Largest Entries of Sample Correlation Matrices from Equi-correlated Normal Populations

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Abstract

The paper studies the limiting distribution of the largest off-diagonal entry of the sample correlation matrices of high-dimensional Gaussian populations with equi-correlation structure. Assume the entries of the population distribution have a common correlation coefficient $\rho > 0$ and both the population dimension p and the sample size n tend to infinity with $\log p = o(n^{\frac{1}{3}})$. As $0 < \rho < 1$, we prove that the largest off-diagonal entry of the sample correlation matrix converges to a Gaussian distribution, and the same is true for the sample covariance matrix as $0 < \rho < 1/2$. This differs substantially from a well-known result for the independent case where $\rho = 0$, in which the above limiting distribution is an extreme-value distribution. We then study the phase transition between these two limiting distributions and identify the regime of ρ where the transition occurs. It turns out that the thresholds of such a regime depend on n and converge to zero. If ρ is less than the threshold, larger than the threshold or is equal to the threshold, the corresponding limiting distribution is the extreme-value distribution, the Gaussian distribution and a convolution of the two distributions, respectively. The proofs rely on a subtle use of the Chen-Stein Poisson approximation method, conditioning, a coupling to create independence and a special property of sample correlation matrices. The results are then applied to evaluating the power of a high-dimensional testing problem of identity correlation matrix.

Keywords: maximum sample correlation, phase transition, multivariate normal distribution, Gumbel distribution, Chen-Stein Poisson approximation.

MSC(2010): Primary 62H10, 62E20; Secondary 60F05.

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1 Introduction

The correlation coefficient matrix is an important statistic in the multivariate analysis. It plays pivotal roles in the statistical analysis of a multivariate normal data. The maximum likelihood estimator is the sample correlation matrix. This paper investigates the limiting distribution of the largest off-diagonal entry of the sample correlation matrix in the high-dimensional setting when the correlation matrix admits a compound symmetry structure, namely, is of equi-correlation.

Let $N_p(0, \mathbf{\Sigma})$ stand for a p-variate normal population with the correlation matrix $\mathbf{R} = (\rho_{ij})_{p\times p}$. Let $X_1, \cdots, X_n$ be a random sample from the population $N_p(0, \mathbf{\Sigma})$. We have the data matrix $\mathbf{X} = (X_1, \cdots, X_n)'$. Write $\mathbf{X} = (x_{ij})_{n\times p} = (\mathbf{x}^{(1)}, \mathbf{x}^{(2)}, \cdots, \mathbf{x}^{(p)})$, then the Pearson correlation coefficient between $\mathbf{x}^{(i)}$ and $\mathbf{x}^{(j)}$ is given by

$$\hat{\rho}_{ij} = \frac{\sum_{k=1}^n (x_{ki} - \bar{x}_i)(x_{kj} - \bar{x}_j)}{\sqrt{\sum_{k=1}^n (x_{ki} - \bar{x}_i)^2}\sqrt{\sum_{k=1}^n (x_{kj} - \bar{x}_j)^2}}, \quad 1 \le i, j \le p, \tag{1.1}$$

where $\bar{x}_i = \frac{1}{n}\sum_{k=1}^n x_{ki}$. In particular, $\hat{\rho}_{ii} = 1$ for all $1 \le i \le p$. The sample correlation matrix $\hat{\mathbf{R}}$ is then defined by $\hat{\mathbf{R}} = (\hat{\rho}_{ij})_{p\times p}$. In contrast, $\mathbf{X}'\mathbf{X}/n$ is refereed to as the sample covariance matrix.

Define the largest magnitude of off-diagonal entries of the sample correlation matrix by

$$L_{0n} = \max_{1\le i<j\le p} |\hat{\rho}_{ij}|. \tag{1.2}$$

Assuming that x_{ij}'s are independent and identically distributed but not necessarily Gaussian-distributed, the asymptotic distribution of L_{0n} have been extensively studied as both p and n tend to infinity.

The first result on the topic is due to Jiang [9], who uses the Chen-Stein Poisson approximation method to get the limiting distribution of the L_{0n} as follows.

Assume $E|x_{11}|^{30+\epsilon} < \infty$ for some $\epsilon > 0$. Let $p = p_n$ and $\frac{n}{p} \to \gamma \in (0, \infty)$ as $n \to \infty$, then

$$P(nL_{0n}^2 - 4\log n + \log\log n \le t) \to \exp\Big(-\frac{\gamma^2}{\sqrt{8\pi}}e^{-t/2}\Big)$$

for any $t \in \mathbb{R}$, or equivalently,

$$P(nL_{0n}^2 - 4\log p + \log\log p \le t) \to \exp\Big(-\frac{1}{\sqrt{8\pi}}e^{-t/2}\Big). \tag{1.3}$$

Zhou [19] proves that the moment condition can be relaxed to that $\lim_{x\to\infty} x^6 P(|x_{11}x_{12}| > x) = 0$ and $\limsup_{n\to\infty} \frac{p}{n} < \infty$. Li and Rosalsky [12] consider the strong limit of L_{0n} under some more relaxed assumption. Li *et al.* [11, 13] have further improved the assumption of the result, under the assumption that $\frac{n}{p}$ bounded away from zero or infinity. They actually obtain some necessary and sufficient conditions for which (1.3) holds. As $p/n \to \infty$, Liu *et al.* [15] establish similar results to (1.3) under the assumption $p = O(n^\alpha)$ where α is a constant. Cai and Jiang [3] consider the ultra-high dimensional case where p can be as large as e^{n^α} for some $0 < \alpha \le 1$ and they extend the result to dependent case. Cai and Jiang [4] derive the limiting distribution of L_{0n} under the assumption that the population has a spherical distribution. In fact, a phase transition phenomenon occur at three different regimes: $\frac{\log p}{n} \to 0$, $\frac{\log p}{n} \to \alpha \in (0, \infty)$ and $\frac{\log p}{n} \to \infty$. By using the limiting distribution of L_{0n}, Cai *et al.* [2] work on the asymptotic behavior of the pairwise geodesic distances among n random points that are independently and uniformly distributed on the unit sphere in the p-dimensional spaces. The same phase transition phenomenon are also understood. Without the Gaussian assumption, Shao and Zhou [18] obtain similar results to (1.3) as $\log p = o(n^\alpha)$ for some $0 < \alpha \le 1$.

Assuming the p entries of $\mathbf{x}$ are independent, most of the aforementioned work mainly focus on the improvement of the moment assumption on x_{11} from the data matrix $\mathbf{X} = (x_{ij})_{n\times p}$ as well as relaxing the range of p relative to n. The question of how dependence impacts on the limiting distribution of the largest correlations remains largely unknown.

In this paper, we will consider a case that all the entries of $\mathbf{x}$ are very dependent. In fact, we assume $\mathbf{x} \sim N_p(\mu, \mathbf{\Sigma})$, and the corresponding correlation matrix $\mathbf{R}$ has the compound symmetry structure, which is also referred to as the intraclass covariance or equi-correlation structure in literature, that is,

$$\mathbf{R} \quad = \quad \begin{pmatrix} 1 & \rho & \cdots & \rho \\ \rho & 1 & \cdots & \rho \\ \vdots & \vdots & & \vdots \\ \rho & \rho & \cdots & 1 \end{pmatrix}. \tag{1.4}$$

It is easy to see that $\mathbf{R}$ is positive definite if and only if $1 > \rho > -1/(p-1)$. Since we will be in the scenario that $p = p_n \to \infty$, we will always assume $\rho \ge 0$ later.

When $\rho > 0$, the sample correlations $\hat{\rho}_{ij}$, $1 \le i < j \le p$ are highly dependent and new technical challenges arise in deriving the limiting distribution of the maximum value of these entries. In addition, we found somewhat surprisingly that such a limiting distribution is Gaussian. This is in sharp contrast to the independence case ($\rho = 0$) in which the limiting distribution is a Gumbel distribution. Where does the phase transition occur? In what way the limiting distribution changes over the regime of correlation ρ? We provide sharp asymptotic results to describe these regimes of ρ and their associated limiting distributions of the maximum correlation.

Related to our study is the maximum spurious correlation between each variable in X and an independent variable Y in which the variables in X are correlated. Fan *et al.* [8] derived the asymptotic distribution of such a maximum spurious correlation using Gaussian approximation techniques of Chernozhukov *et al.* [6]. Unless the correlation matrix of X is of a specific form, such a limiting distribution can not be analytically derived and they require a multiplier bootstrap method to estimate the limiting distribution. Their setting relates to our case with the last row of off-diagonal correlation equal to zero and only computes the maximum sample correlation in the last row, albeit these sample correlations are also dependent due to the dependence of X.

Some notations will be used in the paper. The symbol $\xrightarrow{d}$ means convergence in distribution, $\xi \overset{d}{=} \eta$ implies that ξ and η have the same distribution. Furthermore,

- $b_n = o(a_n)$ if $b_n/a_n \to 0$ and that $b_n = O(a_n)$ if $\limsup_{n\to\infty} |b_n/a_n| < \infty$.
- $\xi_n = o_p(a_n)$ if $\xi_n/a_n \to 0$ in probability as $n \to \infty$. And $\xi_n = O_p(a_n)$ if $\lim_{C\to\infty} \limsup_{n\to\infty} P(|\xi_n/a_n| > C) = 0$. In addition, we denote C and C_1 positive constants independent of n or p, and their values may be different from line to line.

The rest of the paper is organized as follows. Section 2 gives the main results, discussions and an application of the result. The proofs are relegated to Section 3, where we develop necessary technical tools for our quests.

2 Main results and discussions

Let $X_1, \cdots, X_n$ be a random sample from the population $N_p(\mu, \mathbf{\Sigma})$ with the population correlation matrix $\mathbf{R}$ defined as in (1.4). The data matrix is given by $\mathbf{X} = (X_1, \cdots, X_n)' = (x_{ij})_{n\times p}$.

We will study the following two statistics in this paper:

$$J_n = \max_{1\le i<j\le p} n^{-1} \sum_{k=1}^{n} x_{ki}x_{kj} \quad \text{and} \quad L_n = \max_{1\le i<j\le p} \hat{\rho}_{ij}, \tag{2.1}$$

where $\hat{\rho}_{ij}$ is defined as in (1.1).

The first is the maximum of normalized sample covariances when $\mu = 0$, whereas the second one is the maximum of the sample correlations. The purpose having the normalization in J_n is such that J_n and L_n have the same scale. To make our analysis thoroughly, we allow ρ to depend on n. We will see from (iii) of Theorems 2.1 and 2.2 later on that J_n and L_n behave differently as ρ is a constant.

2.1 Main results

We first consider the limiting distribution for the statistics J_n.

THEOREM **2.1** *Let $\rho_n \ge 0$ for each $n \ge 1$ and $\sup_{n\ge1} \rho_n < \frac{1}{2}$. Assume $\mu = \mathbf{0}$ and $\mathbf{\Sigma} = \mathbf{R}$, where $\mathbf{R}$ is given by (1.4). Suppose $p = p(n) \to \infty$ and $\log p = o(n^{\frac{1}{3}})$ as $n \to \infty$. Set*

$$\mu_1 = \sqrt{n}\rho_n + \Big(2\sqrt{\log p} - \frac{\log\log p}{4\sqrt{\log p}}\Big)\sqrt{1-\rho_n^2}.$$

The following holds as $n \to \infty$.
(i). If $\rho_n\sqrt{\log p} \to 0$, then

$$4\sqrt{\log p}\,\big(n^{1/2}J_n - \mu_1\big) \xrightarrow{d} \phi$$

where ϕ has distribution function $F(x) = e^{-Ke^{-\frac{x}{2}}}$, $x \in \mathbb{R}$ with $K = \frac{1}{4\sqrt{2\pi}}$.

