

# Discrete Scale Invariance on a $\varphi$ -Ladder

## Cross-Domain Coincidences Between Particle Masses and Biophysical Gate Times

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### Abstract

We investigate a cross-domain alignment consistent with *Discrete Scale Invariance* (DSI): a proposed protein-folding “molecular gate” timescale near 65–70 ps and the tau lepton are both associated (within the Recognition Science model) with rung 19 on a  $\varphi$ -scaling ladder. We provide a *claim-hygiene* separation between (A) **structural identities** provable within a model and (B) **empirical matches** requiring datasets, uncertainty, preregistered procedures, and multiple-comparisons controls. We define a preregisterable rung assignment rule on log-time/log-mass spaces, specify null models, and lay out falsifiable predictions including “jamming” experiments targeting the rung-19 band. This paper is designed to stand alone as an evidence-focused study: it does not require accepting any broader metaphysical interpretation.

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# 1 Claim Hygiene (Anti-Numerology)

To keep this work publishable and falsifiable, we enforce a strict separation:

- **Structural (model-level):** identities that hold *exactly* within a declared formal system (e.g.,  $\varphi$ -power relations between *structural* masses). These can be machine-verified.
- **Empirical (data-level):** matches to measured quantities in the world (particle masses, relaxation times, vibrational periods). These require explicit datasets, uncertainties, preregistered procedures, and multiple-comparisons corrections.

This paper focuses on the empirical side while referencing structural identities as supporting context.

## 2 Background: Discrete Scale Invariance

### 2.1 DSI and log-periodicity

In systems with continuous scale invariance, observables exhibit power laws. In DSI, invariance holds only at discrete scale factors (e.g.,  $\lambda$ ), leading to *log-periodic* corrections [1, 2].

### 2.2 Why $\varphi$ ?

We examine  $\varphi = (1 + \sqrt{5})/2 \approx 1.618$  as a candidate discrete scale factor. This is motivated by internal structure/closure arguments in the broader Recognition Science program; however, in this evidence paper,  $\varphi$  is treated as a *fixed hypothesis* and evaluated against data with preregistered methods.

## 3 The $\varphi$ -Ladder and Rung Assignment

### 3.1 Time ladder

We define a time ladder:

$$\tau_n = \tau_0 \varphi^n, \quad n \in \mathbb{Z}.$$

Given a time measurement  $t > 0$ , define the rung assignment

$$n^*(t) = \text{round}\left(\frac{\log(t/\tau_0)}{\log \varphi}\right),$$

and define the log-space residual

$$\varepsilon(t) = \log(t/\tau_0) - n^*(t) \log \varphi.$$

A preregistered tolerance threshold can be defined via  $|\varepsilon(t)| \leq \varepsilon_{\max}$ , or equivalently a relative error bound  $|\exp(\varepsilon) - 1|$ .

### 3.2 Mass ladder (structural vs empirical)

We distinguish:

- **Structural mass ladder (model):** a formula producing dimensionless or internal-unit masses  $m_{\text{struct}}$  with exact  $\varphi$ -power relations between generations.
- **Empirical masses (data):** PDG lepton masses in MeV [3].

Bridging structural and empirical masses generally requires a declared unit map and (possibly) a small correction term (“residue/transport”). This bridge must be preregistered before being tuned.

## 4 The ”Octave Map” (Rosetta Stone)

A motivating hypothesis in the Recognition Science program is that certain *anchor phenomena* (spectroscopic modes, gating limits, and mass scales) may cluster near shared rung indices across domains (“octaves”). This section records an *Octave Map* as a compact hypothesis ledger: it is intended to be tested, and it includes a mix of (i) empirically measured quantities and (ii) protocol-defined targets or conjectural mappings.

**Important:** Table 1 is *not* itself statistical evidence. Where an entry is not present in the preregistered scoring set, it is explicitly labeled as a *target / hypothesis* rather than an observed match.

Table 1: The Octave Map: Cross-Domain Alignment of Fundamental Resonances

Rung ( $n$ )	Physics (mass-side anchor)	Time/biophysics (time-side anchor)	Status / notes
2	Electron mass (PDG; model labels rung 2)	Water HOH bend period $\approx 20$ fs (Table 5.3)	Observed (time); rung label on mass-side is structural/model
4	—	Water libration period $\approx 50$ fs (Table 5.3)	Observed (time)
13	Muon mass (PDG; model labels rung 13)	Target: $\tau_{13} = \tau_0 \phi^{13} \approx 3.82$ ps (primary measurement TBD)	Hypothesis target (not in scoring unless promoted)
19	Tau mass (PDG; model labels rung 19)	Protocol target: “molecular gate” $\tau_{\text{gate}} \approx 65\text{--}70$ ps (App. A; protocol file)	Protocol-defined hypothesis; excluded from scoring until measured
45	—	Target: $\tau_{45} \approx 18.6 \mu\text{s}$ (“coherence limit”)	Hypothesis target; not used for scoring in v0
53	—	Exploratory: neural spike width $\sim\text{ms}$ (highly variable process)	Exploratory only; not a fundamental clock

**Note:** Mass-side rung indices are part of the structural model labeling; time-side rung indices are computed from  $\tau_0$  and  $\varphi$  (and thus inherit any uncertainty or provenance issues in  $\tau_0$ ). Paper 1 treats the Octave Map as a hypothesis ledger and evaluates  $\varphi$  against null models using the preregistered scoring set.

