Abstract

We study the secular coefficients of $N \times N$ random unitary matrices $U_N$ drawn from the Circular $\beta$-Ensemble, which are defined as the coefficients of $\{z^n\}$ in the characteristic polynomial $\det(1 - zU_N)$. When $\beta > 4$ we obtain a new class of limiting distributions that arise when both $n$ and $N$ tend to infinity simultaneously. We solve an open problem of Diaconis and Gamburd [DG06] by showing that for $\beta = 2$, the middle coefficient of degree $n = \lfloor \frac{N}{2} \rfloor$ tends to zero as $N \to \infty$. We show how the theory of Gaussian multiplicative chaos (GMC) plays a prominent role in these problems and in the explicit description of the obtained limiting distributions. We extend the remarkable magic square formula of [DG06] for the moments of secular coefficients to all $\beta > 0$ and analyse the asymptotic behaviour of the moments. We obtain estimates on the order of magnitude of the secular coefficients for all $\beta > 0$, and these estimates are sharp when $\beta \geq 2$. These insights motivated us to introduce a new stochastic object associated with the secular coefficients, which we call Holomorphic Multiplicative Chaos (HMC). Viewing the HMC as a random distribution, we prove a sharp result about its regularity in an appropriate Sobolev space. Our proofs expose and exploit several novel connections with other areas, including random permutations, Tauberian theorems and combinatorics.
1 Introduction

Let $\beta > 0$ be a fixed parameter and consider the joint distribution on $N$ points

$$C\beta E_N(\vartheta_1, \ldots, \vartheta_N) \propto \prod_{1 \leq k < j \leq N} |e^{i\vartheta_k} - e^{i\vartheta_j}|^{\beta}$$

(1.1)

where $\vartheta_j \in [0, 2\pi)$ for all $j = 1, \ldots, N$. This is known as the Circular $\beta$-Ensemble. When $\beta = 2$ this distribution arises as the law of the eigenvalues of a Haar distributed unitary matrix and is better known as the CUE (Circular Unitary Ensemble). When $\beta \neq 2$ it also arises from the eigenvalue distribution of certain random matrix models, see e.g. [KN04]. Therefore it makes sense to consider the characteristic polynomial

$$\chi_N(z) = \prod_{j=1}^{N} (1 - ze^{-i\vartheta_j}),$$

(1.2)

which would have the representation $\det(1 - zU_N^*)$ if $\{e^{i\vartheta_j} : 1 \leq j \leq N\}$ were the eigenvalues of a matrix $U_N$.

The goal of this paper is to formulate and solve a new class of probabilistic and combinatorial questions associated with such characteristic polynomials. Our main quantities of interest will be the so-called secular coefficients, defined most simply as the coefficients $c_n^{(N)}$ in the expansion of (1.2) in its Fourier basis,

$$\chi_N(z) = \sum_{n=0}^{N} c_n^{(N)} z^n.$$  

(1.3)

In a remarkable paper [DG06], Diaconis and Gamburd studied these coefficients in the $\beta = 2$ setting. They showed that the joint moments of $\{c_n^{(N)}\}_{n \geq 1}$ are related to the enumeration of combinatorial objects known as magic squares – integer valued square matrices with prescribed row and column sums. For example, when $N \geq nk$, the moment $E(|c_n^{(N)}|^{2k})$ is equal to the number of $k \times k$ magic squares whose rows and columns all sum up to $n$.

In general, combinatorial results on magic squares imply that this quantity has order $n^{(k-1)^2}$ as $n \to \infty$, with a multiplicative constant given by the volume of the $k$th Birkhoff polytope. The determination of these volumes remains a well studied and challenging problem in the combinatorics community. They have been explicitly computed only for $k \leq 10$ and this has required the use of high performance computers. See [BP03, DLLY09, CM09] for this and other perspectives, and for number theoretical applications, see [CG06, KRRGR18].
Given the rich combinatorial structure associated with the moments of \( c_n^{(N)} \), there is a natural probabilistic question that comes to mind: Is there a commensurately richly structured probabilistic object to which \( c_n^{(N)} \) converges as \( N \to \infty \)? What if \( N \) and \( n \) tend to infinity together, in a suitable way? This problem is mentioned in the same paper of Diaconis and Gambaudo (see the discussion below Proposition 4 of [DG06]), however to our knowledge the answer has remained out of reach conjecturally or otherwise, now for almost 15 years. The purpose of this paper is to begin closing this gap, particularly in the general context of the \( \beta \)-ensembles (1.1).

There is one exception where a limiting distribution for \( c_n^{(N)} \) can be obtained with relative ease, namely when the index \( n \) remains finite and we let the matrix size \( N \to \infty \), as discussed in [DG06] for \( \beta = 2 \). By the Newton formula, which relates the elementary and power sum symmetric functions, each \( c_n^{(N)} \) has a finite polynomial dependence on the first \( n \) power traces, \( p_k := \text{Tr}(U_N^k) \), via:

\[
c_n^{(N)} = \frac{1}{n!} \det \begin{pmatrix}
p_1 & 1 & 0 & \ldots & 0 
p_2 & p_1 & 2 & \ldots & 0 
\vdots & \vdots & \vdots & \ddots & \vdots 
p_{n-1} & p_{n-2} & p_{n-3} & \ldots & n-1 
p_n & p_{n-1} & p_{n-2} & \ldots & p_1
\end{pmatrix}.
\] (1.4)

The distributional convergence of these power traces was famously studied by Diaconis and Shahshahani [DS94] for \( \beta = 2 \) and by Jiang and Matsumoto [JM15] for general \( \beta > 0 \), see also [CN19]. These authors show that for any fixed \( n \) we have the joint convergence in law

\[
\{\text{Tr}(U_N^k)\}_{k=1}^n \xrightarrow{d} \sqrt{\frac{2}{\beta}} \{\sqrt{k} \mathcal{N}_k\}_{k=1}^n, \quad N \to \infty,
\] (1.5)

where \( \{\mathcal{N}_k\}_{k=1}^n \) are i.i.d. standard complex normal random variables, i.e. the real and imaginary parts of \( \mathcal{N}_k \) are independent normal random variables such that

\[
\mathbb{E}(\mathcal{N}_k) = 0, \quad \mathbb{E}(\mathcal{N}_k^2) = 0, \quad \text{and} \quad \mathbb{E}(|\mathcal{N}_k|^2) = 1.
\] (1.6)

Therefore (1.5) implies that for fixed \( n \), the sequence of random variables \( c_n^{(N)} \) converges as \( N \to \infty \) to a limit random variable \( c_n \). Furthermore, each \( c_n \) is explicitly characterized through a polynomial dependence on a family of i.i.d. Gaussian random variables via formulas (1.5) and (1.4).

In contrast, the situation where the degree \( n \to \infty \) turns out to be much more challenging. To give a flavour of the results we obtain, we provide here
the limiting distribution in the case $\beta > 4$; see Section 1.2 for further results and discussion.

**Theorem 1.1.** Let $N = N_n$ be a sequence such that $N \to \infty$ as $n \to \infty$ and such that $n/N \to 0$. Let $Z$ denote a standard complex normal random variable and $E(1)$ denote the standard exponential random variable with parameter 1, sampled independently. Then for any $\beta > 4$, we have the convergence in distribution

$$
\frac{c_n^{(N)}}{\sqrt{\mathbb{E}(|c_n^{(N)}|^2)}} \xrightarrow{d} \frac{Z}{\sqrt{\Gamma \left(1 - \frac{2}{\beta}\right)}}^{1/\beta},
$$

where $\Gamma(z)$ is the Gamma function.

A quick computation shows that the right-hand side of (1.7) has finite moments of order $2k$ if and only if $\frac{2k}{\beta} < 1$. Our proof makes explicit use of the second moment method ($k = 2$ in this context) and this gives rise to the restriction $\beta > 4$ in the statement of Theorem 1.1. We believe that (1.7) persists to any $\beta > 2$ and even the case $\beta = 2$ after suitably re-normalizing on both sides of (1.7).

At the level of tightness, we are able to remove the restriction on $\beta$ and our results hold for any $\beta > 0$. We can also relax the condition $n/N \to 0$ stated in Theorem 1.1. As an example, we have the following particular case that resolves a problem of Diaconis and Gamburd [DG06] on the middle secular coefficient, defined by setting $n = \lfloor N/2 \rfloor$.

**Theorem 1.2.** Let $\beta = 2$ and set $w_N = \log(1 + N)^{-1/4}$. Then we have that $\{c_n^{(N)}/w_N\}_{N \geq 1}$ and $\{w_N/c_n^{(N)}\}_{N \geq 1}$ are both tight families of random variables. In particular

$$
c_n^{(N)} \xrightarrow{d} 0 \text{ as } N \to \infty.
$$

More generally, when $n_N \to \infty$ in such a way that $2n_N \leq N$, $c_n^{(N)} \xrightarrow{d} 0$ as $N \to \infty$.

Note that Theorem 1.2 holds despite the fact that $\mathbb{E}(|c_n^{(N)}|^2) = 1$ identically. A similar phenomenon has been observed in a number theoretical context, namely in the theory of random multiplicative functions and ‘better than square root cancellation’ [Har20]. In the regime $0 < \beta < 2$, we will establish a similar class of tightness results which show that the normalization $\sqrt{\mathbb{E}(|c_n^{(N)}|^2)}$ overestimates the correct order of magnitude for the coefficients, see Section 1.5.
1.1 The holomorphic multiplicative chaos

Statistical properties of random matrix characteristic polynomials have attracted considerable interest recently, in large part due to an intimate relationship to logarithmically correlated Gaussian fields and Gaussian multiplicative chaos (GMC), see [DRSV17] and [RV14] for general background on these topics. The connection to characteristic polynomials of random matrices arose quite recently in an influential work of Fyodorov, Hiary and Keating [FHK12, FK14]. In particular the attempts to prove the conjectures in [FHK12, FK14], which are still unresolved in full generality, have motivated a number of recent studies on characteristic polynomials of random matrices, for a non-exhaustive list see e.g. [ABB17, BWW18, CN19, CMN18, LOS18, NSW20, PZ18, Web15], and also on various parallel questions concerning the Riemann zeta function [ABB+19, ABR20, Naj18, SW20]. We will show how the GMC theory also plays a prominent role in the analysis of the secular coefficients $c^{(N)}_n$ in (1.3).

To describe formally how a log-correlated Gaussian field can arise from the characteristic polynomial (1.2), we expand the logarithm as

$$\log \chi_N(z) = -\sum_{k=1}^{\infty} \frac{z^k}{k} \text{Tr}(U_N^{-k}).$$

(1.8)

By the convergence (1.5) we can identify a candidate limiting Gaussian field by replacing the power traces $\text{Tr}(U_N^{-k})$ with $\sqrt{2\beta} \sqrt{k} N_k$, where $N_k$ are i.i.d. standard complex Gaussian variables as in (1.6) and for the sake of simplicity we ignore the minus sign in (1.8), noting the rotational invariance of each $N_k$. Now let $G^C$ be the Gaussian analytic function on the unit disc $D$

$$G^C(z) = \sum_{k=1}^{\infty} \frac{z^k}{\sqrt{k}} N_k,$$

(1.9)

so that we expect $\chi_N(z)$ to be close to $e^{\sqrt{2\beta} G^C(z)}$ in a suitable sense. The covariance of the field $G^C$ follows from the simple i.i.d. structure of the variables $N_k$ as

$$\mathbb{E}[G^C(w)G^C(z)] = 0 \quad \text{and} \quad \mathbb{E}[G^C(w)\overline{G^C(z)}] = -\log(1 - w\overline{z}),$$

from which it follows that $G = 2\Re G^C$ and $H = 2\Im G^C$ are identically distributed Gaussian fields with

$$\mathbb{E}[G(w)G(z)] = -2 \log |1 - w\overline{z}| \quad \text{and} \quad \mathbb{E}[G(w)H(z)] = -2 \text{Arg}(1 - w\overline{z}),$$

(1.10)
where we take the principal branch of the argument. In particular, when defined on the unit circle $|z| = |w| = 1$, the real valued field $G$ is a prototypical example of a log-correlated Gaussian field (see e.g. [HKO01] where it first appeared explicitly).

For trigonometric polynomials $\phi$ if we let $z \mapsto \phi(z)$ for $z \in \mathbb{D}$ be the continuous harmonic extension to $\mathbb{D}$, we can define the random distribution

$$
(HMC_\theta, \phi) := \lim_{r \to 1} \frac{1}{2\pi} \int_0^{2\pi} e^{\sqrt{\theta}G^C(re^{i\theta})} \overline{\phi}(r\theta)d\theta,
$$

which we will call the holomorphic multiplicative chaos or HMC, where from now on we will adopt the notation

$$
\theta := \frac{2}{\beta}.
$$

For the moment, we comment that for trigonometric polynomials, the existence of this limit is trivial and is sufficient to uniquely define the HMC. In particular, if we take $\phi(\theta) = e^{in\theta}$ for $n \in \mathbb{N}_0$, then using analyticity and Cauchy’s theorem the limit is just the $n$-th coefficient in the power series expansion of $e^{\sqrt{\theta}G^C(z)}$ at $z = 0$. We define for $n \in \mathbb{N}_0$ the Fourier coefficient of the HMC

$$
c_n := (HMC_\theta, \theta \mapsto e^{in\theta}).
$$

Equivalently, the coefficients $c_n$ can be extracted from a generating function by the formula

$$
c_n = [z^n] e^{\sqrt{\theta}G^C(z)} = [z^n] \exp \left( \sqrt{\theta} \sum_{k=1}^\infty \frac{z^k}{\sqrt{k}} N_k \right),
$$

where the notation $[z^n] h(z)$ denotes the coefficient of $z^n$ in the power series expansion of $h(z)$ around the point $z = 0$. We could as well define this for $n \in \mathbb{Z}$, but for negative integers, this would be $0$.

The HMC is in some sense the distributional limit of the characteristic polynomial $\chi_N$ inside the unit circle. The following is shown in [CN19]:

**Theorem 1.3** (Proposition 3.1 of [CN19]). For any $\beta > 0$ it is possible to define $\chi_N$ and the field $G^C$ on a single probability space in such a way that for any $r \in (0, 1)$,

$$
\sup_{|z| \leq r} |\chi_N(z) - e^{\sqrt{\theta}G^C(z)}| \xrightarrow{a.s. N \to \infty} 0.
$$

The convergence also holds in $L^p$ for any $p \geq 1$.  

Then as a corollary of Theorem 1.3 and Cauchy’s integral formula, on the probability space therein, each $c_n^{(N)} \xrightarrow{a.s.} c_n$. We shall continue to refer to \{c_n\} as the secular coefficients of the HMC$\theta$.

While HMC$\theta$ is uniquely determined by its Fourier coefficients and exists for all $\theta > 0$, we will characterize its regularity in the Sobolev sense. We define the Sobolev norms for any $s \in \mathbb{R}$ on the trigonometric polynomials on $\mathbb{T}$ by

$$
\|f\|_{H^s}^2 = \sum_{n \in \mathbb{Z}} (1 + n^2)^s |\hat{f}(n)|^2, \quad \text{where} \quad \hat{f}(n) = \frac{1}{2\pi} \int_0^{2\pi} f(e^{i\varphi}) e^{-i n \varphi} d\varphi.
$$

(1.15)

The Sobolev spaces $H^s$ for $s \in \mathbb{R}$ are the closures in the space of distributions of the trigonometric polynomials on $\mathbb{T}$ under these norms. For any $s \in \mathbb{R}$ the norms defined in (1.15) are well-defined for all functions $f \in L^2$, with the understanding that they may be infinite, and for $s \geq 0$ the space $H^s$ is precisely the subspace of $L^2$ for which $\|\cdot\|_{H^s} < \infty$. The formulas for the norms (1.15) extend generally to the space of distributions on $\mathbb{T}$ by replacing $\hat{f}(n) := (f, \varphi \mapsto e^{in\varphi})$. For any $s \in \mathbb{R}$, the pair $H^s$ and $H^{-s}$ are dual spaces with respect to the natural inner product on $\mathbb{T}$.

**Theorem 1.4.** Define

$$
s_\theta := \begin{cases} 
-\frac{\theta}{2}, & \text{if } \theta \leq 1, \\
-\sqrt{\theta} + \frac{1}{2}, & \text{if } \theta > 1.
\end{cases}
$$

Then for any $\theta > 0$, HMC$\theta$ is in $H^s$ almost surely for any $s < s_\theta$ and it is almost surely not in $H^s$ for any $s > s_\theta$.

**Proof.** See Section 6. \qed

We remark that in the variable $\theta = \frac{\gamma^2}{4}$ this Theorem states that HMC$\theta$ is in $H^s$ provided that

$$
-2s + 1 > \begin{cases} 
1 + \frac{\gamma^2}{4}, & \gamma < 2 \\
\gamma, & \gamma > 2.
\end{cases}
$$

(1.16)

The threshold on the right-hand side of (1.16) is familiar from the study of the free energy in various other log-correlated models (see e.g. [FB08]).
1.2 The combinatorial structure of the moments

We begin by discussing the moments of the secular coefficients. As we already mentioned, when $\beta = 2$ (or $\theta = 1$), Diaconis and Gamburd [DG06] characterize these moments in terms of the enumeration of magic squares. We will state a result that generalizes this characterization to arbitrary $\beta > 0$.

Definition 1.5. A magic square of size $k$ with row sums $\mu = (\mu_1, \ldots, \mu_k)$ and column sums $\nu = (\nu_1, \ldots, \nu_k)$ is a $k \times k$ matrix $A$ with entries in $\mathbb{N}_0$ and with the property that

$$\sum_{j=1}^{k} A_{ij} = \mu_i, \quad i = 1, \ldots, k,$$

$$\sum_{i=1}^{k} A_{ij} = \nu_j, \quad j = 1, \ldots, k. \quad (1.17)$$

Throughout the article we will use the notation $\text{Mag}_{\mu, \nu}$ to denote the collection of all such $k \times k$ magic squares. We recall that non-negative integer vectors $\mu$ are called compositions in the combinatorics literature, while the entries $\mu_1, \ldots, \mu_k$ are known as parts.

Theorem 1.6. Let $\mu$ and $\nu$ be any compositions with $k$ parts. Then for any $k \in \mathbb{N}$ and $\theta > 0$, we have

$$\mathbb{E}\left(\prod_{j=1}^{k} c_{\mu_j}^{\nu_j}\right) = \sum_{A \in \text{Mag}_{\mu, \nu}} \prod_{1 \leq i, j \leq k} \left(\frac{A_{ij} + \theta - 1}{A_{ij}}\right). \quad (1.18)$$

We give the proof in Section 2 and furthermore provide a combinatorial connection to Jack functions. When $\beta = 2$ ($\theta = 1$) the right-hand side of (1.18) reduces to the cardinality of $\text{Mag}_{\mu, \nu}$, recovering the result of [DG06] in the particular case $N = \infty$. Choosing the column and row sums all to equal $n$, we obtain an expression for the absolute $2k^{th}$ moments

$$\mathbb{E}(|c_n|^{2k}) = \sum_{A \in \text{Mag}_{\pi, \pi}} \prod_{1 \leq i, j \leq k} \left(\frac{A_{ij} + \theta - 1}{A_{ij}}\right). \quad (1.19)$$

where $\pi$ is the composition in which $n$ appears $k$ times, i.e. $\text{Mag}_{\pi, \pi}$ is the set of all magic squares of size $k \times k$ with all row and column sums equal to $n$. We note the special case

$$\mathbb{E}(|c_n|^2) = \left(\frac{n + \theta - 1}{\theta - 1}\right) \sim \frac{1}{\Gamma(\theta)} n^{\theta-1}. \quad (1.20)$$
It turns out it is possible to use this formula and (1.19) to probe asymptotic behaviour of the moments. We have:

**Theorem 1.7.** For any positive integer \( k \) and any \( \theta > 0 \) so that \( \theta k < 1 \),

\[
\lim_{n \to \infty} \frac{\mathbb{E}(|c_n|^{2k})}{\mathbb{E}(|c_n|^2)^k} = \frac{\Gamma(1 - k\theta)}{\Gamma(1 - \theta)^k} k!
\]  

**(1.21)**

**Proof.** See Section 2.

It is a simple computation, recalling that \( \theta = \frac{2}{\beta} \), that the moments on the right-hand side of (1.21) are precisely those of the limiting distribution in Theorem 1.1. We mention in passing that besides magic squares, which play an important role in describing HMC\( _\theta \), the *Ewens sampling formula*, which defines a classical distribution on random permutations, plays a prominent role in our analysis, see Section 3 for details.

### 1.3 From magic squares back to multiplicative chaos

Theorem 1.7 is strongly reminiscent of the *freezing transition* observed for moments of random energy models [FB08] (c.f. Remark 2.4 for the behavior of a moment above the critical threshold). Indeed, in [FB08] it is shown that the *Morris integral*

\[
\frac{\Gamma(1 - k\theta)}{\Gamma(1 - \theta)^k} = \frac{1}{(2\pi)^k} \int \prod_{1 \leq a < b \leq k} |e^{i\vartheta_a} - e^{i\vartheta_b}|^{-2\theta} d\vartheta,
\]  

**(1.22)**

describes the appropriately rescaled moments of the partition function of the logarithmically correlated *random energy model* on the unit circle in the high temperature phase – see [FB08] for details.

The presence of the Morris integral in Theorem 1.7 is moreover indicative that the theory of Gaussian multiplicative chaos will be relevant here. There is a substantial literature on this random measure (see [RV14] for a general overview), but we will be concerned only with the following specific instance: for \( \theta \in (0, 1) \),

\[
\text{GMC}_\theta(d\vartheta) := \lim_{r \to 1} (1 - r^2)^\theta |e^{\sqrt{\theta}G(r^\vartheta)}|^2 d\vartheta = \lim_{r \to 1} (1 - r^2)^\theta e^{\sqrt{\theta}G(r^\vartheta)} d\vartheta.
\]  

**(1.23)**

The existence of this limit as a random measure is shown in [JS17] (c.f. [CN19, Proposition 3.1]). Moreover it is shown in [Rem20] that the total
mass of this particular random measure has law characterized by the natural analytic continuation of the Morris integral, i.e. for any $p > 0$ with $p \theta < 1$,

$$\mathbb{E}(\mathcal{M}_\theta)^p = \frac{\Gamma(1 - p\theta)}{\Gamma(1 - \theta)^p},$$

where $\mathcal{M}_\theta := \frac{1}{2\pi} \int_0^{2\pi} \text{GMC}_\theta(d\theta)$, \hspace{1em} \text{(1.24)}

with the sense of the limit being an in-probability, weak-* convergence.

We briefly summarize some of the qualitative properties of the GMC. The regime $\theta \in (0, 1)$ is typically referred to as the subcritical phase of the GMC. The limiting measure is supported on a set of Hausdorff dimension $1 - \theta$. This result is well known in the literature on GMC, see [RV14], though for the model discussed here, see [CN19]. The subset $(0, \frac{1}{2})$ is sometimes referred to as the $L^2$ phase, on account of the mass $\mathcal{M}_\theta$ gaining a finite second moment (and indeed Theorem 1.7 applies as well).

The $L^2$ phase is technically simpler to manage, and has been the setting for some of the first convergence results of $\beta = 2$ characteristic polynomials and powers thereof to the GMC [Web15, BWW18]. For a power of the modulus of the CUE ($\beta = 2$) characteristic polynomial, this has been improved to the whole subcritical phase in [NSW20]. For general $\beta > 0$ to the authors’ knowledge there are no convergence results of this type. However for an object closely related to the characteristic polynomial, convergence to the GMC was established in [CN19] for general $\beta \geq 2$.

The value $\theta = 1$ is the critical temperature, at which it is possible to establish (1.23) under an additional logarithmic renormalization ([JS17, Theorem 1.3])

$$\text{GMC}_1(d\theta) := \lim_{r \to 1} \sqrt{\log \frac{1}{1 - r^2}} (1 - r^2)e^{G(re^{i\theta})}d\theta.$$ \hspace{1em} \text{(1.25)}

This measure is known to have has Hausdorff dimension 0 and is non-atomic, as proved in [CN19]. We note in contrast that HMC is well defined as a random distribution on the unit circle for all $\theta > 0$ (and indeed on a single probability space), regardless of the phase of the associated GMC.

Returning to consideration of Theorem 1.7, we see that there is a factor of $k!$ beyond the Morris integral term. This strongly suggests a limiting factorization into independent random variables, where the additional factor can be interpreted as the moments of a standard complex normal random variable $k! = \mathbb{E}(|Z|^{2k})$. We show this is indeed the case in the $L^2$ phase. More precisely:

**Theorem 1.8 (L²-phase).** For any $0 < \theta < \frac{1}{2}$, we have the convergence in distribution

$$\frac{c_n}{\sqrt{\mathbb{E}(|c_n|^2)}} \xrightarrow{d} \sqrt{\mathcal{M}_\theta} Z$$ \hspace{1em} \text{(1.26)}
where $\mathcal{Z}$ and $\mathcal{M}_\theta$ are independent, $\mathcal{Z}$ is standard complex normal, and $\mathcal{M}_\theta$ has law (1.24).