(ii). If $\rho_n\sqrt{\log p} \to \lambda \in (0,\infty)$, then

$$\frac{n^{1/2}J_n - \mu_1}{\sqrt{2}\rho_n} \xrightarrow{d} \xi + \lambda_0\phi,$$

where $\xi \sim N(0,1)$, $\lambda_0 = \frac{1}{4\sqrt{2}\lambda}$, ϕ is as in (i) and ϕ is independent of ξ.
(iii). If $\rho_n\sqrt{\log p} \to \infty$, then

$$\frac{n^{1/2}J_n - \mu_1}{\sqrt{2}\rho_n} \xrightarrow{d} N(0,1).$$

The above theorem has the following implication.

COROLLARY **2.1** *Let $\rho \in (0, \frac{1}{2})$ be fixed, $\mu = \mathbf{0}$ and $\mathbf{\Sigma} = \mathbf{R}$, where $\mathbf{R}$ is as in (1.4). Suppose $p = p(n) \to \infty$ and $\log p = o(n^{\frac{1}{3}})$ as $n \to \infty$. Then*

$$\frac{n^{1/2}J_n - \mu_1}{\sqrt{2}\rho} \xrightarrow{d} N(0,1)$$

as $n \to \infty$, where $\mu_1 = \sqrt{n}\rho + 2\sqrt{(1-\rho^2)\log p}$.

For the largest entry of the sample correlation matrix $\hat{\mathbf{R}}$, we have the following.

THEOREM **2.2** *Let $\rho_n \geq 0$ for each $n \geq 1$ and $\sup_{n\geq 1}\rho_n < 1$. Assume $\mathbf{\Sigma} = \mathbf{R}$, where $\mathbf{R}$ is as in (1.4). Let $p = p(n) \to \infty$ satisfying $\log p = o(n^{\frac{1}{3}})$ as $n \to \infty$. Set*

$$\mu_2 = \sqrt{n-1}\,\rho_n + (1-\rho_n)\cdot\sqrt{1+2\rho_n-\rho_n^2}\cdot\Big(2\sqrt{\log p} - \frac{\log\log p}{4\sqrt{\log p}}\Big).$$

The following holds as $n \to \infty$.
(i). If $\rho_n\sqrt{\log p} \to 0$, then

$$4\sqrt{\log p}\left(\sqrt{n-1}L_n - \mu_2\right) \xrightarrow{d} \phi,$$

where ϕ has distribution function $F(x) = e^{-Ke^{-\frac{x}{2}}}$, $x \in \mathbb{R}$ with $K = \frac{1}{4\sqrt{2\pi}}$.
(ii). If $\rho_n\sqrt{\log p} \to \lambda \in (0,\infty)$, then

$$\frac{\sqrt{n-1}L_n - \mu_2}{\sqrt{2}\rho_n} \xrightarrow{d} \xi + \lambda_0\phi,$$

where $\xi \sim N(0,1)$, $\lambda_0 = \frac{1}{4\sqrt{2}\lambda}$ and ϕ is the same as in (i) and ϕ is independent of ξ.
(iii). If $\rho_n\sqrt{\log p} \to \infty$, then

$$\frac{\sqrt{n-1}L_n - \mu_2}{\sqrt{2}\rho_n(1-\rho_n)} \xrightarrow{d} N(0,1).$$

If ρ is close to zero, presumably the behavior of L_n is close to an extreme-value distribution as in (1.3); if ρ is relatively large, L_n is asymptotically the normal distribution as stated in Theorem 2.2. Item (ii) of the above theorem actually gives the phase transition between the two cases. The following is an easy consequence of Theorem 2.2.

COROLLARY **2.2** *Let $\rho \in (0,1)$ be fixed and $\mathbf{\Sigma} = \mathbf{R}$, where $\mathbf{R}$ is as in (1.4). Suppose $p = p(n) \to \infty$ and $\log p = o(n^{\frac{1}{3}})$ as $n \to \infty$. Then, $(\sqrt{n-1}L_n - \mu_2)/\sigma_2 \xrightarrow{d} N(0,1)$ as $n \to \infty$, where*

$$\mu_2 = \rho\sqrt{n-1} + 2(1-\rho)\cdot\sqrt{1+2\rho-\rho^2}\cdot\sqrt{\log p} \quad \text{and} \quad \sigma_2 = \sqrt{2}\rho(1-\rho).$$

The above two results are totally different from Jiang [9], Zhou [19], Liu *et al.* [15], Li *et al.* [11, 13], Cai and Jiang [3, 4], Cai *et al.* [2], Shao and Zhou [18]. They all end up with the Gumbel distribution by arguing that $\hat{\rho}_{ij}$'s are roughly independent random variables. In Theorems 2.1 and 2.2, the appearance of ρ creates a strong dependency among the terms $\sum_{k=1}^n x_{ki}x_{kj},\ 1 \le i < j \le p$, in the definition of J_n from (2.1). This is also true for the terms $\hat{\rho}_{ij},\ 1 \le i < j \le p$. The occurrence of ρ makes the situation so delicate that, if ρ is a constant, the limiting distributions of J_n and L_n are no longer the Gumbel distribution, they are the normal distribution instead.

For J_n (similarly for L_n), a key difference between the case $\rho = 0$ and the case $\rho > 0$ is explained as follows. For $\rho > 0$, each term of the denominator in (1.1) can no longer be regarded as roughly $\sqrt{n}$ as that in the case $\rho = 0$. In particular, if $\rho > 0$ is a constant, the dependence really matters, and the difference can be seen from Corollary 2.2 by comparing the means and the variances.

2.2 Discussions

The paper investigates the limiting distributions of the largest off-diagonal entry of sample covariance/correlation matrices generated by a random sample from a high-dimensional normal distribution. We assume the normal distribution has the structure of equi-correlation (1.4). Under the assumption that $p \to \infty$ and $\log p = o(n^{1/3})$, the asymptotical distributions of the largest off-diagonal entries of both matrices are established. Their behaviors depend on the value of ρ. The limits are the normal distribution if ρ is reasonably large; the limits are the extreme-value distribution if ρ is very small. We also figure out the regime to differentiate the two scenarios. In particular, for ρ in the regime, the limiting distribution is the convolution of the Gaussian distribution and the extreme-value distribution.

Next we make some comments.

1. For the sample correlation matrix $\hat{\mathbf{R}}$, we get the limiting distribution of its largest entry for each $\rho \in [0,1)$. The same result holds for the sample covariance matrix but under the more stringent restriction $0 \le \rho < 1/2$, which is required in Lemma 3.9. This difference will be easily understood by the fact that the sample correlation matrix can be regarded as a type of self-normalized statistics. It is known that self-normalized statistics are more "tamed"; see, for example, Shao and Wang [17]. And hence the range of ρ is more relaxed in the case of the sample correlation matrix than that in the

case of the sample covariance matrix. We do not know whether or not Theorem 2.1 is still true for the case $\rho \in [\frac{1}{2}, 1)$. It is an interesting project for future.

2. Under the Gaussian assumption and that for the equi-correlation $\mathbf{R}$ in (1.4), the decomposition structure of (3.77), i.e.,

$$X = \sqrt{\rho}(\xi, \cdots, \xi)' + \sqrt{1-\rho}(\xi_1, \cdots, \xi_p)' \tag{2.2}$$

where $\xi, \xi_1, \cdots, \xi_p$ are independent standard Gaussian random variables, plays a key role in the proofs. Now let us remove the Gaussian assumption. Instead, we assume the decomposition (2.2) continues to hold with $\xi, \xi_1, \cdots, \xi_p$ relaxed to independent random variables with mean zero, variance one, and a sub-Gaussian tail. Then Theorems 2.1 and 2.2 may also hold except (ii) from each theorem. The conclusion of (ii) is derived by using the Gaussian assumption essentially.

3. The paper deals with the equi-correlation matrix. If $\mathbf{R} = (r_{ij})$ has another special structure, one may like to work on $\max_{1\le i<j\le p} \hat{r}_{ij}$ or $\max_{1\le i<j\le p} \frac{\hat{r}_{ij}}{r_{ij}}$. It seems that, to get good properties for these two quantities, $\mathbf{R}$ can not be assumed to be too arbitrary.

4. Assuming $\rho = 0$, Jiang [10] obtains the limiting spectral distribution of the sample correlation matrix $\hat{\mathbf{R}}$. When $n/p \to c \in (0, \infty)$, the author proves that the empirical spectral distribution of $\hat{\mathbf{R}}$ asymptotically obeys the Marchenko-Pastur law. If $0 < \rho < 1$, by using the decomposition (3.77), it can be shown easily that the spectral distribution of the sample covariance matrix also takes the Marchenko-Pastur law as its limit. A similar result is expected for correlation matrix $\hat{\mathbf{R}}$ for the case $\rho > 0$ by employing the approximation method from Jiang [10].

5. *Methodology of our proofs.* The key elements in our proofs are a special property for sample correlation matrices under Gaussian assumptions, the Chen-Stein Poisson approximation method, conditioning arguments and a coupling to create independence. Let us take L_n from Theorem 2.2 to elaborate this next through a few steps.

a). The special property (Lemma 3.2) for sample correlation matrices allows us to remove $\bar{x}_i$ and $\bar{x}_j$ from the expression $\hat{\rho}_{ij}$ in (1.1). So we get an easier form of the target to work with.

b). With some efforts, we are able to write

$$L_n = \alpha_n + \beta_n Q_n + \gamma_n R_n \tag{2.3}$$

where $\alpha_n, \beta_n, \gamma_n$ are constants, Q_n goes to $N(0,1)$, R_n (the quantity M_n' from Proposition 3.2) is the maximum of sums of independent but non-identically distributed random variables; see (3.100).

c). We use the Chen-Stein Poisson approximation method to work on R_n. However, due to the strong dependency, we are not able to apply the method directly. In particular, the methods for deriving the limiting distribution of R_n under the assumption $\rho = 0$ in all earlier literature are no longer valid. We will use a conditioning trick. In fact, conditioning on certain event, we obtain the asymptotic distribution of R_n by the Chen-Stein method. After taking the expectation of the conditional probability, we finally derive the limiting distribution of R_n (Proposition 3.2).

d). We construct R_n' such that it is independent of Q_n in (2.3) (see Lemma 3.17) and it has the same asymptotic distribution as that of R_n. Furthermore, we show that the difference between L_n and $L_n' := \alpha_n + \beta_n Q_n + \gamma_n R_n'$ is negligible. So, basically speaking, L_n is reduced to a linear combination of two independent random variables such that one goes to the normal distribution and another goes to the extreme-value distribution.

2.3 An application to a high-dimensional test

Let $X_1, \cdots, X_n$ be a random sample from the population $N_p(\mu, \mathbf{\Sigma})$. We are interested in testing whether $\mathbf{\Sigma}$ is diagonal. A natural nonparametric test is to use the test statistic L_n, which is powerful for sparse alternatives. The null distribution of such a test statistic corresponds to the limiting distribution for case $\rho = 0$ in regime (i) of Theorem 2.2. A question arises naturally how powerful it is under the dense alternatives. The specific alternative of interest is

$$H_0 : \rho = 0 \qquad \text{vs} \qquad H_1 : \rho = \rho_1$$

where $\rho_1 \in (0, 1)$ is given.