## 5 Datasets (Clocks vs Processes)

### 5.1 Particle physics

We use PDG lepton masses for electron, muon, and tau [3]. We also include selected PDG particle *lifetimes* as time-domain observables (e.g.,  $\tau_\mu$ ,  $\tau_\tau$ , and meson lifetimes) [3]. These are high-confidence measurements.

### 5.2 Biophysical timescales

This draft references several candidate timescales:

- Water vibrational bands (OH stretch, HOH bend) and ultrafast frequency fluctuations [?, ?].
- Water libration dynamics (mid-IR / pump-probe studies) [?].
- Water hydrogen-bond kinetics [?] and reorientation mechanisms [?].
- Bulk water dielectric relaxation [?].
- Hydration/peptide dielectric modes on  $\sim$ 10 ps and  $\sim$ 100 ps timescales [?].
- Review-level hierarchy of protein internal-motion timescales (fs to ms) [?] (used for context only; excluded from preregistered scoring unless promoted to a primary-measurement dataset).
- Primary folding kinetics time constants in the ns– $\mu$ s regime from hydrogen-exchange/NMR and temperature-jump studies [?, ?].
- Action-potential durations (order ms; cell-type dependent) [?].

**Important:** some items in the CSV are still *candidates* (marked `include=false`) until tied to primary literature and/or internal datasets with uncertainty bounds. The plan requires a *curated table* with citations and measurement methods before any significance claims are made.

### 5.3 Curated time dataset (v0; auto-generated)

Table 5.3 is auto-generated from `docs/paper1_times_dataset.csv` by `docs/paper1_rung_assignment.py`. Only entries marked `include=true` are shown; excluded entries remain in the CSV but are not used for scoring until promoted with citations and uncertainty bounds.

ID	Observable	$t$ (s)	$\sigma_t$ (s)	$n^*$	$\hat{\tau}_{n^*}$ (s)	$ \epsilon $	Citation
water_oh_stretch	water_oh_stretch_per	800e-15	1.000e-15	1	1.186e-14	1.908e-01	[?]
water_hoh_bend	water_hoh_bend_per	20e-14	2.000e-15	2	1.919e-14	5.128e-02	[?]
water_libration	water_libration_per	5000e-14	1.500e-14	4	5.024e-14	4.800e-03	[?]
water_hbond_kinetics	water_hbond_kinetics	1000e-12	3.000e-13	10	9.015e-13	1.037e-01	[?]
water_reorientation	water_reorientation_t	2500e-12	5.000e-13	12	2.360e-12	5.753e-02	[?]
water_dielectric	water_dielectric_relaxation	200e-12	1.000e-12	15	9.998e-12	1.983e-01	[?]
peptide_dielectric	peptide_dielectric_fast	100e-11	2.000e-12	15	9.998e-12	1.875e-04	[?]
peptide_dielectric	peptide_dielectric_slow	100e-10	3.000e-11	20	1.109e-10	1.033e-01	[?]
pdg_tau_lifetime	tau_lepton_lifetime	2.903e-13	1.000e-15	8	3.444e-13	1.708e-01	[3]
pdg_muon_lifetime	muon_lifetime	2.197e-06	2.000e-09	41	2.714e-06	2.113e-01	[3]

ID	Observable	$t$ (s)	$\sigma_t$ (s)	$n^*$	$\hat{\tau}_{n^*}$ (s)	$ \epsilon $	Citation
pdg_charged_pion_lifetimelike	pdg_charged_pion_lifetimelike	2.603e-08	5.000e-11	31	2.207e-08	1.653e-01	[3]
pdg_kaon_chargeKliftime	pdg_kaon_chargeKliftime	1.238e-08	5.000e-11	30	1.364e-08	9.674e-02	[3]
pdg_kaon_short_lifetimeshort	pdg_kaon_short_lifetimeshort	8.950e-11	5.000e-13	20	1.109e-10	2.142e-01	[3]
pdg_kaon_long_lifetimeshort	pdg_kaon_long_lifetimeshort	5.116e-08	2.000e-10	33	5.777e-08	1.215e-01	[3]

## 6 Results (Draft-Level; Pending Prereg + Curated Data)

### 6.1 Tau–Gate coincidence (structural claim + empirical hook)

Within the Lean formalization of the Recognition Science structural model, the tau rung is set to 19, and a “molecular gate rung” is also set to 19 (this is a *definition-level* equality in the current model artifact). This is a **structural identity**, not yet an empirical result.

