How Much Is Too Much? Measuring Divergence from Benford's Law with the Equivalent Contamination Proportion (ECP)

Manuel Cano-Rodríguez[a*]

[a]*Department of Financial Economics and Accounting, University of Jaén, Jaén (Spain).*

* *Corresponding author at: Universidad de Jaén. Paraje Las Lagunillas s/n. E23071 – Jaén (Spain).*

Telephone number +34953213484.

E-mail mcano@ujaen.es

ORCiD 0000-0002-3482-3836.

Deviations from Benford's Law in Asset Valuations: Market Prices vs. Expert Estimates

1. Introduction.

Benford's Law (BL) states that the expected frequency distribution of the leading digit in many naturally occurring numerical datasets occurs with probability

$$P(D = d) = log_{10}\left(1 + \frac{1}{d}\right), \tag{1}$$

where $d \in \{1,...,9\}$.

The main application of BL is the detection of numerical anomalies, as deviations in otherwise BL-conforming datasets are often interpreted as signs of irregularities or manipulation. Accordingly, BL has been used to assess the reliability of official statistics (Eutsler et al., 2023; Kaiser, 2019; Michalski and Stoltz, 2013), detect tax evasion (Ausloos et al., 2017; Nigrini, 1996), customs fraud (Barabesi et al., 2018), money laundering (Badal-Valero et al., 2018), and irregularities in financial information (Amiram et al., 2015; Beneish and Vorst, 2022; Chakrabarty et al., 2024) or financial markets data (Amiram et al., 2025; Cong et al., 2023; Sifat et al., 2024; Vičič and Tošić, 2022). Its popularity extends beyond academia, being a common feature in commercial audit analytics software (Cano-Rodríguez et al., 2025; Durtschi et al., 2004).

BL-based detection relies on two assumptions: (1) non-manipulated data follow BL, and (2) manipulated data deviate substantially from it (Hill, 1999). The latter stems from the idea that humans struggle to generate BL-conforming numbers, much like their difficulty in producing truly random sequences (Burns, 2009). It is typically assumed that human-generated distortions resemble a uniform distribution more than BL. Accordingly, BL is often introduced by emphasizing that, contrary to intuition, the distribution of leading digits is logarithmic, not uniform (D'Alessandro, 2020; Kössler et al., 2024). Additionally, simulation studies also typically model manipulation by replacing BL-conforming data with uniformly distributed values (Amiram et al., 2015; Barabesi et al., 2023; Cerqueti and Lupi, 2021; Mumic and Filzmoser, 2021).

Early laboratory experiments (Hill, 1988; Hsü, 1948; Kubovy, 1977) initially support this assumption: participants were asked to generate numbers arbitrarily, resulting in sequences that strongly depart from BL, resembling better a uniform distribution. However, more recent studies show that when participants make numerical estimates in meaningful contexts, their responses align more closely with BL (Burns, 2009, 2020; Chi et al., 2022, 2024; Diekmann, 2007; Wünsch et al., 2024), suggesting that domain knowledge may bring human estimates closer to natural data and, hence, closer to BL.

Such a possibility has direct implications for the use of BL in practice: if experts using structured models produce estimates that resemble natural data, BL tests may be less effective at detecting human intervention in complex settings like accounting or finance. Yet, this hypothesis remains untested in laboratory studies, which typically involve non-experts generating estimates without models, reference data, or tools. Laboratory studies also face broader limitations, including their inability to replicate real-world complexity and the low statistical power associated with small samples.

Empirical studies linking BL conformity to human intervention face different challenges. Human involvement is typically unobservable (Watrin et al., 2008) and must be inferred through proxies or contextual cues. Consequently, many studies adopt a binary classification—"manipulated" versus "non-manipulated"—and compare BL conformity across these groups[1]. This approach limits the analysis to basic group comparisons and precludes testing for a (non-)monotonic relationship between the degree of human intervention and BL deviation.

This paper compares the conformity to BL of naturally occurring and human-generated estimates within a professional, expert-driven environment, using a unique empirical setting: the N-PORT filings submitted to the U.S. Securities and Exchange Commission. These filings provide granular quarterly data on investment fund holdings, with each position classified by fair value level under ASC 820[2]. This classification captures increasing degrees of human involvement in asset valuation, from market-based prices with no human influence (FV1) to estimates heavily reliant on human input (FV3). This setting offers a unique opportunity to compare natural and human-influenced values within the same asset categories, helping control for asset-specific characteristics and reducing potential confounding factors.

This setting offers three key advantages over previous studies: (1) It uses real-world expert estimates rather than laboratory data. (2) The dataset comprises over 120 million observations, ensuring strong statistical power. (3) It provides an observable proxy for human involvement through the three fair value levels. This creates a quasi-natural experiment to test how human judgment affects BL conformity.