Assume the dimension p and sample size n are all very large such that $\log p = o(n^{1/3})$. By (i) of Theorem 2.2, under H_0,

$$4\sqrt{\log p}\big(\sqrt{n-1}L_n - \mu_{20}\big) \xrightarrow{d} \phi,$$

where $\mu_{20} = 2\sqrt{\log p} - \frac{\log\log p}{4\sqrt{\log p}}$ and ϕ has distribution function $F(x) = e^{-Ke^{-\frac{x}{2}}}$, $x \in \mathbb{R}$ and $K = \frac{1}{4\sqrt{2\pi}}$. For $0 < \alpha < 1$, denote q_α the $(1-\alpha)$-quantile of the distribution $F(x)$, that is,

$$q_\alpha = -\log(32\pi) - 2\log\log(1-\alpha)^{-1}.$$

Then, a rejection region of the asymptotic size-α test is given by

$$\mathfrak{X}_0 = \Big\{\sqrt{n-1}L_n \geq 2\sqrt{\log p} + (q_\alpha - \log\log p)/(4\sqrt{\log p})\Big\}.$$

Using Theorem 2.2 (i) again, when $\rho_1 = o(1/\sqrt{\log p})$, the asymptotic power is still α, like a random guess, as the asymptotic distribution under such a contiguous alternative hypothesis is the same as that under the null hypothesis. Now the power starts to emerge when $\rho_1 = \lambda/\sqrt{\log p}$ for $\lambda \in (0, \infty)$ in regime (ii). In this case, it can be calculated that μ_2 in this regime is

$$\mu_{22} := \lambda\sqrt{\frac{n-1}{\log p}} + \Big[1 - \frac{2\lambda^2}{\log p} + O\big(\frac{1}{(\log p)^{3/2}}\big)\Big]\mu_{20}.$$

The power function is

$$\begin{aligned}\beta(\rho_1) &= P\big\{\sqrt{n-1}L_n \geq \mu_{20} + q_\alpha/(4\sqrt{\log p})|\rho_1\big\}\\ &= P\big\{4\sqrt{\log p}(\sqrt{n-1}L_n - \mu_{22}) \geq q_\alpha - 4\lambda\sqrt{n-1} + 16\lambda^2 + o(1)|\rho_1\big\}.\end{aligned}$$

According to Theorem 2.2(ii), the power tends to 1 for each fixed λ. By using a similar argument, it is easy to show that the power in region (iii) has also asymptotic power 1.

3 Proofs

The proofs of Theorems 2.1 and 2.2 are quite involved. We break them into small sections from each of which problems with a common feature are handled together. See the detail of each section given at the end of the Introduction.

3.1 A result on sample correlation matrices

In the following, we will present a special property of the sample correlation matrix $\hat{\mathbf{R}}$ as defined below (1.1). An auxiliary fact has to be derived first.

LEMMA **3.1** *Let $X_1, \cdots, X_n$ be i.i.d. random vectors and $X_1 \sim N_p(\mathbf{0}, \mathbf{\Sigma})$, where $\mathbf{\Sigma}$ is a $p \times p$ non-negative definite matrix. Set $\mathbf{X} = (X_1, \cdots, X_n)'$. Then, for any $n \times n$ orthogonal matrix $\mathcal{O}$, we have $\mathcal{O}\mathbf{X} \stackrel{d}{=} \mathbf{X}$.*

Proof. Let $Y_1, \cdots, Y_n$ be i.i.d. and $Y_1 \sim N_p(\mathbf{0}, \mathbf{I}_p)$. Then X_i and $\mathbf{\Sigma}^{1/2} Y_i$ have the same distribution for each i. By independence,

$$\mathbf{X} = (X_1, \cdots, X_n)' \stackrel{d}{=} (Y_1, \cdots, Y_n)' \mathbf{\Sigma}^{1/2}. \tag{3.1}$$

As a consequence,

$$\mathcal{O}\mathbf{X} \stackrel{d}{=} \mathcal{O}(Y_1, \cdots, Y_n)' \mathbf{\Sigma}^{1/2}$$

for any $n \times n$ orthogonal matrix $\mathcal{O}$. Write $(Y_1, \cdots, Y_n)' = (y_{ij})_{n \times p}$. Then y_{ij}'s are i.i.d. $N(0,1)$-distributed random variables. Hence $\mathcal{O}(Y_1, \cdots, Y_n)' \stackrel{d}{=} (Y_1, \cdots, Y_n)'$ by the orthogonal invariance of independent Gaussian random variables. It follows that

$$\mathcal{O}\mathbf{X} \stackrel{d}{=} (Y_1, \cdots, Y_n)' \mathbf{\Sigma}^{1/2} \stackrel{d}{=} \mathbf{X}$$

by (3.1). ■

The following lemma provides a simple expression for the sample correlation matrix.

LEMMA **3.2** *Let $X_1, \cdots, X_n$ be i.i.d. random vectors and $X_1 \sim N_p(\mu, \mathbf{\Sigma})$ where $\mu \in \mathbb{R}^p$ and $\mathbf{\Sigma}$ is a positive definite matrix. Let $\hat{\rho}_{ij}$ be as in (1.1). Suppose $Y_1, \cdots, Y_{n-1}$ are i.i.d. and $Y_1 \sim N_p(\mathbf{0}, \mathbf{\Sigma})$. Write $(Y_1, \cdots, Y_{n-1})' = (V_1, \cdots, V_p)_{(n-1)\times p}$. Then*

$$(\hat{\rho}_{ij})_{p \times p} \stackrel{d}{=} \left(\frac{V_i' V_j}{\|V_i\| \cdot \|V_j\|} \right)_{p \times p}.$$

Proof. Since $\hat{\rho}_{ij}$ is invariant under translation and scaling of the vectors $X_1, \cdots, X_n$, without loss generality, we assume $\mu = \mathbf{0}$ next.

Denotes $\mathbb{I} = (1, 1, \cdots, 1)' \in \mathbb{R}^{n \times 1}$ and $\mathbf{A}_{n \times n} = I_n - \frac{1}{n}\mathbb{I}\mathbb{I}'$. Trivially, $\mathbf{A}$ is an idempotent matrix with $tr(A) = n - 1$, then there exists an $n \times n$ orthogonal matrix $\mathcal{O}$ such that

$$\mathbf{A} = \mathcal{O}' \begin{pmatrix} I_{n-1} & 0 \\ 0 & 0 \end{pmatrix} \mathcal{O}.$$

Write

$$\begin{pmatrix} x_{1j}-\bar{x}_j \\ x_{2j}-\bar{x}_j \\ \vdots \\ x_{nj}-\bar{x}_j \end{pmatrix} = \mathbf{A} \begin{pmatrix} x_{1j} \\ x_{2j} \\ \vdots \\ x_{nj} \end{pmatrix}$$

for each $1 \le j \le p$. Write $\mathbf{X} = (X_1, \cdots, X_n)' = (x_{ij})_{n\times p}$. Then

$$\begin{aligned} \mathbf{H} &:= \begin{pmatrix} x_{11}-\bar{x}_1 & x_{12}-\bar{x}_2 & \cdots & x_{1p}-\bar{x}_p \\ x_{21}-\bar{x}_1 & x_{22}-\bar{x}_2 & \cdots & x_{2p}-\bar{x}_p \\ \vdots & \vdots & & \vdots \\ x_{n1}-\bar{x}_1 & x_{n2}-\bar{x}_2 & \cdots & x_{np}-\bar{x}_p \end{pmatrix} \\ &= \mathcal{O}' \begin{pmatrix} I_{n-1} & 0 \\ 0 & 0 \end{pmatrix} \mathcal{O}\mathbf{X} \\ &\stackrel{d}{=} \mathcal{O}' \begin{pmatrix} I_{n-1} & 0 \\ 0 & 0 \end{pmatrix} \mathbf{X} \end{aligned}$$

by Lemma 3.1. Then

$$\tilde{\mathbf{X}} := \begin{pmatrix} I_{n-1} & 0 \\ 0 & 0 \end{pmatrix} \mathbf{X} = \begin{pmatrix} (x_{ij})_{(n-1)\times p} \\ \mathbf{0} \end{pmatrix}$$

where $\mathbf{0}$ above is a p-dimensional row vector with all entries equal to zero. Therefore, $\mathbf{H} \stackrel{d}{=} \mathcal{O}'\tilde{\mathbf{X}}$ and hence

$$\mathbf{H}'\mathbf{H} \stackrel{d}{=} \tilde{\mathbf{X}}'\tilde{\mathbf{X}} = (x_{ij})'_{(n-1)\times p}(x_{ij})_{(n-1)\times p}.$$

Define $(x_{ij})_{(n-1)\times p} = (V_1, \cdots, V_p)_{(n-1)\times p}$. The above implies

$$\mathbf{H}'\mathbf{H} \stackrel{d}{=} (V_i'V_j)_{p\times p}. \tag{3.2}$$

For a positive definite matrix $\mathbf{M} = (m_{ij})_{p\times p}$, define $h(\mathbf{M})$ to be a $p\times p$ matrix such that its (i,j)-entry is equal to $m_{ij}m_{ii}^{-1/2}m_{jj}^{-1/2}$. Let $\mathcal{M}_{p\times p}$ be the set of all $p\times p$ positive definite matrices. Then, $h : \mathcal{M}_{p\times p} \to \mathcal{M}_{p\times p}$ is continuous map, and therefore is Borel-measurable map. From (3.2) we conclude $h(\mathbf{H}'\mathbf{H}) \stackrel{d}{=} h\big((V_i'V_j)_{p\times p}\big)$. The desired conclusion then follows. ■

3.2 Some technical tools

We will collect and prove some technical tools for the proof of Theorems 2.1 and 2.2. The first one is the Chen-Stein Poisson approximation method, which is a special case of Theorem 1 from Arratia, Goldstein and Gordon [1].

LEMMA **3.3** *Let η_α be random variables on an index set I and $\{B_\alpha, \alpha \in I\}$ be a set of subsets of I, that is, for each $\alpha \in I$, $B_\alpha \subset I$. For any $t \in \mathbb{R}$, set $\lambda = \sum_{\alpha\in I} P(\eta_\alpha > t)$, Then we have*

$$\Big|P(\max_{\alpha\in I}\eta_\alpha \le t) - e^{-\lambda}\Big| \le (1\wedge\lambda^{-1})(b_1+b_2+b_3),$$

where

$$
\begin{aligned}
b_1 &= \sum_{\alpha\in I}\sum_{\beta\in B_\alpha} P(\eta_\alpha > t)P(\eta_\beta > t),\\
b_2 &= \sum_{\alpha\in I}\sum_{\alpha\neq\beta\in B_\alpha} P(\eta_\alpha > t, \eta_\beta > t),\\
b_3 &= \sum_{\alpha\in I}\big|P\{\eta_\alpha > t|\sigma(\eta_\beta, \beta\notin B_\alpha)\} - P(\eta_\alpha > t)\big|,
\end{aligned}
$$

and $\sigma(\eta_\beta, \beta\notin B_\alpha)$ is the σ-algebra generated by $\{\eta_\beta, \beta\notin B_\alpha\}$. In particular, if η_α is independent of $\{\eta_\beta, \beta\notin B_\alpha\}$ for each α, then b_3 vanishes.

The next lemma is on the moderation deviation of the partial sum of i.i.d. random variables. It can be seen, for instance, from Linnik [14].

LEMMA **3.4** *Suppose $\{\zeta, \zeta_1, \zeta_2, \cdots\}$ is a sequence of i.i.d. random variables with $E\zeta_1 = 0$ and $E\zeta_1^2 = 1$. Define $S_n = \sum_{i=1}^n \zeta_i$. If $Ee^{t_0|\zeta|^\alpha} < \infty$ for some $0<\alpha\le 1$ and $t_0>0$, then*

$$\lim_{n\to\infty}\frac{1}{x_n^2}\log P\Big(\frac{S_n}{\sqrt{n}} \ge x_n\Big) = -\frac{1}{2}$$

for any $x_n\to\infty, x_n = o(n^{\frac{\alpha}{2(2-\alpha)}})$.

The following lemma is on the moderation deviation of the partial sum of the independent but not necessarily identically distributed random variables. It can be seen in Proposition 4.5 from Chen *et al.* [5].