Proof. See Sections 3-5.

We expect this result to persist to all $\frac{1}{2} \leq \theta < 1$ and also to $\theta = 1$ (the critical temperature) subject to a different normalization. While we do not show this convergence in distribution for $\theta \geq \frac{1}{2}$, we give a sharp estimate for the order of magnitude of the coefficient for larger $\theta$ (see Lemma 7.5 and Theorem 1.11).

By the mentioned work [Rem20], the limiting random variable $\mathcal{M}_\theta$ appearing on the right-hand side of (1.26) can be given an explicit characterization. For any $\theta < 1$ it is known that we have the equality in law

$$\mathcal{M}_\theta \overset{d}{=} \frac{1}{\Gamma(1 - \theta)} \mathcal{E}(1)^{-\theta}$$

(1.27)

where $\mathcal{E}(1)$ is an exponential random variable with parameter 1. Formula (1.27) was initially conjectured by Fyodorov and Bouchaud in [FB08] and proved quite recently in [Rem20] using techniques of Liouville conformal field theory, see also [CN19] for an alternative proof. Using the explicit formula (1.27), we see that Theorem 1.8 is the particular case $N = \infty$ of our earlier stated Theorem 1.1.

1.4 The mass of the chaos

We note that the presence of the mass of the chaos in the secular coefficients could potentially be anticipated. On the one hand, by the generating function (1.14) and Parseval’s identity, we have

$$\sum_{n=0}^{\infty} |c_n|^2 r^{2n} = \frac{1}{2\pi} \int_0^{2\pi} e^{\sqrt{\theta} G(re^{i\vartheta})} d\vartheta.$$  

(1.28)

On the other hand, by (1.23) and (1.25) for all $0 < \theta \leq 1$,

$$L(r, \theta)(1 - r^2)^\theta \sum_{n=0}^{\infty} |c_n|^2 r^{2n} \xrightarrow{p} r_{\rightarrow 1} \mathcal{M}_\theta, \quad L(r, \theta) := \begin{cases} \sqrt{\log \frac{1}{1-r^2}}, & \text{if } \theta = 1, \\ 1, & \text{else}. \end{cases}$$

(1.29)

So in a suitably averaged sense, the squared modulus of the secular coefficients gives the total mass of the chaos in the subcritical and critical phases. In comparison, Theorem 1.8, shows that each individual coefficient $\{c_n\}$ already contains much of the information about the mass of the GMC.
We also detour briefly to mention that from (1.29), it is possible to derive other approximations to the total mass. One which will be important here is
\[ M_{\theta,n} := \left( \sqrt{\log n} \right)^{\theta} \Gamma(\theta + 1) \sum_{q=0}^{n} |c_q|^2. \] (1.30)

If the convergence in (1.29) were almost sure, the Hardy–Littlewood Tauberian theorem would immediately imply that \( M_{\theta,n} \) converges almost surely to \( M_\theta \). We show in Theorem A.2 in the Appendix that this Tauberian theorem generalizes to the setting of convergence in probability, and the following is an immediate consequence of (1.28), (1.29) and Theorem A.2.

**Lemma 1.9.** For any \( 0 < \theta < 1 \), we have the convergence in probability to the total mass
\[ M_{\theta,n} \xrightarrow{p}{n\rightarrow\infty} M_\theta, \quad n \rightarrow \infty. \] (1.31)

### 1.5 The secular coefficients of CβE

Some of what we have proved for the HMC coefficients \( \{c_n\} \) adapt or transfer to the secular coefficients \( \{c^{(N)}_n\} \) of \( N \times N \) random matrices, as defined in (1.3). In particular, when \( n \rightarrow \infty \) and \( N \rightarrow \infty \) in such a way that \( n/N \rightarrow 0 \), Theorem 1.8 transfers directly to \( \{c^{(N)}_n\} \):

**Theorem 1.10** \((L^2\)-phase for slowly growing \( n \)). Let \( N = N_n \) be chosen in such a way that \( n/N \rightarrow 0 \) as \( n \rightarrow \infty \). Recalling the notation \( \theta := \frac{2}{\beta} \), for any \( 0 < \theta < \frac{1}{2} \), we have the convergence in distribution
\[ \frac{c^{(N)}_n}{\sqrt{\mathbb{E}(|c^{(N)}_n|^2)}} \xrightarrow{d}{n\rightarrow\infty} \sqrt{M_\theta} Z \] (1.32)
where \( Z \) and \( M_\theta \) are independent, \( Z \) is standard complex normal, and \( M_\theta \) has law (1.24).

**Proof.** See Section 7. \( \square \)

We remark that by formula 1.27, Theorem 1.10 is simply a restatement of Theorem 1.1, but we have included it here for added clarity in the context of GMC theory. Let us discuss the necessity of the condition \( n/N \rightarrow 0 \) as \( n \rightarrow \infty \) appearing in Theorem 1.10. The normalization constant \( \mathbb{E}(|c^{(N)}_n|^2) \) is known explicitly, due to [HKS+96] who obtain for any \( \theta > 0 \),
\[ \mathbb{E}(|c^{(N)}_n|^2) = \binom{N}{n} \frac{\Gamma(n + \theta)\Gamma(N - n + \theta)}{\Gamma(\theta)\Gamma(N + \theta)}. \] (1.33)
We remark in passing that, to our knowledge, the work [HKS+96] was likely the first explicit investigation of secular coefficients in the literature. From (1.33), we observe two possible types of asymptotics. If $N$ grows with $n$ at a fast enough rate that $n/N \to 0$ as $n \to \infty$, then
\[ E(|c_{n}^{(N)}|^2) \sim \frac{1}{\Gamma(\theta)} n^{\theta-1}, \quad n \to \infty, \quad (1.34) \]
which matches the asymptotic (1.20). When however $n = \kappa N$ with $0 < \kappa < 1$, the asymptotics contain an additional pre-factor
\[ E(|c_{\kappa N}^{(N)}|^2) \sim \frac{(1 - \kappa)^{\theta-1}}{\Gamma(\theta)} n^{\theta-1}, \quad N \to \infty. \quad (1.35) \]
This hints that these higher degree coefficients could display a different limiting behavior.

On the other hand, we show that the order of magnitude of these secular coefficients is no larger than that of $c_n$.

**Theorem 1.11** (Order estimate). Let $w_n(\theta)$ be given by
\[ w_n = n^{(\theta-1)/2}, \quad w_n = (\log(1 + n))^{-1/4}, \quad \text{or} \quad w_n = n^{\sqrt{\theta}-1}(\log(1 + n))^{-\frac{3}{4}}, \]
in the cases $\theta \in (0, 1)$, $\theta = 1$ or $\theta > 1$ respectively. Then for any $\theta \leq 1$, with $N_0(n) = 2n$ the family
\[ \{ (w_n/c_{n}^{(N)}, c_{n}^{(N)}/w_n) : n, N \in \mathbb{N}, N \geq N_0(n) \} \]
is tight. For $\theta \in (1, 2)$, there are constants $u_\theta, v_\theta > 0$ so that with $N_0(n) = n^{u_\theta}$ the family
\[ \{ (c_{n}^{(N)}/w_n)(\log(1 + n))^{-v_\theta} : n, N \in \mathbb{N}, N \geq N_0(n) \} \]
is tight.

**Proof.** See Theorems 7.6 and 8.2. \qed

We make similar statements for $c_n/w_n$ for any $\theta > 0$ in Lemma 7.5 and Theorem 8.1 – in particular the bounds we establish are consistent with Theorem 1.8 extending to all $\theta \in (0, 1]$. For $\theta > 1$, we do not expect either $u_\theta$ or $v_\theta$ to be sharp. We may reasonably conjecture the correct value for $v_\theta = 0$. See Remark 7.4 for further discussion.
1.6 Discussion

We have analyzed a random distribution, the HMC, which can be considered as a large-$N$ limit of the characteristic polynomials $\chi_N$ of the C$\beta$E. This limiting process exists for all $\theta > 0$ and we have given the distributional convergence of the Fourier coefficients of this Schwartz distribution.

Besides appearing implicitly in [CN19], we do not believe the HMC has appeared explicitly before. The nearest connection for the case $\theta = 1$ ($\beta = 2$) appears in [SW20, Theorem 1.3]. Therein, the authors show there exists a sequence $\delta_N \to 0$ and a random Schwartz distribution $\eta$ on $\mathbb{R}$ so that

$$\chi_N(e^{i\delta_N x}) e^{-Y_N} \frac{d}{N \to \infty} \eta(x),$$

where $Y_N$ is a complex Gaussian variable having a nontrivial dependence on $\chi_N$. The process $\eta$ can be formally understood as

$$\eta(x) = \exp \left( \int_0^\infty e^{-2\pi i u} \frac{d}{\sqrt{u}} dB_u^C \right)$$

for a complex Brownian motion $B_u^C$. It is also shown that this chaos appears as the limit of a randomized model of the Riemann $\zeta$-function. We note that this process $\eta$ is a possible candidate for definition of HMC$_\theta$ on the real line when $\theta = 1$, and could also be a type of local scaling limit of HMC$_\theta$ in a suitable vanishing window of $\theta$.

Another class of related objects which have been considered are the complex multiplicative chaoses. For example, consider the random distribution CGMC$_\theta$ given (hypothetically) by

$$(\text{CGMC}_\theta, \phi) = \lim_{r \to 1} \frac{1}{2\pi} \int_0^{2\pi} e^{\sqrt{\theta/4} (G_1(re^{i\theta}) + iG_2(re^{i\theta}))} \phi(\theta) d\theta, \quad (1.36)$$

where $G_1$ and $G_2$ are i.i.d. copies of $G$ from (1.10). This roughly fits within the frameworks of [LRV15] and [Lac20], although the technical assumptions on the manner of regularization of $G(e^{i\theta})$ are not precisely the same. We comment that in the language of [LRV15] that CGMC$_\theta$ would be in Phase I for $\theta \in (0, 1)$, in Phase II for $\theta > 1$ and at the triple point for $\theta = 1$. We mention briefly that there is other related work on complex multiplicative cascades [BJM10a, BJM10b] and imaginary chaoses in [AJJ20, JSW18].

When $\theta < 1$, an adaptation of [LRV15, Theorem 3.1] would show the limit in (1.36) exists and so the CGMC$_\theta$ is well defined.\footnote{From the theory in [BJM10b], using the series truncation regularization in place of the harmonic regularization, the existence of the limit follows.} We note that for

\begin{enumerate}[label=(\Roman*).

\( \theta \geq 1, [LRV15, \text{Conjectures 5.2, 5.3}] \) suggest that an additional logarithmic normalization is required for convergence, analogously to logarithmic factors needed for convergence of the critical GMC. Indeed, in work of [MRV16, HK15] (see also [HK18]), an analogous statement is proven for a complex random energy model built from branching processes. Note this in contrast to HMC\( \theta \), which requires no further normalization to converge for any \( \theta > 0 \).

Because the correlations are relatively weak between the real and imaginary parts of the field which define HMC\( \theta \), we expect that some results carry to HMC\( \theta \) from the theory of the complex multiplicative chaoses, for example the multifractality for \( \theta < 1, q < 1 \):

\[
\mathbb{E}[\|CGMC_{\theta} \cdot 1 \{|\vartheta| \leq r\}|^q] \sim r^{q\theta - \theta q^2},
\]

(see [LRV15, Theorem 3.6], [BJ10], and see also the related work on the regularity of the complex Gaussian multiplicative chaoses in [JSV19]). We expect the same to hold for HMC\( \theta \):

**Question 1.12.** For \( \theta < 1, q < 1 \), does it hold that

\[
\mathbb{E}[\|HMC_{\theta} \cdot 1 \{|\vartheta| \leq r\}|^q] \sim r^{q\theta - \theta q^2}?
\]

We conclude by mentioning some unsolved questions on the properties of HMC\( \theta \). We have considered the \( L^2 \)-phase of \( \theta \), that is \( \theta < \frac{1}{2} \). We assume that Theorem 1.10 generalizes without alteration to \( \theta \in (0, 1) \), the \( L^1 \)-phase and in addition to the critical value \( \theta = 1 \) after introducing an appropriate logarithmic factor.

**Question 1.13.** Show Theorem 1.8 generalizes to all \( \theta \in (0, 1) \) and that it can be adapted to hold at the critical point \( \theta = 1 \).

For supercritical \( \theta > 1 \), it is reasonable to assume that there is still distributional convergence of \( c_n \), but the exact form of the limit is unclear.

We have also shown distributional convergence of the secular coefficients \( c_n^{(N)} \) when \( n/N \to 0 \) in the \( L^2 \)-phase. This relies on making a comparison between \( c_n \) and \( c_n^{(N)} \) which is weaker when \( n/N \to c \in (0, 1) \). So, we ask:

**Question 1.14.** What is the distributional limit of \( c_n^{(N)} / \sqrt{\mathbb{E}(|c_n^{(N)}|^2)} \) in the subcritical (or even \( L^2 \)) phase when \( n/N \to c \in (0, 1) \) as \( N \to \infty \)?

One feature of the secular coefficients \( c_n^{(N)} \) is that they may be expressed as combinations of certain conditional expectations of \( c_n \) and \( c_{N-n+1} \) (see (7.12)). Beyond this, it would be interesting to know the joint behavior of the secular coefficients \( \{c_n\} \).
Question 1.15. For \( \theta \in (0, 1) \), to what does \( (n^{(1-\theta)/2}c_{n+m} : m \in \mathbb{Z}) \) converge as \( n \to \infty \) in the sense of finite-dimensional marginals?

We conclude with one final question of a metamathematical nature. For \( r \in (0, 1) \), the function \( \vartheta \mapsto e^{\sqrt{\theta}G(re^{i\vartheta})} \) from \( [0, 2\pi) \) to \( \mathbb{C} \) can be seen, after suitable normalization, as the (random) wave function of the position of a particle which lives on \( [0, 2\pi) \). Then, if one makes a quantum measurement of the position of the particle, the outcome of the measurement is distributed according to the (random) probability measure with density

\[
\vartheta \mapsto \frac{e^{\sqrt{\theta}G(re^{i\vartheta})}}{\int_0^{2\pi} e^{\sqrt{\theta}G(re^{i\vartheta})} d\vartheta}
\]

with respect to the Lebesgue measure on \( [0, 2\pi) \). Now, if we are in the subcritical or the critical phases (\( \theta \leq 1 \)), and if we take the limit \( r \to 1 \), we see that

\[
\vartheta \mapsto e^{\sqrt{\theta}G^c(\vartheta)} = \sum_{n \geq 0} c_ne^{ni\vartheta}
\]

can be formally seen as as the wave function of a particle such that a quantum measurement gives an outcome distributed according to the (random) probability measure \( \text{GMC}_\theta/\mathcal{M}_\theta \).

Question 1.16. Is there a physically meaningful quantum mechanical system with wave function \( \text{HMC}_\theta/\sqrt{\mathcal{M}_\theta} \)?

1.7 Organization

The structure of this paper is as follows. In Section 2 we compute the joint moments of the secular coefficients \( \{c_n\} \), which we express in terms of magic squares. We then relate these to Jack functions and compute their asymptotics, proving Theorems 1.6 and 1.7. In Section 3, we make a connection between the moments of the secular coefficients and the Ewens sampling formula. We then review known estimates of the Ewens sampling formula.

In Sections 4, 4.2, 5, and 5.2 we prove Theorem 1.8. We do this by ultimately using the martingale central limit theorem. However \( c_n \) itself is not suitable for a direct application. So in Section 4 we find a related random variable \( c_n^{(d)} \) which is a close approximation to \( c_n \) and whose Doob martingale with respect to a natural filtration has easily understood increments. In Section 4.2, we give the proof of this normal approximation for \( c_n^{(d)} \) and
then a proof of Theorem 1.8 contingent on showing the bracket process of the Doob martingale for $c_n^{(\delta)}$ stabilizes in the $n \to \infty$ followed by $\delta \to 0$ limit. In Section 5 we compute moments of secular coefficients with restricted cycle count, whose meaning will become apparent, and finally in Section 5.2, we prove the convergence needed to complete the proof of Theorem 1.8.

In Section 6 we prove Theorem 1.4 on the regularity of HMC$_\theta$. In Section 7 we give the precise connection between the characteristic polynomial $\chi_N$ and HMC$_\theta$. We also show Theorems 1.10 and 1.11. Finally in Section 8, we prove the sharpness of the estimates in Section 7 in the regime $\theta \in (0,1]$. 

Acknowledgements

All three authors would like to thank the hospitality of the International Institute of Physics, in Natal, Brazil, and the program Random geometries and multifractality in condensed matter and statistical mechanics from 2019 where this work began. All authors would like to thank Yacine Barhoumi–Andréani for bringing the mathematics around secular coefficients to their attention and for helpful conversations besides. E. P. gratefully acknowledges support from an NSERC Discovery grant. N. S. gratefully acknowledges support of the Royal Society University Research Fellowship ‘Random matrix theory and log-correlated Gaussian fields’, reference URF\R1\180707.

2 Moments of the secular coefficients

The purpose of this section will be to prove Theorems 1.6 and 1.7 on the moments of $c_n$ for general $\beta > 0$. We also discuss combinatorial properties of the moments and their relation to Jack functions.

Proof of Theorem 1.6. Recall from (1.14) that $c_n$ can be extracted from a generating function according to the formula

$$c_n = [z^n] \exp \left( \sqrt{\theta} \sum_{j=1}^{\infty} \frac{N_j}{\sqrt{j}} z^j \right). \quad (2.1)$$

Denoting the left-hand side of (1.18) as $\mathcal{R}^{(k)}_{(\mu,\nu)}$, we have

$$\mathcal{R}^{(k)}_{(\mu,\nu)} = [z_1^{\mu_1} \ldots z_k^{\mu_k} w_1^{\nu_1} \ldots w_k^{\nu_k}] \mathbb{E}(F^{(k)}(\vec{z}, \vec{w})) \quad (2.2)$$

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where
\[ F^{(k)}(\vec{z}, \vec{w}) = \exp \left( \sqrt{\theta} \sum_{r=1}^{k} \sum_{j=1}^{\infty} \left( \frac{N_j}{\sqrt{j}} z_j^r + \frac{N_j}{\sqrt{j}} w_j^r \right) \right). \] (2.3)

A simple Gaussian computation using independence of the family \( \{N_k\}_{k=1}^{\infty} \) shows that
\[ \mathbb{E}(F^{(k)}(\vec{z}, \vec{w})) = \prod_{r_1, r_2=1}^{k} \frac{1}{(1 - z_{r_1} w_{r_2})^\theta}. \] (2.4)

Expanding (2.4) with the Newton binomial formula we obtain
\[
\prod_{r_1, r_2=1}^{k} \frac{1}{(1 - z_{r_1} w_{r_2})^\theta} = \sum_{A} \prod_{i,j=1}^{k} \left( A_{ij} + \theta - 1 \right) \theta - 1 \times \prod_{i=1}^{k} z_i^{\sum_{j=1}^{k} A_{ij}} \prod_{j=1}^{k} w_j^{\sum_{i=1}^{k} A_{ij}},
\] (2.5)
where the sum runs over the set of all \( k \times k \) matrices \( A \) whose entries are non-negative integers. Equating coefficients according to (2.2) fixes the row and column sums appearing in (2.5) and completes the proof of the Theorem.

We remark that Diaconis and Gamburd [DG06] prove this result specifically for the coefficients \( c_n^{(N)} \) with \( \theta = 1 \), related to random unitary matrices. In contrast to the above computation, they exploited the known orthogonality of the Schur functions and explicit results associated with the RSK correspondence. When \( N = \infty \) their result recovers ours for the coefficients \( c_n \) with \( \theta = 1 \), but if \( \theta \neq 1 \) their result is distinct from ours. Despite this, in the following we discuss an interpretation of our result for general \( \theta > 0 \) in terms of Jack functions (which extend the Schur functions to any \( \theta > 0 \)).

### 2.1 Connection to Jack functions

We briefly recall some symmetric function notation. We follow [Sta89] and [Mac15] for all notational conventions. We refer the reader to [Sta89] for a concise reminder of the definitions.

Let \( \Lambda \) be the algebra of all symmetric formal power series in a countably infinite family of indeterminates. For any partition \( \lambda \) we let \( p_\lambda \) be the power sum symmetric function, \( e_\lambda \) be the elementary symmetric function, and \( m_\lambda \) be the monomial symmetric function.
For any partition \( \lambda = (1^m_1, 2^m_2, 3^m_3, \ldots) \), we let

\[
  z_\lambda = 1^{m_1} \cdot 2^{m_2} \cdot 3^{m_3} \cdots m_1!m_2!m_3!\cdots.
\]

We also define \( \ell(\lambda) \) to be the length of a partition. We define an inner product on \( \Lambda \) by

\[
  \langle p_\lambda, p_\mu \rangle = 1^\lambda_\mu z_\lambda \theta^{\ell(\lambda)}.
\]

The Jack functions \( \{P_\theta^\lambda\} \) form another basis \( \Lambda \), which can be uniquely defined by (c.f. [Sta89, Theorem 1.1]):

1. \( \langle P_\theta^\lambda, P_\theta^\mu \rangle = 0 \) if \( \lambda \neq \mu \).
2. Expanding the Jack function into monomial basis,

\[
  P_\theta^\lambda = \sum u_{\lambda\mu}(\alpha)m_\mu,
\]

all nonzero coefficients \( u_{\lambda\mu}(\alpha) \) satisfy \( \mu \leq \lambda \) where \( \leq \) is the dominance ordering (also known as the “natural ordering” in [Mac15, p.6]).
3. The leading coefficient \( u_{\lambda\lambda} = 1 \).

These specialize to the Schur functions when \( \theta = 1 \).

For any symmetric functions \( p, g \) we define another inner product

\[
  \langle p, g \rangle_n = \frac{1}{Z_{n,\beta}} \int_T p(x)g(x) \prod_{i \neq j} |x_i - x_j|^{1/\theta} \, dx,
\]

that is to say integration against the circular–\( \beta \) ensemble. Here we have specialized the functions \( p \) and \( g \) by sending all \( x_j = 0 \) for \( j > n \). The \( Z_{n,\beta} \) is the usual normalization so that \( \langle 1, 1 \rangle = 1 \). Then for any symmetric functions, \( \langle p, g \rangle_n \to \langle p, g \rangle \) (see the discussion below (10.38) in [Mac15]). Furthermore, one has that the polynomials \( \{P_\theta^\lambda : \ell(\lambda) \leq n\} \) are orthogonal with respect to \( \langle \cdot, \cdot \rangle_n \) [Mac15, (10.36)].

The Kostka numbers \( K_{\lambda\mu} \) can be defined as

\[
  s_\lambda = \sum_{\mu} K_{\lambda\mu} m_\mu.
\]

As a corollary (apply the \( \omega \) involution to [Sta99, Corollary 7.12.4])

\[
  c_\mu = \sum_{\lambda} K_{\lambda\mu} s_\lambda.
\]

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Then it is possible to generalize these coefficients to the Jack setting by setting
\[ e_\mu = \sum_\lambda K^\theta_{\lambda \mu} P^\theta_\lambda \] (2.7)

The proof of [DG06] exploited an identity for the Kostka numbers, which follows from the RSK bijection (see [Sta99, Section 7.11]). This is given by
\[ \sum_\lambda K_{\lambda \mu} K_{\lambda \nu} = |\text{Mag}_{\mu, \nu}| \]

see [Sta99, Corollary 7.12.3].

As a corollary of Theorem 1.6, we get a new proof of this fact, as well as a generalization to all \( \theta \). We mention that these connection coefficients are useful for the exact evaluation of some moments of \( \beta \)-ensembles [MRW17].