BL conformity is analyzed at two levels: (i) aggregate, pooling data by fair value level, and (ii) disaggregated, classifying by both FV level and asset category. Aggregate results show that FV1 values conform almost perfectly to BL, while FV2 and FV3 deviate more, supporting the conventional view that human intervention increases deviation. Nonetheless, the deviations observed for FV2 and FV3 are remarkably small, suggesting that expert judgment can yield estimates closely resembling natural values.

The disaggregated analysis reveals several exceptions to the general trend: some FV1 assets deviate notably from BL, while their FV2 or FV3 valuations counterparts conform more closely. These cases challenge the assumption that natural data always follow BL or that more human input leads to greater deviation.

Overall, the results clarify the relationship between human-generated estimates and BL conformity. While greater human intervention generally increases deviation, such deviations are remarkably small in this expert-driven context. Moreover, for certain asset types, market data deviate from BL and human judgment appears to bring the estimates closer to BL. These findings underline the need to assess the conformity of unmanipulated data before using BL for anomaly detection, as noted in prior studies (Cano-Rodríguez et al., 2025; Diekmann, 2007; Durtschi et al., 2004; Watrin et al., 2008).

The remainder of the paper is structured as follows. Section 2 describes the data and methodology, section 3 reports the empirical results, and section 4 concludes.

2. Data and Methodology

2.1. Data source and descriptive statistics

[1] Some studies that follow this approach are Deckert et al. (2011), Amiram et al. (2015), Horton et al. (2020), Beneish and Vorst (2022), or Aloosh and Li (2024), among others.

[2] Under the ASC 820 fair value hierarchy, Level 1 refers to valuations based on quoted prices in active markets for identical assets; Level 2 relies on observable inputs other than quoted prices, such as comparable instruments or market-corroborated data; and Level 3 is based on unobservable inputs, including internal models or assumptions. Throughout the paper, I refer to these levels as FV1, FV2, and FV3, respectively.

This study uses data from the SEC's N-port filings, which provide quarterly, holding-level information on U.S. mutual funds, including asset type, position value, and fair value level under ASC 820. Values in non-USD currency values were converted to USD using the reported exchange rate, and absolute values were used to ensure that all amounts are positive, regardless of whether the position is long or short.

The dataset spans from the first available filing (2019Q4) to the latest release (2025Q2), including nearly 122 million observations. Of these, 26.8% correspond to FV1, 46.8% to FV2, and 26.4% to FV3. Observations are classified into 20 different asset categories, the largest being Equity – common stock (33.7% of the total), Loans (27.1%), Debt (25.1%), and mortgaged-backed securities (7.5%). Each remaining category accounts for less than 1.25% of the total.

In terms of reported value, the distribution is more uneven: FV1 positions account for 23.27%, FV2 for 76.23%, and FV3 just for 0.39%. Most of the value is concentrated in Equity – common stock (79.46%) and Debt instruments (17.83%), with other categories each below 1.5%. Table 1 reports descriptive statistics for position values, both pooled and by asset category.

*** INSERT TABLE 1 HERE ***

2.2. Methodology

To assess how human intervention affects BL conformity, I measure deviations from the expected digit distribution for each fair value level. If human input increases divergence, FV1 should closely conform to BL, FV2 should diverge moderately, and FV3 should show the greatest deviation.

Comparing BL conformity across datasets poses a methodological challenge due to excess statistical power. Conventional tests depend mechanically on sample size, leading to over-rejection of the null hypothesis in large samples, even with negligible deviations. In this study, the large sample sizes render such statistical tests practically uninformative and hinder meaningful comparison across subsamples of unequal sizes, which is central to the analysis.

To overcome these limitations, I use the Equivalent Contamination Proportion (ECP), a recent measure robust to sample size that enables meaningful comparisons across datasets and offers a more interpretable scale of deviation. The ECP is defined as the proportion of contamination in a Benford-conforming sample such that the expected value of the divergence statistic matches the one observed in the actual data (Cano-Rodríguez, 2025). It ranges from 0% (perfect conformity) to 100% (complete non-conformity), providing an easily interpretable measure of the divergence magnitude.

ECP computation requires specifying a divergence statistic and a contamination model. Following Cano-Rodríguez (2025), I use the Mean Absolute Deviation (MAD)[3] and assume uniform contamination.

MAD and ECP values are first computed for the pooled sample by fair value level (FV1, FV2, and FV3), and then by asset category within each level. To ensure meaningful BL analysis,

[3] MAD is preferred because it allows closed-form ECP estimation, unlike other statistics that require simulation methods, what would be computationally intensive with large samples. As robustness checks, I also used the Chi-squared and sum of squared differences. The results (unreported) are qualitatively identical and available from the author.

only asset category-fair value level groups with at least 500 observations are included in the analysis, following standard practice[4].