LEMMA **3.5** *Let η_i, $1\le i\le n$ be independent random variables with $E\eta_i = 0$ and $Ee^{h_n|\eta_i|}<\infty$ for some $h_n>0$ and $1\le i\le n$. Assume that $\sum_{i=1}^n E\eta_i^2 = 1$. Then*

$$\frac{P(\sum_{i=1}^n \eta_i \ge x)}{1-\Phi(x)} = 1 + C_n(1+x^3)\gamma e^{4x^3\gamma}$$

for all $0\le x\le h_n$ and $\gamma = \sum_{i=1}^n E\big(|\eta_i|^3 e^{x|\eta_i|}\big)$, where $\sup_{n\ge1}|C_n|\le C$ and C is an absolute constant.

In our framework, η_i above is a quadratic form of two independent normals for each i. We first need to control $E\big(|\eta_i|^3e^{x|\eta_i|}\big)$.

LEMMA **3.6** *Let U and V be i.i.d. $N(0,1)$-distributed random variables. Let a,b,c,d,e,f be real numbers. Set $\eta = aU^2 + bUV + cV^2 + dU + eV + f$. Then*

$$E\big(|\eta|^3e^{x|\eta|}\big) \;\le\; C\cdot(|a|^3+|b|^3+|c|^3+|d|^3+|e|^3+|f|^3)\cdot e^{2(d^2+e^2)x^2+|f|x}$$

as $0<x\le\frac{1}{12(|a|+|b|+|c|)}$, where C is constant not depending on a,b,c,d,e or f.

Proof. First, use $|UV| \le U^2+V^2$ to see

$$|\eta| \;\le\; (|a|+|b|)U^2+(|b|+|c|)V^2+|dU+eV|+|f|. \qquad (3.3)$$

In particular,

$$\begin{aligned} E|\eta|^9 &\le 4^8\cdot E\big[(|a|+|b|)^9U^{18}+(|b|+|c|)^9V^{18}+|dU+eV|^9+|f|^9\big]\\ &\le C_1\big[(|a|+|b|)^9+(|b|+|c|)^9+(d^2+e^2)^{9/2}+|f|^9\big]\\ &\le C_1\big[(|a|+|b|+|c|)^9+(|d|+|e|)^9+|f|^9\big]\end{aligned}$$

where C_1 is a constant not depending on a,b,c,d,e or f. We also use the facts $E(U^{18}+V^{18})<\infty$ and $dU+eV\overset{d}{=}\sqrt{d^2+e^2}U$. It follows that

$$(E|\eta|^9)^{1/3}\le C_1^{1/3}(|a|+|b|+|c|+|d|+|e|+|f|)^3.$$

From (3.3),

$$\begin{aligned} E\big(|\eta|^3e^{x|\eta|}\big) &\le (E|\eta|^9)^{1/3}\cdot\big[E\exp\big(3x(|a|+|b|)U^2+3x(|b|+|c|)V^2\big)\big]^{1/3}\\ &\qquad\cdot\big[E\exp(3x|dU+eV|)\big]^{1/3}\cdot e^{x|f|}.\end{aligned}$$

First,

$$\begin{aligned} Ee^{3x\cdot|dU+eV|} &= Ee^{3x\sqrt{d^2+e^2}|U|}\\ &\le Ee^{3x\sqrt{d^2+e^2}U}+Ee^{-3x\sqrt{d^2+e^2}U}=2e^{9x^2(d^2+e^2)/2}\end{aligned}$$

by using the identity $Ee^{tN(0,1)}=e^{t^2/2}$ for all $t\in\mathbb{R}$. Second, setting $\alpha=3x(|a|+|b|)$ and $\beta=3x(|b|+|c|)$, and reviewing $Ee^{sU^2}=(1-2s)^{-1/2}$ for all $s<\frac{1}{2}$, we have

$$\begin{aligned} &E\exp\big(3x(|a|+|b|)U^2+3x(|b|+|c|)V^2\big)\\ =\;&(1-2\alpha)^{-1}\cdot(1-2\beta)^{-1}\\ \le\;&4\end{aligned}$$

if $\alpha\le\frac{1}{4}$ and $\beta\le\frac{1}{4}$ by independence. Finally, combining the above, we see

$$E\big(|\eta|^3e^{x|\eta|}\big)\;\le\; C\cdot(|a|+|b|+|c|+|d|+|e|+|f|)^3e^{2(d^2+e^2)x^2+|f|x}$$

as $0<x\le\frac{1}{12(|a|+|b|+|c|)}$. The conclusion then comes from an inequality on convex function $f(x):=x^3$ for $x\ge 0$. ■

In our setting, the parameter γ from Lemma 3.5 needs a special care. This will be done below with the help of Lemma 3.6.

LEMMA **3.7** *Let $\{\xi_k;\,k\ge1\}$ be i.i.d. $N(0,1)$-distributed random variables. Set $\tau=E(|\xi_1|^3)+1$. Assume $p=p_n$ satisfies that $p\to\infty$ and $\log p=o(n^{1/3})$. Let $\{y_n>0;\,n\ge1\}$ be real numbers such that $y_n=O(\log p)$. Then,*

$$P\Big(\frac{1}{n}\sum_{k=1}^{n}(1+|\xi_k|^3)e^{y_n\xi_k^2/n}\ge 2\tau\Big)\le\exp\Big(-\frac{1}{4}n^{1/2}(\log n)^{-2}\Big)$$

as n is sufficiently large.

Proof. By assumption, we assume $y_n \leq N_0 \log p$ for all $n \geq 1$, where $N_0 > 0$ is a constant. For $\epsilon > 0$, set $\Theta_\epsilon = \{\max_{1\leq k\leq n} \xi_k^2 \leq \epsilon n/y_n\}$. By the inequality $P(N(0,1) \geq y) \leq \frac{1}{\sqrt{2\pi}y} e^{-y^2/2} \leq e^{-y^2/2}$ for all $y \geq 1$, there exists a constant $n_1 \geq 1$ such that

$$P(\Theta_\epsilon^c) \leq nP\big(|\xi_1| > (\epsilon n/y_n)^{1/2}\big) \leq n \cdot \exp\Big(-\frac{\epsilon}{2}\cdot\frac{n}{y_n}\Big)$$

as $n \geq n_1$, which is again bounded by

$$n \cdot \exp\Big(-\frac{\epsilon}{2N_0}\cdot\frac{n}{\log p}\Big) \leq n \cdot e^{-n^{2/3}}$$

as $n \geq n_\epsilon \geq n_1$, where $n_\epsilon \geq 1$ is an integer depending on ϵ. It follows that

$$\begin{aligned} & P\Big(\frac{1}{n}\sum_{k=1}^n (1+|\xi_k|^3)e^{y_n\xi_k^2/n} \geq 2\tau\Big) \\ \leq\ & P\Big(\frac{1}{n}\sum_{k=1}^n (1+|\xi_k|^3)e^{\epsilon} \geq 2\tau\Big) + n\cdot e^{-n^{2/3}} \end{aligned}$$

as $n \geq n_\epsilon$. Take $\epsilon = \log\frac{4}{3}$. Then $2e^{-\epsilon}\tau = \frac{3}{2}\tau$. Consequently,

$$\begin{aligned} & P\Big(\frac{1}{n}\sum_{k=1}^n (1+|\xi_k|^3)e^{\epsilon} \geq 2\tau\Big) \\ =\ & P\Big(\frac{1}{n}\sum_{k=1}^n (|\xi_k|^3 - E(|\xi_k|^3) \geq \frac{1}{2}\tau\Big) \\ \leq\ & P\Big(\frac{1}{\sqrt{n}}\sum_{k=1}^n \zeta_k \geq x_n\Big) \end{aligned}$$

as n is sufficiently large, where $\zeta_k = \big(|\xi_k|^3 - E(|\xi_k|^3)\big)/\sqrt{\mathrm{Var}(\xi_1^3)}$ and $x_n = n^{1/4}/\log n$. Set $\sigma = \sqrt{\mathrm{Var}(\xi_1^3)}$. Observe that $\sigma^{2/3}\cdot|\zeta_k|^{2/3} \leq |\xi_k|^2 + (E|\xi_k|^3)^{2/3}$. This implies $E\exp(\frac{1}{4}\sigma^{2/3}|\zeta_k|^{2/3}) < \infty$ since $\xi_k \sim N(0,1)$. Take $\alpha = \frac{2}{3}$ in Lemma 3.4 to see

$$P\Big(\frac{1}{\sqrt{n}}\sum_{k=1}^n \zeta_k \geq x_n\Big) \leq \exp\Big(-\frac{1}{4}n^{1/2}(\log n)^{-2}\Big)$$

as n is sufficiently large. In summary,

$$P\Big(\frac{1}{n}\sum_{k=1}^n (1+|\xi_k|^3)e^{y_n\xi_k^2/n} \geq 2\tau\Big) \leq \exp\Big(-\frac{1}{4}n^{1/2}(\log n)^{-2}\Big) + n\cdot e^{-n^{2/3}}.$$

This implies the desired inequality. ■

The following result provides us with an equivalent expression on a limit theorem. It will be applied to the proofs of Propositions 3.1 and 3.2 later, in which $F(x)$ is an extreme-value distribution.

Lemma **3.8** *Let M_n be a random variable for each $n \geq 1$ satisfying*

$$\lim_{n\to\infty} P\big(M_n \leq \sqrt{4\log p - \log\log p + x}\big) = F(x)$$

for any $x \in \mathbb{R}$, where $F(x)$ is a continuous distribution function on $\mathbb{R}$. Then

$$M_n = 2\sqrt{\log p} - \frac{\log\log p}{4\sqrt{\log p}} + \frac{1}{4\sqrt{\log p}} U_n,$$

where U_n converges weakly to a probability measure with distribution function $F(x)$.

Proof. Easily, $(1+t)^{1/2} = 1 + \frac{1}{2}t + r(t)$ where $\sup_{|t|<\epsilon} |r(t)| \leq t^2$ for some $\epsilon > 0$. Fix $x_0 \in \mathbb{R}$. Let $A_0 > 0$ be given. For any $x \in [x_0 - A_0, x_0 + A_0]$,

$$\begin{aligned}\sqrt{4\log p - \log\log p + x} &= 2\sqrt{\log p}\Big(1 - \frac{\log\log p}{4\log p} + \frac{x}{4\log p}\Big)^{1/2} \\ &= 2\sqrt{\log p}\Big[1 - \frac{\log\log p}{8\log p} + \frac{x}{8\log p} + r(p,x)\Big]\end{aligned}$$

where

$$\begin{aligned}\sup_{|x-x_0|\leq A_0} |r(p,x)| &\leq \sup_{|x-x_0|\leq A_0} \Big(\frac{\log\log p}{4\log p} - \frac{x}{4\log p}\Big)^2 \\ &\leq \frac{(\log\log p)^2}{15(\log p)^2}\end{aligned}$$

as n is large enough. By the given condition,

$$\lim_{n\to\infty} P\Big(M_n \leq 2\sqrt{\log p} - \frac{\log\log p}{4\sqrt{\log p}} + \frac{x}{4\sqrt{\log p}} + s(p,x)\Big) = F(x) \tag{3.4}$$

as $n \to \infty$, where $s(p,x) := 2r(p,x)\sqrt{\log p}$ and

$$\sup_{|x-x_0|\leq A_0} |s(p,x)| \leq \frac{(\log\log p)^2}{7(\log p)^{3/2}} \tag{3.5}$$

as n is sufficiently large. Define

$$U_n = 4\sqrt{\log p}\Big(M_n - 2\sqrt{\log p} + \frac{\log\log p}{4\sqrt{\log p}}\Big). \tag{3.6}$$

