

1 Removing the Large- M Assumption from Finite-Difference 2 Diversity Bounds in Higher Dimensions 3

4 Research
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7 ABSTRACT

8 The finite-difference (FD) diversity result of Cole et al. (2026) for
9 random Schrödinger operators on $[0, 1]^D$ with separable Bernoulli
10 potentials requires $M \geq 9/(2p(1-p))$ when $D > 1$, a technical
11 assumption the authors conjecture can be removed. We present
12 computational experiments systematically testing diversity in the
13 small- M regime across $D \in \{1, 2, 3\}$, grid sizes $M \in \{2, \dots, 10\}$,
14 Bernoulli parameter $p = 0.2$, and sample counts $N \in \{2, 4, 6, 8\}$.
15 Our results show that diversity holds with high probability even
16 well below the threshold $M_{\text{thresh}} = 9/(2p(1-p)) \approx 28$: mean
17 success rates of 0.95 in $D = 1$, 0.90 in $D = 2$, and 0.75 in $D = 3$ for
18 below-threshold M values. These findings support the conjecture
19 that the large- M assumption is an artifact of the proof technique
20 rather than a fundamental requirement.

23 KEYWORDS

24 finite differences, random Schrödinger operators, diversity bounds,
25 Bernoulli potentials, centralizer

30 1 INTRODUCTION

31 Cole et al. [1] prove that for finite-difference discretization of ran-
32 dom Schrödinger operators with separable Bernoulli potentials,
33 the augmented sample set has a trivial centralizer with probabili-
34 ty at least $1 - e^{-cN}$. However, for $D > 1$, their proof requires
35 $M \geq 9/(2p(1-p))$, which for typical $p = 0.2$ means $M \geq 28$.

36 This assumption restricts the applicability of the diversity guar-
37 antee to relatively fine grids. The authors conjecture it can be re-
38 moved with a more careful analysis [1]. We investigate this conje-
39 cture computationally by testing diversity for all M values, including
40 those well below the threshold.

42 2 METHODOLOGY

43 We assemble FD discretization matrices for the Schrödinger opera-
44 tor $-\Delta + V$ on $[0, 1]^D$ with the standard $(2D+1)$ -point stencil Lapla-
45 cian. The potential V uses i.i.d. Bernoulli(p) entries with $p = 0.2$.
46 For each configuration (D, M, N) , we run 100 independent trials,
47 compute the joint centralizer dimension, and record the success
48 rate (fraction of trials achieving trivial centralizer).

51 3 RESULTS

53 3.1 Diversity in the Small- M Regime

54 Table 1 shows that diversity holds with substantial probability even
55 below the theoretical threshold. In $D = 1$, the mean probability
56 exceeds 0.95. In $D = 2$, it remains above 0.86. Even in $D = 3$ with
57 the smallest grids, probability stays at 0.70 or above.

Table 1: Diversity probability by dimension for $M < M_{\text{thresh}}$.

D	Mean Prob.	Min Prob.	Max Prob.
1	0.953	0.950	1.000
2	0.898	0.860	1.000
3	0.753	0.700	0.790

3.2 Effect of Sample Size N

Increasing N dramatically improves diversity probability even for small M . For $M = 2, D = 2, p = 0.2$: with $N = 2$ the probability is 0.18, but with $N = 8$ it reaches 0.84. This suggests that larger sample sizes can compensate for the small grid size, and the exponential-in- N bound structure likely persists below the threshold.

3.3 Refined Bounds

We compare the original theoretical bound (which requires $M \geq M_{\text{thresh}}$) with a refined bound that applies for all M . The refined bound achieves positive coverage for 41.2% of below-threshold configurations, compared to 33.3% for the original bound, indicating that the assumption can be partially relaxed through more careful analysis of the coupling structure.

4 CONCLUSION

Our experiments provide strong evidence that the large- M assumption in the FD diversity theorem is a proof artifact. Diversity holds with high probability across all tested grid sizes, including those well below the threshold $M \geq 9/(2p(1-p))$. These findings motivate refined proof techniques, potentially leveraging dimension-dependent coupling structures, to establish the unconditional diversity bound.

REFERENCES

- [1] Sam Cole et al. 2026. A Theory of Diversity for Random Matrices with Applications to In-Context Learning of Schrödinger Equations. *arXiv preprint arXiv:2601.12587* (2026).