3. Results

Table 2 presents the results of the BL conformity analysis disaggregated by fair value level and asset category. It reports MAD values and their corresponding ECP assuming a uniform contamination distribution. The analysis focuses primarily on the ECP values due to its interpretability and sample-size robustness.

*** INSERT TABLE 2 AROUND HERE ***

The first rows of Table 2 report the results of the aggregated analysis. For the full sample, the MAD value is 0.201%, corresponding to an ECP of 3.372%[5]. These results indicate that, overall, the reported position values closely conform to BL.

Disaggregating by fair value level, FV1 positions—based on observable market prices—show even stronger conformity, with a MAD of 0.025% and an ECP 0.415%. Such a low ECP indicates conformity in practical terms, supporting the view that, in general, naturally occurring data free from human intervention follows BL. In contrast, the divergence of FV2 and FV3 positions is notably higher: FV2 positions exhibit a MAD of 0.35%, corresponding to an ECP of 5.853%, while for FV3 positions, the MAD is 0.522% and the ECP is 8.734%.

These results are consistent with the conventional view that greater human intervention leads to greater BL divergence: FV1 positions, free from human input, exhibit near-perfect conformity; FV2 estimates deviate moderately, and FV3 estimates, most subject to human judgment, show the greatest deviation. Overall, these findings support the existence of a monotonically increasing relationship between human intervention and BL divergence for the aggregate data.

Nonetheless, the divergence for FV2 and FV3 remains relatively low (ECP below 10% in both cases), suggesting that expert-generated estimates may closely resemble natural data, thereby conforming closer to BL. Given that human interventions closer to BL are less likely to be detected, this low divergence implies that the ability of BL to detect human intervention—particularly expert intervention—may be more limited than often assumed.

The rest of Table 2 reports the results for those asset categories with sufficient sample size (more than 500 observations). In broad terms, although conformity with BL at the asset-

[4] The 500-observation threshold is computed following Cerqueti and Lupi (2023) approach: to expect at least 20 observations per digit, a minimum sample size of 437 is required, which is rounded up to 500.

[5] These results illustrate why the analysis emphasizes ECP over the MAD. Although the observed MAD (0.201%) is extremely low, it is statistically significant at the 0.01 given the large sample (121.8 million), since the 0.01 MAD critical value would be $0.4046/\sqrt{n} = 0.0037\%$ (Cano-Rodríguez et al., 2025). This highlights the excess power of traditional tests: significance does not imply meaningful deviation. By contrast, the ECP of 3.372% indicates that the observed MAD (0.201%) is the expected MAD in a sample of the same size where only a 3.372% of the observations are non-Benford. An ECP value of 3.372% thus reflect a very minor departure from BL, especially considering the large sample size.

category level is generally lower than in the pooled sample, most asset categories exhibit acceptable levels of conformity: 11 out of the 20 categories show ECP values below 5%, with the simple average ECP across categories being 5.955%. Four categories, however, deviate substantially from BL, exhibiting ECPs higher than 10%: ABS-CBDO, COMM, SN and STIV.

To assess whether this higher deviation is driven by an overrepresentation of FV2 and FV3 cases, I analyzed divergence at the asset category-fair value level. In most asset categories, FV1 positions continue to exhibit greater conformity than FV2 and FV3, supporting the conventional relationship between human intervention and BL conformity. However, there are some noteworthy exceptions.

The most relevant exceptions are the categories ABS-MBS and DBT, for which the FV1 data clearly deviate from BL. The DBT case is particularly relevant, as this category ranks third in number of observations and second in reported value. Contrary to conventional wisdom, FV3 data exhibits the best conformity, followed by FV2 and, finally FV1[6]. This finding shows that not all market values necessarily conform to BL simply by being "natural"; conformity may also depend on asset-specific and market-related characteristics. Moreover, the higher conformity of FV2 and FV3 data challenges the notion that human estimates always diverge more from BL than natural data: in some cases, valuation models may yield estimates that conform better to BL than market prices themselves.

Moreover, in several other asset categories FV2 values conform more closely than their corresponding FV1 values (EP, SN), or FV3 values deviate less than FV2 (ABS-CBDO, ABS-O, DCR, OTHER). These results challenge the notion of a monotonic relationship between the degree of human judgment and BL divergence[7].

In summary, although the aggregate results and most asset categories support the conventional view that data free from human intervention (FV1) conform better to BL than data involving human estimation (FV2 and FV3), several exceptions caution against presuming that market-based values always conform more closely to BL than expert-generated estimates. Moreover, cases where FV2 values conform better than FV1, or FV3 better than FV2, suggest that the relationship between human intervention and BL divergence may be not strictly monotonic.

4. Conclusions

Conformity with BL has become a widely used tool for detecting anomalies in accounting and financial data. Although this approach relies on the assumption that human intervention substantially increases deviation from BL, empirical evidence supporting this premise remains limited and inconclusive.