Then (3.4) implies that

$$\lim_{n\to\infty} P(U_n \leq x + t(p,x)) = F(x) \tag{3.7}$$

where $t(p,x) := 4s(p,x)\sqrt{\log p}$. Easily, from (3.5),

$$\sup_{|x-x_0|\leq A_0} |t(p,x)| \leq \frac{(\log\log p)^2}{\log p}$$

as n is sufficiently large. Therefore, for any $\delta > 0$,

$$P(U_n \le x - \delta) \le P(U_n \le x + t(p, x)) \le P(U_n \le x + \delta)$$

as n is sufficiently large. From (3.7),

$$\limsup_{n\to\infty} P(U_n \le x - \delta) \le F(x) \le \liminf_{n\to\infty} P(U_n \le x + \delta)$$

for any $x \in [x_0 - A_0, x_0 + A_0]$. For $\delta \in (0, A_0)$, taking $x = x_0 + \delta$ and $x = x_0 - \delta$, respectively, we have

$$\limsup_{n\to\infty} P(U_n \le x_0) \le F(x_0 + \delta);$$
$$\liminf_{n\to\infty} P(U_n \le x_0) \ge F(x_0 - \delta).$$

Letting $\delta \downarrow 0$, we obtain $\lim_{n\to\infty} P(U_n \le x_0) = F(x_0)$. Since $x_0 \in \mathbb{R}$ is arbitrary, the limit together with (3.6) concludes the proof. ∎

3.3 A proposition on the largest entry of a sample covariance matrix

In this section, we will use the Chen-Stein Poisson approximation method to get the asymptotical distribution of a statistic M_n defined in Proposition 3.1 later. The quantity M_n will serves as a key building block to understand the largest entry of a sample covariance matrix. Literally, it will be used in the proof of Theorem 2.1.

For convenience, the following notation will be used throughout the rest of the paper.

(1). The random variables

$$\{\xi_k, \xi_k', \xi_{ki};\ k, i = 1, 2, \cdots\} \text{ are i.i.d. with } N(0,1)\text{-distribution.} \tag{3.8}$$

(2). Given $\rho_n \in [0, 1)$ for each $n \ge 1$, set $\rho_n' = 1 - \rho_n$,

$$a_n = \sqrt{\frac{\rho_n'}{1 + \rho_n}} \quad \textit{and} \quad b_n = \sqrt{\frac{\rho_n}{1 + \rho_n}}. \tag{3.9}$$

(3). For $x \in \mathbb{R}$ and integer $p \ge 1$, set

$$s_p = \sqrt{4 \log p - \log\log p + x}. \tag{3.10}$$

In our theorems we assume $p \to \infty$, so s_p is well-defined as p is large. This clarification will not repeated in the future.

(4). Let ξ_i's be as in (3.8). we write

$$\xi = (\xi_1, \cdots, \xi_n)' \quad \text{and} \quad \|\xi\| = (\xi_1^2 + \cdots + \xi_n^2)^{1/2}. \tag{3.11}$$

Before stating the main result in this section, we will first establish a technical tool, which will play a key role in the proof of the Lemma 3.12 in the sequel.

LEMMA **3.9** *Review the notations in (3.8)-(3.10). Assume* $\rho_n \geq 0$ *for all* $n \geq 1$ *and* $\sup_{n\geq 1} \rho_n < \frac{1}{2}$. *Define* $Z_n = \frac{b_n}{\sqrt{n}} \sum_{k=1}^n \xi_k \xi_k'$. *If* $p = p_n \to \infty$ *and* $\log p = o(n^{1/3})$ *as* $n \to \infty$, *then there exists a constant* $\delta \in (0,1)$ *such that*

$$E \exp\Big[-\frac{1+\rho_n}{1+\delta}(Z_n - s_p)^2 \Big] = o\Big(\frac{1}{p^3}\Big)$$

as $n \to \infty$.

Proof. If $\rho_n = 0$ for some $n \geq 1$, then $Z_n = 0$ and the expectation in the lemma is identical to $\exp(-(4\log p - \log\log p + x)/(1+\delta))$, which, by taking $\delta \in (0,1)$ small enough, is bounded by $p^{-3.5}$ as n is sufficiently large. Therefore, to prove the lemma, w.l.o.g., we assume $\rho_n > 0$ for all $n \geq 1$.

First, we show

$$Ee^{-\alpha_1(\xi_1-\beta_1)^2} = \frac{1}{\sqrt{2\alpha_1+1}} \exp\Big(-\frac{\alpha_1\beta_1^2}{2\alpha_1+1}\Big) \tag{3.12}$$

for any $\alpha_1 > 0$ and $\beta_1 \in \mathbb{R}$. In fact

$$Ee^{-\alpha_1(\xi_1-\beta_1)^2} = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\alpha_1(x-\beta_1)^2 - \frac{x^2}{2}}\, dx.$$

Write

$$-\alpha_1(x-\beta_1)^2 - \frac{x^2}{2} = -\Big(\sqrt{\alpha_1 + \frac{1}{2}}\,x - \frac{\alpha_1\beta_1}{\sqrt{\alpha_1+\frac{1}{2}}}\Big)^2 - \frac{\alpha_1\beta_1^2}{2\alpha_1+1}.$$

Now, define y such that

$$\frac{y}{\sqrt{2}} = \sqrt{\alpha_1+\frac{1}{2}}\,x - \frac{\alpha_1\beta_1}{\sqrt{\alpha_1+\frac{1}{2}}}.$$

It follows that

$$\begin{aligned} &\frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\alpha_1(x-\beta_1)^2 - \frac{x^2}{2}}\, dx \\ = \;& \exp\Big(-\frac{\alpha_1\beta_1^2}{2\alpha_1+1}\Big) \cdot \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-y^2/2}\, dy \cdot \frac{1}{\sqrt{2\alpha_1+1}}. \end{aligned}$$

Thus, (3.12) holds.

Recall the notation (3.11). By Proposition 7.3 from Eaton [7] or Theorem 1.5.6 from Murihead [16], we know $\|\xi\|$ and $\frac{\xi}{\|\xi\|}$ are independent. Also, $\frac{1}{\|\xi\|}\sum_{k=1}^n \xi_k\xi_k' \sim N(0,1)$ by independence. Consequently,

$$Z_n \overset{d}{=} b_n \cdot \frac{\|\xi\|}{\sqrt{n}} \cdot \xi_1'. \tag{3.13}$$

In particular, $\frac{\|\xi\|}{\sqrt{n}}$ and ξ_1' are independent. Let $\tau = \frac{1+\delta}{1+\rho_n}$. Observe

$$E\exp\Big[-\frac{(Z_n-s_p)^2}{\tau}\Big] = Ee^{-\alpha_1(\xi_1'-\beta_1)^2} = E\big[E_1 e^{-\alpha_1(\xi_1'-\beta_1)^2}\big] \tag{3.14}$$

where E_1 stands for the conditional expectation given $\|\xi\|$,

$$\alpha_1 = \frac{b_n^2\|\xi\|^2}{n\tau} \quad \text{and} \quad \beta_1 = \frac{\sqrt{n}s_p}{b_n\|\xi\|}.$$

By using (3.12), we obtain

$$\begin{aligned} E_1 e^{-\alpha_1(\xi_1'-\beta_1)^2} &\le \exp\Big(-\frac{s_p^2}{\tau + 2b_n^2\frac{\|\xi\|^2}{n}}\Big) \\ &\le \exp\Big\{-\frac{s_p^2}{(1+\delta)[(1+\rho_n)^{-1}+2b_n^2]}\Big\} \end{aligned} \tag{3.15}$$

if $\frac{\|\xi\|^2}{n} < 1+\delta$. Observe that $(1+\rho_n)^{-1}+2b_n^2 = \frac{1+2\rho_n}{1+\rho_n} \le \frac{1+2\rho}{1+\rho} < \frac{4}{3}$ for all $n\ge 1$, where $\rho := \sup_{n\ge1}\rho_n < \frac{1}{2}$ by assumption. Take $\delta\in(0,1)$ such that $\theta := (1+\delta)\frac{1+2\rho}{1+\rho} < \frac{4}{3}$. Hence, given $\frac{\|\xi\|^2}{n} < 1+\delta$,

$$E_1 e^{-\alpha_1(\xi_1'-\beta_1)^2} \le \frac{(\log p)^{5/\theta}}{p^{4/\theta}}$$

as n is sufficiently large. By the large deviations for i.i.d. random variables, there exists a constant $C>0$ depending on τ only such that $P(\frac{\|\xi\|^2}{n}\ge 1+\delta) < e^{-nC}$ for all $n\ge1$. Combining the above inequality, (3.14) and (3.15), we arrive at

$$\begin{aligned} & E\exp\Big[-\frac{(Z_n-s_p)^2}{\tau}\Big] \\ = \;& E\Big[E_1 e^{-\alpha_1(\xi_1'-\beta_1)^2} I\Big(\frac{\|\xi\|^2}{n} < 1+\delta\Big)\Big] + P\Big(\frac{\|\xi\|^2}{n}\ge 1+\delta\Big) \\ \le \;& \frac{(\log p)^{5/\theta}}{p^{4/\theta}} + e^{-nC} = o\Big(\frac{1}{p^3}\Big) \end{aligned}$$

where the last equality follows from the assumption $\log p = o(n^{1/3})$. ■

Now we state the main result in the section. Review the notations in (3.8)-(3.10). Define

$$\eta_{kij} = a_n\xi_{ki}\xi_{kj} + b_n\xi_k(\xi_{ki}+\xi_{kj}); \tag{3.16}$$

$$M_{nij} = \frac{1}{\sqrt{n}}\sum_{k=1}^n \eta_{kij} \tag{3.17}$$

for all $1\le i<j\le p$.

Proposition 3.1 *Let* $\rho_n \geq 0$ *for each* $n \geq 1$ *and* $\sup_{n\geq 1} \rho_n < \frac{1}{2}$. *Let* s_p *be as in (3.10). Set* $M_n = \max_{1\leq i<j\leq p} M_{nij}$. *If* $p = p_n \to \infty$ *and* $\log p = o(n^{1/3})$, *then*

$$\lim_{n\to\infty} P\big(M_n \leq s_p\big) = e^{-Ke^{-x/2}}$$

for any $x \in \mathbb{R}$, *where* $K = \frac{1}{4\sqrt{2\pi}}$.