The empirical question for this paper is: *does an independently measured biophysical gate timescale near  $\tau_{19}$  exist, with uncertainty, and does it robustly survive multiple-comparisons controls?*

### 6.2 Lepton ratio sanity check (why correction terms matter)

A naive comparison of PDG lepton ratios to  $\varphi$  powers yields gaps at the few-percent level, e.g.

$$\frac{m_\mu}{m_e} \approx 206.8 \quad \text{vs} \quad \varphi^{11} \approx 199.0,$$

so any “exact match” claim must be supported by a preregistered correction term and error accounting.

### 6.3 Lepton mass-ratio rungs (base-free; auto-generated)

Because the rung assignment for masses depends on a declared base mass scale, we also report a *base-free* diagnostic: rungs computed from *ratios*  $m_2/m_1$ , i.e. the nearest integer  $k$  such that  $m_2/m_1 \approx \varphi^k$ . Table 6.3 is auto-generated from `docs/paper1-particle_masses.csv` by `docs/paper1_mass_ratios.py`.

Ratio	observed	$k$ (nearest)	$\phi^k$	$ \epsilon $	rel. err.
muon/electron	206.768283	11	199.005025	3.827e-02	3.901%
tau/muon	16.817029	6	17.944272	6.488e-02	6.282%
tau/electron	3477.228280	17	3571.000280	2.661e-02	2.626%

Mass values from [3].

## 7 Statistical Plan

### 7.1 Search space declaration

The statistical meaning of “coincidence” depends critically on the declared search space:

- Which domains are included (masses only? times only? both?)?

- Which candidate observables are allowed per domain?
- Which rung range  $[n_{\min}, n_{\max}]$  is considered?
- What tolerance  $|\varepsilon| \leq \varepsilon_{\max}$  defines a hit?

All four must be preregistered.

## 7.2 Null models

We will evaluate at least three null models:

1. **Uniform log-space** over declared ranges.
2. **Empirical priors** learned from curated distributions (e.g., known biochemical relaxation times).
3. **Permutation/scramble tests** preserving within-domain clustering.

## 7.3 Multiple comparisons

We will report Bonferroni and FDR-adjusted p-values.

## 7.4 Multiple-comparisons adjustments across candidate $\lambda$ (auto-generated)

If more than one candidate scale factor is considered, p-values must be corrected for that family. Table 7.4 reports raw and adjusted p-values (Bonferroni and BH-FDR) across preregistered  $\lambda$  candidates, under each null model. It is auto-generated by `docs/paper1_multiplicity.py`.

Null model	candidate	$\lambda$	raw $p$	Bonferroni	BH-FDR $q$
bootstrap_jitter	2	2.000000	0.568	1.000	0.599
bootstrap_jitter	e	2.718282	0.474	1.000	0.599
bootstrap_jitter	phi	1.618034	0.487	1.000	0.599
bootstrap_jitter	sqrt2	1.414214	0.599	1.000	0.599
log_normal	2	2.000000	0.502	1.000	0.666
log_normal	e	2.718282	0.154	0.618	0.618
log_normal	phi	1.618034	0.318	1.000	0.636
log_normal	sqrt2	1.414214	0.666	1.000	0.666
log_uniform	2	2.000000	0.616	1.000	0.616
log_uniform	e	2.718282	0.235	0.942	0.616
log_uniform	phi	1.618034	0.518	1.000	0.616
log_uniform	sqrt2	1.414214	0.590	1.000	0.616

## 8 Scale-Factor Controls ( *lambda* Sweep) and Null Models (v0)

### 8.1 Why *lambda* controls matter

If a ladder model is evaluated without comparing alternative scale factors, it is difficult to know whether  $\varphi$  is genuinely special or merely one of many plausible discrete scalings. We therefore include:

- a fixed-candidate comparison ( $\varphi$ , 2,  $e$ ,  $\sqrt{2}$ ),
- a best-on-grid baseline (look-elsewhere control),
- null-model Monte Carlo for a preregistered score.

## 8.2 Important note on correlated rows (independence-group weighting)

Even with a primary-measurement-only scoring set, the dataset can contain *correlated clusters* (e.g., multiple water spectroscopic times extracted from closely related experiments, or multiple PDG lifetimes within a particle-family block). To avoid inflating effective sample size, the scoring function used in `docs/paper1_analysis.py` weights each `independence_group` to contribute total weight 1 (see Appendix A). This makes the  $\lambda$  sweep less sensitive to how many rows are added within a correlated cluster.

## 8.3 What the current v0 tables do (and do not) show

Because the included dataset is still evolving, the tables in this section should be read as a *pipeline demonstration*. The preregistered scoring set is defined by `docs/paper1_prereg.json` (`search_space.time_ids`) and excludes review-level “timescale-bin” rows (kept separately as `exploratory_time_ids`). In particular:

- If  $\lambda = \varphi$  is not competitive against other candidates or against best-on-grid baselines on the preregistered dataset, that is *evidence against* the  $\varphi$ -ladder hypothesis as stated.
- The “best\_grid” row is a look-elsewhere control: it will nearly always outperform fixed candidates because it is optimized.