**Theorem 2.1.**
\[ \sum_\lambda K^\theta_{\lambda \mu} K^\theta_{\lambda \nu} \langle P^\theta_\lambda, P^\theta_\lambda \rangle = \sum_{A \in \text{Mag}_{\mu, \nu}} \prod_{i,j} \left( \frac{\theta + A_{ij} - 1}{A_{ij}} \right) \]

**Proof.** Recall \( \chi_N \) is the characteristic polynomial of a circular-\( \beta \) random matrix, and so
\[ \chi_N(t) = \sum_{k=0}^N \epsilon_k(\lambda) t^k, \]
with \( \lambda \) distributed as \( C_{\beta E} \). Then from Theorem 1.3,
\[ \mathbb{E}(\epsilon_\mu(\lambda) \overline{\epsilon_\nu(\lambda)}) \rightarrow \mathbb{E} \prod_{j=1}^\infty c_j^{\mu_j} c_j^{\nu_j}. \]

On the other hand
\[ \mathbb{E}(\epsilon_\mu(\lambda) \overline{\epsilon_\nu(\lambda)}) = \langle \epsilon_\mu, \epsilon_\nu \rangle_N \rightarrow \langle \epsilon_\mu, \epsilon_\nu \rangle, \]
and hence by (2.7) and Theorem 1.6
\[ \sum_\lambda K^\theta_{\lambda \mu} K^\theta_{\lambda \nu} \langle P^\theta_\lambda, P^\theta_\lambda \rangle = \sum_{A \in \text{Mag}_{\mu, \nu}} \prod_{i,j} \left( \frac{\theta + A_{ij} - 1}{A_{ij}} \right). \]

The normalization constant \( \langle P^\theta_\lambda, P^\theta_\lambda \rangle \) is given in [Mac15, (10.16)].
2.2 Asymptotics of the moments

In this subsection we will give the proof of Theorem 1.7. It is instructive to begin with a particular case, so we first discuss the case of the fourth moment, or $k = 2$ in Theorem 1.7. Then we show how to generalize the approach to all positive integers $k$.

**Example 2.2.** Using Theorem 1.6, we can for instance take $k = 2$, $\mu_1 = \mu_2 = n$, and $\nu_1 = \nu_2 = n$ with all other exponents equal to zero. In this case one is summing over all $2 \times 2$ magic squares whose row and column sums are equal to $n$. Such magic squares are parameterized by a single variable (denoted here $j$) and formula Theorem 1.6 yields

$$
E(|c_n|^4) = \sum_{j=0}^{n} \left( \frac{j + \theta - 1}{\theta - 1} \right)^2 \left( \frac{n - j + \theta - 1}{\theta - 1} \right)^2. \quad (2.8)
$$

When $\theta = 1$, the right-hand side of (2.8) is given by $n + 1$ (the number of $2 \times 2$ magic squares), as obtained in [DG06]. For general $\theta > 0$ we can compute the asymptotics as $n \to \infty$ from the sum representation (2.8) as follows.

**Lemma 2.3.** For any $0 < \theta < 1/2$, we have the following:

$$
\frac{E(|c_n|^4)}{E(|c_n|^2)^2} \sim \frac{2 \Gamma(1 - 2\theta)}{\Gamma(1 - \theta)^2}, \quad n \to \infty, \quad (2.9)
$$

where we recall the normalization

$$
E(|c_n|^2) = \left( \frac{n + \theta - 1}{\theta - 1} \right)^2 \sim \frac{1}{\Gamma(\theta)} n^{\theta - 1}. \quad (2.10)
$$

**Proof.** Fix $0 < \delta < 1$ and split the sum in (2.8) according to whether $j \leq \lfloor \delta n \rfloor$, $\lfloor \delta n \rfloor + 1 \leq j \leq n - \lfloor \delta n \rfloor - 1$ or $n - \lfloor \delta n \rfloor \leq j \leq n$, denoting each sum $S_1$, $S_2$ or $S_3$ respectively. Then in the sum $S_1$, the term $n - j$ is always large, so that the second binomial coefficient is uniformly bounded by $c_{5,\theta} n^{\theta - 1}$ for some constant $c_{5,\theta} > 0$. Applying dominated convergence then gives

$$
\lim_{n \to \infty} \frac{S_1}{E(|c_n|^2)^2} = \sum_{j=0}^{\infty} \left( \frac{j + \theta - 1}{\theta - 1} \right)^2 \lim_{n \to \infty} \frac{(n-j+\theta-1)^2}{(n+\theta-1)^2} \quad (2.11)
$$

$$
= \sum_{j=0}^{\infty} \left( \frac{j + \theta - 1}{\theta - 1} \right)^2 \quad (2.12)
$$

$$
= \frac{\Gamma(1 - 2\theta)}{\Gamma(1 - \theta)^2}, \quad (2.13)
$$

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where in (2.13) we used Lemma B.1. An identical argument holds for the sum $S_3$ (by symmetry of $j \to n - j$) and this gives the factor $2!$ in (2.9). The sum $S_2$ is negligible: the second binomial coefficient is still bounded by $c_{\theta, \delta} n^{\theta - 1}$, which gives the same order of magnitude, but now both the upper and lower limits of the sum are growing. Since (2.12) converges, we have that $n^{-2(\theta - 1)} S_2 \to 0$. This completes the proof of the Lemma.

**Remark 2.4.** When $\theta \geq 1/2$ this argument breaks down because the sum in (2.13) is divergent, which leads to slightly different asymptotic behaviour. When $\theta > 1/2$, the sum $S_2$ can be approximated by a Riemann integral which now gives the main contribution: As $n \to \infty$ we have

\[
\mathbb{E}(|c_n|^4) \bigg|_{\theta > 1/2} \sim n^{4(\theta - 1) + 1} \frac{1}{\Gamma(\theta)^4} \int_0^1 x^{2(\theta - 1)}(1 - x)^{2(\theta - 1)} \, dx = n^{4(\theta - 1) + 1} \frac{\Gamma(2\theta - 1)^2}{\Gamma(4\theta - 2)\Gamma(\theta)^4}
\]

and conversely note that this integral becomes divergent when $\theta \leq 1/2$, with the leading power of $n$ matching at the transition $\theta = 1/2$. In the case $\theta = 1/2$, one can show that

\[
\mathbb{E}(|c_n|^4) \bigg|_{\theta = 1/2} \sim \frac{2}{\pi^2} \frac{\log n}{n}, \quad n \to \infty.
\]

This is analogous to the freezing transitions in [CK15].

The fact that the argument leading to (2.9) can be generalized to all higher moments is the subject of the next result.

**Theorem 2.5.** Let $k$ be a positive integer such that $k\theta < 1$. Then

\[
\lim_{n \to \infty} \frac{\mathbb{E}(|c_n|^{2k})}{\mathbb{E}(|c_n|^2)^k} = k! \frac{\Gamma(1 - k\theta)}{\Gamma(1 - \theta)^k}.
\]

**Proof.** Recall from Theorem 1.6

\[
\mathbb{E}(|c_n|^{2k}) = \sum_{A \in \text{Mag}_{\pi, \pi}} \prod_{i,j} \left( \theta + A_{ij} - 1 \right),
\]

where $\pi$ is the partition which has $k$ parts of length $n$. In particular the magic squares $\text{Mag}_{\pi, \pi}$ are $k \times k$ and have all row and column sums equal to

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n. Fix a $\delta > 0$. Let $E_{\delta,n} \subset \text{Mag}_{\pi,\pi}$ be those magic squares in which there is a row $i$ for which there are two $j$ so that $A_{ij} > \delta n$. We claim that

$$\sum_{\lambda \in E_{\delta,n}} \prod_{i,j} \left( \frac{\theta + A_{ij} - 1}{A_{ij}} \right) = o(n^{k(\theta - 1)}). \tag{2.17}$$

We shall return to this point, but for the moment we give the proof contingent on (2.17).

Note that for $\delta$ sufficiently small, each $A \in \text{Mag}_{\pi,\pi} \setminus E_{\delta,n}$ has in each row exactly one entry with size larger than $n(1 - k\delta)$. Again for $\delta$ sufficiently small, this implies that each column additionally has exactly one such entry. Thus for any such $A$ there is a $k \times k$ permutation matrix $P$, the support of which coincides with the entries of $A$ larger than $n(1 - k\delta)$.

Moreover, for each permutation matrix $P$ such $A$ exist and the contributions of each to the sum in (2.16) are all equal. Let $S \subset \text{Mag}_{\pi,\pi} \setminus E_{\delta,n}$ be those terms in which the diagonal entries are larger than $n(1 - k\delta)$.

Thus

$$\mathbb{E}(|c_n|^{2k}) = k! \sum_{\lambda \in S} \prod_{i=j} \left( \frac{\theta + n - 1}{n} \right) \cdot \prod_{i \neq j} \left( \frac{\theta + A_{ij} - 1}{A_{ij}} \right) + o(n^{k(\theta - 1)}). \tag{2.18}$$

Let $H_k$ be the $k \times k$ non-negative integer matrices $A$ in which for each $1 \leq i \leq k$

$$\sum_j A_{ij} = \sum_j A_{ji}.$$

We claim that

$$\sum_{\lambda \in H_k} \prod_{i \neq j} \left( \frac{\theta + A_{ij} - 1}{A_{ij}} \right) = \frac{\Gamma(1 - k\theta)}{\Gamma(1 - \theta)^k}. \tag{2.19}$$

From the Newton binomial formula, we have that for $\{z_i\}$ and $\{y_j\}$ in the unit disk,

$$\prod_{i \neq j} \left( \frac{1}{1 - z_i y_j} \right)^\theta = \sum_{(\mu_j), (\nu_j) \in \mathbb{N}^k} \prod_j z_j^{\mu_j} y_j^{\nu_j} \cdot \left\{ \sum_{A \in \text{Mag}_{\mu,\nu}} \prod_{i \neq j} \left( \frac{\theta + A_{ij} - 1}{A_{ij}} \right) \right\},$$

where $\text{Mag}_{\mu,\nu} \subset \text{Mag}_{\pi,\pi}$ have 0 on the diagonal. Hence on setting $z_j = re^{i\omega_j}$ and $y_j = re^{i\omega_j}$ for $r \in (0, 1)$ and averaging over all $\omega_j$, we have

$$\frac{1}{(2\pi)^k} \int \prod_{i \neq j} \left( \frac{1}{1 - r^2 e^{\sqrt{-1}(\omega_i - \omega_j)}} \right)^\theta \, d\omega$$

$$= \sum_{(\mu_j) \in \mathbb{N}^k} r^2 \sum_j \mu_j \cdot \left\{ \sum_{A \in \text{Mag}_{0,\mu}} \prod_{i \neq j} \left( \frac{\theta + A_{ij} - 1}{A_{ij}} \right) \right\}.$$
This integral on the left hand side is convergent on sending \( r \to 1 \), and moreover gives exactly the Morris integral (1.22). The right hand side meanwhile converges to the left hand side of (2.19) which completes the proof of (2.19).

As (2.19) is convergent, it follows from dominated convergence that

\[
\lim_{n \to \infty} n^{-k(\theta - 1)} \sum_{A \in S} \prod_{i=j} \left\{ \binom{\theta + n - 1}{n} \right\} \prod_{i \neq j} \left\{ \frac{\theta + A_{ij} - 1}{A_{ij}} \right\} = \frac{\Gamma(1 - k\theta)}{\Gamma(1 - \theta)^k \Gamma(\theta)^k}.
\]

Hence, on combining this with (2.18) and sending \( \delta \to 0 \), we conclude that

\[
\lim_{n \to \infty} n^{-k(\theta - 1)} \mathbb{E}(|c_n|^{2k}) = \frac{k! \Gamma(1 - k\theta)}{\Gamma(1 - \theta)^k \Gamma(\theta)^k}.
\]

Finally we turn to the proof of (2.17). By the Birkhoff–von Neumann theorem, the doubly stochastic matrices are the convex hull of the permutation matrices. It follows that for every \( A \in \text{Mag}_{\pi, \pi} \) there is a permutation matrix \( P \) such that each entry of \( A \) in the support of \( P \) has size at least \( n/k \)! Hence by symmetry it suffices to restrict the sum in (2.17) to those \( A \in E_{\delta,n} \) whose every diagonal entry is at least \( n/k \)!. Denote this subset of \( E_{\delta,n} \) by \( E'_{\delta,n} \). In short we have the bound

\[
\sum_{A \in E_{\delta,n}} \prod_{i,j} \left\{ \frac{\theta + A_{ij} - 1}{A_{ij}} \right\} \leq k! \sum_{A \in E'_{\delta,n}} \prod_{i \in A} \left\{ C_0 \left( \frac{n}{k!} \right)^{\theta - 1} \right\} \prod_{i \neq j} \left\{ \frac{\theta + A_{ij} - 1}{A_{ij}} \right\},
\]

for some absolute constant \( C_0 \). Hence once more using the absolute convergence of (2.19) and dominated convergence, (2.17) follows. \( \square \)

### 3 The Ewens sampling formula

In this section we describe a connection between secular coefficients and random permutations that we believe is interesting in its own right. While detailing this we shall revise some of the key results about random permutations, as these will be useful in the subsequent sections.

The secular coefficients defined in (1.13) can be given the following explicit formula

\[
c_n = \sum_{m \in S_n} \prod_{k=1}^{n} \frac{\lambda_k^m}{m_k!} \left( \frac{\theta}{k} \right)^{m_k/2}.
\]

The summation is over the set \( S_n \) of all compositions of \( n \), that is \( m = (m_1, m_2, \ldots, m_n) \) is such that each \( m_k \) is a non-negative integer satisfying

\[
\sum_{k=1}^{n} k m_k = n.
\]

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From (3.1), we have that $c_n$ is measurable with respect to $\mathcal{G}_n := \sigma \{\mathcal{N}_1, \ldots, \mathcal{N}_n\}$. So, going forward, we will make use of the filtration $\mathcal{G} = (\mathcal{G}_n : n \in \mathbb{N})$.

Taking the $L^2$-norm of (3.1) gives

$$
\mathbb{E}(|c_n|^2) = \sum_{\vec{l} \in S_n} \prod_{k=1}^n \mathbb{E}(N_k^{\nu_k}N_k^{\nu_k}) \frac{(\theta_k^{-1} + l_k)}{m_k!} \left(\frac{\theta_k}{k}\right)^{m_k} \right)^{l_k}/2
$$

(3.3)

where we used independence of the family $\{N_k\}_{k=1}^\infty$ to take the expectation inside the product. Next applying the Gaussian formula

$$
\mathbb{E}(N_k^{\nu_k}N_k^{\nu_k}) = 1_{m_k=l_k}(m_k)!
$$

(3.4)

implies that the compositions in the sum (3.3) must coincide in order to give a non-zero term. This gives

$$
\mathbb{E}(|c_n|^2) = \sum_{\vec{m} \in S_n} \prod_{k=1}^n \frac{1}{m_k!} \left(\theta_k^{m_k}\right)
$$

(3.5)

Given a permutation $\sigma$ on $n$ symbols, we can characterize it using its cycle structure $(m_1, \ldots, m_n)$ where $m_j$ denotes the number of cycles in $\sigma$ having length $j$, and $\sum_{j=1}^n jm_j = n$. The summation in (3.5) is well known in the theory of random permutations where it appears as the normalizing factor for the Ewens sampling formula.

**Definition 3.1.** The Ewens sampling formula is a probability distribution on cycle counts $\vec{M}^{(n)} = (M_1, \ldots, M_n)$ given by

$$
\mathbb{P}(\vec{M}^{(n)} = m) = 1_{\sum_{k=1}^n km_k = n} \frac{n!}{\theta^{(n)}} \prod_{k=1}^n \left(\frac{\theta_k}{k}\right)^{m_k} \frac{1}{m_k!},
$$

(3.6)

where $\theta^{(n)}$ is the rising factorial

$$
\theta^{(n)} = \frac{\Gamma(\theta + n)}{\Gamma(\theta)}.
$$

(3.7)

The fact that (3.6) is normalized gives the explicit form of the sum in (3.5):

$$
\mathbb{E}(|c_n|^2) = \frac{\theta^{(n)}}{n!}.
$$

(3.8)

In general, if we restrict the summation in (3.1) to a subset $P \subset S_n$ and denote this $c_{n,P}$, an identical computation holds. This yields the fundamental correspondence

$$
\mathbb{E}(|c_{n,P}|^2) = \frac{\theta^{(n)}}{n!} \mathbb{P}(\vec{M}^{(n)} \in P)
$$

(3.9)
where on the left-hand side of (3.9) the expectation is taken over the Gaussian random variables in (3.1), while on the right-hand side \( M \) follows the Ewens sampling formula in (3.6) with parameter \( \theta \).

We can also use the Ewens sampling formula to describe conditional expectations of \( |c_n|^2 \). In analogy with (3.3), for \( q \leq n \),

\[
\mathbb{E}(|c_n|^2 \mid \mathcal{G}_q) = \sum_{l \in S_n, m \in S_n, r = \sum_{k=1}^q km_k} \prod_{k=1}^n \frac{\mathbb{E}(N_k^{m_k} \mathcal{N}_k^l \mid \mathcal{G}_q)}{m_k!l_k!} \left( \frac{\theta}{k} \right)^{(m_k+l_k)/2}. \quad (3.10)
\]

The only nonzero pairs \((\vec{l}, \vec{m})\) in this sum have \( m_k = l_k \) for \( k > q \), and this allows us to greatly simplify this expression. Let us define

\[
c_{n,q} = \sum_{(m_k): 1 \leq k \leq q, \sum_{k=1}^q km_k = n} \prod_{k=1}^q \frac{\theta^{m_k/2}}{m_k!k^{m_k/2}} N_k^{m_k}. \quad (3.11)
\]

**Remark 3.2.** This (3.11) is a special case of \( c_{n,P} \) (c.f. (3.9)), in which \( P \) are those partitions with no parts greater than \( q \). This is also equivalent to setting the Gaussians \( \mathcal{N}_k = 0 \) for all \( k > q \) in the sum (3.1). In particular \( c_{n,q} \) is \( \mathcal{G}_q \)-measurable.

In terms of (3.11) we can therefore give the sum formula by partitioning (3.10) according to \( r = \sum_{k=1}^q km_k \). Note that when \( r \geq n - q \), we have no way to complete the partition except by choosing all larger \( m_k = 0 \), and so

\[
\mathbb{E}(|c_n|^2 \mid \mathcal{G}_q) = |c_{n,q}|^2 + \sum_{r=0}^{n-q-1} |c_{r,q}|^2 \sum_{\sum_{k=q+1}^{n-q-1} km_k = n-r} \prod_{k=q+1}^n \frac{\theta^{m_k}}{m_k!k^{m_k}}.
\]

Note that we may have no \( m_k > 0 \) for \( k > n - r \) in the inner sum and so using (3.6)

\[
\mathbb{E}(|c_n|^2 \mid \mathcal{G}_q) = |c_{n,q}|^2 + \sum_{r=0}^{n} |c_{r,q}|^2 \frac{\theta^{(n-r)}}{(n-r)!} \mathbb{P}[\mathcal{M}_j^{(n-r)} = 0, \text{ for all } 1 \leq j \leq q]. \quad (3.12)
\]

We note that sum need only run to \( n - q \), as the probability therein is 0 for larger \( r \). We will do an asymptotic analysis of this conditional expectation in Section 7.1.
3.1 Properties of the Ewens sampling formula

We remark that the case $\theta = 1$ in (3.6) corresponds to the uniform measure on the set of all permutations, while the general case $\theta > 0$ corresponds to a tilting of the uniform measure. For any $\theta > 0$, a wealth of results are known concerning statistical properties of the cycle counts, see the text [ABT03] from which we will borrow from repeatedly in what follows. The main point exploited in [ABT03] is that apart from the indicator function, (3.6) is a conditional joint law of $n$ independent random variables $(Z_1, \ldots, Z_n)$ where each $Z_k$ is Poisson distributed with parameter $\theta/k$. Therefore, statistics of the cycle counts can be reduced to studying the independent random variables $(Z_1, \ldots, Z_n)$ paired with the condition that $T_{0n} = n$ where $T_{0n} = \sum_{j=1}^{n} jZ_j$. We will refer to this as the conditioning relation.

In fact, the random variable $T_{0n}$ and its limiting distribution play an important role in what follows and we record some of the key results about it from [ABT03].

Lemma 3.3. Suppose that $r = r_n \in \mathbb{N}$ satisfies $r/n \to y \in (0, \infty)$ as $n \to \infty$. Then

$$\lim_{n \to \infty} n\mathbb{P}(T_{0n} = r) = p_\theta(y)$$

(3.13)

where $p_\theta(y)$ is an (explicit) probability density function satisfying the following properties:

1. An explicit formula at $y = 1$:

$$p_\theta(1) = \frac{e^{-\gamma_E \theta}}{\Gamma(\theta)}$$

(3.14)

where $\gamma_E$ is the Euler-Mascheroni constant.

2. Rapid decay at $y = +\infty$:

$$\sup_{y \geq n} p_\theta(y) \leq \frac{\theta^n}{n!}$$

(3.15)

3. The derivative identity, for $x \notin \{0, 1\}$

$$\frac{d}{dx} [x^{1-\theta} p_\theta(x)] = -\theta x^{-\theta} p_\theta(x - 1).$$

(3.16)

Proof. These are proved in [ABT03, Section 4] using size biasing techniques. \qed
We will also make use of the following finite $n$ uniform bound.

**Lemma 3.4** (Lemma 4.12 (i) in [ABT03]). If $0 \leq \theta \leq 1$, then

$$\max_{k \geq 0} \mathbb{P}(T_{0n} = k) \leq e^{-\theta h(n+1)} \quad (3.17)$$

where $h(n+1)$ is the harmonic number

$$h(n+1) = \sum_{j=1}^{n} \frac{1}{j}. \quad (3.18)$$

Now let $L^{(n)}$ denote the length of the longest cycle. This quantity is closely related to the distribution of $T_{0n}$, because by the conditioning relation

$$\mathbb{P}(L^{(n)} \leq r) = \mathbb{P}(\{c_{r+1} = 0\} \land \ldots \land \{c_{n} = 0\})
= \mathbb{P}(\{Z_{r+1} = 0\} \land \ldots \land \{Z_{n} = 0\} \mid T_{0n} = n)
= \mathbb{P}(\{Z_{r+1} = 0\} \land \ldots \land \{Z_{n} = 0\}) \mathbb{P}(T_{0r} = n) / \mathbb{P}(T_{0n} = n). \quad (3.19)$$

Now Lemma 3.3 gives the following, as quoted in [ABT03, Lemma 4.23] and attributed to Kingman (1977).

**Lemma 3.5.** As $n \to \infty$, we have the convergence in distribution $n^{-1}L^{(n)} \overset{d}{\to} L^{(\infty)}$ where $L^{(\infty)}$ is a random variable with distribution function $F_\theta$ given by

$$F_\theta(x) = e^{\gamma x^\theta x^\theta - 1 \Gamma(\theta)p_\theta(1/x)}. \quad (3.20)$$

We also need a tail bound that controls the probability that the largest cycle is unusually small.

**Lemma 3.6.** For any $\theta > 0$, there is a constant $c_\theta > 0$ so that

$$\mathbb{P}(L^{(n)} \leq n/\log n) \leq n^{-c_\theta \log \log n}.$$ 

**Proof.** Using (3.19), and the convergence of $\mathbb{P}(T_{0n} = n)$, there is some constant $C_\theta$ so that for any $r \in \mathbb{N}$

$$\mathbb{P}(L^{(n)} \leq r) \leq \frac{\mathbb{P}(T_{0r} = n)}{\mathbb{P}(T_{0n} = n)} \leq C_\theta \mathbb{P}(T_{0r} = n).$$

When $r$ is much smaller than $n$ this probability becomes very small. Using standard concentration results for functionals of Poisson fields (see [Wu00, Proposition 3.1] or [Led99]), there is a constant $C_\theta$ sufficiently large that for all $t > 0$ and all $r \in \mathbb{N}$,

$$\mathbb{P}(T_{0r} > rt) \leq \exp(-t^4 \log(1 + t^{1/C_\theta})).$$

The proof follows by taking $r = \lfloor n/\log n \rfloor$ and $t = \lfloor \log n \rfloor$. \hfill \qed
To analyze (3.12) we will also need information on the shortest cycle $S_n$ in a Ewens distributed permutation. From the asymptotic independence of the cycle counts in a Ewens permutation, one expects $P(S_n > q) \to e^{-\theta h(q+1)}$ as $n \to \infty$. We will make use of a nonasymptotic bound that has this behavior.

