional environments. Instead, the deviations are more strongly associated with firm-level characteristics. Firms with emission targets, firms in environmentally sensitive industries, and firms with external CSR assurance exhibit consistently higher first-digit deviations, whereas firms assured by Big 4 auditors show lower deviations. These results imply that irregularities detected through Benford's Law are driven less by country-level governance quality and more by firm-specific pressure, complexity, and assurance quality.

Our second approach—identifying small year-to-year reductions in emissions—reveals that firms in high-engagement countries disproportionately report marginal improvements, patterns unlikely to arise from natural operational fluctuations. This behavior is less pronounced in middle-cluster countries and weakest in jurisdictions with low governance quality, aligning with differing institutional pressures and target-setting prevalence.

With the third approach, we document systematic bunching of reported emissions just below salient base-ten thresholds. These threshold effects are present across clusters for Scope 1 emissions and are especially strong in high-institutional-quality settings for Scope 2 emissions, where firms have more flexibility to adjust purchased-energy footprints. Together, these additional tests highlight subtle yet pervasive forms of reporting management that extend beyond digit manipulation alone.

Taken together, our findings show that the credibility of climate disclosures is shaped jointly by the strength of institutional enforcement and the degree of climate-related societal expectations. By demonstrating how multiple indicators collectively reveal irregularities in emissions reporting, this study provides a methodological foundation for future research assessing the reliability of sustainability metrics and offers evidence useful for regulators, standard-setters, investors, and assurance providers.

References

Amiram, D., Bozanic, Z., & Rouen, E. (2015). Financial statement errors: Evidence from the distributional properties of financial statement numbers. *Review of accounting studies*, *20*, 1540-1593.

Azar, J., Duro, M., Kadach, I., & Ormazabal, G. (2021). The big three and corporate carbon emissions around the world. *Journal of Financial Economics*, *142*(2), 674-696.

Balakrishnan, C., & Beemamol, M. (2023). Testing CO 2 emissions data during COVID-19 pandemic using Benford's law. *Energy Research Letters*, *4*(2).

Ball, R., Kothari, S. P., & Robin, A. (2000). The effect of international institutional factors on properties of accounting earnings. *Journal of Accounting and Economics*, *29*(1), 1-51.

Beatty, A. L., Ke, B., & Petroni, K. R. (2002). Earnings management to avoid earnings declines across publicly and privately held banks. *The accounting review*, *77*(3), 547-570.

Benford, F. (1938). The law of anomalous numbers. *Proceedings of the American philosophical society*, 551-572.

Berg, F., Huidobro, J.O., & Rigobon, R. (2024). On the importance of assurance in carbon accounting. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4734240

Burgstahler, D., & Dichev, I. (1997). Earnings management to avoid earnings decreases and losses. *Journal of accounting and economics*, *24*(1), 99-126.

Brusco, M. J., Shireman, E., & Steinley, D. (2017). A comparison of latent class, K-means, and K-median methods for clustering dichotomous data. *Psychological methods*, *22*(3), 563.

Busch, T., Cho, C. H., Hoepner, A. G., Michelon, G., & Rogelj, J. (2023). Corporate greenhouse gas emissions' data and the urgent need for a science-led just transition: introduction to a thematic symposium. *Journal of Business Ethics*, 182(4), 897-901.

Byzalov, D., & Basu, S. (2019). Modeling the determinants of meet-or-just-beat behavior in distribution discontinuity tests. *Journal of Accounting and Economics*, *68*(2-3), 101266.

Cahan, S. F., De Villiers, C., Jeter, D. C., Naiker, V., & Van Staden, C. J. (2016). Are CSR disclosures value relevant? Cross-country evidence. *European Accounting Review*, 25(3), 579-611.

Campbell, J. L. (2007). Why would corporations behave in socially responsible ways? An institutional theory of corporate social responsibility. *Academy of Management Review*, 32(3), 946-967.

Cattaneo, M. D., Jansson, M., & Ma, X. (2020). Simple local polynomial density estimators. *Journal of the American Statistical Association*, *115*(531), 1449-1455.

Cedergren, M., & Li, V. (2024). Round number reference points and irregular patterns in reported gross margins. *Review of Accounting Studies*, *29*(4), 3293-3327.

Chen, K. (2009). On coresets for k-median and k-means clustering in metric and euclidean spaces and their applications. *SIAM Journal on Computing*, *39*(3), 923-947.

Choi, B., & Luo, L. (2021). Does the market value greenhouse gas emissions? Evidence from multi-country firm data. *The British Accounting Review*, 53(1), 100909.

Christoffersen, J., Plenborg, T., & Seitz, M. (2026). Intrinsic Benchmark Beating. *Journal of Business Finance & Accounting*.

Cleary, R., & Thibodeau, J. C. (2005). Applying digital analysis using Benford's law to detect fraud: the dangers of type I errors. *Auditing: A Journal of Practice & Theory*, *24*(1), 77-81.

Coracioni, A. T. (2020). Testing of published information on greenhouse gas emissions. Conformity analysis with the Benford's Law Method. *Audit Financiar*, *18*(4), 821-830.

Depoers, F., Jeanjean, T., & Jérôme, T. (2016). Voluntary disclosure of greenhouse gas emissions: Contrasting the carbon disclosure project and corporate reports. *Journal of Business Ethics*, 134(3), 445-461.

Ding, D., Liu, B., & Chang, M. (2023). Carbon emissions and TCFD aligned climate-related information disclosures. *Journal of Business Ethics*, 182(4), 967-1001.

Dhaliwal, D. S., Radhakrishnan, S., Tsang, A., & Yang, Y. G. (2012). Nonfinancial disclosure and analyst forecast accuracy: International evidence on corporate social responsibility disclosure. *The accounting review*, *87*(3), 723-759.

Dragomir, V. D. (2012). The disclosure of industrial greenhouse gas emissions: a critical assessment of corporate sustainability reports. *Journal of Cleaner Production*, 29-30, 222

Drake, P. D., & Nigrini, M. J. (2000). Computer assisted analytical procedures using Benford's Law. *Journal of accounting education*, *18*(2), 127-146.

Döring, S., Drobetz, W., El Ghoul, S., Guedhami, O., & Schröder, H. (2023). Foreign institutional investors, legal origin, and corporate greenhouse gas emissions disclosure. *Journal of Business Ethics*, *182*(4), 903-932.

Dumas, C. F., & Devine, J. H. (2000). Detecting evidence of non-compliance in self-reported pollution emissions data: An application of Benford's Law.

Durtschi, C., Hillison, W., & Pacini, C. (2004). The effective use of Benford's law to assist in detecting fraud in accounting data. *Journal of forensic accounting*, *5*(1), 17-34.

Eccles, R. G., and Klimenko, S. (2019). The Investor Revolution. *Harvard Business Review*, 97(3), 106–116.

Griffin, P. A., Lont, D. H., & Sun, E. Y. (2017). The relevance to investors of greenhouse gas emission disclosures. *Contemporary Accounting Research*, *34*(2), 1265-1297.

Ioannou, I., & Serafeim, G. (2012). What drives corporate social performance? The role of nation-level institutions. *Journal of International Business Studies*, 43(9), 834-864.

Ioannou, I., S. X. Li, and G. Serafeim. 2016. The effect of target difficulty on target completion: The case of reducing carbon emissions. *The Accounting Review* 91 (5): 1467–92, https://doi.org/10.2308/accr-51307

Jensen, R. E. (1971). A cluster analysis study of financial performance of selected business firms. *The Accounting Review*, *46*(1), 36-56.

Johansson, T., & Siverbo, S. (2011). Governing cooperation hazards of outsourced municipal low contractibility transactions: An exploratory configuration approach. *Management Accounting Research*, *22*(4), 292-312.

Jung, J., Herbohn, K., & Clarkson, P. (2018). Carbon risk, carbon risk awareness and the cost of debt financing. *Journal of Business Ethics*, *150*, 1151-1171.

Kinnunen, J., & Koskela, M. (2003). Who is Miss World in cosmetic earnings management? A cross-national comparison of small upward rounding of net income numbers among eighteen countries. *Journal of International Accounting Research*, *2*(1), 39-68.

Kolk, A., Levy, D., & Pinkse, J. (2008). Corporate responses in an emerging climate regime: The institutionalization and commensuration of carbon disclosure. *European Accounting Review*, 77(4), 719-745.

Krueger, P., Sautner, Z., & Starks, L. T. (2020). The importance of climate risks for institutional investors. *The Review of Financial Studies*, 33(3), 1067-1111.

Le, T., & Lobo, G. J. (2022). Audit quality inputs and financial statement conformity to Benford's law. *Journal of Accounting, Auditing & Finance*, *37*(3), 586-602.

Lee, J., Lim, C. Y., Lobo, G. J., & Xu, Y. (2026). Does auditor quality enhance CSR disclosure?. *Accounting and Business Research*, *56*(1), 1-40.

Leuz, C., Nanda, D., & Wysocki, P. D. (2003). Earnings management and investor protection: an international comparison. *Journal of Financial Economics*, *69*(3), 505-527.