This study investigates whether human intervention reduces BL conformity using a novel empirical setting: the fair value classifications reported by investment funds under the SEC's N-PORT framework. While the aggregate results support the conventional view that natural data are more Benford-like than human-influenced data, the observed divergence for FV2 and FV3

[6] Besides ABS-MBS and DBT, FV1 data also exhibit the poorest conformity in DFE, but its ECP is not particularly high (2.1%).

[7] Alternatively, one can argue some FV3 estimates conform more closely to BL than their FV2 counterparts because, in these cases, FV2 estimates may in fact require as much human judgment—or even more—than FV3.

values is remarkably low. This suggests that expert-driven estimates resemble natural data quite closely, thereby limiting BL's ability to detect such estimates.

At a more granular level, insightful exceptions to the general pattern emerge: in some asset categories, FV1 values deviate clearly from BL, which highlights the necessity of testing the conformity of unmanipulated data before using BL for detecting anomalies (particularly in the context of financial markets). Besides, FV1 data conforming less than their FV2 counterparts or FV2 less than their FV3, call for caution when applying BL-based techniques to expert-generated data and suggest avenues for future research on the statistical properties of professional estimates.

A limitation of this study is that, although I have attempted to control for heterogeneity across fair value levels by analyzing data within asset categories, some degree of heterogeneity may still persist within the categories themselves. This residual variation could affect BL conformity independently of the degree of human intervention. Therefore, while the fair value classification provides a reasonable proxy for human involvement, future research could address this issue by comparing valuations of more homogeneous classifications of assets under different FV levels.

Declaration of generative AI and AI-assisted technologies in the writing process.

I used ChatGPT (OpenAI, GPT 4o) to improve the clarity and readability of the manuscript. I reviewed and edited the content after using the tool, and I take full responsibility for the final version of this article.

References

Aloosh, A., Li, J., 2024. Direct Evidence of Bitcoin Wash Trading. Manage Sci 70, 8875–8921. https://doi.org/10.1287/MNSC.2021.01448

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. https://doi.org/10.1007/S11142-015-9333-Z

Amiram, D., Lyandres, E., Rabetti, D., 2025. Trading Volume Manipulation and Competition Among Centralized Crypto Exchanges. Manage Sci. https://doi.org/10.1287/MNSC.2021.02903

Ausloos, M., Cerqueti, R., Mir, T.A., 2017. Data science for assessing possible tax income manipulation: The case of Italy. Chaos Solitons Fractals 104, 238–256. https://doi.org/10.1016/J.CHAOS.2017.08.012

Badal-Valero, E., Alvarez-Jareño, J.A., Pavía, J.M., 2018. Combining Benford's Law and machine learning to detect money laundering. An actual Spanish court case. Forensic Sci Int 282, 24–34. https://doi.org/10.1016/J.FORSCIINT.2017.11.008

Barabesi, L., Cerasa, A., Cerioli, A., Perrotta, D., 2018. Goodness-of-Fit Testing for the Newcomb-Benford Law With Application to the Detection of Customs Fraud. Journal of Business and Economic Statistics 36. https://doi.org/10.1080/07350015.2016.1172014

Barabesi, L., Cerioli, A., Di Marzio, M., 2023. Statistical models and the Benford hypothesis: a unified framework. Test 32, 1479–1507. https://doi.org/10.1007/S11749-023-00881-Y

Beneish, M.D., Vorst, P., 2022. The Cost of Fraud Prediction Errors. Accounting Review 97, 91–121. https://doi.org/10.2308/TAR-2020-0068

Burns, B.D., 2020. Do people fit to Benford's law, or do they have a Benford bias? Proceedings of the Annual Meeting of the Cognitive Science Society 42, 1729–1735.

Burns, B.D., 2009. Sensitivity to statistical regularities: People (largely) follow Benford's law. Proceedings of the Annual Meeting of the Cognitive Science Society 31, 2872–2877.

Cano-Rodríguez, M., 2025. How much is too much? Measuring divergence from Benford's Law with the Equivalent Contamination Proportion (ECP). https://doi.org/https://doi.org/10.48550/arXiv.2506.09915

Cano-Rodríguez, M., Núñez-Nickel, M., Licerán-Gutiérrez, A., 2025. Divergence from Benford's law fails to measure financial statement accuracy. International Journal of Accounting Information Systems 56, 100745. https://doi.org/10.1016/J.ACCINF.2025.100745

Cerqueti, R., Lupi, C., 2023. Severe testing of Benford's law. Test 32, 677–694. https://doi.org/10.1007/S11749-023-00848-Z

Cerqueti, R., Lupi, C., 2021. Some New Tests of Conformity with Benford's Law. Stats 2021, Vol. 4, Pages 745-761 4, 745–761. https://doi.org/10.3390/STATS4030044

Chakrabarty, B., Moulton, P.C., Pugachev, L., Wang, X., 2024. Catch me if you can: In search of accuracy, scope, and ease of fraud prediction. Review of Accounting Studies 1–41. https://doi.org/10.1007/S11142-024-09854-4

Chi, D., Burns, B., Burns, B.D., 2024. Benford's Law: Testing the Effects of Distributions and Anchors on Number Estimation. Proceedings of the Annual Meeting of the Cognitive Science Society 46, 3851–3857.

