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Renormalization-Group Attractors as a Unifying Framework for Physical Convergence and Theory Polygenesis

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ABSTRACT

The independent emergence of identical mathematical structures in distinct scientific communities (polygenesis) and the parallel appearance of similar physical behavior in unrelated systems (convergence) both hint at a shared organizing principle. Existing literature identifies fixed-point structures in scalar-curvature geometry, cosmological attractors, dual-subgradient optimization, strong-randomness renormalization, nonequilibrium functional RG, hierarchical glass models, and quark confinement, but lacks a quantitative link between the geometry of theory space and the likelihood of independent discovery. We model theory space as a metric flow on the space of Lagrangians, define a similarity metric based on functional distance, and derive two complementary quantitative results. First, using the inflationary attractor formulas $n_s = 1 - 2/N$ and $r = 12/N^2$ we obtain a basin-volume scaling $V_{\text{basin}}(N) = 1.0258 N^{-2}$, which yields a polygenesis probability $P_{\text{poly}}(N) = \kappa 1.0258 N^{-2}$ for a uniform prior on efold numbers. Second, we treat discovery trajectories as dual-subgradient iterations on a strongly convex program, obtaining explicit iteration counts $T_{\text{simple}} = \lceil 1/\epsilon \rceil$ and $T_{\text{sliding}} = \lceil \ln(1/\epsilon) \rceil$, and, under a concrete contraction assumption, a projected 458.2 iterations to reach $\epsilon = 10^{-2}$ precision. An alternative Herfindahl-based polygenesis model for an illustrative five-basin landscape gives $P_2 = 0.275$ and $P_3 = 0.08875$. Both frameworks produce falsifiable predictions: the basin-volume scaling predicts a N^{-2} decline of polygenesis with efold number, while the Herfindahl model predicts specific coincidence probabilities for a given basin distribution. The results change practice by providing measurable criteria—basin volume and iteration-count scaling—for assessing redundancy risk in theory development and for designing discovery processes.

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Abstract

The independent emergence of identical mathematical structures in distinct scientific communities (polygenesis) and the parallel appearance of similar physical behavior in unrelated systems (convergence) both hint at a shared organizing principle. Existing literature identifies fixed-point structures in scalar-curvature geometry, cosmological attractors, dual-subgradient optimization, strong-randomness renormalization, nonequilibrium functional RG, hierarchical glass models, and quark confinement, but lacks a quantitative link between the geometry of theory space and the likelihood of independent discovery. We model theory space as a metric flow on the space of Lagrangians, define a similarity metric based on functional distance, and derive two complementary quantitative results. First, using the inflationary attractor formulas $n_s = 1 - 2/N$ and $r = 12/N^2$ we obtain a basin-volume scaling $V_{\text{basin}}(N) = 1.0258 N^{-2}$, which yields a polygenesis probability $P_{\text{poly}}(N) = \kappa 1.0258 N^{-2}$ for a uniform prior on efold numbers. Second, we treat discovery trajectories as dual-subgradient iterations on a strongly convex program, obtaining explicit iteration counts $T_{\text{simple}} = \lceil 1/\epsilon \rceil$ and $T_{\text{sliding}} = \lceil \ln(1/\epsilon) \rceil$, and, under a concrete contraction assumption, a projected 458.2 iterations to reach $\epsilon = 10^{-2}$ precision. An alternative Herfindahl-based polygenesis model for an illustrative five-basin landscape gives $P_2 = 0.275$ and $P_3 = 0.08875$. Both frameworks produce falsifiable predictions: the basin-volume scaling predicts a N^{-2} decline of polygenesis with efold number, while the Herfindahl model predicts specific coincidence

probabilities for a given basin distribution. The results change practice by providing measurable criteria—basin volume and iteration-count scaling—for assessing redundancy risk in theory development and for designing discovery processes.

1. Introduction

Researchers in high-energy theory, cosmology, and the history of science repeatedly encounter cases where distinct groups arrive at the same mathematical structure without direct communication. The independent formulation of the renormalization group (RG) by Wilson and Kadanoff, the parallel invention of calculus by Newton and Leibniz, and the simultaneous emergence of inflationary attractor models in cosmology are emblematic examples. For practitioners, such polygenesis creates redundant effort, delays synthesis, and obscures the underlying unity of physical law. Experimental programs that rely on precise predictions of the scalar spectral index n_s and the tensor-to-scalar ratio r (e.g., CMB missions) must allocate resources to test models that may be mathematically equivalent under an RG fixed point. If a quantitative relationship between the geometry of theory space and the likelihood of independent rediscovery were known, funding agencies could prioritize research programs that explore genuinely novel basins, and theorists could design models whose basins are maximally large, thereby reducing the risk of redundant effort.

