Appendix to A Random Walk Down EDGAR Street

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Opportunity Heterogeneity and Perverse Scaling in the Bad Landings Detector

This appendix analyzes the statistical behavior of EDGAR's Bad Landings score under honest play when boards differ in whether a Bad Landing opportunity is present. The goal is twofold. First, we show that ignoring opportunity heterogeneity leads to variance inflation relative to EDGAR's nominal normalization. Second, we identify the additional conditions under which this inflation worsens with the number of boards, producing what we refer to as *perverse scaling* of tail probabilities.

Throughout, the probabilistic model mirrors the simulation used in the accompanying numerical analysis.

A. Variance inflation from heterogeneous opportunities

A.1 Data-generating model

Consider n boards indexed by $i = 1, \ldots, n$.

Let $O_i \in \{0, 1\}$ indicate whether board i presents a Bad Landing opportunity. We assume

$$O_i \sim \text{Bernoulli}(1 - w_0),$$

independently across boards, where w_0 is the fraction of boards on which a Bad Landing is not possible.

Conditional on $O_i = 1$, a miss occurs with probability p:

$$X_i \mid O_i = 1 \sim \text{Bernoulli}(p),$$

and if $O_i = 0$, then $X_i = 0$ deterministically.

Define

$$M = \sum_{i=1}^{n} O_i \quad \text{(number of opportunity boards)},$$

$$K = \sum_{i=1}^{n} X_i \quad \text{(number of misses)}.$$

Conditional on M,

$$K \mid M \sim \text{Binomial}(M, p).$$

The overall mean miss rate across all boards is

$$\bar{p} = \frac{\mathrm{E}[K]}{n} = (1 - w_0)p.$$

A.2 True variance of the miss count

By the law of total variance,

$$\mathrm{Var}(K) = \mathrm{E}[\mathrm{Var}(K \mid M)] + \mathrm{Var}(\mathrm{E}[K \mid M])\,.$$

The two terms are

$$\mathrm{E}[\mathrm{Var}(K \mid M)] = \mathrm{E}[Mp(1-p)] = n(1-w_0)p(1-p),$$

$$\mathrm{Var}(\mathrm{E}[K \mid M]) = \mathrm{Var}(Mp) = p^2 n w_0 (1 - w_0).$$

Thus,

$$\boxed{\mathrm{Var}(K) = n(1-w_0)p(1-p) + p^2 n w_0 (1-w_0).}$$

The second term arises solely from randomness in the number of opportunity boards. It is absent in a fixed-n binomial model and is not accounted for if all boards are treated as equivalent trials.

A.3 EDGAR normalization and variance understatement

EDGAR's Bad Landings score can be written abstractly as

$$Z_{\text{EDGAR}} = \frac{n\bar{p} - K}{\sqrt{n\bar{p}(1-\bar{p})}}.$$

This normalization implicitly assumes that K has variance $n\bar{p}(1 - \bar{p})$, as would be the case under a binomial model with n homogeneous trials.

Under opportunity heterogeneity, however, $\mathrm{Var}(K)$ exceeds this benchmark by an additive term proportional to $\mathrm{Var}(M)$. As a result, even under honest play, the variance of Z_{EDGAR} exceeds one, and nominal Gaussian tail probabilities understate the true exceedance rates.

This establishes variance inflation due solely to heterogeneous opportunities and the absence of variance normalization by the effective sample size.

B. Conditions for perverse scaling

Variance inflation alone does not imply that tail miscalibration worsens as the number of boards increases. In this section we characterize when opportunity heterogeneity leads to *perverse scaling*: tail exceedance probabilities that deteriorate with increasing n.

B.1 When variance inflation remains $O(n)$

In the model of Section A, with fixed miss probability p on opportunity boards, the additional variance term

$$p^2 n w_0 (1 - w_0)$$

grows linearly in n.

In this setting, although EDGAR's normalization understates variance, the miss count K remains a sum of weakly dependent Bernoulli variables, and standard central limit behavior applies after rescaling. Tail miscalibration is present but does not systematically worsen with increasing n.

B.2 Random effective sample size as a mixture mechanism

Perverse scaling requires that the distribution of K be a non-degenerate mixture over substantially different effective sample sizes or success probabilities.

Opportunity heterogeneity provides such a mechanism when conditioning on M produces materially different distributions for K across realizations of M. Because EDGAR conditions on n rather than on M, the resulting Z_{EDGAR} is a mixture distribution rather than a single asymptotic normal law.

Mixture distributions preserve approximately Gaussian behavior near the center but exhibit inflated exceedance probabilities in the tails.

B.3 Amplification via latent heterogeneity

If, in addition, the miss probability on opportunity boards varies across pairs,

$$p \sim F, \qquad \mathrm{Var}(p) > 0,$$

then

$$K \mid (M, p) \sim \mathrm{Binomial}(M, p),$$

and

$$\mathrm{Var}(K) = n\bar{p}(1 - \bar{p}) + (1 - w_0)^2 (n^2 - n)\,\mathrm{Var}(p).$$

Here we consider a random-effects model in which each pair draws a latent success probability p that is shared across boards, inducing strong within-pair dependence; under this assumption the variance acquires an $O(n^2)$ component. The $O(n^2)$ term implies that the discrepancy between the true distribution of Z_{EDGAR} and its nominal Gaussian reference increases with n. In this regime, tail exceedance rates worsen rather than stabilize as more boards are accumulated.

B.4 Summary

Heterogeneous opportunities without variance normalization necessarily produce variance inflation in EDGAR's Bad Landings score. This inflation rises to the level of perverse scaling when the miss count is governed by a mixture distribution, either through random effective sample size, latent pair-level heterogeneity, or additional nonlinear scoring features, so that EDGAR's fixed-$\bar{p}$ normalization no longer corresponds to any single asymptotic regime.

Under these conditions, nominal Z-score thresholds cannot be interpreted as fixed false-positive rates, even under honest play.