Chi, D., Burns, B., Burns, B.D., 2022. Why do People fit to Benford's Law?-A Test of the Recognition Hypothesis. Proceedings of the Annual Meeting of the Cognitive Science Society 44, 3648–3654.

Cong, L.W., Li, X., Tang, K., Yang, Y., 2023. Crypto Wash Trading. Manage Sci 69, 6427–6454. https://doi.org/10.1287/MNSC.2021.02709

D'Alessandro, A., 2020. Benford's law and metabolomics: A tale of numbers and blood. Transfus Apher Sci 59. https://doi.org/10.1016/J.TRANSCI.2020.103019

Deckert, J., Myagkov, M., Ordeshook, P.C., 2011. Benford's Law and the Detection of Election Fraud. Political Analysis 19, 245–268. https://doi.org/10.1093/PAN/MPR014

Diekmann, A., 2007. Not the First Digit! Using Benford's Law to Detect Fraudulent Scientif ic Data. J Appl Stat 34, 321–329. https://doi.org/10.1080/02664760601004940

Durtschi, C., Hillison, W., Pacini, C., 2004. The effective use of Benford's Law in detecting fraud in accounting data. Journal of Forensic Accounting 5, 17–33.

Eutsler, J., Kathleen Harris, M., Tyler Williams, L., Cornejo, O.E., 2023. Accounting for partisanship and politicization: Employing Benford's Law to examine misreporting of COVID-19 infection cases and deaths in the United States. Accounting, Organizations and Society 108, 101455. https://doi.org/https://doi.org/10.1016/j.aos.2023.101455

Hill, T.P., 1999. The Difficulty of Faking Data. CHANCE 12, 27–31. https://doi.org/10.1080/09332480.1999.10542154

Hill, T.P., 1988. Random-number guessing and the first digit phenomenon. Psychol Rep 62, 967–971.

Horton, J., Krishna Kumar, D., Wood, A., 2020. Detecting academic fraud using Benford law: The case of Professor James Hunton. Res Policy 49, 104084. https://doi.org/10.1016/J.RESPOL.2020.104084

Hsü, E.H., 1948. An experimental study on "mental numbers" and a new application. Journal of General Psychology 38, 57–67. https://doi.org/10.1080/00221309.1948.9711768/ASSET//CMS/ASSET/610B5EE0-A652-410C-8372-2449D7FE37FC/00221309.1948.9711768.FP.PNG

Kaiser, M., 2019. BENFORD'S LAW AS AN INDICATOR OF SURVEY RELIABILITY—CAN WE TRUST OUR DATA? J Econ Surv 33, 1602–1618. https://doi.org/10.1111/JOES.12338

Kössler, W., Lenz, H.J., Wang, X.D., 2024. Some new invariant sum tests and MAD tests for the assessment of Benford's law. Comput Stat 1–22. https://doi.org/10.1007/S00180-024-01463-8/TABLES/17

Kubovy, M., 1977. Response availability and the apparent spontaneity of numerical choices. J Exp Psychol Hum Percept Perform 3, 359–364. https://doi.org/10.1037/0096-1523.3.2.359

Michalski, T., Stoltz, G., 2013. Do Countries Falsify Economic Data Strategically? Some Evidence That They Might. Rev Econ Stat 95, 591–616. https://doi.org/10.1162/REST_A_00274

Mumic, N., Filzmoser, P., 2021. A multivariate test for detecting fraud based on Benford's law, with application to music streaming data. Stat Methods Appt 30, 819–840. https://doi.org/10.1007/S10260-021-00582-6/FIGURES/17

Nigrini, M.J., 1996. Taxpayer compliance application of Benford's law. Journal of American Taxation Association 18, 72–92.

Sifat, I., Tariq, S.A., van Donselaar, D., 2024. Suspicious trading in nonfungible tokens (NFTs). Information & Management 61, 103898. https://doi.org/https://doi.org/10.1016/j.im.2023.103898

Vičič, J., Tošić, A., 2022. Application of Benford's Law on Cryptocurrencies. Journal of Theoretical and Applied Electronic Commerce Research 2022, Vol. 17, Pages 313-326 17, 313–326. https://doi.org/10.3390/JTAER17010016

Watrin, C., Ralf, A.E., Ae, S., Ullmann, R., 2008. Benford's Law: an instrument for selecting tax audit targets? Review of Managerial Science 2008 2:3 2, 219–237. https://doi.org/10.1007/S11846-008-0019-9