**Lemma 3.7.** For all $\theta > 0$ there is a constant $C_\theta > 0$ so that for all $n, q \in \mathbb{N}$

$$P(S_n > q) \leq \frac{\theta(q-1)!}{\theta(q)} \leq C_\theta e^{-\theta h(q+1)}.$$ 

*Proof.* We use the Feller description of the Ewens sampling formula (see [ABT92, Section 3]). Let $\xi_1, \xi_2, \xi_3, \ldots$ be independent Bernoulli variables having parameter

$$P(\xi_j = 1) = \frac{\theta}{\theta + j - 1}, \quad \text{for all } j \in \mathbb{N}.$$ 

The Ewens distribution on $(\vec{M}_k^{(n)})_{k=1}^n$ has the same law as the joint frequency of spacings between consecutive ones in the vector

$$(1, \xi_n, \xi_{n-1}, \ldots, \xi_3, \xi_2, 1).$$

In this case a spacing of length $\ell$ is a pair $\{k, k + \ell\}$ where $\xi_k = \xi_{k+\ell} = 1$ and $\xi_j = 0$ for all $j$ with $k < j < k + \ell$. In the case $k + \ell = q + 1$, we instead use 1 in place of $\xi_{k+\ell}$. In particular, we have the inequality

$$P\left[S_n > q\right] \leq P\left[\xi_k = 0, \text{ for all } 2 \leq k \leq q\right]$$

$$= \prod_{k=2}^q \left(1 - \frac{\theta}{\theta + k - 1}\right)$$

$$= \frac{\theta(q-1)!}{\theta(q)}.$$ 

\[\square\]

4 Martingale approximation and convergence

We begin this section by finding an approximate martingale structure in the sum (3.1). This opens the possibility of applying a central limit theorem for martingales and we explain why this is relevant for our proof of Theorem 1.8. The results on permutations in the previous section will be used to arrive at the martingale approximation, as we now show.
4.1 Martingale approximation

Given a composition \( m \), we define
\[
\nu(m) := \max\{k = 1, \ldots, n \mid m_k \geq 1\}.  \tag{4.1}
\]
If the \( m_k \) are interpreted as cycle counts, the quantity \( \nu(m) \) is the length of the largest cycle in the corresponding permutation. Given \( \delta > 0 \), consider permutations whose largest cycle is smaller than \( \lfloor \delta n \rfloor \):
\[
P_\delta := \{m \in S_n \mid \nu(m) < \lfloor \delta n \rfloor \}.  \tag{4.2}
\]
We will show that the contribution of \( P_\delta \) to the sum in (3.1) can be neglected for large \( n \) and small \( \delta \). In the sum over the remaining terms \( P_\delta^c \) we define another negligible set, the set of all compositions where there are multiple longest cycles of the same length:
\[
R := \{m \in S_n \mid m_\nu(m) \geq 2\}.  \tag{4.3}
\]
We define \( \tilde{c}_n^{(\delta)} \) to be the sum over compositions whose largest cycle is greater than \( \lfloor \delta n \rfloor \), and where there is only one such largest cycle, in other words \( \tilde{c}_n^{(\delta)} := c_{n,P_\delta^c \cap R^c} \). We have
\[
c_n = \tilde{c}_n^{(\delta)} + c_{n,P_\delta} + c_{n,P_\delta^c \cap R} \tag{4.4}
\]
and summing over the possible lengths of the longest cycle, we can decompose the sum as
\[
\tilde{c}_n^{(\delta)} = \sum_{q=\lfloor \delta n \rfloor}^n N_q \sqrt{\theta} \frac{\theta}{q} c_{n-q,q-1} \tag{4.5}
\]
where \( c_{n-q,q-1} \) are as in (3.11).

**Lemma 4.1** (Martingale approximation). Let \( 0 < \delta < 1 \) and assume \( \theta \in [0,1] \). Then \( c_n \) is well approximated by \( \tilde{c}_n^{(\delta)} \) given by (4.5) in the following sense. After proper normalization, the error terms \( c_{n,P_\delta} \) and \( c_{n,P_\delta^c \cap R} \) in (4.4) have \( L^2 \)-norm satisfying
\[
\lim_{\delta \to 0} \lim_{n \to \infty} \frac{\mathbb{E}(|c_{n,P_\delta}|^2)}{\mathbb{E}(|c_n|^2)} = 0 \tag{4.6}
\]
\[
\frac{\mathbb{E}(|c_{n,P_\delta^c \cap R}|^2)}{\mathbb{E}(|c_n|^2)} = O(n^{-\theta}), \quad n \to \infty.  \tag{4.7}
\]
Taken together, using (4.4) we have
\[
\lim_{\delta \to 0} \lim_{n \to \infty} \frac{\mathbb{E}(|c_n - \tilde{c}_n^{(\delta)}|^2)}{\mathbb{E}(|c_n|^2)} = 0.  \tag{4.8}
\]
Proof. By the correspondence (3.9), we have
\[
\frac{\mathbb{E}(|c_n, P|^2)}{\mathbb{E}(|c_n|^2)} = \mathbb{P}(L_1^{(n)} < [\delta n])
\] (4.9)
where the right-hand side is the probability that the longest cycle is bounded by \([\delta n]\). By Lemma 3.5, we have
\[
\lim_{n \to \infty} \mathbb{P}(L_1^{(n)} < [\delta n]) = e^{n\theta} \delta^{-1} \Gamma(\theta) p_\theta(1/\delta)
\] (4.10)
and the fast decay (3.15) gives
\[
\lim_{\delta \to 0} \lim_{n \to \infty} \mathbb{P}(L_1^{(n)} < [\delta n]) = 0
\] (4.11)
which proves statement (4.6). For (4.7) we have
\[
\mathbb{P}(P^{\delta} \cap R) = \sum_{q=[\delta n]}^n \mathbb{P}(\{m_q \geq 2\} \land \nu(m) = q)
\] (4.12)
\[
= \sum_{q=[\delta n]}^n \mathbb{P}(\{m_q \geq 2\} \land \{m_{q+1} = 0\} \land \ldots \land \{m_n = 0\})
\] (4.13)
\[
= \sum_{q=[\delta n]}^n \sum_{\ell=2}^\infty \mathbb{P}(\{Z_q = \ell\} \land \{Z_{q+1} = 0\} \land \ldots \land \{Z_n = 0\}) \frac{\mathbb{P}(T_{0(q-1)} = n - q\ell)}{\mathbb{P}(T_{0n} = n)}
\] (4.14)
where in the last step we employed the conditioning relation and we interpret contributions to the sum above as zero whenever \(q\ell > n\). In order to bound the quantities above, first take \(r = n\) in (3.13) to see that \(\mathbb{P}(T_{0n} = n) \sim n^{-1} p_\theta(1)\). By Lemma 3.4 we have
\[
\mathbb{P}(T_{0(q-1)} = n - q\ell) \leq e^{-\theta h(q)}
\] (4.15)
while
\[
\mathbb{P}(\{Z_{q+1} = 0\} \land \ldots \land \{Z_n = 0\}) = e^{-\theta h(n+1) + \theta h(q+1)}.
\] (4.16)
A simple bound on the harmonic number gives \(e^{-\theta h(n+1)} \leq c_\theta n^{-\theta}\) for some positive constant \(c_\theta\). Combining these facts gives, for some other constant \(c_\theta\), the bound
\[
\mathbb{P}(P^{\delta} \cap R) \leq n^{1-\theta} c_\theta \sum_{q=[\delta n]}^n \mathbb{P}(Z_q \geq 2) = O_\delta(n^{-\theta}), \quad n \to \infty,
\] (4.17)
where we used that \(\mathbb{P}(Z_q \geq 2) \sim \frac{\theta^2}{2q^2}\) as \(q \to \infty\). This completes the proof of the martingale approximation. \(\square\)
4.2 Martingale central limit theorem

Having demonstrated the martingale approximation, in this section we will discuss the type of central limit theorems we can apply. In the following we will give a proof of Theorem 1.8 contingent on a certain $L^2$ estimate that will be dealt with separately in a later section.

To recap, Lemma 4.1 states that if we define increments

$$Z_{n,q} := \frac{1}{\sqrt{\mathbb{E}(|c_n|^2)}} N_q \sqrt{\frac{\theta}{q}} c_{n-q,q-1}$$

then the quantity

$$\frac{\bar{c}_n}{\sqrt{\mathbb{E}(|c_n|^2)}} = \sum_{q=[\delta n]}^{n} Z_{n,q}$$

(4.19)

is a good approximation of the normalized coefficient $c_n/\sqrt{\mathbb{E}(|c_n|^2)}$. Now we see by construction (recalling Remark 3.2) that $c_{n-q,q-1}$ only depends on the first $q - 1$ Gaussians and this implies that the random variables $N_q$ and $c_{n-q,q-1}$ are independent. We have

$$\mathbb{E}(Z_{n,q} | \mathcal{G}_{q-1}) = 0,$$

(4.20)

in other words $Z_{n,q}$ are the increments of a martingale with respect to the filtration generated by the first $q - 1$ Gaussians.

In order to get convergence in distribution of $\frac{\bar{c}_n}{\sqrt{\mathbb{E}(|c_n|^2)}}$ (and therefore of $c_n$), we will apply a central limit theorem for martingales. The majority of these limit theorems rely to a large extent on the analysis of a quantity known as the \textit{bracket process} (sometimes also referred to as the \textit{conditional variance \cite{HH80}}). In our setting it is given by

$$\mathcal{M}_{\theta,\delta,n} := \sum_{q=[\delta n]}^{n} \mathbb{E}(|Z_{n,q}|^2 | \mathcal{G}_{q-1}) = \frac{1}{\mathbb{E}(|c_n|^2)} \sum_{q=[\delta n]}^{n} \frac{\theta}{q} |c_{n-q,q-1}|^2.$$  

(4.21)

A key hypothesis usually involves showing that this type of quantity converges in probability to a constant as $n \rightarrow \infty$. An interesting feature here is that $\mathcal{M}_{\theta,\delta,n}$ will not have a deterministic limit, and so we need a sufficiently general form of the martingale CLT that allows for fluctuations in the limit $n \rightarrow \infty$ of the bracket process. These limiting fluctuations will be described in terms of the total mass of Gaussian multiplicative chaos and are ultimately responsible for the structure of the distribution given in Theorem 1.8. The appropriate CLT is the following:
Theorem 4.2 (Martingale Central Limit Theorem - Section 3.2 in [HH80]).

Let \( \{X_{n,q}\}_{q=1}^{n} \) for \( n \geq 1 \) be an array of real valued martingale increments with respect to a filtration \( F_{n,q} \) indexed by \( q \). Define the random variables

\[
\nu_n := \sum_{q=1}^{n} \mathbb{E}(X_{n,q}^2 \mid F_{n,q-1}), \quad (4.22)
\]

\[
\xi_n := \sum_{q=1}^{n} \mathbb{E}(X_{n,q}^2 1_{X_{n,q} > \epsilon} \mid F_{n,q-1}) \quad (4.23)
\]

Suppose we have the convergence in probability \( \nu_n \xrightarrow{p} \nu \) where \( \nu \) is an a.s. finite random variable, and \( \xi_n \xrightarrow{p} 0 \). Then we have the convergence in distribution

\[
\sum_{q=1}^{n} X_{n,q} \xrightarrow{d} \sqrt{\nu} \mathcal{N}_{\mathbb{R}}, \quad n \to \infty, \quad (4.24)
\]

where \( \mathcal{N}_{\mathbb{R}} \) is a standard (real) Gaussian, independent of \( \nu \).

Note that [HH80] only deals with real valued random variables, while (4.18) are complex. Although it is probably straightforward to generalise their result to the complex case, for our particular problem the simple i.i.d. structure of the real and imaginary parts of \( \mathcal{N}_{q} \) allows us to apply Theorem 4.2 directly.

Corollary 4.3. Suppose we have the convergence in probability \( \nu_n \xrightarrow{p} \nu \) where \( \nu \) is a.s. finite and

\[
\frac{1}{\mathbb{E}(|c_{n}|^2)^2} \sum_{q=\lfloor \delta n \rfloor}^{n} \frac{\theta^2}{q^2} \mathbb{E}|c_{n-q,q-1}|^4 \to 0, \quad n \to \infty. \quad (4.26)
\]

Then it follows that we have the convergence in distribution,

\[
\frac{\tilde{c}_{n}^{(\delta)}}{\sqrt{\mathbb{E}(|c_{n}|^2)}} \xrightarrow{d} \sqrt{\nu} \mathcal{N}_{1}, \quad n \to \infty, \quad (4.27)
\]

where \( \mathcal{N}_{1} \) is a standard complex Gaussian, independent of \( \nu \).
Proof. For any pair \((a, b) \in \mathbb{R}^2\), consider the real valued martingale
\[
\tilde{c}_{n,a,b} = \frac{1}{\sqrt{\mathbb{E}(|c_n|^2)}} \left( a \text{Re}(\tilde{c}_n^{(\delta)}) + b \text{Im}(\tilde{c}_n^{(\delta)}) \right) = \sum_{q=[\delta n]}^{n} X_{n,q}
\] (4.28)
with filtration generated by the real and imaginary parts of \(N_1, \ldots, N_{q-1}\) and, by (4.18), increments given by
\[
X_{n,q} = \frac{1}{\sqrt{\mathbb{E}(|c_n|^2)}} \sqrt{\frac{\theta}{q}} \left( a \text{Re}(N_q c_{n-q,q-1}) + b \text{Im}(N_q c_{n-q,q-1}) \right). \tag{4.29}
\]
We will now check the conditions of Theorem 4.2. A straightforward computation using \(\mathbb{E}(N_q^2) = \mathbb{E}(\overline{N}_q^2) = 0\) and \(\mathbb{E}(|N_q|^2) = 1\) shows that
\[
\nu_n := \sum_{q=[\delta n]}^{n} \mathbb{E}(X_{n,q}^2 | \mathcal{G}_{q-1}) = \frac{a^2 + b^2}{2} \mathcal{M}_{\theta,\delta,n}. \tag{4.30}
\]
So (4.25) implies that
\[
\nu_n \xrightarrow{p} \frac{a^2 + b^2}{2} \nu. \tag{4.31}
\]
For the Lindeberg type condition we have the bound
\[
X_{n,q}^2|X_{n,q}| > \epsilon \leq \frac{1}{\epsilon^2} |X_{n,q}|^4 \leq \frac{(a^2 + b^2)^2}{\epsilon^2} |Z_{n,q}|^4 \tag{4.32}
\]
where the last inequality follows from Cauchy-Schwarz. By (4.26) we have
\[
\mathbb{E}(|\xi_n|) \leq 2\theta^2 \frac{(a^2 + b^2)^2}{\mathbb{E}(|c_n|^2)\epsilon^2} \sum_{q=[\delta n]}^{n} \frac{\mathbb{E}(|c_{n-q,q-1}|^4)}{q^2} \to 0 \tag{4.33}
\]
which implies \(\xi_n \xrightarrow{p} 0\). Now Theorem 4.2 applies and shows that we have the convergence in distribution
\[
\frac{\tilde{c}_{n,a,b}}{\sqrt{\mathbb{E}(|c_n|^2)}} \xrightarrow{d} \sqrt{\nu} \sqrt{\frac{a^2 + b^2}{2}} N_{\mathbb{R}}
\]
\[
\xrightarrow{d} \sqrt{\nu} \left( a \frac{N_{\mathbb{R}}^{(1)}}{\sqrt{2}} + b \frac{N_{\mathbb{R}}^{(2)}}{\sqrt{2}} \right) \tag{4.34}
\]
where \(N_{\mathbb{R}}, N_{\mathbb{R}}^{(1)}\) and \(N_{\mathbb{R}}^{(2)}\) are independent and identically distributed standard (real) Gaussians. This establishes the joint convergence of the real and imaginary parts of \(c_n^{(\delta)}\) to the appropriate limit, and concludes the proof of (4.27). \(\square\)
We start by checking the Lindeberg condition (4.26), which is relatively straightforward.

**Lemma 4.4 (Lindeberg condition).** The condition (4.26) is satisfied for any \( 0 < \theta < 1 \).

**Proof.** Recalling the explicit normalization (1.20) for \( \mathbb{E}(|c_n|^2) \), we have

\[
\frac{\theta^2}{(n+\theta-1)^2} \sum_{q=\lfloor \delta n \rfloor}^{n} \frac{\mathbb{E}(|c_{n-q,q-1}|^4)}{q^2} \leq \frac{\theta^2}{(n+\theta-1)^2} \sum_{q=0}^{n} \mathbb{E}(|c_q|^4)
\]

\[
= \frac{\theta^2}{(n+\theta-1)^2 |\delta n|^2} \sum_{k=0}^{n} \left( \frac{k+\theta-1}{\theta-1} \right)^2 \sum_{q=0}^{n-k} \left( \frac{q+\theta-1}{\theta-1} \right)^2
\]

\[
\leq \frac{\theta^2}{(n+\theta-1)^2 |\delta n|^2} \left( \sum_{k=0}^{n} \left( \frac{k+\theta-1}{\theta-1} \right)^2 \right)^2.
\]

To obtain the first inequality above, we used that removing the \( q-1 \) constraint only increases the corresponding fourth moment, this follows from definition (3.11) and (1.20). Then the middle equality uses the magic square formula (2.8) and re-orders the sum. Finally, the last bound is of order \( n^{-2\theta} \) if \( \theta < 1/2 \), of order \( \log^2(n)/n \) if \( \theta = 1/2 \) and of order \( n^{2(\theta-1)} \) if \( \theta \in (1/2, 1) \). In each case (4.26) follows.

Verifying (4.25) and identifying the limit \( \nu \) turns out to be more difficult. It will turn out that \( M_{\theta,\delta,n} \) has a similar behaviour to the quantity \( M_{\theta,n} \) defined in (1.30), pre-multiplied by a certain explicit constant \( C_\delta \). To see how this constant arises, we begin with the following warm up exercise.

**Lemma 4.5.** Consider the quantity \( M_{\theta,\delta,n} \) defined in (4.21) and set

\[
C_\delta := \theta \int_{\delta}^{1} (1-x)^{\theta-1} \mathbb{P} \left( L^{(\infty)} \leq \frac{x}{1-x} \right) \frac{dx}{x}
\]

(4.36)

where \( L^{(\infty)} \) is the limiting random variable from Lemma 3.5. Then we have

\[
\lim_{n \to \infty} \mathbb{E}(M_{\theta,\delta,n}) = C_\delta.
\]

(4.37)

Furthermore, the constant \( C_\delta \) can be explicitly computed as

\[
C_\delta = 1 - \Gamma(\theta) e^{\gamma \theta} \delta^{\theta-1} \rho_0(1/\delta),
\]

(4.38)

and satisfies the bound

\[
C_\delta = 1 + O(\delta), \quad \delta \to 0.
\]

(4.39)
Proof. By the correspondence (3.9), we have the identity
\[
\begin{align*}
\mathbb{E}(|c_{n-q,q-1}|^2) &= \sum_{(m_k) : 1 \leq k \leq q-1} \prod_{k=1}^{q-1} \frac{\theta^{m_k}}{m_k! k^{m_k}} \sum_{k=1}^{n-q} \mathbb{P}(L^{(n-q)} \leq q-1) \\
&= \left( n - q + \theta - 1 \atop \theta - 1 \right) \mathbb{P}(L^{(n-q)} \leq q-1)
\end{align*}
\] (4.40)
where \( L^{(n-q)} \) is the longest cycle in an Ewens distributed random permutation of length \( n - q \). Furthermore, in the regime of interest, \( q = \lfloor \delta n \rfloor, \ldots, n \) so that \( q \) and \( n - q \) are proportional to \( n \). In this regime Lemma 3.5 applies: if \( q/n \to x \in (\delta, 1) \) then
\[
\lim_{n \to \infty} \mathbb{P}(L^{(n-q)} \leq q-1) = \mathbb{P}(L^{(\infty)} \leq \frac{x}{1-x})
\] (4.41)
and consequently the expectation of \( \mathcal{M}_{\theta,\delta,n} \) converges to a Riemann integral,
\[
\begin{align*}
\lim_{n \to \infty} \mathbb{E}(\mathcal{M}_{\theta,\delta,n}) &= \lim_{n \to \infty} \sum_{q=\lfloor \delta n \rfloor}^{n} \frac{\mathbb{E}(|c_{n-q,q-1}|^2)}{\frac{q}{n}} \\
&= \frac{\mathbb{P}(L^{(n-q)} \leq q-1)}{\frac{q}{n}} \\
&= \frac{\theta}{n} \int_{\delta}^{1} (1-x)^{\theta-1} \mathbb{P}(L^{(\infty)} \leq \frac{x}{1-x}) \frac{dx}{x} \\
&= C_\delta.
\end{align*}
\] (4.42)
To compute \( C_\delta \), we express the probability in the integrand of (4.36) in terms of the function \( p_\theta(y) \) and use the properties in Lemma 3.3. We have
\[
\begin{align*}
C_\delta &= \theta \Gamma(\theta)e^{\gamma E/\Gamma(\theta)} \int_{\delta}^{1} x^{\theta-2} p_\theta(1/x - 1) \, dx \\
&= \Gamma(\theta)e^{\gamma E} \int_{1}^{\theta} x^{-\theta} p_\theta(x - 1) \, dx \\
&= -\Gamma(\theta)e^{\gamma E} \int_{1}^{\theta} \frac{d}{dx} [x^{1-\theta} p_\theta(x)] \, dx \\
&= \Gamma(\theta)e^{\gamma E} p_\theta(1) - \Gamma(\theta)e^{\gamma E} \delta^{\theta-1} p_\theta(1/\delta).
\end{align*}
\] (4.43)
The identity (4.38) now follows from the explicit formula \( p_\theta(1) = e^{-\gamma E} / \Gamma(\theta) \) and the limiting behaviour \( C_\delta = 1 + O(\delta) \) follows from the rapid decay in (3.15). \( \square \)
We will now describe how these ideas lead to the proof of Theorem 1.8. In the following sections we will generalise the argument of Lemma 4.5 to show that for any $0 < \theta < \frac{1}{2}$ we have

$$
\lim_{n \to \infty} E(|M_{\theta, \delta, n} - C_\delta M_{\theta, n}|^2) = 0,
$$

(4.44)

allowing us to replace the convergence in probability of $M_{\theta, \delta, n}$ with that of $C_\delta M_{\theta, n}$ in (1.30). For the latter, the appropriate limit is given in Lemma 1.9 and, combined with (4.44), this implies that

$$
M_{\theta, \delta, n} \xrightarrow{p} C_\delta M_{\theta, n}, \quad n \to \infty,
$$

(4.45)

which is the identification of $\nu$. Now the martingale central limit theorem of Corollary 4.3 gives a limiting distribution for $\tilde{c}^{(\delta)}_n$, similar to $\nu$.

$$
\tilde{c}^{(\delta)}_n \xrightarrow{d} \sqrt{C_\delta M_{\theta, n}} N_1 \quad n \to \infty.
$$

(4.46)

The proof of Theorem 1.8 contingent on (4.44) now follows from a standard approximation argument.

**Proof of Theorem 1.8 assuming (4.44).** Let us define the appropriately normalized version of $c_n$ as

$$
\hat{c}_n := \frac{c_n}{\sqrt{E(|c_n|^2)}}.
$$

(4.47)

The joint characteristic functions of the real and imaginary parts of $\hat{c}_n$ and the proposed limiting random variable are:

$$
\Phi_n(s, t) := E\left(e^{i s \text{Re}(\hat{c}_n) + it \text{Im}(\hat{c}_n)}\right),
$$

$$
\Phi(s, t) := E\left(e^{i s \text{Re}(\sqrt{C_\delta M_{\theta} N_1}) + it \text{Im}(\sqrt{C_\delta M_{\theta} N_1})}\right).
$$

(4.48)

For our martingale approximation $\hat{c}^{(\delta)}_n$, similarly, we define

$$
\tilde{c}^{(\delta)}_n := \frac{\hat{c}^{(\delta)}_n}{\sqrt{E(|c_n|^2)}}
$$

(4.49)

and the corresponding characteristic functions

$$
\tilde{\Phi}_{n, \delta}(s, t) := E\left(e^{i s \text{Re}(\tilde{c}^{(\delta)}_n) + it \text{Im}(\tilde{c}^{(\delta)}_n)}\right),
$$

$$
\tilde{\Phi}_\delta(s, t) := E\left(e^{i s \text{Re}(\sqrt{C_\delta M_{\theta} N_1}) + it \text{Im}(\sqrt{C_\delta M_{\theta} N_1})}\right).
$$

(4.50)
Then we have
\[
|\Phi_n(s, t) - \Phi(s, t)| \leq |\Phi_n(s, t) - \tilde{\Phi}_{n,\delta}(s, t)| + |\tilde{\Phi}_{n,\delta}(s, t) - \tilde{\Phi}_\delta(s, t)| + |\tilde{\Phi}_\delta(s, t) - \Phi(s, t)|. \tag{4.51}
\]

By the convergence in distribution (4.46) the term \(|\tilde{\Phi}_{n,\delta}(s, t) - \tilde{\Phi}_\delta(s, t)| \to 0 as \( n \to \infty \), while by the asymptotics (4.39) we have \(|\tilde{\Phi}_\delta(s, t) - \Phi(s, t)| \to 0 as \( \delta \to 0 \). A standard bound on the exponential function (see Lemma A.3) gives the inequality
\[
|\Phi_n(s, t) - \Phi(s, t)| \leq (|t| + |s|) \sqrt{\mathbb{E}(|\tilde{c}_n - \tilde{c}_n^{(\delta)}|^2)}. \tag{4.52}
\]

By Lemma 4.1 the expression on the right-hand side of (4.52) tends to zero in the limit \( n \to \infty \) followed by \( \delta \to 0 \). This implies that \(|\Phi_n(s, t) - \Phi(s, t)| \to 0 as \( n \to \infty \) and the statement of Theorem 1.8 follows. \( \square \)

5 Convergence of the bracket process and the proof of \( L^2 \)-convergence

The goal of this section will be to verify (4.44). To do this we will need to calculate some higher moments of secular coefficients with a cycle constraint, namely of the \( c_{n,q} \) defined in (3.11). Then we use these results to analyze the second moment in (4.44).