Liesen, A., Hoepner, A. G., Patten, D. M., & Figge, F. (2015). Does stakeholder pressure influence corporate GHG emissions reporting? Empirical evidence from Europe. *Accounting, Auditing & Accountability Journal*, 28(7), 1047-1074.

Marquis, C., Toffel, M. W., & Zhou, Y. (2016). Scrutiny, norms, and selective disclosure: A global study of greenwashing. *Organization Science*, 27(2), 483-504.

Matsumura, E. M., Prakash, R., & Vera-Muñoz, S. C. (2014). Firm-value effects of carbon emissions and carbon disclosures. *The Accounting Review*, *89*(2), 695-724.

McCrary, J. (2008). Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of econometrics*, *142*(2), 698-714.

Nigrini, Mark J.. *Benford's Law : Applications for Forensic Accounting, Auditing, and Fraud Detection*, John Wiley & Sons, Incorporated, 2012.

Prado-Lorenzo, J. M., & Garcia-Sanchez, I. M. (2010). The role of the board of directors in disseminating relevant information on greenhouse gases. Journal of Business Ethics, 97, 391-424.

Qu, H., Steinberg, R., & Burger, R. (2020). Abiding by the law? Using Benford's law to examine the accuracy of nonprofit financial reports. *Nonprofit and Voluntary Sector Quarterly*, *49*(3), 548-570.

Srinivasan, S., Wahid, A. S., & Yu, G. (2015). Admitting mistakes: Home country effect on the reliability of restatement reporting. *The Accounting Review*, *90*(3), 1201-1240.

Stice, D., Stice, E. K., Stice, H., & Stice-Lawrence, L. (2022). The power of numbers: base-ten threshold effects in reported revenue. *Contemporary Accounting Research*, *39*(4), 2903-2940.

Talbot, D., & Boiral, O. (2018). GHG reporting and impression management: an assessment of sustainability reports from the energy sector. *Journal of Business Ethics,* 147, 367-383.

Tsang, A., Wang, K. T., Wu, Y., & Lee, J. (2024). Nonfinancial corporate social responsibility reporting and firm value: International evidence on the role of financial analysts. *European Accounting Review*, *33*(2), 399-434.

UNEP FI. (2013). Portfolio Carbon. Measuring, disclosing and managing the carbon intensity of investments and investment portfolios. UNEP Finance Initiative. Available at: https://www.unep.org/resources/report/portfolio-carbon-measuring-disclosing-and-managing-carbon-intensity-investments

Wallace, W. A. (2002). Assessing the quality of data used for benchmarking and decision-making. *The Journal of Government Financial Management*, *51*(3), 16.

Figure 1A: Benford Analysis of Scope 1 Emissions for the Whole Sample

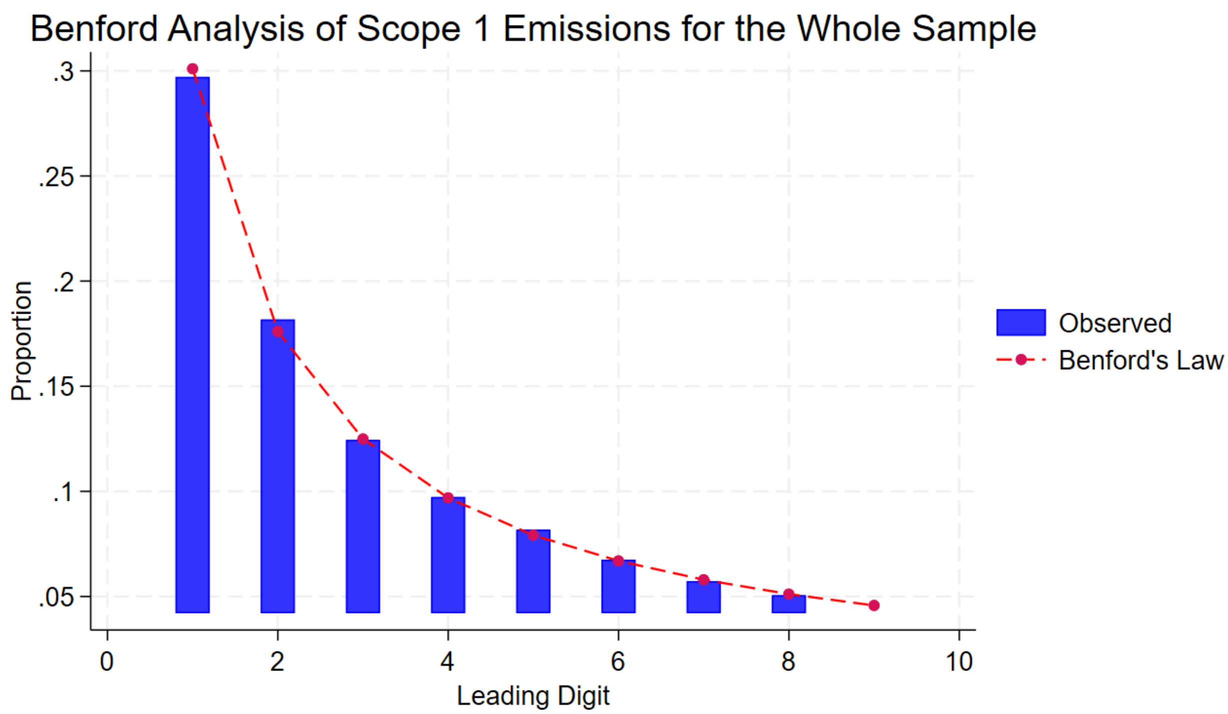


Figure 1B: Benford Analysis of Scope 2 Emissions for the Whole Sample

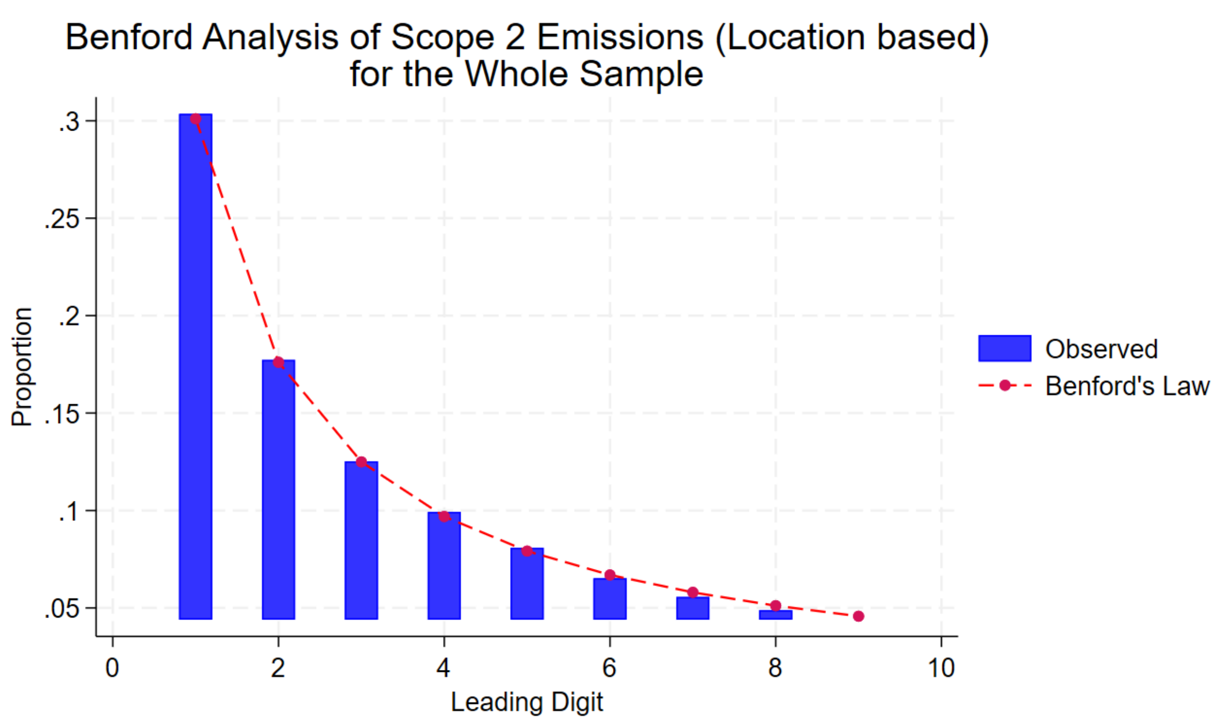


Figure 1C: First digit frequency according to Benford's law and reported data

First digit	Benford's law	Sample Scope 1	Sample Scope 2 Location-based
1	0.3010	0.2971	0.3035
2	0.1761	0.1818	0.1772
3	0.1249	0.1245	0.1252
4	0.0969	0.0973	0.0992
5	0.0792	0.0818	0.0808
6	0.0669	0.0675	0.0652
7	0.0580	0.0573	0.0556
8	0.0512	0.0506	0.0488
9	0.0458	0.0420	0.0439