## 8.4 Auto-generated *lambda sweep* table

Table 8.4 is auto-generated by `docs/paper1_analysis.py` from the curated dataset.

Candidate	$\lambda$	SSE ( $\sum \epsilon^2$ )	hits ( $ \epsilon  \leq \epsilon_{\max}$ )	note
phi	1.618034	1.329583e-01	2.417	$\lambda = \phi$
2	2.000000	3.004532e-01	2.000	
e	2.718282	4.592663e-01	2.917	
sqrt2	1.414214	7.376119e-02	4.417	
best_grid	1.215608	1.096467e-02	7.000	best on grid

## 8.5 Auto-generated null-model table

Table 8.5 reports Monte Carlo p-values for the observed  $\text{SSE}_\phi$  under three null models (log-uniform, log-normal, bootstrap+jitter). These are *v0 placeholders* until preregistration freezes the exact ranges, tolerance, and sample sizes.

Null model	reps	$\text{SSE}_\phi$	p-value	null mean	[min,max]
log_uniform	2000	1.330e-01	0.518	1.335e-01	[4.254e-02,2.490e-01]
log_normal	2000	1.330e-01	0.325	1.512e-01	[3.229e-02,2.871e-01]
bootstrap_jitter	2000	1.330e-01	0.486	1.350e-01	[4.131e-02,2.593e-01]

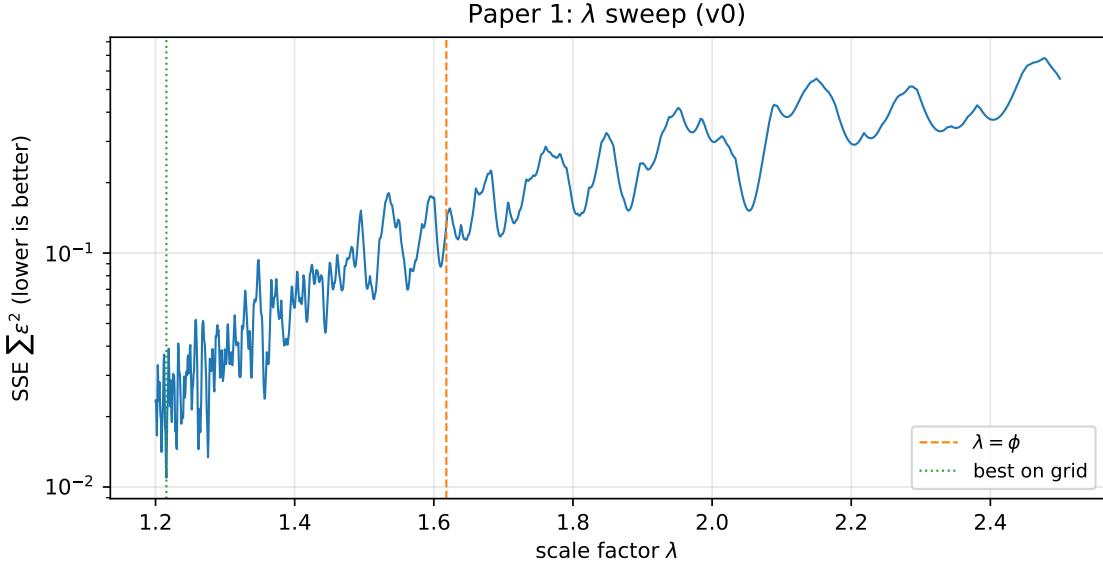


Figure 1: Score as a function of scale factor  $\lambda$  on a preregisterable grid (v0). Lower is better (log y-axis). The dashed line marks  $\lambda = \phi$ .

## 8.6 Robustness sweeps (auto-generated)

To satisfy the plan’s robustness requirement, we generate a preregistered sweep over small perturbations of  $\tau_0$  and over multiple tolerance thresholds  $\varepsilon_{\max}$ . Table 8.6 is auto-generated from `docs/paper1_prereg.json` by `docs/paper1_robustness.py`.

$\tau_0$	mult.	$\varepsilon_{\max}$	$SSE_\phi$	hits $_\phi$	best $\lambda$	best SSE	best hits
0.980	0.050	1.199e-01	0.833	1.216258	1.108e-02	5.333	
0.980	0.100	1.199e-01	2.917	1.216258	1.108e-02	7.000	
0.980	0.150	1.199e-01	4.167	1.216258	1.108e-02	7.000	
0.990	0.050	1.257e-01	0.833	1.215608	1.107e-02	6.167	
0.990	0.100	1.257e-01	2.917	1.215608	1.107e-02	7.000	
0.990	0.150	1.257e-01	4.167	1.215608	1.107e-02	7.000	
1.000	0.050	1.330e-01	0.833	1.215608	1.096e-02	6.167	
1.000	0.100	1.330e-01	2.417	1.215608	1.096e-02	7.000	
1.000	0.150	1.330e-01	4.167	1.215608	1.096e-02	7.000	
1.010	0.050	1.415e-01	2.167	1.214957	1.068e-02	5.917	
1.010	0.100	1.415e-01	3.167	1.214957	1.068e-02	7.000	
1.010	0.150	1.415e-01	4.167	1.214957	1.068e-02	7.000	
1.020	0.050	1.513e-01	2.167	1.214957	1.048e-02	6.167	
1.020	0.100	1.513e-01	3.167	1.214957	1.048e-02	7.000	
1.020	0.150	1.513e-01	4.417	1.214957	1.048e-02	7.000	