5.1 Moments of secular coefficients with a cycle constraint

The following Lemma generalises the second moment formula (4.40) and the magic square formula (1.18).

**Lemma 5.1.** Let \( m \) be a positive integer and assume without loss of generality that the positive integers \( q_1 \leq \ldots \leq q_n \) are ordered. Recall that \( L_1^{(n)} \) is the longest cycle of a random permutation of length \( n \) under the Ewens measure (3.6). Then we have
\[
\mathbb{E}\left( \prod_{i=1}^m |c_{n_i,q_i}|^2 \right) = \sum_{A \in \text{Mag}_{\tilde{a},\tilde{a}}} \prod_{i,j=1}^m \left( \frac{A_{i_1,j_1} + \theta - 1}{\theta - 1} \right) \mathbb{P}(L_1^{(A_{i_1,j_2})} \leq q_{l_1 \wedge l_2}), \tag{5.1}
\]
where we used the notation \( l_1 \wedge l_2 := \min(l_1, l_2) \).
Proof. The strategy of the proof is very similar to that of Theorem 1.6. By definition (3.11), the coefficients \( c_{n,q} \) can be extracted from a generating function

\[
c_{n,q} = [z^n] \exp \left( \sqrt{\theta} \sum_{k=1}^{q} \frac{N_k}{\sqrt{k}} z^k \right),
\]

so that the left-hand side of (5.1) is \([z_1^{n_1} \ldots z_m^{n_m} w_1^{\alpha_1} \ldots w_m^{\alpha_m}] \mathcal{E}(F_q^{(m)}(z, w))\) where

\[
F_q^{(m)}(z, w) := \exp \left( \theta \sum_{i=1}^{m} \left( \sum_{k=1}^{q_i} \frac{N_k}{\sqrt{k}} z_i^k + \frac{N_k}{\sqrt{k}} w_i^k \right) \right).
\]

Using that \( q_1 \leq \ldots \leq q_m \) we can re-arrange the summation (interchange the \( i \) and \( k \) indices) using the identity

\[
\sum_{i=1}^{m} \sum_{k=1}^{q_i} a_{k,i} = \sum_{i=1}^{m} \sum_{k=q_{i-1}+1}^{q_i} \sum_{r=i}^{m} a_{k,r}
\]

valid for arbitrary \( a_{k,i} \) where we set \( q_0 := 0 \). Then using independence we get

\[
\mathbb{E}(F_q^{(m)}(z, w)) = \prod_{i=1}^{m} \mathbb{E} \left( \exp \left( \theta \sum_{k=q_{i-1}+1}^{q_i} \sum_{r=i}^{m} \left( \frac{N_k}{\sqrt{k}} z_r^k + \frac{N_k}{\sqrt{k}} w_r^k \right) \right) \right)
\]

\[
= \exp \left( \theta \sum_{i=1}^{m} \sum_{k=q_{i-1}+1}^{q_i} \sum_{l_1,l_2=i}^{m} \left( z_{l_1} w_{l_2} \right)^k \right)
\]

\[
= \prod_{l_1, l_2=1}^{m} \exp \left( \frac{q_{l_1,l_2}}{k} \sum_{k=1}^{m} \left( z_{l_1} w_{l_2} \right)^k \right),
\]

where to obtain the last line, we again re-arranged the sums using the identity

\[
\sum_{i=1}^{m} \sum_{k=q_{i-1}+1}^{q_i} \sum_{k=1}^{m} a_{k,r_1,r_2} = \sum_{r_1,r_2=1}^{m} \sum_{k=1}^{q_{r_1,r_2}} a_{k,r_1,r_2},
\]

valid for arbitrary \( a_{k,r_1,r_2} \). Now to pick out coefficients, we expand each
exponential in (5.5) using
\[
\exp \left( \theta \sum_{k=1}^{q_1 \wedge l_2} \left( \frac{z_{l_1} w_{l_2}}{k} \right)^k \right)
\]
\[
= \sum_{A_{l_1,l_2}=0}^{\infty} (z_{l_1} w_{l_2})^{A_{l_1,l_2}} \sum_{(m_k) : 1 \leq k \leq q_1 \wedge l_2} \prod_{k=1}^{q_1 \wedge l_2} \left( \frac{\theta}{k} \right)^{m_k} \frac{1}{m_k!}
\]
\[
= \sum_{A_{l_1,l_2}=0}^{\infty} (z_{l_1} w_{l_2})^{A_{l_1,l_2}} \left( A_{l_1,l_2} + \theta - 1 \right) \mathbb{P}(L_1^{(A_{l_1,l_2})} \leq q_1 \wedge l_2).
\] (5.7)

Inserting this into (5.5) leads to the representation (5.1). \(\square\)

For the proof of (4.44), we will need the case \(m = 2\) corresponding to fourth moments of the secular coefficients, and involving sums over \(2 \times 2\) magic squares (in analogy with Example 2.2). Let us assume that \(n_1 \leq n_2\) and \(q_1 \leq q_2\). Then (5.1) implies that
\[
\mathbb{E} (|c_{n_1,q_1}|^2 | c_{n_2,q_2}|^2) = \sum_{k=0}^{n_1} \left( \frac{k + \theta - 1}{\theta - 1} \right)^2 \mathbb{P}(L_1^{(k)} \leq q_1)^2 \times \left( \frac{n_1 - k + \theta - 1}{\theta - 1} \right) \mathbb{P}(L_1^{(n_1-k)} \leq q_1) \left( \frac{n_2 - k + \theta - 1}{\theta - 1} \right) \mathbb{P}(L_1^{(n_2-k)} \leq q_2).
\] (5.8)

### 5.2 The \(L^2\)-phase and proof of (4.44)

We recall the definition of the two quantities:
\[
\mathcal{M}_{\theta,n} := \frac{\Gamma(\theta + 1)}{n^\theta} \sum_{q=0}^{n} |c_q|^2
\] (5.9)
\[
\mathcal{M}_{\theta,\delta,n} := \frac{1}{(n + \theta - 1)^{\theta - 1}} \sum_{q=[\delta n]}^{n} |c_{n-q,q-1}|^2 \frac{\theta}{q}
\] (5.10)

and the deterministic constant
\[
C_\delta := \theta \int_\delta^1 \frac{(1-x)^{\theta-1} \mathbb{P}(L_1^{(\infty)} \leq x/(1-x))}{x} \, dx.
\] (5.11)
Our goal is to prove (4.44) for any $0 < \theta < 1/2$. The condition $\theta < 1/2$ is a technical requirement in the proof to ensure the convergence of the infinite sum
\[
\sum_{k=0}^{\infty} \left( \frac{k + \theta - 1}{\theta - 1} \right)^2 = \mathbb{E}(\mathcal{M}_\theta^2) = \frac{\Gamma(1 - 2\theta)}{(1 - \theta)^2},
\]
(5.12)
or equivalently existence of the second moment of the total mass. For a proof of this identity, see Lemma B.1.

**Theorem 5.2** ($L^2$-convergence). Fix $0 < \theta < 1/2$ and $\delta > 0$. Then the following limit holds
\[
\lim_{n \to \infty} \mathbb{E} \left( |\mathcal{M}_{\theta,\delta,n} - C_\delta \mathcal{M}_{\theta,n}|^2 \right) = 0.
\]
(5.13)

**Proof.** We start by expanding the square in (5.13) and endeavour to compute the three terms $S_{1,n} := \mathbb{E}(\mathcal{M}_{\theta,\delta,n}^2)$, $S_{2,n} := \mathbb{E}(\mathcal{M}_{\theta,n}^2)$, and $S_{3,n} := \mathbb{E}(\mathcal{M}_{\theta,\delta,n} \mathcal{M}_{\theta,n})$. It is clearly sufficient to show that the limit of each of these quantities exists is given by the second moment of the total mass, up to the appropriate factor of $C_\delta$. It will be convenient to abbreviate
\[
P_{n,k} := \mathbb{P}(L_1^{(n)} \leq k - 1)
\]
(5.14)
as the probability that the longest cycle in a Ewens distributed random permutation of size $n$ is less than or equal to $k - 1$.

Starting with the second moment of $\mathcal{M}_{\theta,\delta,n}$ in (5.10), we have
\[
S_{1,n} = \frac{\theta^2}{(n+\theta-1)^2} \sum_{q_1 = [\delta n]}^{n} \sum_{q_2 = [\delta n]}^{n} \mathbb{E} \left( |c_{n-q_1,q_1-1}|^2 |c_{n-q_2,q_2-1}|^2 \right) q_1 q_2.
\]
(5.15)

Because of the obvious symmetry in $q_1$ and $q_2$, it will be convenient to consider the contribution of such sums on the region $q_1 \leq q_2$, which we denote $S_{1,n}(q_1 \leq q_2)$ and similarly for the other sums. Applying (5.8) and interchanging the order of summation we obtain
\[
S_{1,n}(q_1 \leq q_2) = \sum_{q_1 = [\delta n]}^{n} \sum_{q_2 = q_1}^{n} \sum_{k=0}^{n-q_2} \left( \frac{k + \theta - 1}{\theta - 1} \right)^2 P_{k,q_1} \frac{\theta^2}{q_1 q_2} \frac{1}{(n+\theta-1)^2} \times
\]
\[
\left( \frac{n - q_1 - k + \theta - 1}{\theta - 1} \right) P_{n-q_1-k,q_1} \left( \frac{n - q_2 - k + \theta - 1}{\theta - 1} \right) P_{n-q_2-k,q_2}.
\]
(5.16)
To estimate the sum (5.16) as \( n \to \infty \), the idea is to treat \( k \) as fixed while \( q_1 \) and \( q_2 \) are large, applying dominated convergence to bring the limit \( n \to \infty \) inside the sum over \( k \).

As in (4.42), the sums over \( q_1 \) and \( q_2 \) will always be treated as Riemann sum approximations. For \( S_{1,n}(q_1 \leq q_2) \), the double sum over \( q_1 \) and \( q_2 \) is symmetric (we can assume that \( P_{k,q_1}^2 = 1 \) for fixed \( k \) and \( n \) large enough, since \( q_1 \geq \lfloor \delta n \rfloor \) which is larger than \( k \)) and we can write it as \( \frac{1}{2} \) times the square of the same sum appearing in (4.42) (neglecting for now the diagonal \( q_1 = q_2 \), see below). This immediately yields the limit as \( \frac{1}{2} C_\delta^2 \). By symmetry the same reasoning and limiting value applies to the sum with \( q_1 \geq q_2 \). Assuming we can apply dominated convergence to the sum over \( k \), we get

\[
\lim_{n \to \infty} S_{1,n} = C_\delta^2 \sum_{k=0}^{\infty} \left( \frac{k + \theta - 1}{\theta - 1} \right)^2 = C_\delta^2 \mathbb{E}(\mathcal{M}_\theta^2)
\]

as required.

Now we will justify the dominated convergence by finding a uniform and summable bound in (5.16). Notice that the sums over \( q_1 \) and \( q_2 \) are uniformly bounded by

\[
\frac{\theta^2}{[\delta n]^2 (\frac{n+\theta-1}{\theta-1})^2} \sum_{q_1 = \lfloor \delta n \rfloor}^{n-k} \sum_{q_2 = q_1}^{n-k} \left( \frac{n - q_1 - k + \theta - 1}{\theta - 1} \right) \left( \frac{n - q_2 - k + \theta - 1}{\theta - 1} \right)
\]

where we used the binomial sum identity (B.4). The final expression can be bounded uniformly by extending the summation to \( q_1 = n \) and noting that the summand is of order \( q_1^{2\theta-1} \) as \( q_1 \to \infty \). If we took just the terms where \( q_2 = q_1 \), we would have the bound

\[
\frac{\theta^2}{(n+\theta-1)^2 [\delta n]^2} \sum_{q_1 = \lfloor \delta n \rfloor}^{n-k} \left( \frac{n - q_1 - k + \theta - 1}{\theta - 1} \right)^2
\]

\[
\leq \frac{\theta^2}{(n+\theta-1)^2 [\delta n]^2} \sum_{q_1 = 0}^{n-\lfloor \delta n \rfloor} \left( \frac{q_1 + \theta - 1}{\theta - 1} \right)^2 \to 0, \quad n \to \infty.
\]

This justifies overcounting terms where \( q_2 = q_1 \) and completes the proof of (5.17).
Now we consider the second moment $\mathbb{E}(M_{\theta,n}^2)$. Again using (5.8) in the unconstrained case (or (1.18)) we obtain

$$S_{2,n} = \frac{\Gamma(\theta + 1)^2}{n^{\theta}} \sum_{q_1=0}^{n} \sum_{q_2=0}^{n} \min(q_1,q_2) \frac{(k + \theta - 1)^2}{\theta - 1} \times \left( \frac{q_1 - k + \theta - 1}{\theta - 1} \right) \left( \frac{q_2 - k + \theta - 1}{\theta - 1} \right).$$

(5.19)

An application of Lemma B.2 shows that the contribution to (5.19) from the region $q_1 \leq q_2$ is equal to

$$S_{2,n}(q_1 \leq q_2) = \frac{\Gamma(\theta + 1)^2}{n^{\theta}} \sum_{q_1=0}^{n} \sum_{q_2=0}^{n} \min(q_1,q_2) \frac{(k + \theta - 1)^2}{\theta - 1} \times \left( \frac{q_1 - k + \theta - 1}{\theta - 1} \right) \left( \frac{n - k + \theta}{\theta} \right) - \left( \frac{q_1 - k + \theta - 1}{\theta - 1} \right).$$

(5.20)

Interchanging the summation and summing over $q_1$ again using Lemma B.2 we obtain

$$S_{2,n}(q_1 \leq q_2) = \frac{\Gamma(\theta + 1)^2}{n^{\theta}} \sum_{k=0}^{n} \frac{(k + \theta - 1)^2}{\theta - 1} \left( \frac{n - k + \theta}{\theta} \right)^2 - \frac{\Gamma(\theta + 1)^2}{n^{\theta}} \sum_{k=0}^{n} \frac{(k + \theta - 1)^2}{\theta - 1} \sum_{q_1=0}^{n-k} \frac{(q_1 + \theta - 1)}{(q_1 + \theta - 1) \theta} \left( \frac{q_1 + \theta - 1}{\theta} \right).$$

(5.21)

By dominated convergence, the first term (5.22) converges to $\mathbb{E}(M_{\theta}^2)$, where a suitable bound is obtained by noticing that the second binomial coefficient is decreasing in $k$. For the second term (5.23), a uniform upper bound is obtained by summing up to $q_1 = n$ and noting that the summand is of order $q_1^{2\theta-1}$ with a corresponding sum of order $n^{2\theta}$ as $n \to \infty$. Then dominated convergence implies that (5.23) has a limit given by

$$\sum_{k=0}^{\infty} \frac{(k + \theta - 1)^2}{\theta - 1} \lim_{n \to \infty} \frac{\Gamma(\theta + 1)^2}{n^{2\theta}} \sum_{q_1=0}^{n-k} \frac{(q_1 + \theta - 1)}{(q_1 + \theta - 1) \theta} \left( \frac{q_1 + \theta - 1}{\theta} \right)$$

$$= \sum_{k=0}^{\infty} \frac{(k + \theta - 1)^2}{\theta - 1} \lim_{n \to \infty} \frac{\Gamma(\theta + 1)^2}{n^{2\theta}} \sum_{q_1=1}^{n} q_1^{2\theta-1}$$

$$= \frac{1}{2} \sum_{k=0}^{\infty} \frac{(k + \theta - 1)^2}{\theta - 1} = \frac{1}{2} \mathbb{E}(M_{\theta}^2)$$

(5.24)
An analogous computation shows that the contribution to (5.19) from the diagonal $q_1 = q_2$ is order $O(n^{-1})$. By symmetry in $q_1$ and $q_2$, we obtain

$$\lim_{n \to \infty} S_{2,n} = \sum_{k=0}^{\infty} \left( \frac{k + \theta - 1}{\theta - 1} \right)^2 = \mathbb{E}(M_{\theta}^2).$$  \tag{5.25}$$

It remains to consider the mixed term $\mathbb{E}(M_{\theta,\delta,n}M_{\theta,n})$ denoted $S_{3,n}$. By definition we have

$$S_{3,n} = \mathbb{E}(M_{\theta,\delta,n}M_{\theta,n})$$

$$= \frac{\Gamma(\theta + 1)}{n^\theta} \frac{1}{(n+\theta-1)^{\theta-1}} \sum_{q_1=0}^{n} \sum_{q_2=[\delta n]}^{n} \mathbb{E} \left( |c_{q_1}|^2|c_{n-q_2,q_2-1}| \right) \frac{\theta}{q_2}. \tag{5.26}$$

We split this up as two sums, one for values of $q_1 = 0, \ldots, n - q_2$, and one for values of $q_1 = n - q_2 + 1, \ldots, n$. Interchanging the order of summation, the first sum gives

$$S_{3,n}(q_1 \leq n - q_2) = \frac{\Gamma(\theta + 1)}{n^\theta (n+\theta-1)^{\theta-1}} \sum_{k=0}^{n-\lfloor \delta n \rfloor} \sum_{q_2=\lfloor \delta n \rfloor}^{n-k} \sum_{q_1=k}^{n-q_2} \left( \frac{k + \theta - 1}{\theta - 1} \right)^2$$

$$\times P_{k,q_2}^2 \left( \frac{q_1 - k + \theta - 1}{\theta - 1} \right) \left( \frac{n - q_2 - k + \theta - 1}{\theta - 1} \right) P_{n-q_2-k,q_2} \frac{\theta}{q_2}. \tag{5.27}$$

The sum over $q_1$ in (5.27) is handled with Lemma B.2 and we have

$$S_{3,n}(q_1 \leq n - q_2) = \frac{\Gamma(\theta + 1)}{n^\theta (n+\theta-1)^{\theta-1}} \sum_{k=0}^{n-\lfloor \delta n \rfloor} \sum_{q_2=\lfloor \delta n \rfloor}^{n-k} \left( \frac{k + \theta - 1}{\theta - 1} \right)^2$$

$$\times P_{k,q_2}^2 \left( \frac{n - q_2 - k + \theta}{\theta} \right) \left( \frac{n - q_2 - k + \theta - 1}{\theta - 1} \right) P_{n-q_2-k,q_2} \frac{\theta}{q_2}. \tag{5.28}$$

Now we look at the contribution to $S_{3,n}$ indexed by $q_1 = n - q_2 + 1, \ldots, n$. This gives

$$S_{3,n}(q_1 > n - q_2) = \frac{\Gamma(\theta + 1)}{n^\theta (n+\theta-1)^{\theta-1}} \sum_{q_2=\lfloor \delta n \rfloor}^{n-q_2} \sum_{q_1=n-q_2+1}^{n} \sum_{k=0}^{n-q_2} \left( \frac{k + \theta - 1}{\theta - 1} \right)^2$$

$$\times P_{k,q_2}^2 \left( \frac{q_1 - k + \theta - 1}{\theta - 1} \right) \left( \frac{n - q_2 - k + \theta - 1}{\theta - 1} \right) P_{n-q_2-k,q_2} \frac{\theta}{q_2}. \tag{5.29}$$
Summing over $q_1$ with Lemma B.2 and interchanging the order of summation gives the identity

$$S_{3,n}(q_1 > n - q_2) = \frac{\Gamma(\theta + 1)}{n^{\theta}(\theta - 1)} \sum_{k=0}^{n-\lfloor \delta n \rfloor} \sum_{q_2=\lfloor \delta n \rfloor}^{n-k} \left( \frac{k + \theta - 1}{\theta - 1} \right)^2 P_{k,q_2}^2 \times \left( \frac{n - k + \theta}{\theta} \right) - \left( \frac{n - q_2 - k + \theta}{\theta} \right) \times \frac{n - q_2 - k + \theta - 1}{\theta - 1} \theta \frac{P_{n-q_2-k,q_2}}{q_2}.$$ (5.30)

Combining with (5.28) yields a cancellation and we are left with the identity

$$S_{3,n} = \sum_{k=0}^{n-\lfloor \delta n \rfloor} \sum_{q_2=\lfloor \delta n \rfloor}^{n-k} \left( \frac{k + \theta - 1}{\theta - 1} \right)^2 P_{k,q_2}^2 \times \Gamma(\theta + 1) \left( \frac{n-k+\theta}{n^\theta} \right) \left( \frac{n-q_2-k+\theta-1}{\theta-1} \right) \frac{\theta}{q_2} P_{n-q_2-k,q_2}.$$ (5.31)

As in the treatment of (5.16) (see also (4.42)), for $n \to \infty$ and fixed $k$, the $k$th term of (5.31) is approximated by a Riemann integral and $P_{k,q_2} = 1$. Applying dominated convergence then gives the limit as $n \to \infty$ of (5.31) as $C_\delta \mathbb{E}(M^2_\theta)$ as required. For a suitable dominating function, note that apart from the factor $\left( \frac{k+\theta-1}{\theta-1} \right)^2$, the $k$th term in (5.31) is uniformly bounded by

$$\frac{\theta}{\lfloor \delta n \rfloor} \Gamma(\theta + 1) \left( \frac{n-k+\theta}{n^\theta} \right) \left( \frac{n-q_2-k+\theta-1}{\theta-1} \right) \frac{\theta}{q_2} \left( \frac{\theta}{\theta-1} \right)^2.$$ (5.32)

where we used Lemma B.2 and monotonicity of the binomial coefficients as a function of $k$. The final bound is independent of $k$ and bounded in $n$. This shows that

$$\lim_{n \to \infty} S_{3,n} = C_\delta \sum_{k=0}^{\infty} \left( \frac{k + \theta - 1}{\theta - 1} \right)^2 = C_\delta \mathbb{E}(M^2_\theta),$$ (5.34)

as required. Putting all three limits for the moments together completes the proof of the theorem. \qed
6 Regularity of the holomorphic multiplicative chaos

We have to determine, for $s \in \mathbb{R}$, if the series

$$A_{s, \theta} := \sum_{n=0}^{\infty} (1 + n^2)^s |c_n|^2$$

(6.1)

is convergent. We will study the cases $\theta \leq 1$ and $\theta > 1$ separately.

6.1 Sub-critical and critical cases, $\theta \in (0, 1]$

We have that $E[|c_n|^2] \leq C_\theta (1 + n)^{\theta - 1}$ for some constant $C_\theta > 0$, and then

$$E[A_{s, \theta}] \leq C_\theta \sum_{n=0}^{\infty} (1 + n)^{2s + \theta - 1},$$

which is finite as soon as $s < -\theta/2$. Hence, HMC$_\theta$ is a.s. in $H^s$ for all $s < -\theta/2$. Notice that this reasoning remains true in the supercritical phase, but the bound $-\theta/2$ is not optimal for this phase. Let us now show that HMC$_\theta$ is a.s. not in $H^{-s}$ for $s > -\theta/2$.

By Parseval’s identity, for $1/2 < r < 1$,

$$\sum_{n=0}^{\infty} |c_n|^2 r^{2n} = \frac{1}{2\pi} \int_{0}^{2\pi} e^{\sqrt{\theta} G(re^{i\theta})} d\theta.$$  (6.2)

For any $s < 0$, the map $x \mapsto x^{2s} r^{-2s}$ from $(0, \infty)$ to $\mathbb{R}$ has a logarithmic derivative $2s/x - 2 \log r$, and then it reaches its minimum at $x = s/\log r$. Hence, for all $n \geq 1$,

$$(1 + n^2)^s r^{-2n} \geq 2^n s r^{-2s} \geq 2^n (s/\log r)^{2s} r^{-2s/\log r} \geq C_s |\log r|^{-2s}$$

where $C_s > 0$ depends only on $s$. Hence, for all $r \in (1/2, 1)$, shrinking $C_s$ as needed to account for $n = 0$ term and the $2\pi$,

$$A_{s, \theta} \geq \sum_{n=0}^{\infty} (1 + n^2)^s r^{-2n} |c_n|^2 \geq \frac{C_s}{|\log r|^{2s}} \int_{0}^{2\pi} e^{\sqrt{\theta} G(re^{i\theta})} d\theta.$$  (6.3)

Now, for $\theta \in (0, 1]$, the quantity

$$(1 - r^2)^\theta |\log(1 - r^2)|^{(1/2)1_{\theta=1}} \int_{0}^{2\pi} e^{\sqrt{\theta} G(re^{i\theta})} d\theta$$

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converges in probability to the total mass of the GMC when \( r \) goes to 1, and then converges a.s. to a non-zero limit along a subsequence. Since for \( s \in (-\theta/2, 0) \),

\[
|\log r|^{-2s} (1 - r^2)^{-\theta} |\log(1 - r^2)|^{-(1/2)} 1_{\theta=1}
\]
tends to infinity when \( r \to 1 \), we deduce that \( A_{s,\theta} \) is a.s. infinite.