Figure 2: Clustering of countries by institutional characteristics

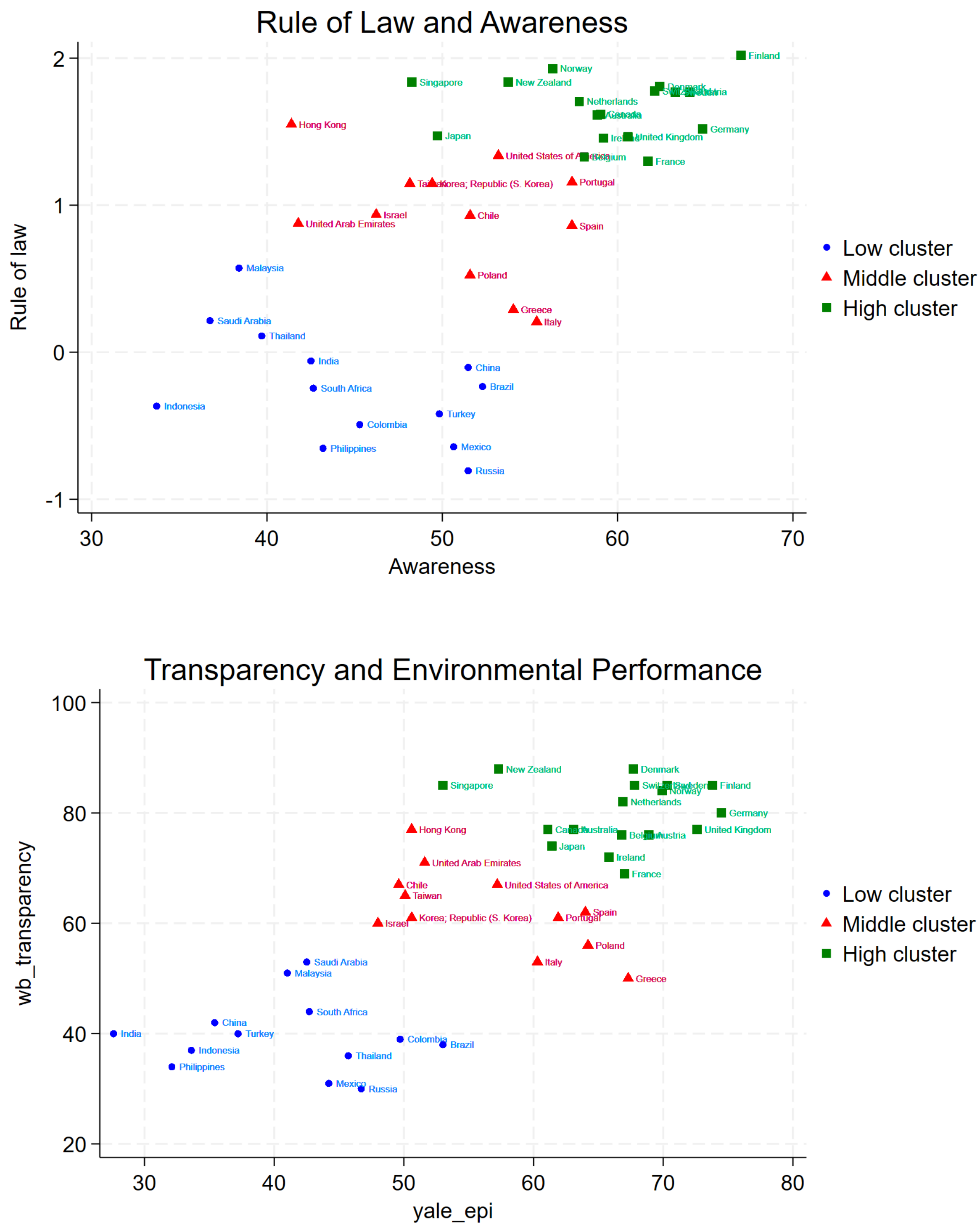
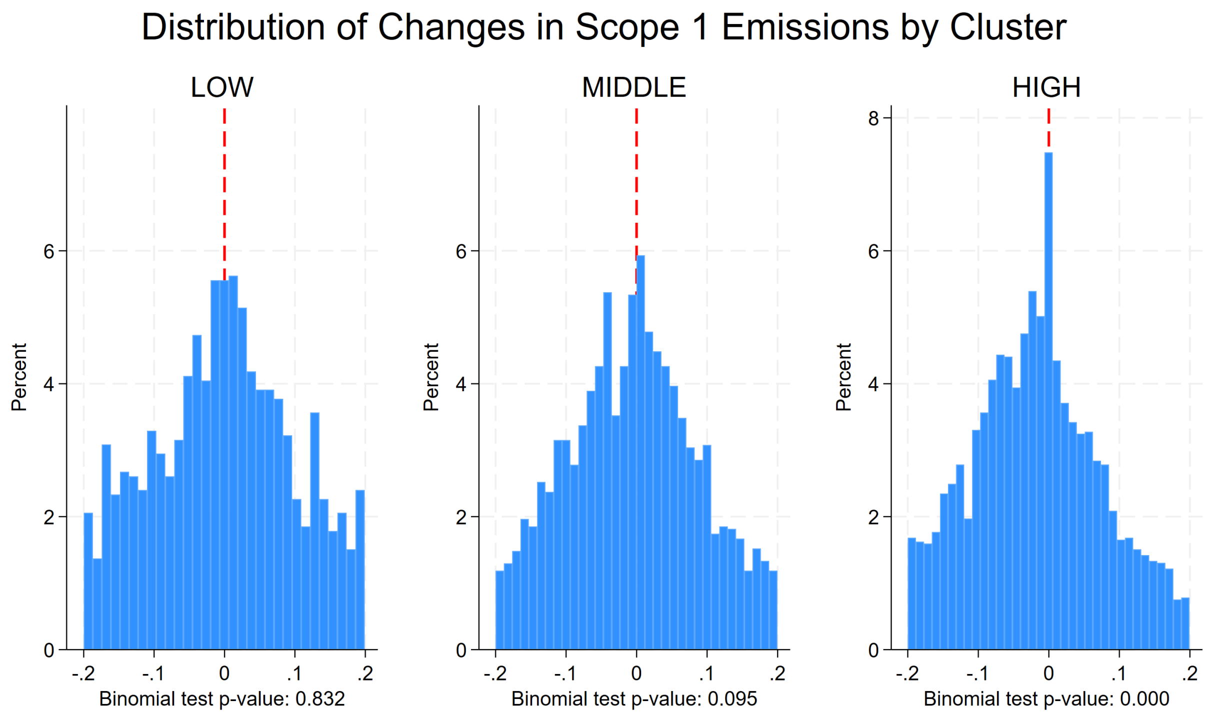