Contributions.

- **C1.** Formal definition of a metric on theory space and derivation of basin-volume scaling $V_{\text{basin}}(N) = 1.0258 N^{-2}$ (Sections 3–4.1).
- **C2.** Explicit computation of iteration counts for dual-subgradient methods at tolerances $\epsilon = 10^{-3}$ and $\epsilon = 10^{-6}$ (Section 4.2).
- **C3.** Derivation of a polygenesis probability proportional to basin volume, yielding $P_{\text{poly}}(N) = \kappa 1.0258 N^{-2}$ (Section 4.3).
- **C4.** Development of an alternative Herfindahl-based polygenesis model for an illustrative five-basin landscape, giving $P_2 = 0.275$ and $P_3 = 0.08875$ (Section 4.4).
- **C5.** Projection of iteration count 458.2 for a contraction-parameterized discovery trajectory (Section 4.5).
- **C6.** Presentation of falsifiability criteria based on historical polygenesis frequencies (Section 6).
- **C7.** Practical pathway for assessing and engineering basin volumes in future theory-building efforts (Section 7).

2. Background and Related Work

The literature provides multiple instances of fixed-point structures governing both physical dynamics and theory construction.

[1] formulates Conjecture 7.1 that three-dimensional manifolds homeomorphic to tori with $\text{Scal}_j \geq -1/j$ and $\text{MinA}(M_j^3) \geq \alpha > 0$ have a subsequence converging in the $\mathcal{VF}$ sense to a flat torus, and notes the Ricci analogue was proven by Colding.

[2] studies α - and ξ -attractor inflationary models and proves that the tree-level predictions $n_s = 1 - 2/N + O(N^{-2})$ and $r = 12/N^2 + O(N^{-3})$ are invariant under RG-improved quantum corrections, establishing a universal fixed point for a broad class of cosmological theories.

[3] treats the convergence time of dual-subgradient methods for strongly convex programs, and we adopt the iteration formulas $T_{\text{simple}} = \lceil 1/\epsilon \rceil$ and $T_{\text{sliding}} = \lceil \ln(1/\epsilon) \rceil$ as our own assumptions.

[4] reviews strong-randomness renormalization-group approaches to disordered quantum systems.

[5] introduces the nonequilibrium functional renormalization group.

[6] investigates renormalization-group techniques for disordered systems.

[7] reviews quark confinement in the context of renormalization-group methods.

[8] proposes a meta-analysis that treats convergence (ontological similarity) and consilience (epistemic similarity) as symmetric faces of a hierarchical reality shaped by RG attractors, supplying worked examples from gauge theory, effective field theory, universality, quantum geometry, and non-equilibrium dynamics.

Collectively, these works demonstrate that (i) RG fixed points attract physical systems across diverse domains, (ii) theoretical frameworks often share invariant predictions under RG flow, and (iii) the geometry of the underlying possibility space influences both physical convergence and intellectual consilience.

3. Methods

We model **theory space** $\mathcal{T}$ as the set of all admissible Lagrangians $\mathcal{L}$ equipped with a metric $d(\mathcal{L}_1, \mathcal{L}_2)$ defined by the L^2 norm of the difference of their functional coefficients after a common field redefinition:

$$d(\mathcal{L}_1, \mathcal{L}_2) = \sqrt{\sum_i (a_i - b_i)^2},$$

where $\mathcal{L}_1 = \sum_i a_i \mathcal{O}_i$ and $\mathcal{L}_2 = \sum_i b_i \mathcal{O}_i$.

The **RG flow** $\Phi_t : \mathcal{T} \rightarrow \mathcal{T}$ satisfies

$$\frac{\partial \mathcal{L}}{\partial t} = \beta[\mathcal{L}],$$

with $\beta[\cdot]$ the beta functional derived from integrating out high-energy modes. Fixed points $\mathcal{L}^*$ satisfy $\beta[\mathcal{L}^*] = 0$.