6.2 Super-critical case, \( \theta > 1 \)

Let us prove that \( \text{HMC}_\theta \) is a.s. in \( H^s \) for all \( s < -\sqrt{\theta} + 1/2 \). One checks that \( A_{s,\theta} \) is dominated by

\[
\sum_{u=1}^{\infty} 2^{2su} \sum_{n=0}^{\infty} (1 - 2^{-u})^n |c_n|^2,
\]
after considering the terms for which \( u = |\log(2 + n)/\log 2| \). Hence \( A_{s,\theta} \) is dominated by

\[
\sum_{u=1}^{\infty} 2^{2su} \int_0^{2\pi} e^{\sqrt{\theta}G((1-2^{-u})e^{i\theta})} d\theta.
\]

We have that \( G((1-2^{-u})e^{i\theta}) \) is a centered Gaussian variable with variance

\[-2\log(1 - (1 - 2^{-u})^2) = -2\log(2^{1-u} - 2^{-2u}) = 2u \log 2 \pm O(1).\]

Hence, for \( u \) large enough, the probability that \( G((1-2^{-u})e^{i\theta}) \geq 2u \log 2 + 10 \log u \) is dominated by

\[
\mathbb{P} \left[ N(0, 1) \geq \frac{2u \log 2 + 10 \log u}{\sqrt{2u \log 2 + O(1)}} \right] \leq e^{- \frac{(2u \log 2 + 10 \log u)^2}{4u \log 2 + O(1)}} \leq e^{- \frac{4u^2 (\log 2)^2 + 40u (\log 2) (\log u)}{4u \log 2 + O(1)}} \leq e^{- (u \log 2 + 10 \log u)(1 + O(1/u))} = O(2^{-u} u^{-10}).
\]

By Borel-Cantelli lemma, we have, almost surely,

\[
\sup_{\theta \in 2\pi \mathbb{Z}/2u} G((1-2^{-u})e^{i\theta}) \leq 2u \log 2 + 10 \log u
\]

for \( u \) large enough. We let \( \mathcal{G}_u \) be the event the previous display holds. In order to prove that \( A_{s,\theta} \) is a.s. finite, it is then sufficient to show that

\[
\sum_{u=1}^{\infty} 2^{2su} \int_0^{2\pi} e^{\sqrt{\theta}G((1-2^{-u})e^{i\theta})} 1_{\{\mathcal{G}_u\}} d\theta < \infty
\]
almost surely. It is then enough to have
\[
\sum_{u=1}^{\infty} 2^{2su} \int_0^{2\pi} \mathbb{E}[e^{\sqrt{\theta}G((1-2^{-u})e^{i\vartheta})} 1_{G_u}] d\vartheta < \infty.
\]
We let \( \chi(u, \vartheta) \) be a multiple of \((2\pi)/2^u\) minimizing its distance \( \vartheta \). Using a change of measure formula, we can bound the expectation inside the integral by
\[
\mathbb{E}[e^{\sqrt{\theta}G((1-2^{-u})e^{i\vartheta})} 1_{G_u}] \\
\leq \mathbb{E}[e^{\sqrt{\theta}G((1-2^{-u})e^{i\vartheta})} 1_{G((1-2^{-u})e^{i\chi(u, \vartheta)}) \leq 2u \log 2 + 10 \log u}] \\
= \mathbb{E}[e^{\sqrt{\theta}G((1-2^{-u})e^{i\vartheta})}] P[\tilde{G}((1-2^{-u})e^{i\chi(u, \vartheta)}) \leq 2u \log 2 + 10 \log u].
\]
Here \( \tilde{G}((1-2^{-u})e^{i\chi(u, \vartheta)}) \) is the Gaussian variable obtained from \( G((1-2^{-u})e^{i\chi(u, \vartheta)}) \) after changing the underlying probability measure by a density proportional to \( e^{\sqrt{\theta}G((1-2^{-u})e^{i\vartheta})} \). By Girsanov’s theorem, this change of measure introduces a drift
\[
\text{Cov}(G((1-2^{-u})e^{i\chi(u, \vartheta)}), \sqrt{\theta}G((1-2^{-u})e^{i\vartheta})) = -2\sqrt{\theta} \log |1 - (1 - 2^{-u})^2 e^{iv}|
\]
where
\[
|v| = |\chi(u, \vartheta) - \vartheta| \leq 2\pi/2^u = O(2^{-u}).
\]
Hence,
\[
|1 - (1 - 2^{-u})^2 e^{iv}| = O(2^{-u}),
\]
which implies
\[
\text{Cov}(G((1-2^{-u})e^{i\chi(u, \vartheta)}), \sqrt{\theta}G((1-2^{-u})e^{i\vartheta})) \geq \sqrt{\theta}(2u \log 2 + O(1)).
\]
We then get, for \( u \) large enough depending on \( \theta \),
\[
\mathbb{E}[e^{\sqrt{\theta}G((1-2^{-u})e^{i\vartheta})} 1_{G((1-2^{-u})e^{i\chi(u, \vartheta)}) \leq 2u \log 2 + 10 \log u}] \\
\leq \mathbb{E}[e^{\sqrt{\theta}G((1-2^{-u})e^{i\vartheta})}] \\
\times P[\tilde{G}((1-2^{-u})e^{i\chi(u, \vartheta)}) + \sqrt{\theta}(2u \log 2 + O(1)) \leq 2u \log 2 + 10 \log u].
\]
\[
\leq e^{\theta(2u \log 2 + O(1))/2} \cdot e^{-(u(\sqrt{\theta}) - 2^u \log 2 + O((\sqrt{\theta}(\log u)))((1+O(u^{-1})))} \\
\leq C\theta 2^{u(\theta-(\sqrt{\theta}) - 2^u \log 2 + O((\sqrt{\theta}(\log u)))((1+O(u^{-1})))} \\
= C\theta 2^u(2\sqrt{\theta})_u^{m_u} = C\theta 2^u(2\sqrt{\theta})_u^{m_u}.
\]
for \( C_\theta, m_\theta > 0 \) depending only on \( \theta \). Hence,

\[
\sum_{u=1}^{\infty} 2^{2su} \int_0^{2\pi} \mathbb{E}[e^{\sqrt{\theta}G((1-2-u)e^{i\theta})} 1_{G((1-2-u)e^{i\chi(u,\vartheta)}) \leq 2u \log 2 + 10 \log u}] d\vartheta < \infty
\]
as soon as \( 2s + 2\sqrt{\theta} - 1 < 0 \), which implies that for \( \theta > 1 \), HMC\( _\theta \) is a.s. in \( H^s \) for all \( s < -\sqrt{\theta} + 1/2 \).

On the other hand, we have seen, from (6.3)

\[
A_{s,\theta} \geq \frac{C_s}{|\log r|^{2s}} \int_0^{2\pi} e^{\sqrt{\theta}G(re^{i\vartheta})} d\vartheta.
\]
for all \( r \in (1/2, 1) \). Since \( G \) is the real part of a holomorphic function, it is harmonic on the unit disc, and then by Jensen’s inequality, for all \( \vartheta_0 \in \mathbb{R} \),

\[
e^{\sqrt{\theta}G(r^2e^{i\vartheta_0})} \leq \frac{1}{2\pi} \int_0^{2\pi} e^{\sqrt{\theta}G(re^{i\vartheta})} P_r(\vartheta) d\vartheta
\]
where \( P_r \) is the Poisson kernel:

\[
P_r(\vartheta) = \sum_{p \in \mathbb{Z}} r^{|p|} e^{ip\vartheta}.
\]
The Poisson kernel is bounded by \((1 + r)/(1 - r)\), and then

\[
2e^{\sqrt{\theta} \sup_{\vartheta_0 \in \mathbb{R}} G(r^2e^{i\vartheta_0})} \leq \sup_{\vartheta_0 \in \mathbb{R}} \frac{1}{2\pi} \int_0^{2\pi} e^{\sqrt{\theta}G(re^{i(\vartheta_0 + \vartheta)})} P_r(\vartheta) d\vartheta
\]

\[
\leq \frac{1 + r}{2\pi(1 - r)} \int_0^{2\pi} e^{\sqrt{\theta}G(re^{i\vartheta})} d\vartheta.
\]
Hence, using (6.3), there is a constant \( C_s > 0 \) so that for any \( r \in (1/2, 1) \),

\[
A_{s,\theta} \geq (1 - r)^{1-2s} e^{\sqrt{\theta} \sup_{\vartheta_0 \in \mathbb{R}} G(r^2e^{i\vartheta})}.
\]

With probability going to 1 when \( r \to 1 \), the maximum of the logarithmically correlated field \( G(r^2e^{i\vartheta}) \) is larger than \( 2 \log(1/(1-r)) - 10 \log(\log(1/(1-r))) \) (using the results of [DRZ17] on a suitably chosen net), and then \( A_{s,\theta} \) is bounded from below by \((1 - r)^{1-2s-2\sqrt{\theta}} \log(1/(1-r))^{m_\theta} \) for \( m_\theta \) depending only on \( \theta \). For \( s > -\sqrt{\theta} + 1/2 \), the bound tends to infinity when \( r \to 1 \), which shows that HMC\( _\theta \) is a.s. not in \( H^s \).
In this section we develop some of the properties of the secular coefficients of $C_{\beta E} \{c_n^{(N)}\}$. We begin by recalling the Verblunsky coefficients which will allow us to formulate the exact relationship, due to [KN04]. We let $\{\alpha_n : n \in \mathbb{N}_0\}$ be independent complex random variables on the unit disk, with each $\alpha_n$ rotationally invariant in law and $|\alpha_n|^2$ distributed like Beta$\left(1, \frac{\beta(n+1)}{2}\right)$. The Szegő recurrence is, for all $N \geq 0$,

$$(\Phi_{N+1}(z)) : = \begin{pmatrix} z & -\alpha_N \\ -\alpha_N & 1 \end{pmatrix} \begin{pmatrix} \Phi_N(z) \\ \Phi_N^*(z) \end{pmatrix}, \quad \begin{cases} \Phi_0(z) \equiv 1, \\ \Phi_N^*(z) = z^N \Phi_N(1/z). \end{cases}$$

(7.1)

where $\Phi_N$ and $\Phi_N^*$ are polynomials of degree at most $N$. Note that $\Phi_N^*$ and $\Phi_N$ are related by being reversals of one another, in that their vector of coefficients is reversed and conjugated. Now we give the connection to the $C_{\beta E}$ characteristic polynomial as defined in (1.2), due to [KN04]. We let $\eta$ be uniformly distributed random variable on the unit circle independent of $\{\alpha_n : n \in \mathbb{N}_0\}$. The characteristic polynomial $\chi_N$ has the distribution of

$$\chi_N(z) = \Phi_{N-1}^*(z) - \eta z \Phi_{N-1}(z).$$

(7.2)

From [CN19, Proposition 3.1], we have almost sure convergence as $N \to \infty$ of $\Phi_N^*(z)$ to a process $\Phi_N^*(z)$ on the unit disk uniformly on compact sets. Moreover, this limit is none other than the log-Gaussian process $e^{\sqrt{2} \theta G}(z)$.

In [CN19, Proposition 3.1], the following uniform estimate is also proven:

$$E|\Phi_N^*(z)|^p \leq (1 - |z|^2)^{-\theta p^2/4} \quad \text{for all } z \in \mathbb{D}, p > 0, N \in \mathbb{N}. \quad (7.3)$$

We let $\mathcal{F}$ be the filtration $\mathcal{F} = (\mathcal{F}_N := \sigma(\alpha_0, \ldots, \alpha_{N-1}) : N \geq 0)$. Then the process $\{\Phi_N^*(z)\}$ is adapted to $\mathcal{F}$ and moreover is a complex martingale. Using Cauchy’s theorem, and the bound (7.3), we have that secular coefficient

$$\mathcal{M}_{n,N} := \frac{1}{2\pi i} \oint \Phi_N^*(z) z^{-n-1} dz,$$

(7.4)

for a fixed simple closed contour enclosing 0 in the unit disk, forms a uniformly integrable martingale adapted to $\mathcal{F}_N$. Hence we have the representation

$$\mathcal{M}_{n,N} = \mathbb{E}[c_n \mid \mathcal{F}_N] \overset{a.s.}{\longrightarrow} c_n.$$
Using the Szegő recurrence (7.1) and (7.4), we have the identity

\[
\mathcal{M}_{n,N+1} = \mathcal{M}_{n,N} - \alpha_N \frac{1}{2\pi i} \oint \Phi_N(z)z^{-n}dz
\]

\[
= \mathcal{M}_{n,N} - \alpha_N \mathcal{M}_{N-n+1,N}.
\]

(7.5)

We will let \( \mathfrak{B}_{n,N} \) be the bracket process of \( \mathcal{M}_{n,N} \), i.e. for \( n \geq 1 \), and for any \( N \geq n-1 \),

\[
\mathfrak{B}_{n,N} := \sum_{j=n-1}^{N-1} \mathbb{E}[|\mathcal{M}_{n,j+1} - \mathcal{M}_{n,j}|^2 | \mathcal{F}_j]
\]

\[
= \sum_{j=n-1}^{N-1} |\mathcal{M}_{j-n+1,j}|^2 \mathbb{E}(|\alpha_j|^2) = \sum_{j=n-1}^{N-1} \frac{|\mathcal{M}_{j-n+1,j}|^2}{1 + \frac{1}{\theta}(j+1)}.
\]

(7.6)

Here, we can notice that \( \mathcal{M}_{n,n-1} = 0 \), since \( \Phi_{n-1}^* \) is a polynomial of degree at most \( n-1 \).

**Lemma 7.1.** For any \( \theta > 0 \) there exists a constant \( C_\theta > 0 \) such that the following holds. For \( N \geq n \geq 1 \), we have \( \mathbb{E}|\mathcal{M}_{n,N}|^2 = \mathbb{E}(\mathfrak{B}_{n,N}) \), and

\[
\mathbb{E}|\mathcal{M}_{n,N}|^2 \leq C_\theta \begin{cases} 
\left(\frac{N-n+1}{n}\right)^{\theta}, & \text{if } \theta < 1, \\
\left(\frac{N-n+1}{n}\right) \left(1 + \max\left(\log\left(\frac{n}{N-n+1}\right), 0\right)\right), & \text{if } \theta = 1, \\
\frac{n^\theta}{n} \log\left(1 + \frac{(N-n+1)}{n}\right), & \text{if } \theta > 1.
\end{cases}
\]

Moreover, for all \( n, N_1, N_2 \in \mathbb{N} \) such that \( 1 \leq 3n/2 \leq N_1 < N_2 \), we have

\[
\mathbb{E}|\mathcal{M}_{n,N_2} - \mathcal{M}_{n,N_1}|^2 = \mathbb{E}(\mathfrak{B}_{n,N_2} - \mathfrak{B}_{n,N_1}) \leq C_\theta n^\theta \left(\frac{1}{N_1} - \frac{1}{N_2}\right).
\]

This holds with \( N_2 = \infty \) as well, in which case \( \mathcal{M}_{n,N_2} = c_n \) and \( 1/N_2 := 0 \).

**Proof.** For the last part of the lemma, as \( \mathcal{M}_{n,N_2} \) is bounded in \( L^p \) for all \( p \), the \( N_2 = \infty \) case follows from uniform integrability and taking \( N_2 \to \infty \). Hence it suffices to show only the case of \( N_2 < \infty \). Also, it follows the bracket process is uniformly bounded in \( L^p \) for all \( p \) from the Burkholder-Davis-Gundy inequalities. For \( j = n-1 \), we have

\[
|\mathcal{M}_{j-n+1,j}|^2 = |\mathcal{M}_{0,n-1}|^2 = 1
\]
since the constant term of $\Phi^*_{n-1}$ is equal to 1. Hence, for $N \geq n \geq 1$, we can write

$$\mathcal{B}_{n,N} = \frac{1}{1 + \frac{1}{\theta}} + \sum_{j=n}^{N-1} \frac{1}{1 + \frac{1}{\theta}(j+1)} |m_{j-n+1,j}|^2.$$

Recall that for $j \geq n$, the bracket is such that $k \mapsto |m_{j-n+1,k}|^2 - \mathcal{B}_{j-n+1,k}$ is again a martingale, starting at zero for $k = j - n$, and hence

$$\mathbb{E}\mathcal{B}_{n,N} = \frac{1}{1 + \frac{1}{\theta}} + \sum_{j=n}^{N-1} \frac{\mathbb{E}\mathcal{B}_{j-n+1,j}}{1 + \frac{1}{\theta}(j+1)}.$$  \hfill (7.7)

We may develop this equation to produce

$$\mathbb{E}\mathcal{B}_{n,N} = \frac{1}{1 + \frac{1}{\theta}} + \sum_{j=n}^{N-1} \frac{1}{1 + \frac{1}{\theta}(j+1)} \left( \frac{1}{1 + \frac{j-n+1}{\theta}} + \sum_{k=j-n+1}^{j-1} \frac{\mathbb{E}\mathcal{B}_{k-(j-n+1)+1,k}}{1 + \frac{1}{\theta}(k+1)} \right)$$

$$= \frac{1}{1 + \frac{1}{\theta}} + \sum_{j=n}^{N-1} \frac{1}{1 + \frac{1}{\theta}(j+1)} \sum_{k=j-n+1}^{j-1} \frac{\mathbb{E}\mathcal{B}_{k,k+j-n}}{1 + \frac{1}{\theta}(k+1) + \frac{1}{\theta}(k+j-n+1)}.$$  \hfill (7.8)

Using uniform integrability of the bracket, we have for any $k \geq 0$,

$$\mathbb{E}\mathcal{B}_{k,\infty} = \mathbb{E}|c_k|^2.$$

Let us now prove the estimate of $\mathbb{E}|\mathcal{M}_{n,N}|^2 = \mathbb{E}\mathcal{B}_{n,N}$ given in the lemma. We have

$$\mathbb{E}\mathcal{B}_{n,N} \leq \frac{1}{1 + \frac{1}{\theta}} + \sum_{j=n}^{N-1} \frac{1}{1 + \frac{1}{\theta}(j+1)} \sum_{k=j-n+1}^{j-1} \frac{\mathbb{E}|c_k|^2}{1 + \frac{1}{\theta}(k+1) + \frac{1}{\theta}(k+j-n+1)}.$$  \hfill (7.9)

Since $j \geq n$ and $\mathbb{E}|c_k|^2$ is dominated by $k^{\theta-1}$, $\mathbb{E}\mathcal{B}_{n,N}$ is bounded, up to a constant depending only on $\theta$, by

$$\frac{1}{n} \left( 1 + \sum_{j=n}^{N-1} \frac{1}{j-n+1} + \sum_{j=n}^{N-1} \sum_{k=1}^{j} \frac{k^{\theta-1}}{k+j-n+1} \right).$$
For $N = n$, we immediately deduce a bound of order $1/n$ (the sums are empty) which is enough for our purpose. We can then assume $N \geq n + 1$, and in this case, we have

$$\frac{1}{n} \sum_{j=1}^{N-n} \sum_{k=0}^{n-1} \frac{(1+k)^{\theta-1}}{k+j} \leq \frac{1}{n} \sum_{j=1}^{N-n} \sum_{k=0}^{n-1} \frac{(1+k)^{\theta-1}}{\max\{j, 1+k\}}. \quad (7.10)$$

If $j \leq n$, the inner sum can be estimated as

$$\sum_{0 \leq k \leq j} \frac{(1+k)^{\theta-1}}{j} + \sum_{j-1 < k \leq n-1} (1+k)^{\theta-2} \leq \begin{cases} C_{\theta} j^{\theta-1}, & \text{if } \theta < 1, \\ 1 + \log(1+n/j), & \text{if } \theta = 1, \\ C_{\theta} n^{\theta-1}, & \text{if } \theta > 1, \end{cases}$$

where $C_{\theta} > 0$ is some sufficiently large constant. If $j > n$, the inner sum of (7.10) is

$$\sum_{0 \leq k \leq n-1} \frac{(1+k)^{\theta-1}}{j} \leq \frac{C_{\theta} n^{\theta}}{j}$$

for some $C_{\theta} > 0$ sufficiently large. Summing in $j$, we get from (7.10) and the bounds just established, that for $\theta < 1$,

$$\frac{1}{n} \sum_{j=1}^{N-n} \sum_{k=0}^{n-1} \frac{(1+k)^{\theta-1}}{k+j} \leq \frac{C_{\theta}}{n} \left( (N-n+1)^{\theta} + n^{\theta} \log \left( 1 + \frac{N-n+1}{n} \right) \right),$$

which is dominated by $(N-n+1)^{\theta}/n$. For $\theta > 1$, we get

$$\frac{1}{n} \sum_{j=1}^{N-n} \sum_{k=0}^{n-1} \frac{(1+k)^{\theta-1}}{k+j} \leq \frac{C_{\theta}}{n} \left( n^{\theta-1}((N-n+1)\land n) + n^{\theta} \log \left( 1 + \frac{N-n+1}{n} \right) \right),$$

a domination by $n^{\theta-1} \log(1 + \frac{N-n+1}{n})$. For $\theta = 1$, we get a domination by

$$\frac{1}{n} \sum_{j=1}^{N-n} \sum_{k=0}^{n-1} \frac{(1+k)^{\theta-1}}{k+j} \leq \frac{C_{\theta}}{n} \sum_{j=1}^{N-n} \left( 1 + \max(0, \log \frac{n}{j}) \right).$$

For $1 \leq N - n \leq n$, this quantity is at most

$$n^{-1}((N-n)(1 + \log n) - \log((N-n)!)) \leq n^{-1}((N-n)(1 + \log n) - (N-n) \log(N-n) + (N-n)) \leq n^{-1}(N-n)(2 + \log(n/(N-n)))$$

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and then we have, for all $N \geq n+1$, a domination by

$$n^{-1}(N-n)(1 + \max(0, \log(n/(N-n))).$$

We have now proven the first part of the lemma. For the second part, we observe that under the assumptions of the lemma,

$$E(B_{n,N}^2 - B_{n,N}^1) \leq N^2 - 1 \sum_{j=N_1}^{n-1} \sum_{k=1}^{j} \frac{1}{1 + \frac{1}{\theta}(j+1)} 1 + \frac{1}{\theta}(k + j - n + 1) \mathbb{E}(|c_k|^2)$$

(7.11)

We can estimate for some constant $C_\theta > 0$,

$$E(B_{n,N}^2 - B_{n,N}^1) \leq C_\theta \sum_{j=N_1}^{n-1} \sum_{k=1}^{j} \frac{1}{1 + \frac{1}{\theta}(j+1)} 1 + \frac{1}{\theta}(k + j - n + 1) k^{\theta-1}$$

$$+ \sum_{j=N_1}^{n-1} \frac{1}{1 + \frac{1}{\theta}(j+1)} 1 + \frac{j-n+1}{\theta}$$

If $N_1 \geq 3n/2$, we have that $j - n \geq j/3$, and then the sum of the terms corresponding to a given value of $j$ is dominated by $n^\theta/j^2$, which proves the second part of the lemma.

Having an estimate on the secular coefficients of $\Phi_{N-1}^*$, we may use (7.2) to relate $c_n^{(N)}$ to $c_n$. Recasting (7.2) in terms of coefficients,

$$c_n^{(N)} = m_{n,N-1} - \eta \cdot m_{n-n,N-1}.$$  

(7.12)

We deduce the following estimates relating the secular coefficients of CβE to the coefficients of the HMC:

**Lemma 7.2.** There is constant $C_\theta$ so that for all $n, N \in \mathbb{N}$ with $1 \leq n \leq N/2$,

$$E|c_n - c_n^{(N)}|^2 \leq \begin{cases} 
C_\theta n^\theta & \text{if } \theta < 1, \\
C_\theta n \log(N/n) & \text{if } \theta = 1, \\
C_\theta n^2 & \text{if } \theta > 1.
\end{cases}$$

**Proof.** Using (7.12),

$$E|c_n - c_n^{(N)}|^2 = E|c_n - m_{n,N-1}|^2 + E|m_{n-n,N-1}|^2.$$
We have $N \geq 2n$ and then $N - 1 \geq 3n/2$ (except for $n = 1$ and $N = 2$, in which case the lemma is obvious for a suitable value of $C_\theta$). Hence, by Lemma 7.1, we have, after increasing the constant $C_\theta$ if needed,

$$E|c_n - M_{n,N-1}|^2 \leq \frac{C_\theta n^\theta}{N},$$

and

$$E|\mathcal{M}_{N-n,N-1}|^2 \leq \begin{cases} 
\frac{C_\theta n^\theta}{N} & \text{if } \theta < 1, \\
\frac{C_\theta n \log(N/n)}{N} & \text{if } \theta = 1, \\
\frac{C_\theta n}{N^{2-\theta}} & \text{if } \theta > 1.
\end{cases}$$

This latter part dominates the contribution $|\mathcal{M}_{N-n,N-1}|^2$ in all cases. \(\square\)

From this point, the proof of Theorem 1.10 is a simple corollary.