Figure 3: Histogram of changes in emissions by clusters

Figure 3A: Changes of absolute emissions scaled by previous year emissions



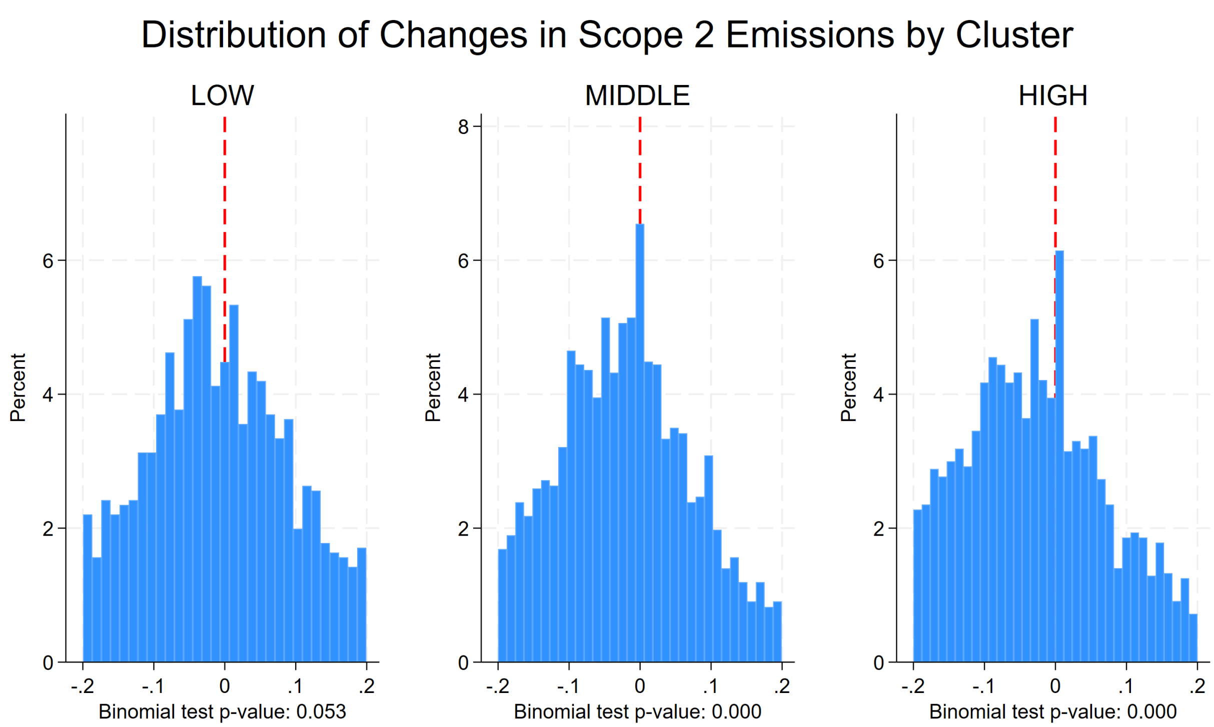
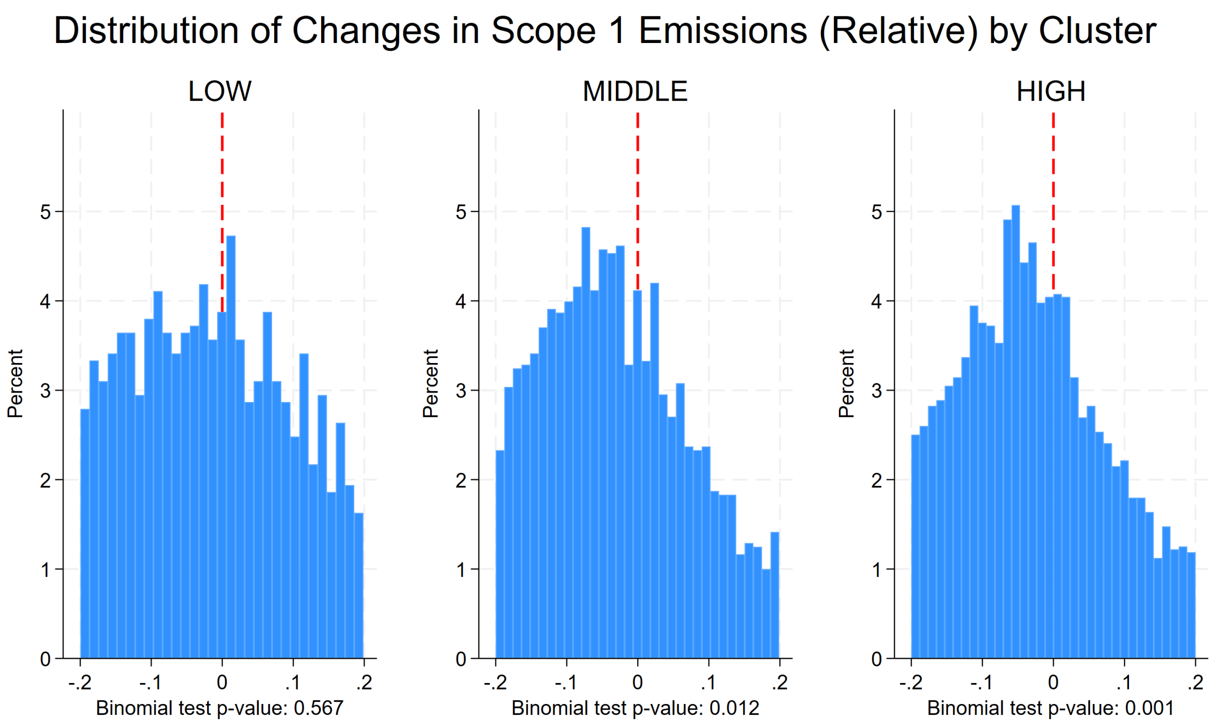


Figure 3B: Changes of relative emissions (emissions/total revenues) scaled by previous year values



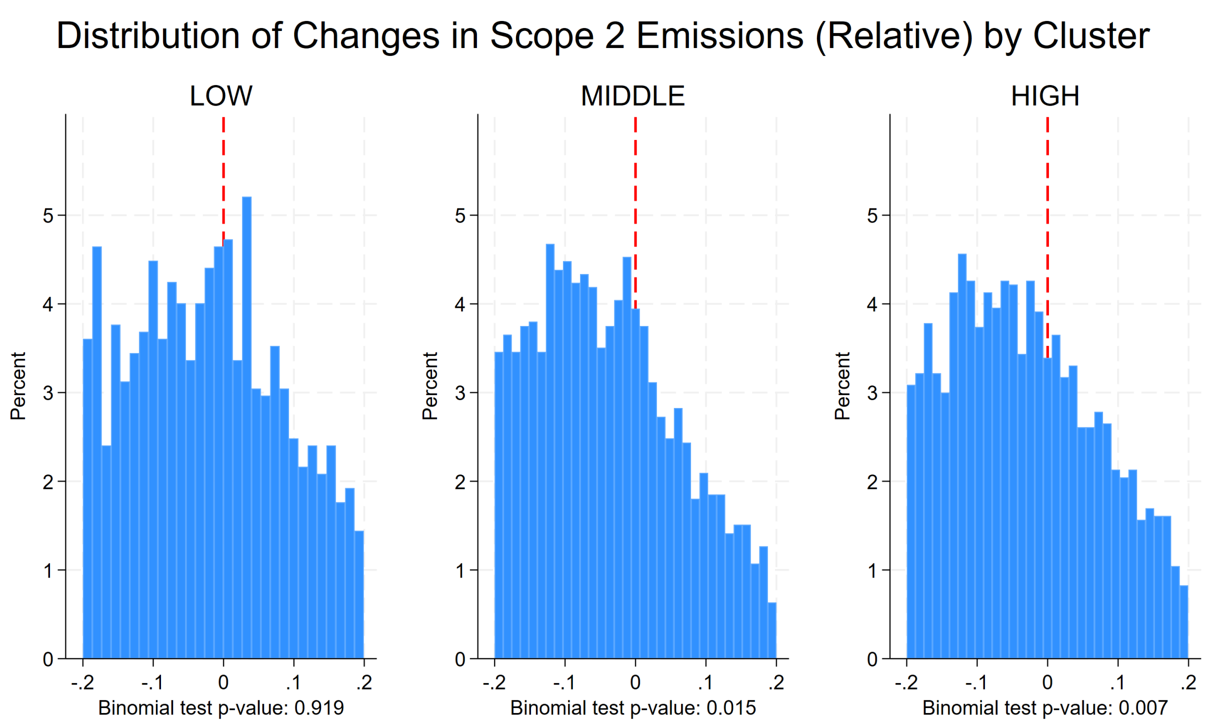
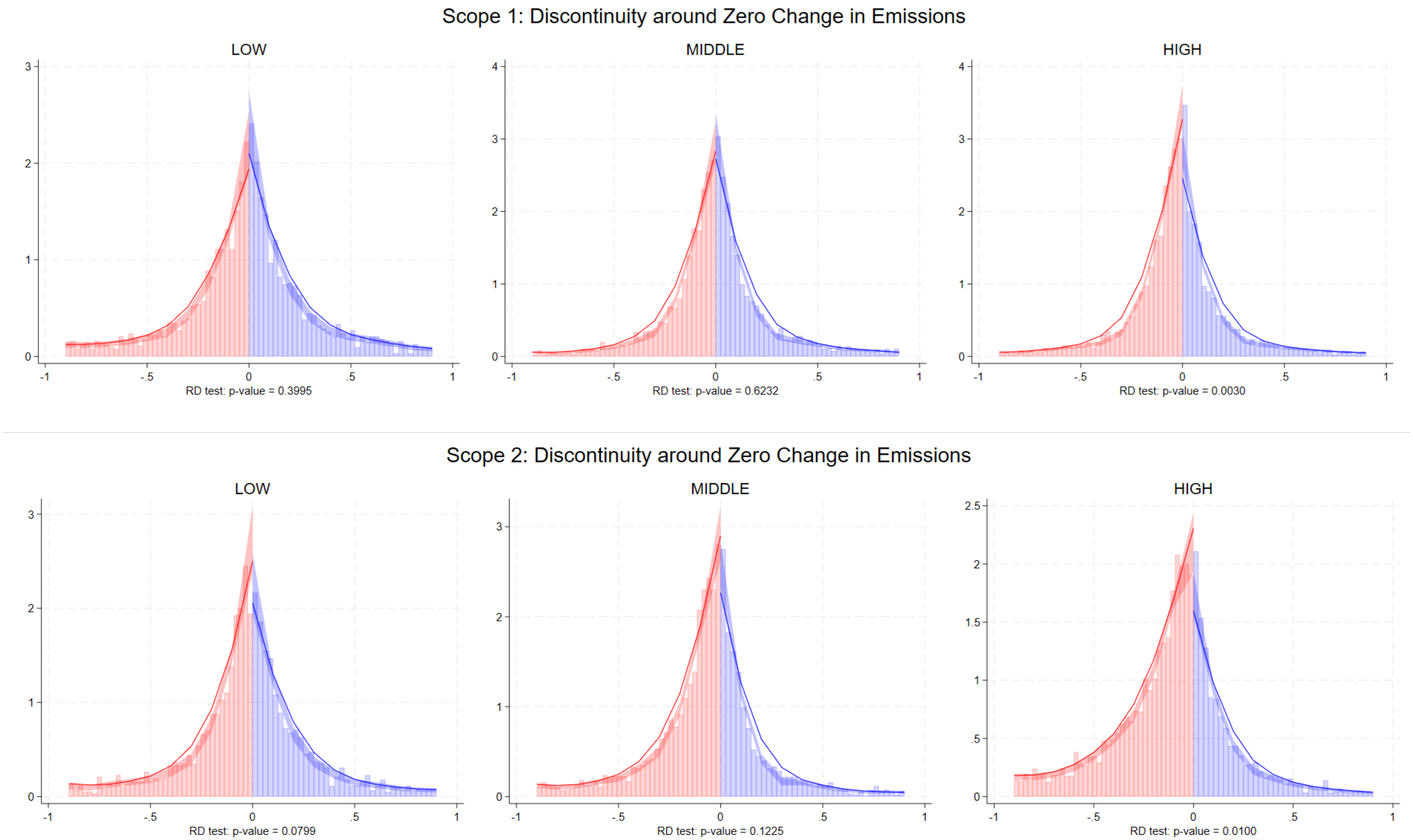
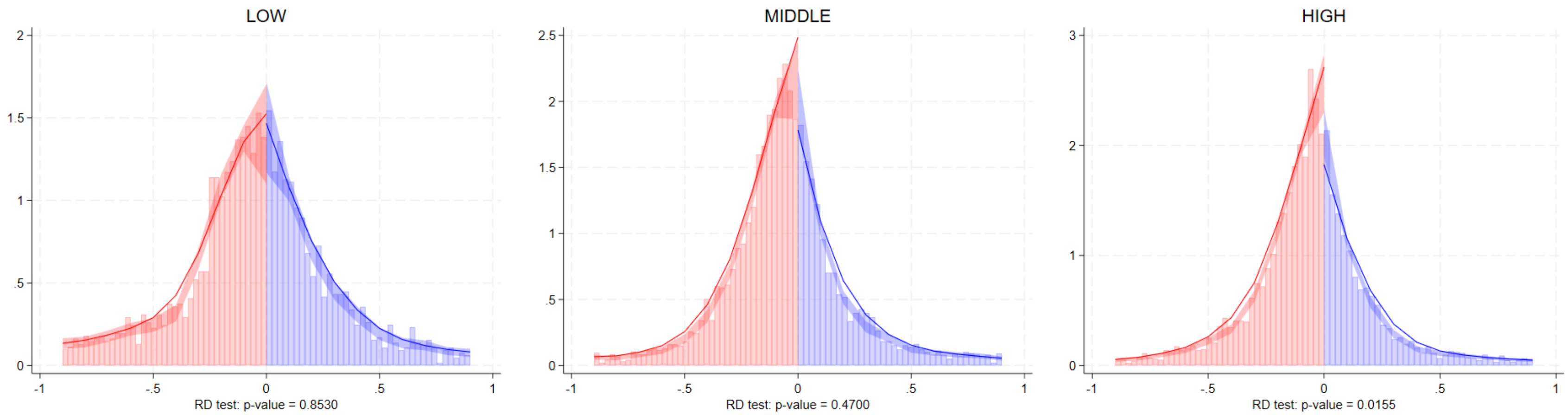