A **basin of attraction** $\mathcal{B}(\mathcal{L}^*)$ is the set of initial Lagrangians whose RG trajectories converge to $\mathcal{L}^*$ as $t \rightarrow \infty$. Assuming isotropy near the fixed point, we approximate the basin as a k -dimensional hypersphere of radius R :

$$V_{\text{basin}} \approx \frac{\pi^{k/2}}{\Gamma(k/2 + 1)} R^k,$$

where k is the effective dimensionality of the relevant coupling subspace.

To connect V_{basin} to observable parameters we use the inflationary attractor formulas from [2]:

$$n_s = 1 - \frac{2}{N} + O(N^{-2}), \quad r = \frac{12}{N^2} + O(N^{-3}),$$

with N the number of e-folds. The Euclidean distance between two models with efold numbers N_1 and N_2 in the observable space (n_s, r) is

$$d_{12} = \sqrt{\left(\frac{2}{N_2} - \frac{2}{N_1}\right)^2 + \left(12\left(\frac{1}{N_1^2} - \frac{1}{N_2^2}\right)\right)^2}.$$

For N_1, N_2 of the same order the first term dominates, yielding the approximation

$$d_{12} \approx 2 \left| \frac{1}{N_2} - \frac{1}{N_1} \right|.$$

Assuming a uniform distribution of N over $[N_{\min}, N_{\max}]$, the maximal distance from a reference model N_0 occurs at the interval endpoints, giving a basin radius

$$R = 2 \max\left(\left|\frac{1}{N_{\min}} - \frac{1}{N_0}\right|, \left|\frac{1}{N_{\max}} - \frac{1}{N_0}\right|\right).$$

Choosing $N_0 = (N_{\min} + N_{\max})/2$ simplifies to

$$R = \frac{2}{N_{\min}} - \frac{2}{N_{\max}}.$$

For the **algorithmic convergence** side we adopt the dual-subgradient iteration count formulas from [3]:

$$T_{\text{simple}} = \left\lceil \frac{1}{\epsilon} \right\rceil, \quad T_{\text{sliding}} = \left\lceil \ln\left(\frac{1}{\epsilon}\right) \right\rceil,$$

where ϵ is a prescribed tolerance.

We also consider an **alternative polygenesis model** based on the Herfindahl concentration of basin-volume fractions $\{p_i\}$ (Section 4.4). The probability that k independent trajectories land in the same basin is

$$P_k = \sum_{i=1}^{N_b} p_i^k.$$

All calculations are analytical; no empirical data beyond the cited formulas are introduced.

4. Analysis

4.1 Basin-volume scaling from inflationary attractors

Using $N_{\min} = 50$ and $N_{\max} = 70$ we compute

$$\frac{2}{N_{\min}} = \frac{2}{50} = 0.04, \quad \frac{2}{N_{\max}} = \frac{2}{70} \approx 0.0285714,$$

$$R = 0.04 - 0.0285714 = 0.0114286.$$

Treating the basin as a 2-dimensional disk ($k = 2$) gives

$$V_{\text{basin}} = \pi R^2 = \pi (0.0114286)^2 \approx \pi \times 1.3061 \times 10^{-4} \approx 4.103 \times 10^{-4}.$$

Normalizing to $N = 50$ yields the constant

$$C = V_{\text{basin}}(50) \times 50^2 = 4.103 \times 10^{-4} \times 2500 = 1.0258,$$

so the explicit scaling law is

$$\boxed{V_{\text{basin}}(N) = 1.0258 N^{-2}}.$$

4.2 Iteration counts for dual-subgradient convergence

For a tolerance $\epsilon = 10^{-3}$:

$$T_{\text{simple}} = \lceil 10^3 \rceil = 1000, \quad T_{\text{sliding}} = \lceil \ln(10^3) \rceil = \lceil 6.9078 \rceil = 7.$$

For $\epsilon = 10^{-6}$:

$$T_{\text{simple}} = \lceil 10^6 \rceil = 1\,000\,000, \quad T_{\text{sliding}} = \lceil \ln(10^6) \rceil = \lceil 13.8155 \rceil = 14.$$

4.3 Linking basin volume to polygenesis probability

Assuming polygenesis probability is proportional to basin volume,

$$P_{\text{poly}}(N) = \kappa V_{\text{basin}}(N) = \kappa 1.0258 N^{-2}.$$

Setting $\kappa = 1$ for a dimensionless scale gives

$$P_{\text{poly}}(50) = 1.0258 \times 50^{-2} = 4.103 \times 10^{-4}, \quad P_{\text{poly}}(60) = 1.0258 \times 60^{-2} = 2.849 \times 10^{-4}.$$

The ratio $P_{\text{poly}}(60)/P_{\text{poly}}(50) = 0.694$, a 30% reduction when the required efold number increases from 50 to 60.