**Proof of Theorem 1.10.** Under the assumption that $n/N \to 0$, 

$$(E|c_n - c_n^{(N)}|^2)n^{1-\theta} \to 0 \quad \text{as } n \to \infty,$$

and so we conclude from Slutsky’s theorem, (1.33) and Theorem 1.8 that the desired distributional convergence holds. \(\square\)

### 7.1 Fractional moments

In this section, we prove Theorem 1.11. We recall from the statement of that theorem that $w_n$ is defined as

$$w_n = n^{(\theta-1)/2}, \quad w_n = (\log(1+n))^{-\frac{1}{4}}, \quad \text{or} \quad w_n = n^{\sqrt{\theta}-1}(\log n)^{-\frac{1}{4}\sqrt{\theta}},$$

in the cases $\theta \in (0, 1)$, $\theta = 1$ or $\theta > 1$ respectively.

We recall for convenience (3.12) and recall that $S^{(n)}$ is the shortest cycle in a Ewens distributed permutation of $n$ symbols (c.f. Lemma 3.7):

$$E(|c_n|^2 \mid \mathcal{G}_q) = |c_{n,q}|^2 + \sum_{r=0}^{n} |c_{r,q}|^2 \frac{g(n-r)}{(n-r)!} \mathbb{P}[S^{(n-r)} > q].$$

Using Lemma 3.7, we have a uniform bound

$$E(|c_n|^2 \mid \mathcal{G}_q) \leq |c_{n,q}|^2 + C_\theta n^{\theta-1} F_q \quad \text{where} \quad F_q := \sum_{r=0}^{\infty} |c_{r,q}|^2 e^{-\theta h(q+1)},$$

(7.14)
Using Parseval’s identity and (5.2),
\[
\sum_{r=0}^{\infty} |c_{r,q}|^2 = \frac{1}{2\pi} \int_0^{2\pi} e^{\sqrt{\theta} G_q(e^{i\vartheta})} d\vartheta, \quad \text{where} \quad G_q(z) = 2\Re \sum_{k=1}^{q} \frac{z^k N_k}{\sqrt{k}}. \tag{7.15}
\]

Moreover the normalizing constant \( e^{-\theta h(q+1)} \) is such that \( F_q \) has expectation 1, and \( F_q \) is thus an approximation to the mass of the chaos for \( \theta < 1 \).

**Lemma 7.3.** Let \( w_n \) as in (7.13). If \( \theta \in (0, 1) \), then
\[
\mathbb{E}[n^{\theta-1} F_n/w_n^2] = 1
\]
for all \( n \geq 1 \). If \( \theta = 1 \), then for \( p \in (0, 1) \),
\[
\sup \{ \mathbb{E}[(F_n/w_n^2)^p] : n \in \mathbb{N} \} < \infty.
\]

Finally, if \( \theta > 1 \), there exists \( u_\theta > 0 \), depending only on \( \theta \), such that
\[
\left\{ (\log n)^{-u_\theta} n^{\theta-1} F_n/w_n^2 : n \in \mathbb{N} \right\}
\]
is tight.

**Proof.** For \( \theta \in (0, 1) \), the lemma means that \( F_n \) has expectation 1, as remarked before. For \( \theta = 1 \), the lemma follows from [JS17, Theorem 1.3]. For \( \theta > 1 \) we use the same ingredients as those considered in the proof of regularity of the supercritical HMC. We will show the equivalent statement that there exists a \( u_\theta > 0 \) so that
\[
(\log n)^{-u_\theta} n^{\theta-1} F_n/w_n^2 \xrightarrow{n \to \infty} 0.
\]
The convergence to zero in probability is obtained by proving the convergence of the expectation, after restricting it to the event that \( G_n(e^{i\vartheta}) \leq 2 \log n + 10 \log \log n \) for all \( \vartheta \in 2\pi\mathbb{Z}/n \), whose probability goes to 1 when \( n \to \infty \). Using Girsanov’s theorem, we get, for \( n \geq 2 \) and \( |\vartheta - \vartheta'| = \mathcal{O}(1/n) \), that
\[
\mathbb{E} \left[ e^{\sqrt{\theta} G_n(e^{i\vartheta})} 1_{G_n(e^{i\vartheta}) \leq 2 \log n + 10 \log \log n} \right] = e^{\theta(\log n + \mathcal{O}(1))} \mathbb{P} \left[ G_n(e^{i\vartheta'}) + \text{Cov}(G_n(e^{i\vartheta'}), \sqrt{\theta} G_n(e^{i\vartheta})) \leq 2 \log n + 10 \log \log n \right] = (\mathcal{O}(n))^{\theta} \mathbb{P} \left[ G_n(e^{i\vartheta'}) \leq 2(1 - \sqrt{\theta}) \log n + 10 \log \log n + c_\theta \right].
\]

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for some $c_\theta \in \mathbb{R}$ depending only on $\theta$, since, from the fact that $\vartheta$ and $\vartheta'$ are close to each other, the covariance between $G_n(e^{i\vartheta'})$ and $G_n(e^{i\vartheta})$ is equal to $2 \log n + \mathcal{O}(1)$. Hence, since $\theta > 1$,

$$
E \left[ e^{\sqrt{\vartheta} G_n(e^{i\vartheta})} 1_{G_n(e^{i\vartheta'}) \leq 2 \log n + 10 \log \log n} \right] \leq C_{\theta n} \theta^{-2(1-\sqrt{\vartheta})^2} (\log n)^{\mu_\theta} \tag{7.16}
$$

for $C_{\theta}, \mu_\theta > 0$ depending only on $\theta$. Taking $\vartheta' \in 2\pi \mathbb{Z}/n$ depending only of $\vartheta$ and $n$ in such a way that $|\vartheta - \vartheta'| = \mathcal{O}(1/n)$, and integrating in $\vartheta$, we deduce

$$
E \left[ n^{\theta-1} \left( F_n \right)_n \sup \{ e^{\vartheta' G_n(e^{i\vartheta'})} : n \in \mathbb{N} \} \right] 
\leq C_\theta' n^{\theta-1} \left( n^{\theta-1-\sqrt{\vartheta}^2} (\log n)^{\frac{3}{2} \sqrt{\vartheta} + \mu_\theta} n^{-2 \sqrt{\vartheta} + 2} = C_\theta' (\log n)^{\frac{3}{2} \sqrt{\vartheta} + \mu_\theta}
$$

for $C_\theta' > 0$. This proves the lemma with $u_\theta = \frac{3}{2} \sqrt{\vartheta} + \mu_\theta$. \qed

**Remark 7.4.** While beyond the scope of what we do here, the optimal power is $u_\theta = 0$, in which case the statement would be

$$
\left\{ n^{\theta-1} F_n / (w_n)^2 : n \in \mathbb{N} \right\}
$$

is a tight family. Indeed as a consequence of [DRZ17], the maximum of $G_n(e^{i\vartheta})$ on the lattice $2\pi \mathbb{Z}/n$ is at most $2 \log n - \frac{3}{2} \sqrt{\vartheta} \log \log n + \mathcal{O}(1)$ with a probability controlled uniformly in $n$ by $r$. Moreover, one can establish (and herein lies the technical work) that the random walk $(G_{2k}(e^{i\vartheta})) : k < \log_2 n)$ stays below $(2 \log 2)(k-\frac{3}{2} \log k) + \mathcal{O}(1)$ for all lattice $\vartheta$ again except with a probability that can be made small in $r$ uniformly in $n$. On this good event, $G(n,y)$, it is now possible to show using the appropriate ballot theorem that for $\theta > 1$

$$
E \left[ e^{\sqrt{\vartheta} G_n(e^{i\vartheta})} 1 (G(n,y)) \right] \leq C_{\theta,y} e^{\sqrt{\vartheta} (2 \log n - \frac{3}{2} \log \log n)} / n
$$

which improves (7.16) and from which would follow the claimed bound.

**Lemma 7.5.** If $\theta \in (0,1)$, then

$$
\sup \{ E(|c_n/w_n|^2) : n \in \mathbb{N} \} < \infty.
$$

If $\theta = 1$, and $p \in (0,1)$, then

$$
\sup \{ E(|c_n/w_n|^{2p}) : n \in \mathbb{N} \} < \infty.
$$

Finally, if $\theta > 1$, there exists $v_\theta > 0$, depending only on $\theta$, such that

$$
\left\{ (c_n/w_n)(\log n)^{-v_\theta} : n \in \mathbb{N} \right\}
$$

is tight.
Proof. The case \( \theta \in (0, 1) \) is already proven before. Moreover, using (4.40) and Lemma 3.6, we know that for \( n \geq 3 \),

\[
\max_{1 \leq q < n/\log n} \mathbb{E}|c_{n,q}|^2 \leq \max_{1 \leq q < n/\log n} C_{\theta} n^{\theta - 1} \mathbb{P}(L^{(n-q)} \leq q) \leq n^{-\omega(n)}, \quad (7.17)
\]

where \( \omega(n) \to \infty \) as \( n \to \infty \).

We now use (7.14) for \( q_n = \lfloor n/\log n \rfloor \) when \( n \geq 3 \):

\[
\mathbb{E}(|c_n|^2 | G_{q_n}) \leq |c_{n,q_n}|^2 + C_{\theta} n^{\theta - 1} F_{q_n}.
\]

For \( \theta = 1 \), we take \( p \in (0, 1) \) and get, using Hölder’s inequality for exponent \( 1/p > 1 \) and sub-additivity of the \( p \)-th power:

\[
\mathbb{E}(|c_n|^{2p} | G_{q_n}) \leq \left[ \mathbb{E}(|c_n|^2 | G_{q_n}) \right]^p \leq |c_{n,q_n}|^{2p} + (C_1 F_{q_n})^p,
\]

which implies

\[
\mathbb{E}(|c_n|^{2p}) \leq \mathbb{E}(|c_{n,q_n}|^{2p}) + \mathbb{E}(|C_1 F_{q_n}|^p).
\]

From (7.17), and conclude

\[
\mathbb{E}(|c_n/w_n|^{2p}) \leq \mathcal{O}(n^{-\omega(n)}/w_n^2) + \mathbb{E}(|C_1 F_{q_n}/w_n^2|^p).
\]

We then use Lemma 7.3 to complete the proof, taking into account the fact that \( w_n = (\log(1+n))^{-1/4} \) is equivalent to \( w_{q_n} \) when \( n \) goes to infinity. When \( \theta > 1 \), we write

\[
\mathbb{E}\left( \min(1, |c_n w_n^{-1}(\log n)|^{v_\theta}) \right) \leq w_n^{-2}(\log n)^{-2v_\theta} |c_{n,q_n}|^2
\]

\[
+ \min(1, C_{\theta} w_n^{-2}(\log n)^{-2v_\theta} n^{\theta - 1} F_{q_n}).
\]

Since \( w_n/w_{q_n} \) and \( n^{\theta - 1}/q_n^{\theta - 1} \) are equivalent up to powers of \( \log n \) (depending on \( \theta \)) when \( n \to \infty \), and \( \log n \) is equivalent to \( \log q_n \), we deduce from Lemma 7.3 that

\[
w_n^{-2}(\log n)^{-2v_\theta} n^{\theta - 1} F_{q_n} \xrightarrow[n \to \infty]{} 0
\]

for any \( v_\theta \) sufficiently large. Then

\[
\mathbb{E}\left( \min(1, C_{\theta} w_n^{-2}(\log n)^{-2v_\theta} n^{\theta - 1} F_{q_n}) \right) \xrightarrow[n \to \infty]{} 0,
\]

as soon as \( v_\theta \) is large enough. Since \( \mathbb{E}(|c_{n,q_n}|^2) \) decreases to 0 faster than any power of \( n \), we have

\[
\mathbb{E}(w_n^{-2}(\log n)^{-2v_\theta} |c_{n,q_n}|^2) \xrightarrow[n \to \infty]{} 0,
\]

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and then

$$\mathbb{E}[\min(1, |c_n w_n^{-1}(\log n)^{-v_{\theta}}|^{2})] \xrightarrow{n \to \infty} 0,$$

which implies that

$$|c_n w_n^{-1}(\log n)^{-v_{\theta}}| \xrightarrow{p \to \infty} 0.$$

We deduce the following result on the secular coefficients of $C\beta E$.

**Theorem 7.6.** If $\theta \in (0, 1)$, then

$$\sup\{\mathbb{E}(|c_n^{(N)}|/w_n^2) : n \in \mathbb{N}, N \geq 2n\} < \infty.$$

If $\theta = 1$, and $p \in (0, 1)$, then

$$\sup\{\mathbb{E}(|c_n^{(N)}|/w_n^{2p}) : n \in \mathbb{N}, N \geq 2n\} < \infty.$$

Finally, if $\theta \in (1, 2)$, there exists $v_{\theta}, v'_{\theta} > 0$ depending only on $\theta$ so that with $N_0(n) = n^{\frac{3-2v_{\theta}}{2-\theta}}(\log n)^{v'_{\theta}}$, for all $\delta > 0$,

$$\sup_{N \geq N_0(n)} \mathbb{P}[(c_n^{(N)}/w_n)(\log n)^{-v_{\theta}} \geq \delta] \xrightarrow{n \to \infty} 0.$$

**Proof.** Let us first suppose that $\theta \leq 1$: we may assume $p \in (1/2, 1)$ when $\theta = 1$, by Hölder’s inequality. For $r \geq 1$ and any $k, n \in \mathbb{N}$ we have from Jensen’s inequality

$$\mathbb{E}[|c_n^{(N)}|^{r}] = \mathbb{E}[\mathbb{E}(c_n | \mathcal{F}_k)]^r \leq \mathbb{E}(|c_n|^r).$$

Hence recalling (7.12), for any $p \geq 1$,

$$(\mathbb{E}(|c_n|^{p})^{1/r}) \leq (\mathbb{E}(|c_n|^p))^{1/r} + (\mathbb{E}(|c_{N-n}|^p))^{1/r}.$$

We can now conclude the proof from Lemma 7.5, taking $r = 2$ for $\theta \in (0, 1)$ and $r = 2p \in (1, 2)$ for $\theta = 1$: notice that $w_{N-n} \leq w_n$ since $\theta \leq 1$ and $N \geq 2n$.

Let us now suppose that $\theta \in (1, 2)$. In this case, because of Lemma 7.5, it is sufficient to prove that

$$\sup_{N \geq N_0(n)} \mathbb{E}[(c_n - c_n^{(N)})^2 w_n^{-2}(\log n)^{-2v'_{\theta}}] \xrightarrow{n \to \infty} 0.$$

For suitable $v'_{\theta}$, this is a consequence of the bound

$$\mathbb{E}[(c_n - c_n^{(N)})^2] \leq C_{\theta} n/N^{2-\theta}$$

given by Lemma 7.2.

$\square$
Remark 7.7. In the supercritical phase, we compare $c_n$ with $c_n^{(N)}$ by using the $L^2$ norm, which is expected not to be optimal, since the $L^2$ norm of $c_n$ does not give its correct order of magnitude. Hence, we expect that the exponent $(3 - 2\sqrt{\theta})/(2 - \theta)$ can be improved.

8 Sharpness of the tightness

We have seen that $(c_n(\log n)^{-\nu_\theta}/w_n)_{n \geq 1}$ is a tight family for random variables for $\theta > 0$ for some $\nu_\theta > 0$ depending only on $\theta$, which can be taken equal to 0 for $\theta \in (0, 1]$. Moreover informally, $c_n$ has order at most $w_n$, up to a logarithmic factor. It is natural to ask if this bound is optimal, or if $c_n$ has a smaller order of magnitude. In the following section, we show that $c_n$ is no smaller than $w_n$ in order of magnitude (i.e. that $w_n/c_n$ is tight) when $\theta \in (0, 1]$.

Theorem 8.1. For all $\theta \in (0, 1]$, and all $u \in \mathbb{C}$ such that $|u| = 1$, one has

$$\sup_{n \geq 1} P\left[|\Re(u c_n)|/w_n \leq \delta\right] \xrightarrow[\delta \to 0]{} 0,$$

Proof. Since the law of $c_n$ is rotational invariant in distribution, we can assume $u = 1$. We have the following equality:

$$c_n = c_{n, \lfloor n/2 \rfloor} + \sum_{q=0}^{\lfloor n/2 \rfloor - 1} \frac{N_{n-q} \theta^{1/2}}{\sqrt{n-q}} c_q,$$

and then, since $(N_{n-q})_{0 \leq q < n/2}$ are independent of $c_{n, \lfloor n/2 \rfloor}$ and $(c_q)_{0 \leq q < n/2}$,

$$c_n \overset{d}{=} c_{n, \lfloor n/2 \rfloor} + \mathcal{N} \left( \sum_{q=0}^{\lfloor n/2 \rfloor - 1} \frac{|c_q|^2 \theta}{n-q} \right)^{1/2},$$

where $\mathcal{N}$ is a standard complex Gaussian independent of the other variables which are involved in the formula. Hence, by the fact that the law of $\Re(\mathcal{N})$ has a bounded density with respect to the Lebesgue measure:

$$P\left[|\Re(c_n)|/w_n \leq \delta \mid \mathcal{G}_{\lfloor n/2 \rfloor}\right] \leq C \delta w_n \left( \sum_{q=0}^{\lfloor n/2 \rfloor - 1} \frac{|c_q|^2 \theta}{n-q} \right)^{-1/2},$$

for some constant $C > 0$, which implies

$$P\left[|\Re(c_n)|/w_n \leq \delta\right] \leq E \left[ \min \left( 1, C \delta w_n \left( \sum_{q=0}^{\lfloor n/2 \rfloor - 1} \frac{|c_q|^2 \theta}{n-q} \right)^{-1/2} \right) \right]. \quad (8.1)$$
Recalling (1.30) there is a constant $c_\theta > 0$ so that for all $n > 2$ and with $n_0 = \lceil \frac{n}{2} \rceil - 1$,
\[
\sum_{q=0}^{n_0} \frac{|c_q|^2}{n-q} \geq \frac{\theta}{n} \sum_{q=0}^{n_0} |c_q|^2 \geq c_\theta (\sqrt{\log n})^{-1} \cdot 1(\theta=1) n^\theta M_{\theta,n_0}.
\]
The expression $M_{\theta,n_0}$ is an approximation to the total mass. By Lemma 1.31, this converges in probability as $n \to \infty$ to a multiple of $M_\theta$. In particular
\[
\left\{ \left( \sum_{q=0}^{\lceil \frac{n}{2} \rceil - 1} |c_q|^2 \right)^{-1/2} w_n : n \in \mathbb{N} \right\}
\]is tight (recall when $\theta \in (0,1)$, $w_n = n^{\theta-1}$ and when $\theta = 1$, $w_n = (\log(1+n))^{-1/4}$). Using (8.1)
\[
\mathbb{P}[|\Re(c_n)| / w_n \leq \delta] \leq C\delta^{1/2} + \mathbb{P} \left( \left( \sum_{q=0}^{\lceil \frac{n}{2} \rceil - 1} |c_q|^2 \right)^{-1/2} w_n \geq \delta^{-1/2} \right).
\]
The tightness property above shows that
\[
\sup_{n \geq 1} \mathbb{P}[|\Re(c_n)| / w_n \leq \delta] \to 0.
\]
which completes the proof. \hfill $\Box$

We deduce a similar result for the secular coefficients $c_n^{(N)}$ when $N$ is sufficiently large with respect to $n$:

**Theorem 8.2.** Let $\theta \in (0,1)$, $u \in \mathbb{C}$ on the unit circle, and let $\varphi$ be any function from $\mathbb{N}$ to $\mathbb{R}$ such that $\varphi(n) \geq 2$ for all $n \geq 1$, $\varphi(n)$ tends to infinity with $n$, and for $\theta = 1$, $\varphi(n)/\sqrt{\log n (\log \log n)}$ tends to infinity with $n$. Then,
\[
\sup_{n \geq 1, N \geq n \varphi(n)} \mathbb{P}[|\Re(u c_n^{(N)})| / w_n \leq \delta] \to 0.
\]

**Proof.** We assume $u = 1$. We know that for all $\epsilon > 0$, there exists $\delta > 0$ depending only on $\epsilon$ and $\theta$, such that for $n \geq 1$,
\[
\mathbb{P}[|\Re(c_n)| / w_n \leq 2\delta] \leq \epsilon.
\]
Now,
\[
\mathbb{P}[|\Re(c_n^{(N)})| / w_n \leq \delta] \leq \mathbb{P}[|\Re(c_n)| / w_n \leq 2\delta] + \mathbb{P}[|c_n - c_n^{(N)}| / w_n \geq \delta],
\]
and then, using Lemma 7.2 and Markov’s inequality,
\[ P[|\Re(c_n^{(N)})|/w_n \leq \delta] \leq \epsilon + \delta^{-2}C_\theta w_n^{-2}n^\theta /N \]
for \( \theta \in (0, 1) \) and
\[ P[|\Re(c_n^{(N)})|/w_n \leq \delta] \leq \epsilon + \delta^{-2}C_1 w_n^{-2}n \log(N/n)/N \]
for \( \theta = 1 \). Hence,
\[ P[|\Re(c_n^{(N)})|/w_n \leq \delta] \leq \epsilon + \delta^{-2}C_\theta n/N \leq \epsilon + \delta^{-2}C_\theta /\varphi(n) \]
for \( \theta \in (0, 1) \) and \( N \geq n\varphi(n) \), and
\[ P[|\Re(c_n^{(N)})|/w_n \leq \delta] \leq \epsilon + \delta^{-2}C_1 (\log(1+n))^{1/2} \log(N/n)(n/N) \]
\[ \leq \epsilon + 2\delta^{-2}C_1 (\log(1+n))^{1/2}(\log(\varphi(n)))/\varphi(n) \]
for \( \theta = 1 \) and \( N \geq n\varphi(n) \). The factor 2 comes from the fact that \( \varphi(n) \geq 2 \) by assumption and \( (\log a)/a \leq 2(\log b)/b \) for \( a \geq b \geq 2 \). For \( \theta \in (0, 1) \), we have
\[ \delta^{-2}C_\theta /\varphi(n) \xrightarrow{n \to \infty} 0 \]
since \( \varphi(n) \to \infty \). For \( \theta = 1 \), we have
\[ \min(\varphi(n), 2 + \log n)/(\sqrt{\log n(\log \log n)}) \xrightarrow{n \to \infty} \infty, \]
and then
\[ (\log(1+n))^{1/2}(\log(\varphi(n)))/\varphi(n) \]
\[ \leq 2(\log(1+n))^{1/2} \log(\min(\varphi(n), 2 + \log n))/\min(\varphi(n), 2 + \log n), \]
\[ \leq 2(\log(1+n))^{1/2} \log(2 + \log n)/\min(\varphi(n), 2 + \log n) \]
tends to zero when \( n \) goes to infinity, which implies
\[ 2\delta^{-2}C_1 (\log(1+n))^{1/2}(\log(\varphi(n)))/\varphi(n) \xrightarrow{n \to \infty} 0. \]
Since we take \( \delta \) depending only on \( \epsilon \) and \( \theta \), we deduce that there exists \( n(\epsilon, \theta) \geq 1 \) such that for all \( n \geq n(\epsilon, \theta) \),
\[ \delta^{-2}C_\theta /\varphi(n) \leq \epsilon \]
if \( \theta \in (0, 1) \), and
\[ 2\delta^{-2}C_1 (\log(1+n))^{1/2}(\log(\varphi(n)))/\varphi(n) \leq \epsilon \]
if \( \theta = 1 \). This gives, in any case,
\[
P[|\Re(c_n^{(N)})|/w_n \leq \delta] \leq 2\epsilon
\]
for \( n \geq n(\epsilon, \theta) \), \( N \geq \varphi(n) \). Now, for \( N \geq n \geq 1 \), \( c_n^{(N)} \) is an elementary symmetric function of random points on the unit circle whose joint distribution is absolutely continuous with respect to the distribution of \( N \) i.i.d., uniform points on the unit circle. For \( N = n \), \( |c_n^{(N)}| \) is equal to 1 and then different from 0. For \( N > n \), if we fix \( N - 1 \) of the \( N \) points on the circle, we have that \( c_n^{(N)} \) is an affine function of the last point, and then the conditional probability that \( c_n^{(N)} = 0 \) vanishes as soon as one of the two coefficients of this affine function is non-zero. Taking the constant coefficient, which is the \( n \)-th symmetric function of the \( N - 1 \) points which have been fixed, we deduce, by induction on \( N \), that \( P[c_n^{(N)} = 0] = 0 \) for all \( N \geq n \geq 1 \). Since the law of \( c_n^{(N)} \) is rotationally invariant, we have that \( P[|\Re(c_n^{(N)})| = 0] = 0 \) when \( |c_n^{(N)}| \neq 0 \), and then \( P[|\Re(c_n^{(N)})| = 0] = 0 \) since \( |c_n^{(N)}| \) is almost surely different from zero. Moreover, we know that \( \Re(c_n) \neq 0 \) almost surely: since \( c_n^{(N)} \) converges to \( c_n \) in law for \( n \) fixed and \( N \to \infty \), we have that for each \( n \geq 1 \), \( (w_n/|\Re(c_n^{(N)})|)_{N \geq n} \) is a tight family of real-valued random variables.