Figure 4: Discontinuity test (McCrary test) around zero change



Scope 1 Scaled by Revenues: Discontinuity around Zero Change



Scope 2 Scaled by Revenues: Discontinuity around Zero Change

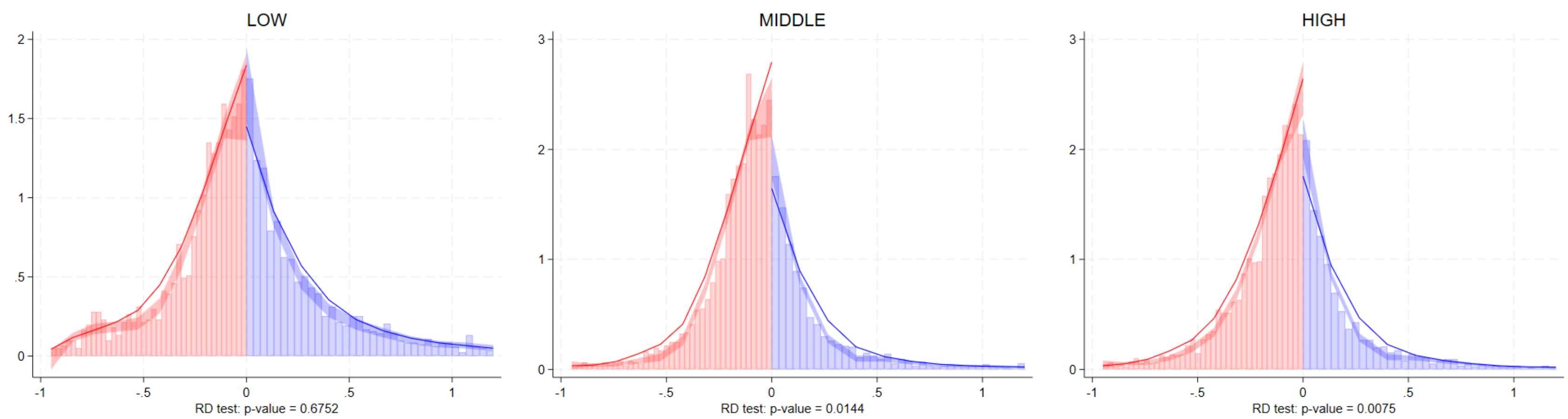
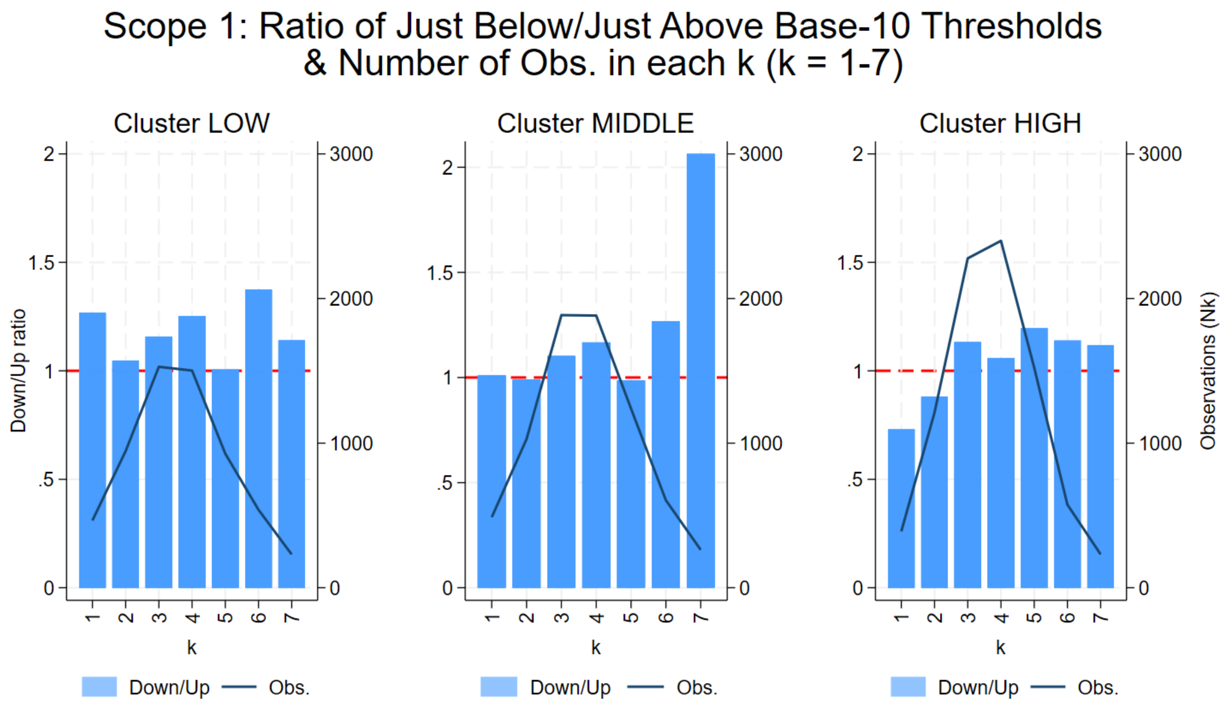