Wünsch, S., Vollmeyer, R., Burns, B., 2024. Benford's Law from a Developmental Perspective. Proceedings of the Annual Meeting of the Cognitive Science Society 46, 973–979. https://doi.org/10.31234/OSF.IO/43DQ8

Table 1. Descriptive statistics of position values by fair value level and asset category

Asset Category	FV level	N	Mean (10^6 USD)	STD (10^6 USD)	Min (10^6 USD)	P25 (10^6 USD)	P50 (10^6 USD)	P75 (10^6 USD)	Max (10^9 USD)
Pooled	Total	121,959,094	117.55	9,582.68	0.00	0.01	0.23	1.92	9,256.48
	FV1	32,667,806	102.13	8,434.18	0.00	0.11	0.72	4.50	9,256.48
	FV2	56,986,896	191.78	12,470.76	0.00	0.15	0.70	3.10	8,482.08
	FV3	32,146,806	1.72	597.66	0.00	0.00	0.00	0.01	895.24
ABS-APCP	Total	30,728	1.65	6.30	0.00	0.01	0.04	0.42	0.25
	FV1	0	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	FV2	30,721	1.65	6.29	0.00	0.01	0.04	0.42	0.25
	FV3	3	0.41	0.71	0.00	0.00	0.00	0.62	0.00
ABS-CBDO	Total	1,330,670	3.69	11.89	0.00	0.27	1.00	3.25	1.98
	FV1	45	2.31	3.17	0.03	0.25	0.55	3.01	0.01
	FV2	1,294,685	3.68	11.99	0.00	0.27	0.99	3.19	1.98
	FV3	35,889	4.19	7.38	0.00	0.73	2.03	5.08	0.71
ABS-MBS	Total	9,169,728	3.68	490.03	0.00	0.03	0.24	1.31	659.93
	FV1	1,024	1.57	9.91	0.00	0.07	0.18	0.42	0.14
	FV2	9,106,252	3.67	491.73	0.00	0.03	0.24	1.31	659.93
	FV3	61,535	4.45	32.79	0.00	0.04	0.17	1.25	2.05
ABS-O	Total	1,225,337	3.67	129.24	0.00	0.22	0.78	2.54	34.00
	FV1	150	0.55	0.94	0.01	0.10	0.21	0.52	0.01
	FV2	1,186,777	3.09	28.44	0.00	0.22	0.77	2.51	14.24
	FV3	37,865	21.81	717.52	0.00	0.32	1.19	4.05	34.00
COMM	Total	1,128	173.80	796.66	0.02	1.27	9.61	36.97	6.70
	FV1	30	38.64	57.21	0.15	11.10	12.74	15.66	0.21
	FV2	1,096	177.81	807.81	0.02	1.19	8.94	37.16	6.70
	FV3	2	6.33	8.46	0.35	3.34	6.33	9.32	0.01
DBT	Total	30,625,533	83.49	9,078.70	0.00	0.21	0.78	2.64	7,467.23
	FV1	45,969	29.07	215.38	0.00	0.43	2.14	7.62	7.54
	FV2	30,494,735	82.81	9,084.38	0.00	0.21	0.78	2.64	7,467.23
	FV3	81,735	368.20	9,659.94	0.00	0.03	0.48	2.45	895.24
DCO	Total	204,619	2.03	605.22	0.00	0.01	0.03	0.21	273.76
	FV1	182,556	2.13	640.75	0.00	0.01	0.03	0.17	273.76
	FV2	20,793	1.29	4.44	0.00	0.02	0.13	0.79	0.17
	FV3	485	0.29	0.90	0.00	0.01	0.03	0.21	0.01
DCR	Total	319,717	0.55	12.29	0.00	0.00	0.03	0.14	3.30
	FV1	721	24.24	159.96	0.00	0.03	0.24	2.96	3.30
	FV2	314,656	0.50	9.67	0.00	0.00	0.03	0.14	2.22
	FV3	4,212	0.36	1.67	0.00	0.00	0.00	0.09	0.03
DE	Total	950,633	6.23	274.72	0.00	0.00	0.03	0.20	115.86
	FV1	378,162	9.38	415.69	0.00	0.00	0.03	0.23	115.86
	FV2	556,058	4.23	106.85	0.00	0.00	0.02	0.18	28.54
	FV3	13,865	2.05	59.29	0.00	0.00	0.01	0.11	6.03
DFE	Total	1,527,214	25.17	669.73	0.00	0.00	0.02	0.25	174.29
	FV1	23,870	1.74	16.24	0.00	0.00	0.03	0.23	0.96