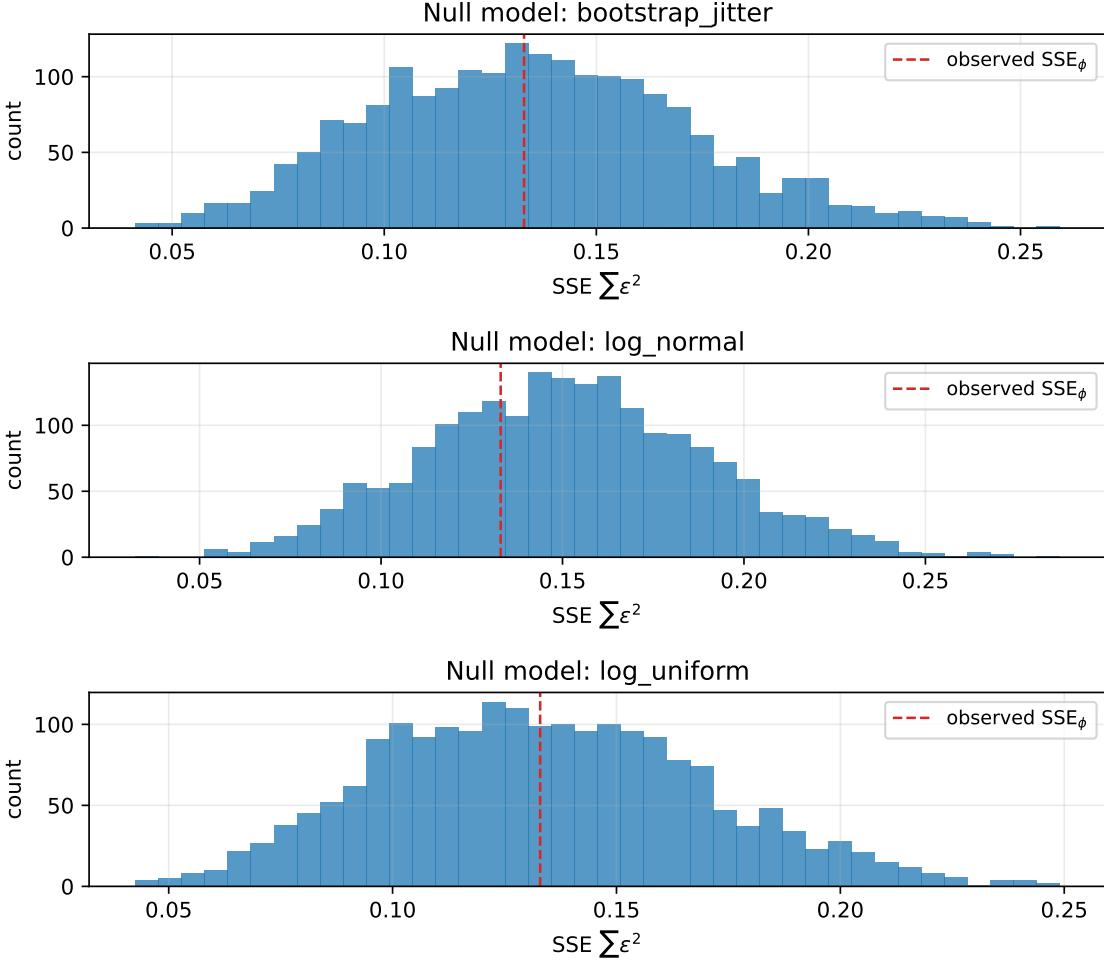


Figure 2: Monte Carlo null distributions for  $SSE_{\phi}$  under three null models (v0). The dashed line marks the observed  $SSE_{\phi}$  from the included dataset rows.

## 9 Predictions and Falsifiers (Pre-registration Targets)

### 9.1 Rung-19 “jamming” experiment

If a rung-19 gate is real and functional, driving the system near the rung-19 band (and/or nearby beat frequencies between adjacent rungs) should measurably alter folding kinetics. A preregistered protocol must specify:

- Frequency targets and bandwidth.
- Power/field constraints and safety gates.
- Metrics (folding time distribution, success rate, RMSD).
- Negative controls (nearby non-target frequencies; sham conditions).