4.4 Alternative Herfindahl-based polygenesis model

Assume an illustrative landscape with five basins:

$$p_1 = 0.40, p_2 = 0.25, p_3 = 0.20, p_4 = 0.10, p_5 = 0.05,$$

which sum to 1.

Pairwise coincidence:

$$P_2 = \sum_{i=1}^5 p_i^2 = 0.1600 + 0.0625 + 0.0400 + 0.0100 + 0.0025 = 0.2750.$$

Triple coincidence:

$$P_3 = \sum_{i=1}^5 p_i^3 = 0.064000 + 0.015625 + 0.008000 + 0.001000 + 0.000125 = 0.088750.$$

Dominant-basin share:

$$\frac{p_1^2}{P_2} = \frac{0.1600}{0.2750} = 0.581818 \approx 0.582.$$

Odds ratio between dominant and runner-up basins:

$$\frac{p_1^2}{p_2^2} = \left(\frac{0.40}{0.25} \right)^2 = 2.56.$$

These numbers illustrate how the Herfindahl concentration of basin volumes directly determines polygenesis frequencies.

4.5 Convergence time of a discovery trajectory (contraction projection)

Assume a strongly convex evidence functional with strong-convexity parameter μ and step size η such that $\mu\eta = 0.01$ (so $q = 1 - \mu\eta = 0.99$). With initial distance $d_0 = 1$ and target precision $\epsilon = 10^{-2}$, the iteration count n satisfies $d_0 q^n \leq \epsilon$:

$$n = \frac{\ln(\epsilon/d_0)}{\ln q} = \frac{\ln(10^{-2})}{\ln(0.99)} = \frac{-4.605170}{-0.01005034} = 458.21 \approx 458.2.$$

Thus, under the stated contraction parameters, a discovery trajectory reaches 1% precision after roughly 458 iterations.

5. Results

1. **Basin-volume formula.** $V_{\text{basin}}(N) = 1.0258 N^{-2}$ (Section 4.1). For $N \in [50, 70]$, $V_{\text{basin}} = 4.1 \times 10^{-4}$.
2. **Iteration counts.** Simple method: 1000 ($\epsilon = 10^{-3}$) and 1 000 000 ($\epsilon = 10^{-6}$). Sliding method: 7 and 14 respectively (Section 4.2).
3. **Polygenesis probability (basin-volume model).** $P_{\text{poly}}(50) = 4.1 \times 10^{-4}$, $P_{\text{poly}}(60) = 2.8 \times 10^{-4}$ (Section 4.3).
4. **Herfindahl polygenesis model.** $P_2 = 0.275$, $P_3 = 0.08875$, odds ratio 2.56 (Section 4.4).
5. **Contraction-based iteration projection.** 458.2 iterations to reach $\epsilon = 10^{-2}$ (Section 4.5).

These quantitative outcomes connect the geometry of theory space (via N or basin fractions) to both computational effort (via ϵ) and the likelihood of convergent discovery.

6. Discussion

6.1 Limitations

- **L1. Metric choice.** The L^2 metric on coupling coefficients assumes linearity and neglects possible curvature of theory space; alternative metrics could modify the N^{-2} scaling.
- **L2. Dimensionality k .** We set $k = 2$ because n_s and r span the observable subspace; inclusion of additional observables (e.g., non-Gaussianity) would increase k and steepen the basin-volume decay.
- **L3. Uniform N distribution.** The derivation assumes a uniform prior over N ; realistic model-building practices may favor certain N ranges, altering R .
- **L4. Neglect of higher-order terms.** The $O(N^{-2})$ and $O(N^{-3})$ corrections in [2] are omitted; for small N these corrections could be non-negligible.
- **L5. Algorithmic constants.** The iteration formulas from [3] are asymptotic bounds; actual implementations may have prefactors that change absolute iteration counts.
- **L6. Herfindahl assumptions.** The illustrative five-basin distribution is an assumption (A1); real theory landscapes may have different basin fractions, affecting P_k values.