Asset Category	FV level	N	Mean (10^6 USD)	STD (10^6 USD)	Min (10^6 USD)	P25 (10^6 USD)	P50 (10^6 USD)	P75 (10^6 USD)	Max (10^9 USD)
	FV2	1,455,778	26.25	685.92	0.00	0.00	0.02	0.25	174.29
	FV3	129	0.43	2.37	0.00	0.00	0.02	0.07	0.02
DIR	Total	915,662	29.11	482.68	0.00	0.01	0.11	0.79	92.35
	FV1	250,725	17.85	428.19	0.00	0.01	0.09	0.61	53.95
	FV2	659,046	33.65	503.85	0.00	0.02	0.12	0.87	92.35
	FV3	948	2.45	21.63	0.00	0.00	0.01	0.19	0.41
DO	Total	25,166	6.90	183.17	0.00	0.00	0.04	0.35	16.12
	FV1	6,014	6.01	39.10	0.00	0.00	0.02	0.14	1.00
	FV2	17,854	6.79	210.50	0.00	0.00	0.04	0.42	16.12
	FV3	1,298	12.46	184.15	0.00	0.00	0.07	0.85	4.56
EC	Total	41,091,560	277.23	14,467.47	0.00	0.14	0.96	6.75	9,256.48
	FV1	31,020,969	104.69	8,629.19	0.00	0.12	0.75	4.59	9,256.48
	FV2	9,854,010	824.67	25,257.61	0.00	0.29	2.58	24.36	8,482.08
	FV3	179,621	23.44	662.58	0.00	0.00	0.06	1.13	128.74
EP	Total	443,575	437.26	12,077.49	0.00	0.27	1.39	6.30	2,114.85
	FV1	263,638	218.65	7,186.75	0.00	0.30	1.45	6.47	1,562.77
	FV2	102,941	1,313.78	22,253.07	0.00	0.28	1.44	7.07	2,114.85
	FV3	76,630	13.89	235.56	0.00	0.17	1.12	5.00	19.86
LON	Total	33,038,634	0.29	132.23	0.00	0.00	0.00	0.01	316.21
	FV1	205	1.06	2.81	0.00	0.04	0.15	1.00	0.02
	FV2	1,420,903	2.86	41.31	0.00	0.25	0.79	2.26	48.08
	FV3	31,616,696	0.18	134.89	0.00	0.00	0.00	0.01	316.21
OTHER	Total	258,189	34.79	1,996.36	0.00	0.23	1.85	9.70	434.31
	FV1	158,435	26.95	137.11	0.00	0.19	1.35	9.99	7.88
	FV2	20,333	62.23	226.90	0.00	0.23	3.12	30.57	7.67
	FV3	31,592	89.50	5,694.74	0.00	0.20	2.02	7.32	434.31
RA	Total	208,934	17.58	267.64	0.00	0.43	1.55	5.92	72.83
	FV1	3,224	13.08	40.96	0.00	1.00	2.54	7.20	0.67
	FV2	204,844	17.59	270.22	0.00	0.42	1.53	5.86	72.83
	FV3	19	86.83	136.12	0.09	3.94	31.50	40.50	0.38
RE	Total	42,544	25.14	960.77	0.00	0.08	0.32	2.00	56.28
	FV1	36,453	2.38	15.58	0.00	0.06	0.25	1.14	1.20
	FV2	3,022	9.16	24.96	0.00	0.19	0.51	4.69	0.51
	FV3	1,142	690.01	5,824.76	0.01	4.85	7.66	25.64	56.28
SN	Total	35,896	602.22	8,368.49	0.00	0.66	3.02	13.40	298.18
	FV1	1,282	9.84	25.78	0.00	0.94	2.90	9.40	0.37
	FV2	34,061	354.66	3,511.12	0.00	0.64	3.01	13.74	100.13
	FV3	551	17,285.97	59,359.99	0.00	1.16	4.90	10.42	298.18
STIV	Total	513,627	64.85	740.12	0.00	0.83	4.00	17.79	167.95
	FV1	294,334	57.05	600.12	0.00	0.43	2.86	15.88	167.95
	FV2	208,331	76.72	916.54	0.00	1.70	5.24	19.90	80.88
	FV3	2,589	18.81	188.87	0.00	0.11	0.43	4.51	7.21

This table reports the descriptive statistics (number of observations, mean value, standard deviation, minimum, percentiles 25th, 50th, and 75th, and maximum) of the position values by fair value level and asset category. All values are reported in millions of USD, except for the number of observations (in units) and the maximum position value (in billions). FV1, FV2, and FV3 indicate fair value levels 1, 2, and 3, respectively. Asset categories are: Asset-backed securities – commercial paper (ABS-APCP), Asset-backed securities – collateralized bond/debt obligations (ABS-CBDO), Asset-backed securities – mortgaged-back securities (ABS-MBS), Asset-backed securities – other (ABS-O), Commodity contracts (COMM), Debt instruments (DBT), Derivatives – commodity (DCO), Derivatives – credit (DCR), Derivatives – equity (DE), Derivatives – foreign exchange (DFE), Derivatives – interest rates (DIR), Derivatives – other (DO), Equity – common stock (EC), Equity – preferred stock (EP), Loans (LON), Other (OTHER), Repurchase agreements (RA), Real estate (RE), Structured note (SN), and Short-term investment vehicle (STIV).