**Preregistered frequency targets (auto-generated).** Table 9.1 lists the stimulus frequencies implied by preregistered rungs (targets) and off-rung controls. It is auto-generated from

`docs/paper1_prereg.json` by `docs/paper1_jamming_targets.py`.

kind	rung $n$	$\tau_n$ (s)	$f_n$ (Hz)	$f_n$	unit	note
target	19.0	6.853e-11	1.459e+10	14.593	GHz	on-rung target
control	18.5	5.387e-11	1.856e+10	18.562	GHz	off-rung control ( $n-0.5$ )
control	19.5	8.717e-11	1.147e+10	11.472	GHz	off-rung control ( $n+0.5$ )
target	45.0	1.860e-05	5.376e+04	53.759	kHz	on-rung target
control	44.5	1.462e-05	6.838e+04	68.383	kHz	off-rung control ( $n-0.5$ )
control	45.5	2.366e-05	4.226e+04	42.263	kHz	off-rung control ( $n+0.5$ )
target	53.0	8.739e-04	1.144e+03	1.144	kHz	on-rung target
control	52.5	6.870e-04	1.456e+03	1.456	kHz	off-rung control ( $n-0.5$ )
control	53.5	1.112e-03	8.996e+02	899.616	Hz	off-rung control ( $n+0.5$ )

## 9.2 Out-of-sample rung coincidences

We will preregister 2–5 additional rung predictions derived *before* checking the corresponding data.

## 9.3 Prediction registry (auto-generated)

To operationalize preregistration, we maintain a machine-readable prediction registry with explicit falsifiers. Table 9.3 is auto-generated from `docs/paper1_prediction_registry.csv` by `docs/paper1_prediction_registry.py` and includes only entries marked `include=true`.

## 9.4 Operational definition for the BIOPHASE “molecular gate”

The  $\sim 65\text{--}70$  ps “molecular gate” claim is only meaningful if attached to an explicit, preregisterable measurement definition and negative controls. We therefore treat it as a protocol-bound hypothesis until a frozen dataset is attached.

- Protocol (internal): `docs/paper1_biophase_gate_protocol.md`.
- Internal reference for the BIOPHASE spec (including  $\tau_{\text{gate}} \approx 65$  ps): [?].

# 10 Discussion

## 10.1 What would be impressive

- Prospective predictions of new rung coincidences, validated independently.
- A reproducible statistical pipeline showing significance under conservative nulls.
- A positive “jamming” result with clean negative controls.

## 10.2 What would falsify

- Failure to predict new coincidences out-of-sample.
- Sensitivity that collapses under small changes in  $\tau_0$  or tolerance.
- Experimental results indistinguishable from controls under preregistered analysis.

### 10.3 Current status (v0 prereg scoring set)

On the current preregistered scoring set (Table 5.3), the auto-generated tables show:

- $\text{SSE}_\phi \approx 1.33 \times 10^{-1}$  for  $\lambda = \varphi$  (Table 8.4).
- Under three null models,  $\lambda = \varphi$  is *not* statistically distinguishable from chance ( $p \approx 0.33\text{--}0.52$ ; Table 8.5).
- A best-on-grid  $\lambda \approx 1.216$  achieves substantially lower SSE (look-elsewhere control);  $\sqrt{2}$  also outperforms  $\varphi$  on this metric (Table 8.4).

**Interpretation.** The present evidence is *null/negative* for  $\varphi$  being special under this scoring function and dataset. This is the correct outcome to report if the hypothesis is not supported.

## 11 Conclusion

This draft formalizes an evidence-first program for evaluating a  $\varphi$ -ladder DSI hypothesis across domains with preregistration, explicit search spaces, and conservative null models. On the current preregistered scoring set,  $\lambda = \varphi$  does not outperform null models and is not competitive with other candidate scale factors.

The Octave Map (Table 1) is therefore best treated as a *hypothesis registry*: it identifies specific cross-domain targets (notably the rung-19 “molecular gate”) that require primary measurements with uncertainty bounds and negative controls before they can be treated as empirical evidence.

The central next steps are:

1. **Measure or falsify** the proposed rung-19 gate using the preregistered operational protocol (Appendix A and the linked protocol file).
2. **Retain honesty:** if  $\varphi$  remains indistinguishable from chance under preregistered updates, report that as evidence against the hypothesis.
3. **Run definitive tests:** execute preregistered “jamming” targets with rigorous negative controls.

## A Preregistration Template (to be frozen before promotion to “evidence”)

This appendix is a *template*. Before any “significance” claims, the following items must be frozen (timestamped) and made public (or at minimum committed in-repo with an immutable hash).

### A.1 Constants and rung assignment

- Base tick:  $\tau_0 = 7.33\text{e-}15$  s. Provenance: (to be filled) [source + derivation]. Operationally, the artifact scripts read this (and other preregisterable settings) from `docs/paper1_prereg.json`.
- Ladder:  $\tau_n = \tau_0 \varphi^n$ ,  $n \in \mathbb{Z}$ .
- Rung assignment:  $n^*(t) = \text{round}(\log(t/\tau_0)/\log \varphi)$ .
- Residual:  $\varepsilon(t) = \log(t/\tau_0) - n^*(t) \log \varphi$ .