6.2 Failure modes and falsifiability

The central claim—that polygenesis probability scales as N^{-2} (basin-volume model) or as the Herfindahl concentration (alternative model)—would be falsified if a systematic historical analysis revealed a flat or increasing rate of independent rediscovery for models with larger N , or if observed coincidence frequencies for a well-characterized basin distribution deviated from the predicted P_k values.

Falsification criterion (basin-volume model). Compile a database of historically independent derivations of inflationary attractor models, record the efold numbers N , and compute the empirical frequency $f(N)$. If $f(N)$ does not decrease at least as fast as N^{-2} across $N \in [40, 80]$, the basin-volume scaling hypothesis fails.

Falsification criterion (Herfindahl model). For a field where basin fractions $\{p_i\}$ can be estimated (e.g., via RG flow sampling), compute P_2 and P_3 and compare to observed pairwise and triple coincidence rates. Significant deviation beyond statistical uncertainty falsifies the Herfindahl prediction.

6.3 Open questions

- How does inclusion of reheating parameters modify the basin geometry and the N^{-2} scaling?
- Can the metric be refined to incorporate functional RG flow information from nonequilibrium systems [5]?

- What is the impact of disorder-induced fixed points [6] on the universality of basin volumes across statistical physics and cosmology?
- How robust are the contraction parameters assumed in Section 4.5 for real research processes?

7. Practical Implications and Engineering Pathways

(a) Users and decisions. Theory developers, funding agencies, and interdisciplinary research consortia would use the basin-volume formula $V_{\text{basin}}(N) = 1.0258 N^{-2}$ to assess the risk of redundant effort when proposing new inflationary or more general RG-based models. A model with a larger predicted basin volume (smaller N) would be flagged as having higher polygenesis risk, prompting either a shift toward novel parameter regimes or an explicit coordination effort.

(b) Readiness level. The present work is a purely analytical derivation that has not undergone peer review; according to NASA TRL definitions, it resides at TRL 1–2.

(c) Smallest next experiment. A “polygenesis audit” constitutes the minimal prototype. The audit would collect timestamps of independent publications that derive the same attractor structure, extract the associated N values (for the basin-volume model) or basin-fraction estimates (for the Herfindahl model), and compute empirical frequencies. Observation of a frequency scaling inconsistent with N^{-2} (or with the predicted P_k) would falsify the corresponding model.

(d) Engineering constraints. The primary constraint is the availability of reliable historical metadata (publication dates, citation networks, and model parameters). No material, computational, or manufacturing constraints arise because the result is analytical.

(e) Projected cost bounds. Assuming a modest literature-mining effort requiring 10^4 USD in researcher time and database access fees, the projected cost of the polygenesis audit is $O(10^4 \text{ USD})$, with uncertainty dominated by the completeness of the bibliographic corpus.

(f) Risks and misuse. Misapplication could occur if agencies use the basin-volume metric to suppress high- N research without considering scientific merit, potentially stifling exploration of genuinely novel regimes. Careful contextualization of the metric is therefore essential.

8. Conclusion

We have formalized theory space as a metric flow under the renormalization group, derived an explicit basin-volume scaling $V_{\text{basin}}(N) = 1.0258 N^{-2}$ from inflationary attractor formulas, and linked this geometric quantity to the probability of independent rediscovery of a theory. By coupling the basin-volume analysis with concrete iteration-count formulas for dual-subgradient convergence, we provide a unified quantitative framework that treats physical convergence and intellectual consilience as two faces of the same RG attractor landscape. The framework yields falsifiable predictions about the decline of polygenesis with increasing efold number and about coincidence probabilities for a given basin distribution, offering a practical tool for theory developers and funding bodies to manage redundancy in scientific research. Future work should refine the metric on theory space, incorporate additional observables, and perform the proposed historical audit to test the scaling laws empirically.

Provenance and AI Involvement

- This paper was drafted, reconciled, reviewed, revised and checked by the QNFO automated research pipeline (qnfo-research-exec 0.28.1-proportionate-notice). Language models were tools in that process; they are not authors. The named author is accountable for the content.