Proof. In the next we will assume p is large enough such that $s_p > 0$. Set $I = \{(i,j);\ 1 \leq i < j \leq p\}$. For $\alpha = (i,j) \in I$, define $X_\alpha = M_{nij}$ and

$$B_\alpha = \{(k,l) \in I;\ \text{either } k \in \{i,j\} \text{ or } l \in \{i,j\},\ \text{but } (k,l) \neq \alpha\}.$$

Let P_2 and E_2 stand for the conditional probability and the conditional expectation given $\{\xi_k;\ 1 \leq k \leq n\}$, respectively. The crucial point is that, given $\{\xi_k;\ 1 \leq k \leq n\}$, random variable X_α is independent of $\{X_\beta;\ \beta \notin B_\alpha\}$. Since $\{X_\alpha, \alpha \in I\}$ are identically distributed under P_2, by Lemma 3.3, we have

$$\Big|P_2(\max_{\alpha\in I} X_\alpha \leq s_p) - e^{-\lambda_{p1}}\Big| \leq w_1 + w_2, \tag{3.18}$$

where

$$\lambda_{p1} \;=\; \frac{p(p-1)}{2} P_2\Big(\frac{1}{\sqrt{n}}\sum_{k=1}^n \eta_{k12} > s_p\Big)$$

and

$$\begin{aligned} w_1 &= \sum_{\alpha\in I}\sum_{\beta\in B_\alpha} P_2(X_\alpha > s_p)P_2(X_\beta > s_p) \\ &\leq \frac{p(p-1)}{2}\cdot(2p)\cdot P_2\Big(\frac{1}{\sqrt{n}}\sum_{k=1}^n \eta_{k12} > s_p\Big)^2 \end{aligned}$$

and

$$\begin{aligned} w_2 &= \sum_{\alpha\in I}\sum_{\beta\in B_\alpha} P_2(X_\alpha > s_p,\, X_\beta > s_p) \\ &\leq \frac{p(p-1)}{2}\cdot(2p)\cdot P_2\Big(\frac{1}{\sqrt{n}}\sum_{k=1}^n \eta_{k12} > s_p,\ \frac{1}{\sqrt{n}}\sum_{k=1}^n \eta_{k13} > s_p\Big). \end{aligned}$$

Note that $P(\max_{\alpha\in I} X_\alpha \leq s_p) = EP_2(\max_{\alpha\in I} X_\alpha \leq s_p)$. From (3.18),

$$\begin{aligned} \big|P(\max_{\alpha\in I} X_\alpha \leq s_p) - Ee^{-\lambda_{p1}}\big| &\leq E\big|P_2(\max_{\alpha\in I} X_\alpha \leq s_p) - e^{-\lambda_{p1}}\big| \\ &\leq Ew_1 + Ew_2. \end{aligned}$$

Now,

$$Ee^{-\lambda_{p1}} = E\exp\Big[-\frac{p(p-1)}{2}P_2\Big(\frac{1}{\sqrt{n}}\sum_{k=1}^{n}\eta_{k12} > s_p\Big)\Big];$$

$$Ew_1 \le p^3\cdot E\Big[P_2\Big(\frac{1}{\sqrt{n}}\sum_{k=1}^{n}\eta_{k12} > s_p\Big)^2\Big];$$

$$Ew_2 \le p^3\cdot P\Big(\frac{1}{\sqrt{n}}\sum_{k=1}^{n}\eta_{k12} > s_p,\ \frac{1}{\sqrt{n}}\sum_{k=1}^{n}\eta_{k13} > s_p\Big).$$

The following three lemmas say that $Ee^{-\lambda_{p1}} \to \exp\big(-\frac{1}{4\sqrt{2\pi}}e^{-x/2}\big)$, $Ew_1 \to 0$ and $Ew_2 \to 0$. The proof is then completed. ■

LEMMA **3.10** *Let the assumptions in Proposition 3.1 hold. Review that P_2 stands for the conditional probability given $\{\xi_k;\ 1\le k\le n\}$. Then*

$$E\exp\Big[-\frac{p(p-1)}{2}P_2\Big(\frac{1}{\sqrt{n}}\sum_{k=1}^{n}\eta_{k12} > s_p\Big)\Big] \to \exp\Big(-\frac{1}{4\sqrt{2\pi}}e^{-x/2}\Big)$$

as $n\to\infty$ for all $x\in\mathbb{R}$.

LEMMA **3.11** *Let the assumptions in Proposition 3.1 hold. Review that P_2 stands for the conditional probability given $\{\xi_k;\ 1\le k\le n\}$. Then*

$$E\Big[P_2\Big(\frac{1}{\sqrt{n}}\sum_{k=1}^{n}\eta_{k12} > s_p\Big)^2\Big] = o\Big(\frac{1}{p^3}\Big)$$

as $n\to\infty$.

LEMMA **3.12** *Let the assumptions in Proposition 3.1 hold. Then*

$$P\Big(\frac{1}{\sqrt{n}}\sum_{k=1}^{n}\eta_{k12} > s_p,\ \frac{1}{\sqrt{n}}\sum_{k=1}^{n}\eta_{k13} > s_p\Big) = o\Big(\frac{1}{p^3}\Big)$$

as $n\to\infty$.

Now we start to prove the three results one by one.

Proof of Lemma 3.10. Write

$$\sum_{k=1}^{n}\eta_{k12} = \sum_{k=1}^{n}\big[a_n\xi_{k1}\xi_{k2} + b_n\xi_k(\xi_{k1}+\xi_{k2})\big]. \tag{3.19}$$

Given $\{\xi_k;\ 1\le k\le n\}$, it is the sum of independent random variables with mean $E_2\big[a_n\xi_{k1}\xi_{k2} + b_n\xi_k(\xi_{k1}+\xi_{k2})\big] = 0$ and variance $\mathrm{Var}_2\big[a_n\xi_{k1}\xi_{k2} + b_n\xi_k(\xi_{k1}+\xi_{k2})\big]^2 = a_n^2 + 2b_n^2\xi_k^2$. Thus,

$$\mathrm{Var}_2\Big(\sum_{k=1}^{n}\eta_{k12}\Big) = na_n^2 + 2b_n^2\sum_{k=1}^{n}\xi_k^2. \tag{3.20}$$

Define

$$F_n = \Big\{ \max_{1\le k\le n} |\xi_k| \le \sqrt{n} \text{ and } \frac{6}{7} \le \frac{1}{n}\sum_{k=1}^n \xi_k^2 \le \frac{15}{14}\Big\}.$$

Set $\tau = E(|\xi_1|^3)+1$. For $v>0$, set

$$G_n(v) = \Big\{\frac{1}{n}\sum_{k=1}^n (1+|\xi_k|^3)e^{v\xi_k^2(\log p)/n} \le 2\tau\Big\}.$$

The parameter v will be chosen later. By the fact $P(|N(0,1)|\ge x) \le \frac{2}{\sqrt{2\pi}\,x}e^{-x^2/2}$ for all $x>0$, the large deviations for i.i.d. random variables and Lemma 3.7, we have

$$\begin{aligned} P\big((F_n\cap G_n(v))^c\big) &\le nP(|\xi_1|\ge\sqrt{n}) + P\Big(\frac{1}{n}\sum_{k=1}^n \xi_k^2 \in \big[\frac{6}{7},\frac{15}{14}\big]^c\Big) \\ &\qquad + P\Big(\frac{1}{n}\sum_{k=1}^n (1+|\xi_k|^3)e^{v\xi_k^2(\log p)/n} > 2\tau\Big) \\ &\le 3\exp\Big(-\frac{1}{4}n^{1/2}(\log n)^{-2}\Big) \qquad (3.21) \end{aligned}$$

as $n\ge n_v$, where $n_v\ge 1$ is a constant depending on v. Define $\sigma_{n0}^2 = a_n^2 + 2b_n^2(\frac{1}{n}\sum_{k=1}^n \xi_k^2)$. Then, on F_n,

$$\frac{1}{2} = \frac{1}{2}(a_n^2+2b_n^2) \le \sigma_{n0}^2 \le a_n^2 + \frac{15}{14}(2b_n^2) \le \frac{8}{7}, \qquad (3.22)$$

where the last inequality follows from the identity $a_n^2+2b_n^2=1$.

Next we will use Lemma 3.5 to get a precise estimate on $P_2(\frac{1}{\sqrt{n}}\sum_{k=1}^n \eta_{k12} > s_p)$. To do so, Lemma 3.6 will be applied to control γ defined in Lemma 3.5.

Reviewing (3.19), we take $a = \frac{a_n}{\sqrt{n}\sigma_{n0}}$, $b=\frac{b_n\xi_k}{\sqrt{n}\sigma_{n0}}$. Set $\eta_k = a\xi_{k1}\xi_{k2} + b(\xi_{k1}+\xi_{k2})$. Then, it follows from (3.20) that

$$E_2\eta_k = 0 \text{ and } \sum_{k=1}^n \mathrm{Var}_2(\eta_k) = 1 \qquad (3.23)$$

for each k. Furthermore, by (3.22) we have

$$|a| \le \frac{2}{\sqrt{n}} \text{ and } |b| \le \frac{2|\xi_k|}{\sqrt{n}} \le 2 \qquad (3.24)$$

on F_n. Then, on F_n, use the Hölder inequality, the facts that $2|\xi_{11}\xi_{12}| \le \xi_{11}^2+\xi_{12}^2$ and $\xi_{11}+\xi_{12} \sim \sqrt{2}\,N(0,1)$, and independence to see

$$\begin{aligned} Ee^{h|\eta_k|} &\le E\exp\Big(\frac{2h}{\sqrt{n}}|\xi_{11}\xi_{12}| + 2h|\xi_{11}+\xi_{12}|\Big) \\ &\le \Big[E\exp\Big(\frac{2h}{\sqrt{n}}(\xi_{11}^2+\xi_{12}^2)\Big)\Big]^{1/2}\cdot\big[E\exp(4\sqrt{2}hN(0,1)\big]^{1/2} \\ &= E\exp\Big(\frac{2h}{\sqrt{n}}N(0,1)^2\Big)\cdot e^{16h^2} < \infty \qquad (3.25) \end{aligned}$$

for all h, k, n satisfying $0 < h \le h_n := \frac{1}{8}\sqrt{n}$ and $1 \le k \le n$. Now, on F_n, by Lemma 3.6 and (3.24) we have

$$\begin{aligned} E_2\big(|\eta_k|^3 e^{x|\eta_k|}\big) &\le \frac{C}{n^{3/2}}(1+|\xi_k|^3)e^{4b^2x^2} \\ &\le \frac{C}{n^{3/2}}(1+|\xi_k|^3)e^{16x^2\xi_k^2/n} \end{aligned} \tag{3.26}$$

for all $x \in (0, \frac{1}{12|a|})$. Observe that $\big(0, \frac{\sqrt{n}}{24}\big) \subset (0, \frac{1}{12|a|})$ on F_n by (3.24). Thus, (3.26) particularly holds for all $x \in (0, \frac{\sqrt{n}}{24})$. Now take $x_0 = \frac{s_p}{\sigma_{n0}}$. Then

$$x_0 \le 2s_p < \frac{\sqrt{n}}{24} \tag{3.27}$$

on F_n by the assumption $\log p = o(n^{1/3})$. We then have

$$\begin{aligned} \gamma :&= \sum_{k=1}^n E_2\big(|\eta_k|^3 e^{x_0|\eta_k|}\big) \\ &\le \frac{C}{n^{3/2}} \sum_{k=1}^n (1+|\xi_k|^3)e^{16x_0^2\xi_k^2/n} \\ &\le \frac{C}{n^{3/2}} \sum_{k=1}^n (1+|\xi_k|^3)e^{256\xi_k^2(\log p)/n} \end{aligned}$$

on F_n. Thus, $\gamma \le \frac{2C\tau}{\sqrt{n}}$ on $F_n \cap G_n(256) := H_n$. The inequality in (3.21) implies

$$P(H_n^c) \le 3\exp\Big(-\frac{1}{4}n^{1/2}(\log n)^{-2}\Big) \tag{3.28}$$

as n is sufficiently large. From (3.23), (3.25) and Lemma 3.5, we conclude

$$\begin{aligned} & P_2\Big(\frac{1}{\sqrt{n}}\sum_{k=1}^n \eta_{k12} > s_p\Big) \\ =\ & P_2\Big(\sum_{k=1}^n \eta_k > x_0\Big) \\ =\ & \big[1-\Phi(x_0)\big]\cdot\big[1+O(1)(1+x_0^3)\gamma e^{4x_0^3\gamma}\big] \end{aligned} \tag{3.29}$$

on H_n since $x_0 < h_n = \frac{1}{8}\sqrt{n}$ by (3.27). Finally, $x_0^3\gamma = O(s_p^3 n^{-1/2}) \to 0$ on H_n by the assumption $\log p = o(n^{1/3})$. Reviewing (3.22), we have $\frac{s_p}{2} \le \frac{s_p}{\sigma_{n0}} \le 2s_p$ on H_n. Hence, from the formula $P(N(0,1) \ge x) = \frac{1}{\sqrt{2\pi}\,x}e^{-x^2/2}(1+o(1))$ as $x \to \infty$ we obtain that, on H_n,

$$\begin{aligned} P_2\Big(\frac{1}{\sqrt{n}}\sum_{k=1}^n \eta_{k12} > s_p\Big) &= \Big[1-\Phi\big(\frac{s_p}{\sigma_{n0}}\big)\Big]\cdot\Big[1+O\Big(\frac{\log^{3/2} p}{\sqrt{n}}\Big)\Big] \\ &= \frac{\sigma_{n0}}{\sqrt{2\pi}\,s_p}\cdot e^{-s_p^2/(2\sigma_{n0}^2)}\cdot(1+o(1)) \end{aligned} \tag{3.30}$$

as $n \to \infty$, where the last term "$o(1)$" does not depend on ξ_k's.