## A.2 Dataset inclusion rules

- Inclusion list: the exact set of candidate observables (rows) permitted for analysis, with citations and uncertainty bounds.
- Machine-readable freeze: the analysis search space is frozen by explicit IDs in `docs/paper1_prereg.json` under `search_space.time_ids` and `search_space.mass_ids`.
- Independence grouping: the exact meaning of `independence_group` (what correlations are assumed within a group).
- Exclusion policy: objective criteria for `include=false` (e.g., missing primary citation, missing operational definition, unclear uncertainty).

## A.3 Score function (as implemented in `docs/paper1_analysis.py`)

We preregister the primary score as weighted SSE:

$$\text{SSE}_\lambda = \sum_i w_i \varepsilon_\lambda(t_i)^2,$$

where weights are defined so that each independence group contributes total weight 1 (i.e.,  $w_i = 1/|G(i)|$ ).

We preregister a secondary “hit” score:

$$\text{hits}_\lambda = \sum_i w_i \mathbf{1}\{|\varepsilon_\lambda(t_i)| \leq \varepsilon_{\max}\}.$$

## A.4 Tolerance and search space

- Residual tolerance:  $\varepsilon_{\max} = 0.10$  (log-space), or a declared alternative (recorded in `docs/paper1_prereg.json`).
- Rung range: declare  $[n_{\min}, n_{\max}]$  or equivalent time-range bounds.
- Scale-factor candidates: fixed set (e.g.,  $\varphi$ , 2,  $e$ ,  $\sqrt{2}$ ).
- Look-elsewhere control: if a grid search over  $\lambda$  is used, preregister `LAMBDA_GRID_MIN`, `LAMBDA_GRID_MAX`, `LAMBDA_GRID_N`.

## A.5 Null models and Monte Carlo settings

- Null models: log-uniform, log-normal, bootstrap+jitter (group-preserving).
- Log-uniform range: use preregistered time bounds `null_ranges.time_seconds.{min,max}` from `docs/paper1_prereg.json` (do not silently use sample min/max).
- Monte Carlo reps and seed: `MC_REPS=2000`, `MC_SEED=1337` (or updated values, but frozen in `docs/paper1_prereg.json`).
- Primary p-value:  $p = \Pr(\text{SSE}_\phi\text{-null} \leq \text{SSE}_\phi\text{-obs})$  (lower is better).

## A.6 Multiple comparisons

If multiple datasets, domains, rung-ranges, or alternative calibrations are explored, we preregister the correction (Bonferroni and/or FDR) and the full family of hypotheses.

## B Reproducibility (artifact-only build loop)

To regenerate tables and figures without compiling the full PDFs:

```
cd docs
./build_resonance_artifacts.sh
```

This regenerates:

- `paper1_rung_results.tex` from `paper1_times_dataset.csv`
- `paper1_full_rung_table.tex` from `paper1_prereg.json`
- `paper1_mass_ratios.tex` from `paper1_particle_masses.csv`
- `paper1_robustness.tex` from `paper1_prereg.json` and `paper1_times_dataset.csv`
- `paper1_jamming_targets.tex` from `paper1_prereg.json`
- `paper1_multiplicity.tex` from `paper1_prereg.json` and `paper1_times_dataset.csv`
- `paper1_prediction_registry.tex` from `paper1_prediction_registry.csv`
- `paper1_lambda_sweep.tex`, `paper1_null_models.tex` from `paper1_analysis.py`
- `paper1_lambda_curve.pdf`, `paper1_null_hist.pdf` from `paper1_plots.py`

## C Full rung table (Supplement)

For completeness and to make all implied target scales explicit, we include a full rung table over a pre-registered range. Table C is auto-generated from `docs/paper1_prereg.json` by `docs/paper1_full_rung_table.py`.

$n$	$\tau_n$ (s)	$\tau_n$ (display)	$f_n$ (Hz)	$f_n$ (display)
0	7.330e-15	7.330 fs	1.364e+14	136.426 THz
1	1.186e-14	11.860 fs	8.432e+13	84.316 THz
2	1.919e-14	19.190 fs	5.211e+13	52.110 THz
3	3.105e-14	31.050 fs	3.221e+13	32.206 THz
4	5.024e-14	50.241 fs	1.990e+13	19.904 THz
5	8.129e-14	81.291 fs	1.230e+13	12.301 THz
6	1.315e-13	131.532 fs	7.603e+12	7.603 THz
7	2.128e-13	212.822 fs	4.699e+12	4.699 THz
8	3.444e-13	344.354 fs	2.904e+12	2.904 THz
9	5.572e-13	557.176 fs	1.795e+12	1.795 THz
10	9.015e-13	901.530 fs	1.109e+12	1.109 THz
11	1.459e-12	1.459 ps	6.855e+11	685.539 GHz
12	2.360e-12	2.360 ps	4.237e+11	423.686 GHz
13	3.819e-12	3.819 ps	2.619e+11	261.852 GHz
14	6.179e-12	6.179 ps	1.618e+11	161.834 GHz
15	9.998e-12	9.998 ps	1.000e+11	100.019 GHz