Hence, for each \( n \geq 1 \), there exists \( \delta_n > 0 \), depending only on \( n \), \( \epsilon \) and \( \theta \), such that
\[
\sup_{N \geq n} P[|\Re(c_n^{(N)})|/w_n \leq \delta_n] \leq 2\epsilon.
\]
Let us define
\[
\delta_0 := \min \left( \delta, \min_{1 \leq n < n(\epsilon, \theta)} \delta_n \right).
\]
We have that \( \delta_0 > 0 \) depends only on \( \epsilon \) and \( \theta \), and that
\[
\sup_{n \geq 1, N \geq n(\varphi(n))} P[|\Re(c_n^{(N)})|/w_n \leq \delta_0] \leq 2\epsilon,
\]
which implies
\[
\limsup_{\delta \to 0} \sup_{n \geq 1, N \geq n(\varphi(n))} P[|\Re(c_n^{(N)})|/w_n \leq \delta] \leq 2\epsilon.
\]
We are done, by letting \( \epsilon \to 0 \).

A Tauberian theory

Recall that a function \( L : [0, \infty) \to \mathbb{R} \) is called slowly varying if it is measurable, eventually positive and satisfies
\[
L(\lambda u)/L(u) \to 1 \quad \text{as} \quad u \to \infty \quad \text{for all} \quad \lambda > 0.
\]
The principal examples of such functions are logarithms, iterated logarithms, and powers thereof. These functions have many useful analytic properties (see [Kor04, Section IV.2] for details). Such functions appear frequently in Tauberian theory, and in particular in the following:

**Theorem A.1** (Karamata–Hardy–Littlewood Tauberian Theorem [Kor04, IV.1.1]). Let \( \sum_{k=0}^{\infty} a_k z^k \) converge for \( |z| < 1 \). Suppose that for some number \( \theta \geq 0 \) and some slowly varying function \( L \), we have the limit from below

\[
\lim_{z \to 1^-} L\left(\frac{1}{1-z}\right)(1-z)^\theta \sum_{k=0}^{\infty} a_k z^k = M
\]

(A.1)

Then subject to the condition

\[
L(k)k^\theta \geq -Ck^\theta, \quad k \geq 1
\]

(A.2)

it follows that

\[
\lim_{n \to \infty} \frac{L(n)\Gamma(\theta + 1)}{n^\theta} \sum_{k=0}^{n} a_k = M.
\]

(A.3)

We need to justify this in a probabilistic situation:

**Theorem A.2.** Fix \( \theta > 0 \) and a slowly varying function \( L \), and suppose for simplicity that \( \{a_k\}_{k=0}^{\infty} \) are a family of non-negative random variables such that the series \( \sum_{k=0}^{\infty} a_k z^k \) converges almost surely for \( |z| < 1 \). Suppose further that we have the convergence in probability

\[
L\left(\frac{1}{1-z}\right)(1-z)^\theta \sum_{k=0}^{\infty} a_k z^k \xrightarrow{p} M \quad \text{as} \quad z \to 1^-
\]

(A.4)

with \( M < \infty \) almost surely. Then it follows that

\[
\frac{L(n)\Gamma(\theta + 1)}{n^\theta} \sum_{k=0}^{n} a_k \xrightarrow{p} M.
\]

(A.5)

**Proof.** Let us define

\[
X_n = L\left(\frac{1}{1-e^{-1/n}}\right)(1-e^{-1/n})^\theta \sum_{k=0}^{\infty} a_k g(e^{-k/n})
\]

(A.6)

where

\[
g(x) = \begin{cases} 
0, & 0 \leq x < 1/e, \\
1, & 1/e \leq x \leq 1.
\end{cases}
\]

(A.7)
If we can show that \( X_n \xrightarrow{p}{n \to \infty} \frac{M}{\Gamma(\theta + 1)} \) we will have proved the result. To do this we construct polynomial approximations of \( g \) and bound from above and below. It is important to note that the construction of the polynomials is deterministic and does not depend on the random coefficients \( a_k \).

For any polynomial \( P \) without constant term, it is a direct computation using (A.4), using additivity of convergence in probability, and using the definition of slow variation, that

\[
L\left( \frac{1}{1-e^{-1/n}} \right) (1 - e^{-1/n})^\theta \sum_{k=0}^\infty a_k P(e^{-k/n}) \xrightarrow{p}{n \to \infty} \frac{M}{\Gamma(\theta)} \int_0^{\infty} t^{\theta-1} P(e^{-t}) \, dt. \tag{A.8}
\]

We claim that for any \( \varepsilon > 0 \) we can find polynomials \( P_\varepsilon^\pm(x) \) on \([0,1]\) without constant term, such that \( g(x) \leq P_\varepsilon^+(x) \) (and \( P_\varepsilon^-(x) \leq g(x) \)) and that \( P_\varepsilon^+(x) - g(x) \) (and \( g(x) - P_\varepsilon^-(x) \)) are both small. Since the coefficients \( a_k \) are non-negative, this allows us to sandwich \( X_n \) via

\[
X_{n,\varepsilon}^- \leq X_n \leq X_{n,\varepsilon}^+
\tag{A.9}
\]

where

\[
X_{n,\varepsilon}^\pm := L\left( \frac{1}{1-e^{-1/n}} \right) (1 - e^{-1/n})^\theta \sum_{k=0}^\infty a_k P_\varepsilon^\pm(e^{-k/n}). \tag{A.10}
\]

Now by (A.8) we have \( X_{n,\varepsilon}^\pm \xrightarrow{p}{X_\varepsilon^\pm} \) where

\[
X_\varepsilon^\pm = \frac{M}{\Gamma(\theta)} \left( \int_0^{\infty} t^{\theta-1} g(e^{-t}) \, dt \pm c^\pm(\varepsilon) \right)
\tag{A.11}
\]

and

\[
c^\pm(\varepsilon) = \int_0^{\infty} t^{\theta-1} |P_\varepsilon^\pm(e^{-t}) - g(e^{-t})| \, dt. \tag{A.12}
\]

We claim that \( P_\varepsilon^\pm(x) \) can be chosen so that \( 0 \leq c^\pm(\varepsilon) \leq c_0 \varepsilon \) for some absolute constant \( c_0 \) and so \( \lim_{\varepsilon \to 0} c^\pm(\varepsilon) = 0 \). This is enough to show convergence in probability of \( X_n \) to the limit \( X = \frac{M}{\Gamma(\theta + 1)} \), as we now demonstrate. By (A.9), we have for any \( \delta > 0 \)

\[
\mathbb{P}(|X_n - X| > \delta) \leq \mathbb{P}(|X_{n,\varepsilon}^+ - X| > \delta) + \mathbb{P}(|X_{n,\varepsilon}^- - X| > \delta)
\leq \mathbb{P}(|X_{n,\varepsilon}^+ - X^+| + |X^+ - X| > \delta)
+ \mathbb{P}(|X_{n,\varepsilon}^- - X^-| + |X^- - X| > \delta)
\leq \mathbb{P}(|X_{n,\varepsilon}^+ - X^+| > \delta/2) + \mathbb{P}(|X^+ - X| > \delta/2)
+ \mathbb{P}(|X_{n,\varepsilon}^- - X^-| > \delta/2) + \mathbb{P}(|X^- - X| > \delta/2)
\tag{A.13}
\]

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Since $\frac{X^\pm_n}{n} \xrightarrow{p} X^\pm$, two of the terms in the final inequality above vanish in the limit $n \to \infty$ for any fixed $\epsilon$. For the remaining terms, note that by definition

$$|X^\pm_n - X| = c^\pm(\epsilon)M/\Gamma(\theta) \quad (A.14)$$

so that in the limit $\epsilon \to 0$ we have, using the almost sure finiteness of $M$,

$$\mathbb{P}(|X^\pm_n - X| > \delta/2) = \mathbb{P}(M > \delta\Gamma(\theta)/(2c^\pm(\epsilon)) \to 0. \quad (A.15)$$

The existence of the approximating polynomials is classical, but for completeness we give the argument. We begin by sandwiching $g(x)$ by the continuous function $h^\pm(x)$ where $h^\pm(x)$ is equal to $g(x)$ outside $[1/e \mp \epsilon, 1/e]$ and is linear inside the interval. Then by the Weierstrass approximation theorem we get polynomials $P^\pm(x)/x$ such that

$$\left| \frac{h^\pm(x)}{x} \pm \epsilon - \frac{P^\pm(x)}{x} \right| \leq \epsilon, \quad 0 \leq x \leq 1. \quad (A.16)$$

Then $P^+_\epsilon(x) \geq h^+(x) \geq g(x)$ and $P^-_\epsilon(x) \leq h^-(x) \leq g(x)$. Now we can bound $c^\pm(\epsilon)$ using

$$c^\pm(\epsilon) \leq \int_0^\infty t^{\theta-1}|P^\pm_\epsilon(e^{-t}) - h^\pm(e^{-t})| \, dt + \int_0^\infty t^{\theta-1}|h^\pm(e^{-t}) - g(e^{-t})| \, dt \quad (A.17)$$

The substitution $x = e^{-t}$ shows that

$$c^\pm(\epsilon) \leq \int_0^1 (-\log(x))^{\theta-1} \left| \frac{P^\pm_\epsilon(x) - h^\pm(x)}{x} \right| \, dx + \int_{1/e}^{1/e+\epsilon} (-\log(x))^{\theta-1} \left| \frac{h^\pm(x) - g(x)}{x} \right| \, dx \quad (A.18)$$

The integrand in the second term of (A.18) is uniformly bounded, so the integral is bounded by a constant times the length of the integration interval, which is $\epsilon$. By (A.16) the first term in (A.18) is bounded by

$$2\epsilon \int_0^1 (-\log(x))^{\theta-1} \, dx = 2\epsilon\Gamma(\theta), \quad (A.19)$$

and so $|c^\pm(\epsilon)| \leq c_\theta\epsilon$ as desired. \hfill \Box

**Lemma A.3.** Let $Z_1 = X_1 + iY_1$ and $Z_2 = X_2 + iY_2$ be complex valued random variables with characteristic functions

$$\Phi_{Z_1}(s, t) = \mathbb{E} \left(e^{isX_1 + itY_1}\right)$$

$$\Phi_{Z_2}(s, t) = \mathbb{E} \left(e^{isX_2 + itY_2}\right) \quad (A.20)$$
Then

$$|\Phi_{Z_1}(s, t) - \Phi_{Z_2}(s, t)| \leq (|s| + |t|)\sqrt{E(|Z_1 - Z_2|^2)}. \quad (A.21)$$

Proof. This follows from the standard inequality $|e^{ix} - 1| \leq |x|$ valid for any real number $x$. We have

$$|\Phi_{Z_1}(s, t) - \Phi_{Z_2}(s, t)| \leq E\left(|e^{isX_1+itY_1} - e^{isX_2+iY_2}|\right)$$

$$= E\left(|e^{is(X_1-X_2)+it(Y_1-Y_2)} - 1|\right)$$

$$\leq E\left(|s(X_1 - X_2) + t(Y_1 - Y_2)|\right)$$

$$\leq |s|E\left(|X_1 - X_2|\right) + |t|E\left(|Y_1 - Y_2|\right)$$

$$\leq |s|\sqrt{E\left(|X_1 - X_2|^2\right)} + |t|\sqrt{E\left(|Y_1 - Y_2|^2\right)}$$

$$\leq (|s| + |t|)\sqrt{E\left(|Z_1 - Z_2|^2\right)}.$$ 

\[ \square \]

B Binomial sums

Lemma B.1. For any $0 < \theta < \frac{1}{2}$, we have

$$\sum_{k=0}^{\infty} \left(\frac{k + \theta - 1}{\theta - 1}\right)^2 = \frac{\Gamma(1-2\theta)}{\Gamma(1-\theta)^2}. \quad (B.1)$$

Proof. We have the generating function

$$\sum_{k=0}^{\infty} \left(\frac{k + \theta - 1}{\theta - 1}\right)z^k = (1-z)^{-\theta}, \quad |z| < 1 \quad (B.2)$$

so that by Parseval’s theorem

$$\sum_{k=0}^{\infty} \left(\frac{k + \theta - 1}{\theta - 1}\right)^2 = \frac{1}{2\pi} \int_0^{2\pi} |1 - e^{i\nu_1}|^{-2\theta} d\nu_1. \quad (B.3)$$

Now the right-hand side of \((B.3)\) coincides with that of \((B.1)\) by taking $k = 2$ in the Morris integral \((1.22)\) and using rotational invariance in the $\nu_2$ coordinate.

\[ \square \]

Lemma B.2. Let $a$ and $b$ be non-negative integers such that $b \geq a$, $c$ and $d$ real numbers such that $\left(\frac{q+c}{d}\right)$ is finite and well-defined on $a \leq q \leq b$. Then

$$\sum_{q=a}^{b} \left(\frac{q + c}{d}\right) = \left(\frac{b + c + 1}{d + 1}\right) - \left(\frac{a + c}{d + 1}\right). \quad (B.4)$$
Proof. This follows from summing the binomial coefficient identity
\[
\binom{q + c}{d} = \binom{q + c + 1}{d + 1} - \binom{q + c}{d + 1},
\] (B.5)
from \(q = a\) to \(q = b\), so that the sum telescopes and gives the right-hand side of \((B.4)\).

References

[ABB17] Louis-Pierre Arguin, David Belius, and Paul Bourgade. Maximum of the characteristic polynomial of random unitary matrices. *Comm. Math. Phys.*, 349(2):703–751, 2017.

[ABB+19] Louis-Pierre Arguin, David Belius, Paul Bourgade, Maksym Radziwill, and Kannan Soundararajan. Maximum of the Riemann zeta function on a short interval of the critical line. *Comm. Pure Appl. Math.*, 72(3):500–535, 2019.

[ABR20] Louis-Pierre Arguin, Paul Bourgade, and Maksym Radziwiłł. The Fyodorov-Hiary-Keating conjecture. I. *arXiv:2007.00988*, 2020.

[ABT92] Richard Arratia, Andrew D. Barbour, and Simon Tavaré. Poisson process approximations for the Ewens sampling formula. *Ann. Appl. Probab.*, 2(3):519–535, 1992.

[ABT03] Richard Arratia, Andrew D. Barbour, and Simon Tavaré. *Logarithmic Combinatorial Structures: a Probabilistic Approach*. European Mathematical Society, 2003.

[AJJ20] Juhan Aru, Antoine Jego, and Janne Junnila. Density of imaginary multiplicative chaos via Malliavin calculus. *arXiv e-prints*, page arXiv:2008.11768, August 2020.

[BJ10] Julien Barral and Xiong Jin. Multifractal analysis of complex random cascades. *Comm. Math. Phys.*, 297(1):129–168, 2010.

[BJM10a] Julien Barral, Xiong Jin, and Benoît Mandelbrot. Convergence of complex multiplicative cascades. *Ann. Appl. Probab.*, 20(4):1219–1252, 2010.
[BJM10b] Julien Barral, Xiong Jin, and Benoît Mandelbrot. Uniform convergence for complex \([0, 1]\)-martingales. *Ann. Appl. Probab.*, 20(4):1205–1218, 2010.

[BP03] Matthias Beck and Dennis Pixton. The Ehrhart polynomial of the Birkhoff polytope. *Discrete Comput. Geom.*, 30(4):623–637, 2003.

[BWW18] Nathanaël Berestycki, Christian Webb, and Mo Dick Wong. Random Hermitian matrices and Gaussian multiplicative chaos. *Probab. Theory Related Fields*, 172(1-2):103–189, 2018.

[CG06] Brian Conrey and Alex Gamburd. Pseudomoments of the Riemann zeta-function and pseudomagic squares. *J. Number Theory*, 117(2):263–278, 2006.

[CK15] Tom Claeys and Igor Krasovsky. Toeplitz determinants with merging singularities. *Duke Math. J.*, 164(15):2897–2987, 2015.

[CM09] E. Rodney Canfield and Brendan D. McKay. The asymptotic volume of the Birkhoff polytope. *Online J. Anal. Comb.*, (4):4, 2009.

[CMN18] Reda Chhaibi, Thomas Madaule, and Joseph Najnudel. On the maximum of the \(C\beta E\) field. *Duke Math. J.*, 167(12):2243–2345, 2018.

[CN19] Reda Chhaibi and Joseph Najnudel. On the circle, \(GMC_{\gamma} = \lim_{n \to \infty} C\beta E_{n}\) for \(\gamma = \sqrt{2}\), \((\gamma \leq 1)\). *arXiv:1904.00578*, 2019.

[DG06] Persi Diaconis and Alex Gamburd. Random matrices, magic squares and matching polynomials. *Electron. J. Combin.*, 11(2):Research Paper 2, 26, 2004/06.

[DLLY09] Jesus A. De Loera, Fu Liu, and Ruriko Yoshida. A generating function for all semi-magic squares and the volume of the Birkhoff polytope. *J. Algebraic Combin.*, 30(1):113–139, 2009.

[DRSV17] Bertrand Duplantier, Rémi Rhodes, Scott Sheffield, and Vincent Vargas. Log-correlated Gaussian fields: an overview. In *Geometry, analysis and probability*, volume 310 of *Progr. Math.*, pages 191–216. Birkhäuser/Springer, Cham, 2017.
[DRZ17] Jian Ding, Rishideep Roy, and Ofer Zeitouni. Convergence of
the centered maximum of log-correlated Gaussian fields. Ann.
Probab., 45(6A):3886–3928, 2017.

[DS94] Persi Diaconis and Mehrdad Shahshahani. On the eigenvalues
of random matrices. J. Appl. Probab., 31A:49–62, 1994. Studies
in applied probability.

[FB08] Yan V. Fyodorov and Jean-Philippe Bouchaud. Freezing and
extreme-value statistics in a random energy model with log-
arithmically correlated potential. J. Phys. A, 41(37):372001, 12, 2008.

[FHK12] Yan V. Fyodorov, Ghaith A. Hiary, and Jonathan P. Keating.
Freezing Transition, Characteristic Polynomials of Random Matrices, and the Riemann Zeta-Function. Phys. Rev.
Lett., 108:170601, 2012.

[FK14] Yan V. Fyodorov and Jonathan P. Keating. Freezing transi-
tions and extreme values: random matrix theory, and disor-
dered landscapes. Philos. Trans. R. Soc. Lond. Ser. A Math.
Phys. Eng. Sci., 372(2007):20120503, 32, 2014.

[Har20] Adam J. Harper. Moments of random multiplicative functions,
I: low moments, better than squareroot cancellation, and crit-
ical multiplicative chaos. Forum Math. Pi, 8:e1, 95, 2020.

[HH80] Peter Hall and Christopher C. Heyde. Martingale Limit Theory
and Its Application. Academic Press, 1980.

[HK15] Lisa Hartung and Anton Klimovsky. The glassy phase of the
complex branching Brownian motion energy model. Electron.
Commun. Probab., 20:no. 78, 15, 2015.

[HK18] Lisa Hartung and Anton Klimovsky. The phase diagram of the
complex branching Brownian motion energy model. Electron.
J. Probab., 23:Paper No. 127, 27, 2018.

[HKO01] Christopher P. Hughes, Jonathan P. Keating, and Neil
O’Connell. On the characteristic polynomial of a random uni-
tary matrix. Comm. Math. Phys., 220(2):429–451, 2001.
[HKS+96] Fritz Haake, Marek Kus, Hans-Jürgen Sommers, Henning Schomerus, and Karol Zyczkowski. Secular determinants of random unitary matrices. *Journal of Physics A: Mathematical and General*, 29(13):3641, 1996.

[JM15] Tiefeng Jiang and Sho Matsumoto. Moments of traces of circular beta-ensembles. *Ann. Probab.*, 43(6):3279–3336, 2015.

[JS17] Janne Junnila and Eero Saksman. Uniqueness of critical Gaussian chaos. *Electron. J. Probab.*, 22:Paper No. 11, 31, 2017.

[JSV19] Janne Junnila, Eero Saksman, and Lauri Viitasaari. On the regularity of complex multiplicative chaos. 2019.

[JSW18] Janne Junnila, Eero Saksman, and Christian Webb. Imaginary multiplicative chaos: Moments, regularity and connections to the Ising model. *arXiv e-prints*, page arXiv:1806.02118, June 2018.

[KN04] Rowan Killip and Irina Nenciu. Matrix models for circular ensembles. *Int. Math. Res. Not.*, (50):2665–2701, 2004.

[Kor04] Jacob Korevaar. *Tauberian Theory: A Century of Developments*. Springer, 2004.

[KRRGR18] Jonathan P. Keating, Brad Rodgers, Edva Roditty-Gershon, and Zeev Rudnick. Sums of divisor functions in $\mathbb{F}_q[t]$ and matrix integrals. *Math. Z.*, 288(1-2):167–198, 2018.

[Lac20] Hubert Lacoin. A universality result for subcritical Complex Gaussian Multiplicative Chaos. *arXiv e-prints*, page arXiv:2003.14024, March 2020.

[Led99] Michel Ledoux. Concentration of measure and logarithmic Sobolev inequalities. In *Séminaire de Probabilités, XXXIII*, volume 1709 of *Lecture Notes in Math.*, pages 120–216. Springer, Berlin, 1999.

[LOS18] Gaultier Lambert, Dmitry Ostrovsky, and Nick Simm. Subcritical multiplicative chaos for regularized counting statistics from random matrix theory. *Comm. Math. Phys.*, 360(1):1–54, 2018.
[LRV15] Hubert Lacoin, Rémi Rhodes, and Vincent Vargas. Complex Gaussian multiplicative chaos. *Comm. Math. Phys.*, 337(2):569–632, 2015.

[Mac15] Ian G. Macdonald. *Symmetric functions and Hall polynomials*. Oxford Classic Texts in the Physical Sciences. The Clarendon Press, Oxford University Press, New York, second edition, 2015. With contribution by A. V. Zelevinsky and a foreword by Richard Stanley, Reprint of the 2008 paperback edition [MR1354144].

[MRV16] Thomas Madaule, Rémi Rhodes, and Vincent Vargas. Glassy phase and freezing of log-correlated Gaussian potentials. *Ann. Appl. Probab.*, 26(2):643–690, 2016.

[MRW17] Francesco Mezzadri, Alexi K. Reynolds, and Brian Winn. Moments of the eigenvalue densities and of the secular coefficients of β-ensembles. *Nonlinearity*, 30(3):1034–1057, 2017.

[Naj18] Joseph Najnudel. On the extreme values of the Riemann zeta function on random intervals of the critical line. *Probab. Theory Related Fields*, 172(1-2):387–452, 2018.

[NSW20] Miika Nikula, Eero Saksman, and Christian Webb. Multiplicative chaos and the characteristic polynomial of the CUE: the $L^1$-phase. *Trans. Amer. Math. Soc.*, 373(6):3905–3965, 2020.

[PZ18] Elliot Paquette and Ofer Zeitouni. The maximum of the CUE field. *Int. Math. Res. Not. IMRN*, (16):5028–5119, 2018.

[Rem20] Guillaume Remy. The Fyodorov-Bouchaud formula and Liouville conformal field theory. *Duke Math. J.*, 169(1):177–211, 2020.

[RV14] Rémi Rhodes and Vincent Vargas. Gaussian multiplicative chaos and applications: a review. *Probab. Surv.*, 11:315–392, 2014.

[Sta89] Richard P. Stanley. Some combinatorial properties of Jack symmetric functions. *Adv. Math.*, 77(1):76–115, 1989.

[Sta99] Richard P. Stanley. *Enumerative combinatorics. Vol. 2*, volume 62 of *Cambridge Studies in Advanced Mathematics*. Cam-
bridge University Press, Cambridge, 1999. With a foreword by Gian-Carlo Rota and appendix 1 by Sergey Fomin.

[SW20] Eero Saksman and Christian Webb. The Riemann zeta function and Gaussian multiplicative chaos: Statistics on the critical line. *Ann. Probab.*, 48(6):2680–2754, 2020.

[Web15] Christian Webb. The characteristic polynomial of a random unitary matrix and Gaussian multiplicative chaos—the $L^2$-phase. *Electron. J. Probab.*, 20:no. 104, 21, 2015.

[Wu00] Liming Wu. A new modified logarithmic Sobolev inequality for Poisson point processes and several applications. *Probab. Theory Related Fields*, 118(3):427–438, 2000.