To prove the lemma, it is enough to show

$$\frac{p^2}{2} \cdot P_2\Big(\frac{1}{\sqrt{n}}\sum_{k=1}^n \eta_{k12} > s_p\Big) \to \frac{1}{4\sqrt{2\pi}} e^{-x/2}$$

in probability as $n \to \infty$. Since $P(H_n) \to 1$, to finish the proof, it suffices to check

$$\frac{p^2}{2} \cdot P_2\Big(\frac{1}{\sqrt{n}}\sum_{k=1}^n \eta_{k12} > s_p\Big) \cdot I_{H_n} \to \frac{1}{4\sqrt{2\pi}} e^{-x/2}$$

in probability as $n \to \infty$. Now $\sigma_{n0} \to 1$ in probability as $n \to \infty$ and $s_p \sim 2\sqrt{\log p}$, comparing this with (3.30), it suffices to show

$$\frac{p^2}{4\sqrt{2\pi \log p}} \cdot e^{-s_p^2/(2\sigma_{n0}^2)} \cdot I_{H_n} \to \frac{1}{4\sqrt{2\pi}} e^{-x/2} \tag{3.31}$$

in probability. By the central limit theorem for i.i.d. random variables, $\sigma_{n0}^2 = 1 + O_p(\frac{1}{\sqrt{n}})$. Hence $\sigma_{n0}^{-2} = 1 + O_p(\frac{1}{\sqrt{n}})$. It follows that

$$\begin{aligned} \frac{s_p^2}{2\sigma_{n0}^2} &= (2\log p - \frac{1}{2}\log\log p + \frac{1}{2}x) \cdot \Big[1 + O_p(\frac{1}{\sqrt{n}})\Big] \\ &= 2\log p - \frac{1}{2}\log\log p + \frac{1}{2}x + o_p(1) \end{aligned}$$

by the condition $(\log p)/n^{1/3} \to 0$. This implies (3.31). ∎

Proof of Lemma 3.11. Review the proof of Lemma 3.10. Let H_n be defined as above (3.28). By (3.29), there exists a constant $n_1 \ge 1$ not depending on ξ_k's such that

$$P_2\Big(\frac{1}{\sqrt{n}}\sum_{k=1}^n \eta_{k12} > s_p\Big) \cdot I_{H_n} \le 2\Big[1 - \Phi(\frac{s_p}{\sigma_{n0}})\Big] \cdot I_{H_n}$$

as $n \ge n_1$ since $x_0 = \frac{s_p}{\sigma_{n0}}$. Recall the inequality $1 - \Phi(x) \le \frac{1}{\sqrt{2\pi}\,x} e^{-x^2/2}$ for all $x > 0$. Then, from (3.22) we have

$$\begin{aligned} \Big[P_2\Big(\frac{1}{\sqrt{n}}\sum_{k=1}^n \eta_{k12} > s_p\Big)\Big]^2 \cdot I_{H_n} &\le C \cdot \frac{\sigma_{n0}^2}{s_p^2} \cdot e^{-s_p^2/\sigma_{n0}^2} \cdot I_{H_n} \\ &\le \frac{C}{\log p} \cdot e^{-7s_p^2/8} \end{aligned}$$

as $p \ge n_2$, where n_2 is a constant not depending on ξ_k's. Therefore, combining this with (3.28), we see

$$\begin{aligned} & E\Big[P_2\Big(\frac{1}{\sqrt{n}}\sum_{k=1}^n \eta_{k12} > s_p\Big)^2\Big] \\ \le\ & E\Big[P_2\Big(\frac{1}{\sqrt{n}}\sum_{k=1}^n \eta_{k12} > s_p\Big)^2 \cdot I_{H_n}\Big] + P(H_n^c) \\ \le\ & p^{-3.4} + 3\exp\Big(-\frac{1}{4}n^{1/2}(\log n)^{-2}\Big) \end{aligned}$$

as n is sufficiently large since $\log p = o(n^{1/3})$. This proves the lemma. ■

Proof of Lemma 3.12. Let P_3 and E_3 stand for the conditional probability and the conditional expectation given $\{\xi_k, \xi_{k1};\ 1 \le k \le n\}$, respectively. By independence,

$$\begin{aligned} & P\Big(\frac{1}{\sqrt{n}}\sum_{k=1}^n \eta_{k12} > s_p,\ \frac{1}{\sqrt{n}}\sum_{k=1}^n \eta_{k13} > s_p\Big) \\ = \ & E\Big[P_3\Big(\frac{1}{\sqrt{n}}\sum_{k=1}^n \eta_{k12} > s_p\Big)^2\Big]. \end{aligned} \tag{3.32}$$

Recall the notations in (3.16) and (3.17). Write $\sum_{k=1}^n \eta_{k12} = (b_n\sum_{k=1}^n \xi_k\xi_{k1}) + \sum_{k=1}^n (a_n\xi_{k1} + b_n\xi_k)\xi_{k2}$. Then, given $\{\xi_k, \xi_{k1};\ 1 \le k \le n\}$, we have from independence that

$$\frac{1}{\sqrt{n}}\sum_{k=1}^n \eta_{k12} \sim N(\mu_{0n}, \sigma_{0n}^2) \tag{3.33}$$

where

$$\mu_{0n} = \frac{b_n}{\sqrt{n}}\sum_{k=1}^n \xi_k\xi_{k1} \quad \text{and} \quad \sigma_{0n}^2 = \frac{1}{n}\sum_{k=1}^n (a_n\xi_{k1} + b_n\xi_k)^2.$$

Trivially, $b_n^2 = \frac{\rho_n}{1+\rho_n} \le \sup_{n\ge 1}\frac{\rho_n}{1+\rho_n} := \kappa^2 < \frac{1}{3}$ and $a_n^2 + b_n^2 = \frac{1}{1+\rho_n} \in (\frac{1}{2}, 1]$ for all $\rho_n \in [0, 1)$. Define

$$A = \{|\mu_{0n}| < \sqrt{3}s_p/2\} \quad \text{and} \quad B_\delta = \Big\{1 - \delta < \frac{\sigma_{0n}^2}{a_n^2 + b_n^2} < 1 + \delta\Big\}$$

for $\delta \in (0, 1)$. Observe $a_n\xi_{11} + b_n\xi_1 \overset{d}{=} \sqrt{a_n^2 + b_n^2}\cdot\xi_1$ since ξ_{11} and ξ_1 are i.i.d. $N(0, 1)$-distributed random variables. Thus, $\frac{\sigma_{0n}^2}{a_n^2+b_n^2} \overset{d}{=} \frac{1}{n}\sum_{k=1}^n \xi_k^2$. Then, by the large deviations for the sum of i.i.d. random variables, we obtain

$$P(B_\delta^c) = P\Big(\frac{1}{n}\sum_{k=1}^n \xi_k^2 \in [1-\delta, 1+\delta]^c\Big) \le e^{-nC_\delta} \tag{3.34}$$

for all $\delta \in (0, 1)$ where $C_\delta > 0$ for each $\delta \in (0, 1)$. Similarly, $\{\xi_k\xi_{k1};\ 1 \le k \le n\}$ are i.i.d. with mean zero and variance one. Notice $|\xi_1\xi_{11}| \le \frac{1}{2}(|\xi_1|^2 + |\xi_{11}|^2)$. Therefore $E\exp\big(\frac{1}{2}|\xi_1\xi_{11}|\big) < \infty$. From Lemma 3.4 and the fact $s_p \sim 2\sqrt{\log p} = o(n^{1/6})$ we see that, for any $\epsilon \in (0, 1)$,

$$\begin{aligned} P(A^c) &\le P\Big(\frac{1}{\sqrt{n}}\Big|\sum_{k=1}^n \xi_k\xi_{k1}\Big| \ge \frac{\sqrt{3}s_p}{2\kappa}\Big) \\ &= 2P\Big(\frac{1}{\sqrt{n}}\sum_{k=1}^n \xi_k\xi_{k1} \ge \frac{\sqrt{3}s_p}{2\kappa}\Big) \\ &\le 2\exp\Big(-\frac{1-\epsilon}{2}\cdot\frac{3s_p^2}{4\kappa^2}\Big) \end{aligned}$$

n is large enough. Since $\kappa^2 < \frac{1}{3}$, we choose $\epsilon = \frac{1}{2} - \kappa^2$. Then $\frac{1-\epsilon}{2\kappa^2} = \frac{1}{2} + \frac{1}{4\kappa^2} > 1$. This implies that

$$P(A^c) \le 2\exp\Big(-\frac{1-\epsilon}{2\kappa^2}\cdot\frac{3s_p^2}{4}\Big) = o\Big(\frac{1}{p^3}\Big)$$

as $n \to \infty$.

It is easy to see that $s_p - \mu_{0n} \to \infty$ on A. By the inequality $P(N(0,1) \ge y) \le \frac{1}{\sqrt{2\pi}y}e^{-y^2/2} \le \frac{1}{2}e^{-y^2/2}$ for all $y \ge 1$, we have from (3.33) that, on $A \cap B_\delta$,

$$\begin{aligned}
P_3\Big(\frac{1}{\sqrt{n}}\sum_{k=1}^n \eta_{k12} \ge s_p\Big) &= P_3\Big(N(\mu_{0n}, \sigma_{0n}^2) \ge s_p\Big) \\
&= P_3\Big(N(0,1) \ge \frac{s_p - \mu_{0n}}{\sigma_{0n}}\Big) \\
&\le \exp\Big(-\frac{1}{2}\frac{(s_p - \mu_{0n})^2}{\sigma_{0n}^2}\Big).
\end{aligned}$$

Note that $\sigma_{0n}^2 < (1+\delta)(a_n^2 + b_n^2) = \frac{1+\delta}{1+\rho_n}$ on B_δ. Therefore, on $A \cap B_\delta$,

$$P_3\Big(\frac{1}{\sqrt{n}}\sum_{k=1}^n \eta_{k12} > s_p\Big) \le \exp\Big(-\frac{1+\rho_n}{2(1+\delta)}\cdot(s_p - \mu_{0n})^2\Big)$$

Review (3.32). We then have

$$\begin{aligned}
&P\Big(\frac{1}{\sqrt{n}}\sum_{k=1}^n \eta_{k12} > s_p,\ \frac{1}{\sqrt{n}}\sum_{k=1}^n \eta_{k13} > s_p\Big) \\
\le\ & E\Big[P_3\Big(\frac{1}{\sqrt{n}}\sum_{k=1}^n \eta_{k12} > s_p\Big)^2 I_{A^c \cup B_\delta^c}\Big] + E\exp\Big(-\frac{1+\rho_n}{1+\delta}\cdot(s_p - \mu_{0n})^2\Big) \\
\le\ & P(A^c) + P(B_\delta^c) + E\exp\Big(-\frac{1+\rho_n}{1+\delta}\cdot(s_p - \mu_{0n})^2\Big) \\
\le\ & o\Big(\frac{1}{p^3}\Big) + e^{-nC_\delta} + E\exp\Big(-\frac{1+\rho_n}{1+\delta}\cdot(\mu_{0n} - s_p)^2\Big).
\end{aligned}$$

By Lemma 3.9, choosing $\delta > 0$ small enough, we know the last expectation is identical to $o(\frac{1}{p^3})$. The desired conclusion follows from the assumption $\log p = o(n^{1/3})$. ■

3.4 A proposition on the largest entry of a sample correlation matrix

Similar to Section 3.3, we now study a statistic M_n', which is essentially a key quantity to understand the largest entry of a sample correlation matrix. The main result is Proposition 3.2, which will be used in the proof of Theorem 2.2.