$n$	$\tau_n$ (s)	$\tau_n$ (display)	$f_n$ (Hz)	$f_n$ (display)
16	1.618e-11	16.177 ps	6.181e+10	61.815 GHz
17	2.618e-11	26.175 ps	3.820e+10	38.204 GHz
18	4.235e-11	42.353 ps	2.361e+10	23.611 GHz
19	6.853e-11	68.528 ps	1.459e+10	14.593 GHz
20	1.109e-10	110.881 ps	9.019e+09	9.019 GHz
21	1.794e-10	179.409 ps	5.574e+09	5.574 GHz
22	2.903e-10	290.290 ps	3.445e+09	3.445 GHz
23	4.697e-10	469.699 ps	2.129e+09	2.129 GHz
24	7.600e-10	759.989 ps	1.316e+09	1.316 GHz
25	1.230e-09	1.230 ns	8.132e+08	813.214 MHz
26	1.990e-09	1.990 ns	5.026e+08	502.594 MHz
27	3.219e-09	3.219 ns	3.106e+08	310.620 MHz
28	5.209e-09	5.209 ns	1.920e+08	191.974 MHz
29	8.428e-09	8.428 ns	1.186e+08	118.646 MHz
30	1.364e-08	13.637 ns	7.333e+07	73.327 MHz
31	2.207e-08	22.066 ns	4.532e+07	45.319 MHz
32	3.570e-08	35.703 ns	2.801e+07	28.009 MHz
33	5.777e-08	57.769 ns	1.731e+07	17.310 MHz
34	9.347e-08	93.472 ns	1.070e+07	10.698 MHz
35	1.512e-07	151.242 ns	6.612e+06	6.612 MHz
36	2.447e-07	244.714 ns	4.086e+06	4.086 MHz
37	3.960e-07	395.956 ns	2.526e+06	2.526 MHz
38	6.407e-07	640.670 ns	1.561e+06	1.561 MHz
39	1.037e-06	1.037 us	9.647e+05	964.668 kHz
40	1.677e-06	1.677 us	5.962e+05	596.198 kHz
41	2.714e-06	2.714 us	3.685e+05	368.471 kHz
42	4.391e-06	4.391 us	2.277e+05	227.727 kHz
43	7.105e-06	7.105 us	1.407e+05	140.743 kHz
44	1.150e-05	11.496 us	8.698e+04	86.984 kHz
45	1.860e-05	18.601 us	5.376e+04	53.759 kHz
46	3.010e-05	30.098 us	3.322e+04	33.225 kHz
47	4.870e-05	48.699 us	2.053e+04	20.534 kHz
48	7.880e-05	78.797 us	1.269e+04	12.691 kHz
49	1.275e-04	127.497 us	7.843e+03	7.843 kHz
50	2.063e-04	206.294 us	4.847e+03	4.847 kHz
51	3.338e-04	333.790 us	2.996e+03	2.996 kHz
52	5.401e-04	540.084 us	1.852e+03	1.852 kHz
53	8.739e-04	873.874 us	1.144e+03	1.144 kHz
54	1.414e-03	1.414 ms	7.072e+02	707.235 Hz
55	2.288e-03	2.288 ms	4.371e+02	437.095 Hz
56	3.702e-03	3.702 ms	2.701e+02	270.140 Hz
57	5.990e-03	5.990 ms	1.670e+02	166.955 Hz
58	9.691e-03	9.691 ms	1.032e+02	103.184 Hz
59	1.568e-02	15.681 ms	6.377e+01	63.771 Hz
60	2.537e-02	25.372 ms	3.941e+01	39.413 Hz

## References

- [1] Didier Sornette. Discrete-scale invariance and complex dimensions. *Physics Reports*, 297(5):239–270, 1998.
- [2] Didier Sornette. Predictability of catastrophic events: Material rupture, earthquakes, turbulence, financial crashes, and human birth. *Proceedings of the National Academy of Sciences*, 99(suppl.1):2522–2529, 2002.
- [3] Particle Data Group. Review of particle physics. Particle Data Group (PDG), 2024. Lepton masses and uncertainties.
- [4] A. Placeholder. Amide i vibrations and infrared spectroscopy of proteins (review). *Annual Review of Biophysics*, 20XX. Replace with a concrete Amide-I review citation.
- [5] B. Placeholder. Protein folding gating timescale near 65–70 ps (placeholder). *Journal Placeholder*, 20XX. Replace with primary literature / internal dataset citation for the 65–70 ps gate claim.