- Models: drafting by openai/gpt-oss-120b, zai-org/glm-5.3-flash; reconciliation, completion, review, revision and verification by openai/gpt-oss-120b, zai-org/glm-5.3-flash, moonshotai/kimi-k2.6, with the QNFO model router as a fallback.
- Sources: every reference is drawn from a bibliography retrieved from arXiv and the QNFO corpus before drafting; every cited work's full text was retrieved (arXiv HTML, or the QNFO paper's body) and the writers were given excerpts of its own sections; statements about a cited work are restricted to its retrieved title, abstract and those excerpts.
- Checks passed before publication: required sections present and finished, cross-references resolve, reference list rendered from the retrieved bibliography, no assistant residue or placeholders, adversarial model review with its blocking findings resolved, and a citation existence check at publication.
- Independent recomputation: a separately generated script recomputed 16 quantitative claims from the paper's stated inputs; 0 differed from the stated value at the stated precision.
- Not checked: whether each cited source supports the sentence that cites it beyond the retrieved full-text excerpts; derivation steps other than the recomputed claims. This paper has not been peer reviewed, and this version was published by the pipeline without a prior manual review by the author.

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Appendix A. Divergence report

The three independent drafts converged on the definition of theory space, the metric, and the use of RG flow. Divergent claims arise in the quantitative modeling of polygenesis and iteration counts.

Divergent Claim	Draft A (baseline)	Draft B (alternative)	Chosen Convention for Main Text	Reason for Choice
Polygenesis probability model	$P_{\text{poly}}(N) = \kappa 1.0258 N^{-2}$ (Section 4.3)	$P_k = \sum_i p_i^k$ with illustrative p_i (Section 4.4)	Basin-volume model (baseline)	Directly ties polygenesis to the inflationary efold number, uses only inputs from [2] and the derived basin-volume scaling; provides a clear N^{-2} prediction.
Numerical polygenesis values	$P_{\text{poly}}(50) = 4.1 \times 10^{-4}$, $P_{\text{poly}}(60) = 2.8 \times 10^{-4}$	$P_2 = 0.275$, $P_3 = 0.08875$ (illustrative)	Basin-volume values	Derived from the analytic $V_{\text{basin}}(N)$ without additional assumptions about basin fractions.
Iteration-count formula	$T_{\text{simple}} = \lceil 1/\epsilon \rceil$, $T_{\text{sliding}} = \lceil \ln(1/\epsilon) \rceil$ (Section 4.2)	Contraction-based projection $n = 458.2$ for $\epsilon = 10^{-2}$ (Section 4.5)	Both presented	The $O(1/\epsilon)$ formulas are exact theorems from [3]; the contraction projection is an explicit numerical illustration under additional assumptions (A2). Both are retained as complementary.
Basin-volume dimensionality k	$k = 2$ (observable subspace)	Not specified (implicit in Herfindahl model)	$k = 2$	Directly follows from the two observables n_s and r used in the derivation.
Falsifiability criterion	Frequency vs N^{-2} decline (Section 6)	Odds ratio 2.56 vs observed basin hierarchy (Section 4.4)	Both criteria reported	Each follows from its respective model; both are valid falsification tests.

Appendix B. Claim attribution

Claim ID	Description	Source Draft(s)	Agreement
C1	Definition of metric on theory space and basin-volume approximation	A, B, C	Convergent
C2	Derivation of $V_{\text{basin}}(N) = 1.0258 N^{-2}$	A, B, C	Convergent
C3	Computation of basin volume for $N \in [50, 70]$ yielding 4.1×10^{-4}	A, B, C	Convergent
C4	Iteration counts T_{simple} and T_{sliding} from [3]	A, B, C	Convergent
C5	Projection of 458.2 iterations under contraction assumption	A, B, C	Convergent
C6	Polygenesis probability scaling $P_{\text{poly}}(N) = \kappa 1.0258 N^{-2}$	A, B, C	Convergent
C7	Herfindahl-based polygenesis probabilities $P_2 = 0.275$, $P_3 = 0.08875$	B, C	Convergent
C8	Odds ratio $(p_1/p_2)^2 = 2.56$ for illustrative landscape	B, C	Convergent
C9	Limitations list (L1–L6)	A, B, C	Convergent
C10	Falsifiability criteria for both models	A, B, C	Convergent
C11	Practical implications (users, TRL, next experiment, constraints, cost, risks)	A, B, C	Convergent
C12	Background citations of works [1]–[8] with specific points	A, B, C	Convergent