Figure 5: Base-Ten threshold effects at each k for Scope 1 and Scope 2

Panel A



Panel B

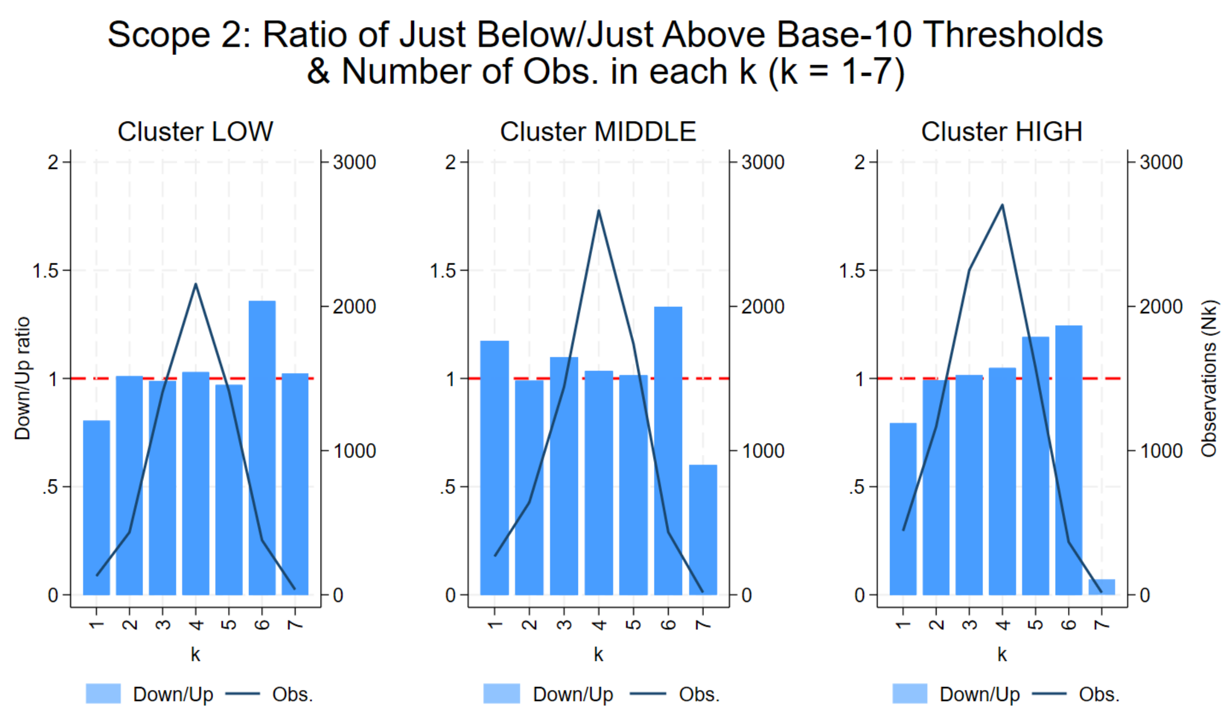


Figure 6: Testing Base-Ten threshold effects with Discontinuity test around thresholds for Scope 1 and Scope 2

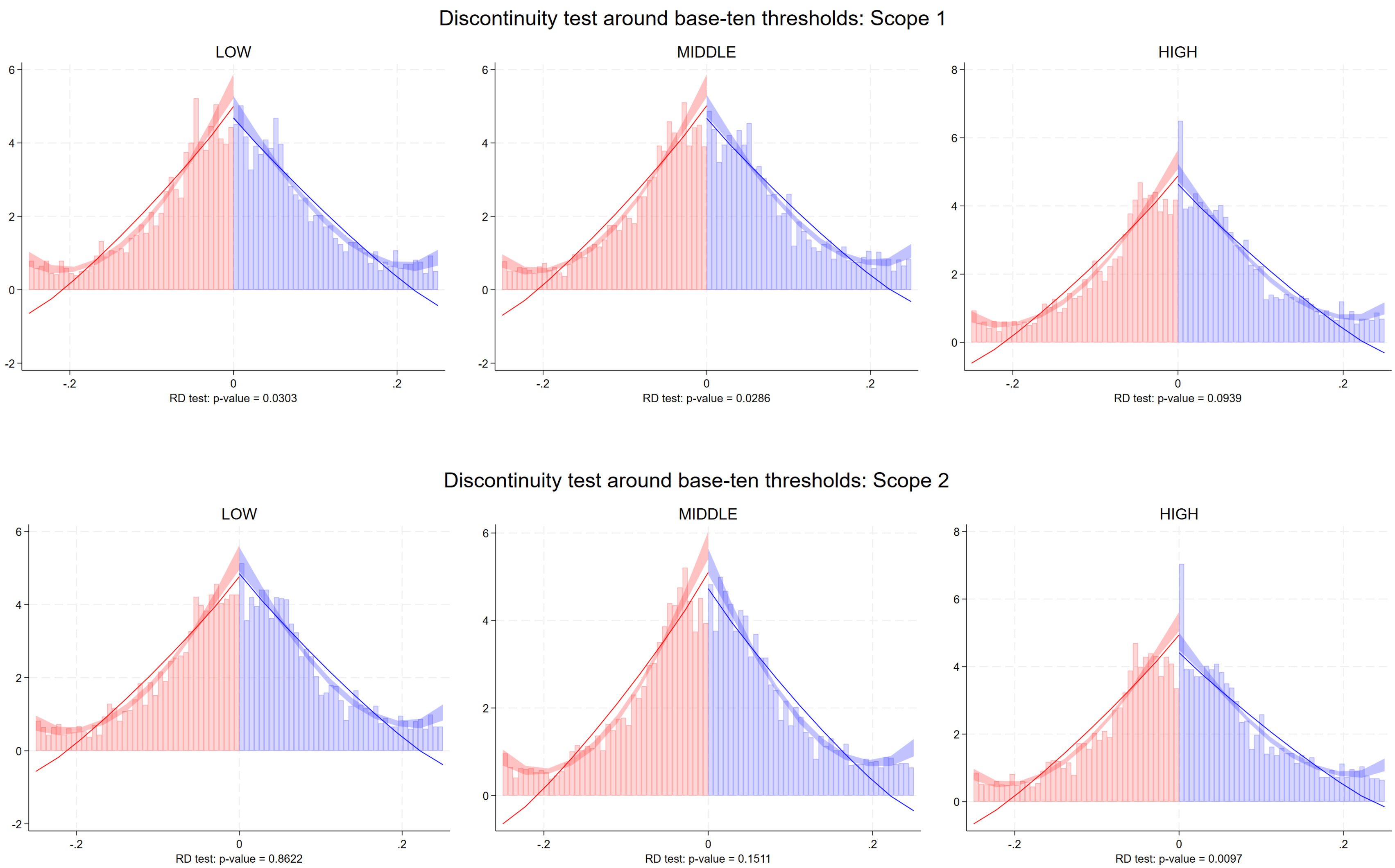


Table 1: Sample composition by year and by country

Panel A: Sample composition by year

Fiscal year	Frequency	Percent
Total	23002	100
2020	1713	7.45
2021	2519	10.95
2022	2546	11.07
2023	7370	32.04
2024	8854	38.49

Panel B: Sample composition by country (jurisdiction) and their institutional characteristics

Country of headquarters	Freq.	%	Transparency	Rule of law	Awareness	Yale EPI
Australia	456	1.98	77	1.62	58.85	63.1
Austria	104	0.45	76	1.77	64.12	68.9
Belgium	143	0.62	76	1.33	58.1	66.8
Brazil	475	2.06	38	-0.23	52.28	53
Canada	639	2.78	77	1.62	59.02	61.1
Chile	79	0.34	67	0.93	51.59	49.6
China	2,379	10.34	42	-0.1	51.47	35.4
Colombia	43	0.19	39	-0.49	45.28	49.7
Denmark	156	0.68	88	1.81	62.41	67.7
Finland	206	0.9	85	2.02	67.04	73.8
France	592	2.57	69	1.3	61.74	67
Germany	548	2.38	80	1.52	64.85	74.5
Greece	82	0.36	50	0.29	54.05	67.3
Hong Kong	961	4.18	77	1.55	41.39	50.6
India	1,552	6.75	40	-0.06	42.5	27.6
Indonesia	232	1.01	37	-0.37	33.7	33.6
Ireland	154	0.67	72	1.46	59.18	65.8
Israel	74	0.32	60	0.94	46.23	48
Italy	358	1.56	53	0.21	55.39	60.3
Japan	3,077	13.37	74	1.47	49.73	61.4
Korea Republic (South Korea)	869	3.78	61	1.15	49.42	50.6
Malaysia	461	2	51	0.57	38.4	41
Mexico	125	0.54	31	-0.64	50.64	44.2
Netherlands	224	0.97	82	1.71	57.81	66.9
New Zealand	111	0.48	88	1.84	53.75	57.3
Norway	237	1.03	84	1.93	56.29	69.9
Philippines	151	0.66	34	-0.65	43.19	32.1
Poland	108	0.47	56	0.52	51.58	64.2
Portugal	48	0.21	61	1.16	57.4	61.9
Russia	58	0.25	30	-0.81	51.47	46.7
Saudi Arabia	46	0.2	53	0.22	36.75	42.5
Singapore	260	1.13	85	1.84	48.26	53
South Africa	332	1.44	44	-0.24	42.64	42.7
Spain	254	1.1	62	0.86	57.4	64
Sweden	501	2.18	85	1.77	63.3	70.3
Switzerland	405	1.76	85	1.78	62.12	67.8
Taiwan	1,251	5.44	65	1.15	48.15	50.1
Thailand	272	1.18	36	0.11	39.69	45.7
Turkey	250	1.09	40	-0.42	49.82	37.2
United Arab Emirates	89	0.39	71	0.88	41.79	51.6
United Kingdom	1,201	5.22	77	1.46	60.59	72.6
United States of America	3,443	14.97	67	1.34	53.2	57.2