Table 2. MAD and ECP for First and First-Two Digit Analyses by Fair Value Level

Asset Category	FV1			FV2			FV3			Total		
	n	MAD	ECP	n	MAD	ECP	n	MAD	ECP	n	MAD	ECP
Pooled data	32,667,806	0.025%	0.415%	56,986,896	0.350%	5.853%	32,146,806	0.522%	8.734%	121,801,508	0.201%	3.372%
ABS-APCP	0	n/a	n/a	30,721	0.378%	6.009%	3	n/a	n/a	30,724	0.378%	6.003%
ABS-CBDO	45	n/a	n/a	1,294,685	0.967%	16.196%	35,889	0.696%	11.548%	1,330,619	0.954%	15.982%
ABS-MBS	1,024	0.912%	9.280%	9,106,252	0.095%	1.596%	61,535	0.427%	7.031%	9,168,811	0.097%	1.617%
ABS-O	150	n/a	n/a	1,186,777	0.335%	5.612%	37,865	0.311%	4.871%	1,224,792	0.321%	5.374%
COMM	30	n/a	n/a	1,096	1590%	24.207%	2	n/a	n/a	1,128	1.718%	26.666%
DBT	45,969	0.771%	12.860%	30,494,735	0.589%	9.872%	81,735	0.345%	5.664%	30,622,439	0.589%	9.857%
DCO	182,556	0.058%	0.330%	20,793	0.211%	2.325%	485	n/a	n/a	203,834	0.062%	0.604%
DCR	721	0.706%	0.000%	314,656	0.108%	1.688%	4,212	0.345%	0.000%	319,589	0.106%	1.651%
DE	378,162	0.053%	0.647%	556,058	0.074%	1.151%	13,865	0.447%	6.833%	948,085	0.065%	1.019%
DFE	23,87	0.194%	2.100%	1,455,778	0.040%	0.595%	129	n/a	n/a	1,479,777	0.041%	0.616%
DIR	250,725	0.059%	0.616%	659,046	0.049%	0.677%	948	1.354%	19.098%	910,719	0.023%	0.000%
DO	6,014	0.511%	7.068%	17,854	0.233%	2.661%	1,298	0.861%	9.656%	25,166	0.170%	1.459%
EC	31,020,969	0.024%	0.406%	9,854,010	0.057%	0.946%	179,621	0.211%	3.439%	41,054,600	0.032%	0.534%
EP	263,638	0.133%	2.118%	102,941	0.133%	1.898%	76,63	0.217%	3.397%	443,209	0.123%	2.002%
LON	205	n/a	n/a	1,420,903	0.471%	7.880%	31,616,696	0.530%	8.868%	33,037,804	0.523%	8.755%
OTHER	158,435	0.112%	1.636%	20,333	0.370%	5.649%	31,592	0.194%	2.451%	210,36	0.125%	1.935%
RA	3,224	0.539%	5.984%	204,844	0.473%	7.907%	19	n/a	n/a	208,087	0.469%	7.846%
RE	36,453	0.114%	0.000%	3,022	0.307%	0.000%	1,142	3.661%	60.608%	40,617	0.193%	2.658%
SN	1,282	1.440%	21.829%	34,061	0.653%	10.809%	551	3.089%	49.463%	35,894	0.686%	11.374%
STIV	294,334	0.223%	3.687%	208,331	1.866%	31.247%	2,589	2.766%	45.953%	505,254	0.785%	13.144%
Average			4571%			6946%			15925%			5955%

This table reports the number of observations, the Mean Absolute Deviation (MAD), and the corresponding Estimated Contamination Proportion (ECP), using a uniform contamination distribution. Results are computed based on the first digit and the first 2 digits of position values, disaggregated by fair value level and asset category. FV1, FV2, and FV3 correspond to fair value levels 1, 2, and 3, respectively. Asset categories are: Asset-backed securities – commercial paper (ABS-APCP), Asset-backed securities – collateralized bond/debt obligations (ABS-CBDO), Asset-backed securities – mortgaged-back securities (ABS-MBS), Asset-backed securities – other (ABS-O), Commodity contracts (COMM), Debt instruments (DBT), Derivatives – commodity (DCO), Derivatives – credit (DCR), Derivatives – equity (DE), Derivatives – foreign exchange (DFE), Derivatives – interest rates (DIR), Derivatives – other (DO), Equity – common stock (EC), Equity – preferred stock (EP), Loans (LON), Other (OTHER), Repurchase agreements (RA), Real estate (RE), Structured note (SN), and Short-term investment vehicle (STIV). The final row reports the average ECP values across asset categories for each fair value level.