Table 2: Clustering

Panel A: Cluster membership

Cluster LOW (16 countries)	Cluster MIDDLE (13 Countries/Jurisdictions)	Cluster HIGH (17 countries)
Brazil, China, Colombia, India, Indonesia, Malaysia, Mexico, Nigeria, Pakistan, Peru, Philippines, Russia, Saudi Arabia, South Africa, Thailand, Turkey	Chile, Hungary, Hong Kong, Greece, Israel, Italy, Poland, Portugal, Korea Republic (South Korea), Spain, Taiwan, United Arab Emirates, United States of America	Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Japan, Netherlands, New Zealand, Norway, Singapore, Sweden, Switzerland, United Kingdom

Panel B: Mean value of institutional characteristics

Cluster	Rule of law	Transparency	Yale EPI	Climate Change Awareness
LOW	-0.10	41.00	36.39	46.37
MIDDLE	1.20	66.03	54.82	50.49
HIGH	1.56	77.37	65.61	56.77
Mean	0.98	63.53	53.94	51.81

Panel C: GHGE Descriptive statistics by clusters

Clusters	LOW	MIDDLE	HIGH
Number of observations	6378 (27.72%)	7615 (33.10%)	9013 (39.18%)
Number of unique firms	3590	3354	3506
Scope 1 - Mean	2,485,499	1,297,137	917,280
Scope 1 - Median	9,869	11,800	11,942
Scope 2 (Location-based) - Mean	6,188,048	358,260	244,324
Scope 2 (Location-based) - Median	27,612	35,041	19,457
CSR audit	0.28	0.37	0.45
CSR audit is Big4	0.11	0.12	0.29
Same CSR auditor and FS auditor	0.06	0.10	0.23
Emission target	0.36	0.50	0.64
Sensitive industries	0.43	0.38	0.45

Table 3: Benford's law conformity comparison between three clusters

Panel A: Guidelines for testing conformity of MAD (Drake & Nigrini, 2000)

MAD	Close conformity	Acceptable conformity	Marginally acceptable conformity	Nonconformity
First digit	0.000-0.004	0.004-0.008	0.008-0.012	> 0.012
First two digits	0.0000-0.0006	0.0006-0.0012	0.0012-0.0018	>0.0018
Second digit	0.000-0.008	0.008-0.012	0.012-0.016	> 0.016

Panel B: First digit analysis

Cluster	First digit**: Scope 1 emissions**				First digit**: Scope 2 emissions**			
	MAX	*MAD - mean*	*MAD - min*	*MAD - max*	*MAX*	*MAD -mean*	*MAD - min*	*MAD - max*
LOW	0.034	***0.014***	0.005	0.028	0.034	***0.014***	0.004	0.027
MIDDLE	0.035	***0.014***	0.005	0.030	0.034	***0.014***	0.004	0.032
HIGH	0.035	***0.014***	0.003	0.028	0.033	0.013	0.003	0.029

Panel C: First two-digit analysis

Cluster	First 2 digits**: Scope 1 emissions**				First 2 digits**: Scope 2 emissions**			
	MAX	*MAD - mean*	*MAD -min*	*MAD - max*	*MAX*	*MAD - mean*	*MAD - min*	*MAD - max*
LOW	0.011	0.002	0.002	0.003	0.012	0.003	0.002	0.003
MIDDLE	0.011	0.003	0.002	0.003	0.011	0.003	0.002	0.003
HIGH	0.011	0.003	0.002	0.003	0.011	0.003	0.002	0.003

Panel D: Second digit analysis

Cluster	Second digit**: Scope 1 emissions**				Second digit**: Scope 2 emissions**			
	MAX	*MAD - mean*	*MAD -min*	*MAD - max*	*MAX*	*MAD - mean*	*MAD - min*	*MAD - max*
LOW	0.032	0.014	0.004	0.028	0.032	0.014	0.005	0.026
MIDDLE	0.032	0.014	0.005	0.029	0.032	0.014	0.005	0.027
HIGH	0.032	0.014	0.004	0.025	0.032	0.014	0.004	0.028

Note:
MAX is the maximum deviation from Benford's law among all digits.

MAD is the means of absolute deviation from Benford's law across all digits. In the panels, marginal deviation is in ***Bold Italic*** and non-conformity is in **Bold**.

Table 4: Benford's law conformity comparison between three clusters

Panel A: Scope 1 – subsample division by emission target

Cluster	First digit: Scope 1 emissions Emission target: No				First digit: Scope 1 emissions Emission target: Yes			
	MAX	MAD - mean	MAD - min	MAD - max	MAX	MAD - mean	MAD - min	MAD - max
LOW	0.032	0.013	0.004	0.029	0.036	***0.015***	0.005	0.032
MIDDLE	0.036	***0.015***	0.004	0.029	0.037	***0.015***	0.004	0.029
HIGH	0.035	***0.014***	0.005	0.032	0.037	***0.015***	0.004	0.029

Panel B: Scope 2 – subsample division by emission target

Cluster	First digit: Scope 2 emissions Emission target: No				First digit: Scope 2 emissions Emission target: Yes			
	MAX	MAD - mean	MAD - min	MAD - max	MAX	MAD - mean	MAD - min	MAD - max
LOW	0.033	***0.014***	0.004	0.027	0.038	***0.016***	0.005	0.031
MIDDLE	0.036	***0.014***	0.005	0.027	0.034	***0.014***	0.004	0.031
HIGH	0.032	0.013	0.004	0.028	0.033	***0.014***	0.005	0.030

Panel C: Scope 1 – subsample division by sensitive industries

Cluster	First digit: Scope 1 emissions Sensitive industry: No				First digit: Scope 1 emissions Sensitive industry: Yes			
	MAX	MAD - mean	MAD - min	MAD - max	MAX	MAD - mean	MAD - min	MAD - max
LOW	0.035	***0.014***	0.004	0.029	0.037	***0.014***	0.004	0.036
MIDDLE	0.034	***0.014***	0.003	0.027	0.036	***0.015***	0.005	0.032
HIGH	0.034	***0.014***	0.004	0.029	0.037	***0.015***	0.004	0.028

Panel D: Scope 2 – subsample division by sensitive industries

Cluster	First digit: Scope 2 emissions Sensitive industry: No				First digit: Scope 2 emissions Sensitive industry: Yes			
	MAX	MAD - mean	MAD - min	MAD - max	MAX	MAD - mean	MAD - min	MAD - max
LOW	0.035	***0.014***	0.004	0.029	0.034	***0.014***	0.004	0.028
MIDDLE	0.035	***0.014***	0.004	0.029	0.034	***0.014***	0.005	0.029
HIGH	0.033	0.013	0.004	0.027	0.032	0.013	0.004	0.030

Panel E: Scope 1 – subsample division by CSR external audit

Cluster	First digit: Scope 1 emissions CSR audit: No				First digit: Scope 1 emissions CSR audit: Yes			
	MAX	MAD - mean	MAD - min	MAD - max	MAX	MAD - mean	MAD - min	MAD - max
LOW	0.033	***0.014***	0.005	0.029	0.036	***0.015***	0.005	0.033
MIDDLE	0.034	***0.014***	0.005	0.029	0.039	***0.015***	0.004	0.030
HIGH	0.035	***0.014***	0.004	0.030	0.042	**0.016**	0.005	0.031

Panel F: Scope 2 – subsample division by CSR external audit

Cluster	First digit: Scope 2 emissions CSR audit: No				First digit: Scope 2 emissions CSR audit: Yes			
	MAX	MAD - mean	MAD - min	MAD - max	MAX	MAD - mean	MAD - min	MAD - max
LOW	0.033	***0.014***	0.005	0.028	0.040	***0.016***	0.005	0.031
MIDDLE	0.035	***0.014***	0.004	0.030	0.034	***0.014***	0.004	0.029
HIGH	0.034	***0.014***	0.004	0.028	0.032	0.013	0.004	0.032

Panel G: Scope 1 – subsample division by Big4 CSR external audit

Cluster	First digit: Scope 1 emissions Big4 CSR audit: No				First digit: Scope 1 emissions Big4 CSR audit: Yes			
	MAX	MAD - mean	MAD - min	MAD - max	MAX	MAD - mean	MAD - min	MAD - max
LOW	0.037	***0.015***	0.004	0.029	0.033	***0.014***	0.005	0.024
MIDDLE	0.041	***0.016***	0.004	0.033	0.036	***0.016***	0.005	0.027
HIGH	0.043	***0.016***	0.006	0.031	0.040	***0.016***	0.005	0.031

Panel H: Scope 2 – subsample division by Big4 CSR external audit

Cluster	First digit: Scope 2 emissions Big4 CSR audit: No				First digit: Scope 2 emissions Big4 CSR audit: Yes			
	MAX	MAD - mean	MAD - min	MAD - max	MAX	MAD - mean	MAD - min	MAD - max
LOW	0.041	***0.015***	0.005	0.029	0.038	**0.018**	0.009	0.028
MIDDLE	0.036	***0.015***	0.005	0.031	0.034	***0.014***	0.006	0.028
HIGH	0.034	***0.014***	0.004	0.029	0.032	0.013	0.004	0.026

Note:
MAX is the maximum deviation from Benford's law among all digits.

MAD is the means of absolute deviation from Benford's law across all digits. In the panels, marginal deviation is in ***Bold Italic*** and non-conformity is in **Bold**.

Table 5 Small reduction in emissions (absolute and relative values)

Panel A Percentage of firms that report small reduction in absolute and relative emissions by cluster

Cluster	*DSMALL _S1*	*DSMALL _S2*	*DSMALL _S1REL*	*DSMALL _S2REL*
LOW	0.021	0.018	0.012	0.014
MIDDLE	0.035	0.040	0.020	0.024
HIGH	0.042	0.039	0.024	0.021

Panel B Absolute value of emissions

Dependent variable:		*DSMALL _S1*			*DSMALL _S2*	
	(1)	(2)	(3)	(4)	(5)	(6)
SIZE	0.200	0.203	0.180	0.192**	0.180**	0.190**
	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)
LEV	0.006***	0.007***	0.005***	-0.025	-0.026	-0.026
	(0.534)	(0.536)	(0.550)	(0.549)	(0.548)	(0.565)
ROA	2.041***	2.140***	1.691***	0.743	0.721	0.64
	(0.147)	(0.147)	(0.147)	(0.135)	(0.135)	(0.136)
SENS_IND	0.558	0.538	0.532	0.099**	0.096***	0.068***
	(0.105)	(0.105)	(0.107)	(0.105)	(0.106)	(0.109)
EMIS_TARGET	0.128	0.145	0.149	0.257*	0.288*	0.292
	(0.109)	(0.109)	(0.110)	(0.109)	(0.109)	(0.111)
CSR_AUDIT	0.143*	0.137*	0.137	0.204	0.195	0.141
	(0.111)	(0.110)	(0.118)	(0.111)	(0.110)	(0.118)
BIG4_CSR	-0.210	-0.188***	-0.053***	-0.151***	-0.144***	0.036***
	(0.095)	(2.054)	(2.042)	(0.100)	(2.051)	(2.036)
RULEOFLAW	0.113**			0.388		
	(0.006)			(0.006)		
YALE_EPI	0.014***			-0.002***		
	(2.055)			(2.054)		
MIDDLE		0.463***			0.731***	
		(0.107)			(0.112)	
HIGH		0.650***			0.682***	
		(1.620)			(1.617)	
Intercept	-8.416***	-7.981***	-6.875***	-7.298***	-7.379***	-7.093***
	(0.024)	(0.025)	(0.027)	(0.024)	(0.025)	(0.027)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	Yes	No	No	Yes
Observations	23,000	23,000	23,000	23,000	23,000	23,000
Penalized Log-Lik	-3093.19	-3094.9	-3023.14	-3112.1	-3108.66	-3046.34

Panel C Relative value of emissions

Dependent variable:	*DSMALL _S1REL*			*DSMALL _S2 REL*		
	(1)	(2)	(3)	(4)	(5)	(6)
SIZE	0.237	0.238	0.221	0.169	0.153	0.134
	(0.016)	(0.016)	(0.016)	(0.015)	(0.015)	(0.014)
LEV	-0.018**	-0.017**	-0.018**	-0.013***	-0.014***	-0.015***
	(0.724)	(0.725)	(0.746)	(0.675)	(0.671)	(0.687)
ROA	1.678**	1.774*	1.521*	2.251	2.239	2.155
	(0.193)	(0.192)	(0.190)	(0.171)	(0.172)	(0.170)
SENS_IND	0.389	0.373	0.354	-0.068	-0.06	-0.094
	(0.140)	(0.141)	(0.141)	(0.136)	(0.137)	(0.139)
EMIS_TARGET	0.061**	0.085**	0.092**	0.121***	0.164***	0.202***
	(0.146)	(0.146)	(0.147)	(0.143)	(0.144)	(0.144)
CSR_AUDIT	0.333*	0.321	0.329	0.449	0.44	0.435
	(0.145)	(0.143)	(0.154)	(0.140)	(0.139)	(0.150)
BIG4_CSR	-0.264	-0.228***	-0.124***	-0.12	-0.068***	-0.027***
	(0.127)	(2.057)	(2.031)	(0.122)	(2.046)	(2.025)
RULEOFLAW	0.133**			0.164		
	(0.007)			(0.007)		
YALE_EPI	0.015***			0.003***		
	(2.058)			(2.046)		
MIDDLE		0.511***			0.600***	
		(0.141)			(0.135)	
HIGH		0.676***			0.417***	
		(1.726)			(1.688)	
Intercept	-10.020***	-9.534***	-9.038***	-7.459***	-7.261***	-6.943***
	(0.032)	(0.032)	(0.035)	(0.030)	(0.031)	(0.033)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	Yes	No	No	Yes
Observations	23,000	23,000	23,000	23,000	23,000	23,000
Penalized Log-Lik	-1927.98	-1931.63	-1885.71	-2068.27	-2065.73	-2020.47

Note:

DSMALL_S1 and *DSMALL_S2* are the binary variables for small reduction in absolute Scope 1 and Scope 2, respectively. *DSMALL _S1REL* and *DSMALL _S2REL* are the binary variables for small reduction in relative Scope 1 and Scope 2 (emission scaled by total revenues), respectively. These variables equal one if reduction is less than 2% of previous year's value.

Panel B and Panel C present the results of Firth logit regression, which is used for rare outcomes. *SIZE, LEV, ROA* are winsorized at 1% each tail. *SENS_IND, EMIS_TARGET, CSR_AUDIT, BIG4_CSR* are dummy variables for the sensitive industries, the existence of emission target, the existence of CSR external audit, and whether the CSR auditors are BIG 4, respectively.

***, **, * denotes the significant level at 1%, 5%, and 10% respectively.

Figure 3 complements this table.

Table 6: Base-Ten threshold effects in reported emissions

Panel A: The list of base-ten thresholds for analysis (all points of the form $T = N \times 10^k$, where $1 \leq k \leq 7$)

k = 1	10	k = 3	1000	k = 5	100000	k = 7	10000000
	20		2000		200000		20000000
	30		3000		300000		30000000
	40		4000		400000		40000000
	50		5000		500000		50000000
	60		6000		600000		60000000
	70		7000		700000		70000000
	80		8000		800000		80000000
	90		9000		900000		90000000
k = 2	100	k = 4	10000	k = 6	1000000		
	200		20000		2000000		
	300		30000		3000000		
	400		40000		4000000		
	500		50000		5000000		
	600		60000		6000000		
	700		70000		7000000		
	800		80000		8000000		
	900		90000		9000000		

Panel B: Base-Ten threshold effects with different bins for scope 1 emissions

Bin width	Cluster	No. Obs Just below	No. Obs Just above	Ratio Just below/ Just above	P-value Binomial test
0.025	LOW	674	583	1.156	0.011
0.025	MIDDLE	770	692	1.113	0.044
0.025	HIGH	928	812	1.143	0.006
0.05	LOW	1305	1145	1.140	0.001
0.05	MIDDLE	1555	1393	1.116	0.003
0.05	HIGH	1817	1598	1.137	0.000
0.1	LOW	2107	2005	1.051	0.115
0.1	MIDDLE	2512	2410	1.042	0.150
0.1	HIGH	2914	2788	1.045	0.098
0.15	LOW	2514	2443	1.029	0.320
0.15	MIDDLE	3018	2911	1.037	0.169
0.15	HIGH	3483	3351	1.039	0.113

Panel C: Base-Ten threshold effects with different bins for scope 2 emissions

Bin width	Cluster	No. Obs Just below	No. Obs Just above	Ratio Just below/ Just above	P-value Binomial test
0.025	LOW	585	561	1.043	0.497
0.025	MIDDLE	748	704	1.062	0.259
0.025	HIGH	927	737	1.258	0.000
0.05	LOW	1154	1130	1.021	0.630
0.05	MIDDLE	1527	1384	1.103	0.008
0.05	HIGH	1762	1498	1.176	0.000
0.1	LOW	1901	1960	0.907	0.351
0.1	MIDDLE	2444	2281	1.071	0.018
0.1	HIGH	2901	2568	1.130	0.000
0.15	LOW	2274	2356	0.965	0.234
0.15	MIDDLE	2913	2749	1.060	0.030
0.15	HIGH	3452	3179	1.086	0.001

Panel D: Base-Ten threshold effects for different subsamples

	Scope1			Scope2		
	LOW	MIDDLE	HIGH	LOW	MIDDLE	HIGH
CSR audit: No	1.254	1.268	1.089	1.034	1.218	1.225
CSR audit: Yes	1.432	1.137	1.095	1.131	1.185	0.928
CSR audit & non-Big 4	1.647	1.096	1.249	1.161	1.126	0.822
CSR audit & Big4	1.430	1.182	1.113	0.949	1.274	1.149
Emis target: No	1.312	1.183	1.256	1.065	1.259	1.061
Emis target: Yes	1.250	1.145	1.102	1.065	1.032	0.944
Sensitive Ind: No	1.228	1.280	1.145	1.044	1.10	1.076
Sensitive Ind: Yes	1.070	1.217	1.105	1.059	1.203	1.051