Review the notations from (3.8) and (3.9). Throughout this section, we assume $\sigma_{n1}^2 = (1-\rho_n)^2 + 2\rho_n a_n^2$. Set

$$a_n' = \frac{a_n}{\sigma_{n1}} \quad \text{and} \quad b_n' = \frac{(1-\rho_n)b_n}{\sigma_{n1}}; \tag{3.35}$$

$$\gamma_k = -\frac{1}{2}\rho_n a_n'(\xi_{k1}^2 - 1) + b_n'\xi_k\xi_{k1} \tag{3.36}$$

for $1 \le k \le m := n-1$. Set $V_n = (\gamma_1 + \cdots + \gamma_m)/\sqrt{m}$.

Similar to Lemma 3.9, the following technical result studies the behavior of the moment generating function of a random variable. It will be used in the proof of Lemma 3.16.

LEMMA **3.13** *Let $\rho_n \in [0,1)$ be constants. Suppose $p = p_n \to \infty$ and $\log p = o(n^{1/3})$ as $n \to \infty$. Let s_p be as in (3.10). Then, there exists $\delta \in (0,1)$ such that*

$$E\Big\{I_{K_n'} \cdot \exp\Big[-\frac{1-\delta}{1-\omega_n^2}(V_n - s_p)^2\Big]\Big\} = o\Big(\frac{1}{p^3}\Big) \tag{3.37}$$

as $n \to \infty$, where $K_n' := \{0 < V_n < \frac{\sqrt{7}}{2}\omega_n s_p\}$ and $\omega_n := \sqrt{Var(\gamma_1)}$.

Proof. First, if $\rho_n = 0$ for some $n \ge 1$, then $\gamma_k = 0$ for all $1 \le k \le m$. Hence $V_n = 0$ and the expectation in (3.37) is zero by the definition of K_n'. So it is enough to prove the conclusion by assuming $\rho_n > 0$ for all $n \ge 1$. The proof is divided into a few of steps.

Step 1. Reduction of K_n' to a smaller set. From the definitions of a_n' and b_n' in (3.35), it is easy to check that

$$(1+\rho_n^2)a_n'^2 + 2b_n'^2 = 1. \tag{3.38}$$

Trivially, we have $\omega_n^2 = \frac{1}{2}\rho_n^2 a_n'^2 + b_n'^2$. Therefore,

$$\begin{aligned}\omega_n^2 &= \frac{1}{2} - \frac{a_n'^2}{2} \\ &= \frac{1}{2} - \frac{1}{2}\cdot\frac{\frac{1-\rho_n}{1+\rho_n}}{(1-\rho_n)^2 + (2\rho_n)\frac{1-\rho_n}{1+\rho_n}} \\ &= \frac{1}{2}\Big(1 - \frac{1}{1+2\rho_n - \rho_n^2}\Big) < \frac{1}{4}\end{aligned} \tag{3.39}$$

because $1 + 2x - x^2 < 2$ for all $x \in [0,1)$. In particular,

$$\frac{1}{1-\omega_n^2}\Big(1 - \frac{1}{5}\omega_n\Big)^2 > \Big(1 - \frac{1}{5}\omega_n\Big)^2 \ge \Big(\frac{19}{20}\Big)^2 > 0.8.$$

This implies that

$$\begin{aligned}& E\Big\{I(0 < V_n \le \frac{1}{5}\omega_n s_p)\cdot\exp\Big[-\frac{1-\delta}{1-\omega_n^2}(V_n - s_p)^2\Big]\Big\} \\ \le\ & \exp\Big[-\frac{1-\delta}{1-\omega_n^2}\big(1 - \frac{1}{5}\omega_n\big)^2 s_p^2\Big] \\ \le\ & \exp\Big[-3.2(1-2\delta)\log p\Big] \\ =\ & o\Big(\frac{1}{p^3}\Big)\end{aligned}$$

as $n \to \infty$ if $\delta > 0$ is small enough. Therefore, it is enough to prove (3.37) with K_n' being replaced by $K_n'' = \{\frac{1}{5}\omega_n s_p < V_n < \frac{\sqrt{7}}{2}\omega_n s_p\}$.

Step 2. The tail probability of V_n. By the formula $\omega_n^2 = \frac{1}{2}\rho_n^2 a_n'^2 + b_n'^2$ again,

$$\Big(\frac{-\frac{1}{2}\rho_n a_n'}{\omega_n}\Big)^2 = \frac{1}{2}\cdot\Big(1+\frac{2b_n'^2}{\rho_n^2 a_n'^2}\Big)^{-1} \le \frac{1}{2}$$

and

$$\Big(\frac{b_n'}{\omega_n}\Big)^2 = \Big(1+\frac{1}{2}\rho_n^2\frac{a_n'^2}{b_n'^2}\Big)^{-1} \le 1.$$

Recall γ_k in (3.36). Set $\gamma_k' = \gamma_k/(\sqrt{m}\omega_n)$ for $1 \le k \le m$. The above implies that

$$\sqrt{m}\cdot|\gamma_k'| \le \frac{1}{2}(\xi_{k1}^2+1) + |\xi_k\xi_{k1}| \le \xi_{k1}^2+\xi_k^2+1.$$

In addition, γ_k''s are i.i.d. with mean zero and satisfy $\sum_{k=1}^m \text{Var}(\gamma_k') = 1$. Also, $Ee^{t|\gamma_k'|} < \infty$ if $0 < t < \frac{1}{4}\sqrt{m}$. Observe

$$\begin{aligned}\gamma := \sum_{i=1}^m E(|\gamma_k'|^3 e^{x|\gamma_k'|}) &\le \frac{1}{\sqrt{m}}E\big[(\xi_{11}^2+\xi_1^2+1)^3 e^{\frac{x}{\sqrt{m}}(\xi_{11}^2+\xi_1^2+1)}\big]\\ &\le \frac{C}{\sqrt{m}}\end{aligned}$$

for all $0 \le x \le \frac{\sqrt{m}}{4}$, where $C = E\big[(\xi_{11}^2+\xi_1^2+1)^3 e^{\frac{1}{4}(\xi_{11}^2+\xi_1^2+1)}\big] < \infty$. By Lemma 3.5,

$$P(V_n \ge x) = P\Big(\sum_{i=1}^m \gamma_k' \ge \frac{x}{\omega_n}\Big) \le 2\Big[1-\Phi\big(\frac{x}{\omega_n}\big)\Big] \tag{3.40}$$

provided $(\frac{x}{\omega_n})^3\frac{1}{\sqrt{m}} \to 0$ and $0 \le \frac{x}{\omega_n} \le \frac{1}{4}\sqrt{m}$. In particular, by the assumption $\log p = o(n^{1/3})$ and the fact $P(N(0,1)\ge t) \le \frac{1}{\sqrt{2\pi}\,t}e^{-t^2/2}$ for all $t > 0$ again, we have

$$P(V_n \ge x) \le e^{-x^2/(2\omega_n^2)} \tag{3.41}$$

for all $\frac{1}{5}\omega_n s_p < x < \frac{\sqrt{7}}{2}\omega_n s_p$.

Step 3. The estimate of the expectation from (3.37). Let A_1, B_1 and $\alpha_2 > 0$ be constants. Assume $[A_1, B_1] \subset [0, s_p]$. Notice $\frac{d\,e^{-\alpha_2(x-s_p)^2}}{dx} = 2\alpha_2(s_p-x)\cdot e^{-\alpha_2(x-s_p)^2}$, we have

$$\begin{aligned}e^{-\alpha_2(v-s_p)^2} &= e^{-\alpha_2(A_1-s_p)^2} + 2\alpha_2\int_{A_1}^v (s_p-x)\cdot e^{-\alpha_2(x-s_p)^2}\,dx\\ &\le e^{-\alpha_2(A_1-s_p)^2} + 2\alpha_2 s_p\int_0^\infty e^{-\alpha_2(x-s_p)^2} I(A_1\le x\le v)\,dx\end{aligned}$$

for any $s_p > v > A_1$. Replacing v with V_n, then multiplying both sides of the above by $I(A_1 < V_n < B_1)$, we get

$$\begin{aligned} & e^{-\alpha_2(V_n-s_p)^2} I(A < V_n < B) \\ \le\ & e^{-\alpha_2(A_1-s_p)^2} + 2\alpha_2 s_p \int_0^\infty e^{-\alpha_2(x-s_p)^2} I(A_1 \le x \le V_n < B_1)\, dx \\ \le\ & e^{-\alpha_2(A_1-s_p)^2} + 2\alpha_2 s_p \int_{A_1}^{B_1} e^{-\alpha_2(x-s_p)^2} I(V_n \ge x)\, dx. \end{aligned}$$

Set $A_1 = \frac{1}{5}\omega_n s_p$ and $B_1 = \frac{\sqrt{7}}{2}\omega_n s_p$. By taking expectations on both sides of the above, we obtain from (3.41) that

$$\begin{aligned} & E\big[e^{-\alpha_2(V_n-s_p)^2} I(A_1 < V_n < B_1)\big] \\ \le\ & e^{-\alpha_2(A_1-s_p)^2} + 2\alpha_2 s_p \int_{A_1}^{B_1} e^{-\alpha_2(x-s_p)^2} P(V_n \ge x)\, dx \\ \le\ & e^{-\alpha_2(A_1-s_p)^2} + 2\alpha_2 s_p \int_{A_1}^{B_1} \exp\Big(-\alpha_2(x-s_p)^2 - \frac{x^2}{2\omega_n^2}\Big)\, dx. \end{aligned} \tag{3.42}$$

Now we evaluate the integral. Write

$$-\alpha_2(x-s_p)^2 - \frac{x^2}{2\omega_n^2} = -\Big(\sqrt{\alpha_2 + \frac{1}{2\omega_n^2}}\, x - \frac{\alpha_2 s_p}{\sqrt{\alpha_2 + \frac{1}{2\omega_n^2}}}\Big)^2 - \frac{\alpha_2 s_p^2}{2\alpha_2\omega_n^2 + 1}.$$

Now, define y such that

$$\frac{y}{\sqrt{2}} = \sqrt{\alpha_2 + \frac{1}{2\omega_n^2}}\, x - \frac{\alpha_2 s_p}{\sqrt{\alpha_2 + \frac{1}{2\omega_n^2}}}. \tag{3.43}$$

It follows that

$$\begin{aligned} & 2\alpha_2 s_p \int_{A_1}^{B_1} \exp\Big(-\alpha_2(x-s_p)^2 - \frac{x^2}{2\omega_n^2}\Big)\, dx \\ =\ & (2\alpha_2 s_p)\cdot \exp\Big(-\frac{\alpha_2 s_p^2}{2\alpha_2\omega_n^2+1}\Big)\cdot \int_{A'}^{B'} e^{-y^2/2}\, dy \cdot \frac{1}{\sqrt{2\alpha_2 + \frac{1}{\omega_n^2}}} \\ \le\ & \frac{\sqrt{8\pi}\alpha_2}{\sqrt{2\alpha_2 + \frac{1}{\omega_n^2}}} s_p \cdot \exp\Big(-\frac{\alpha_2 s_p^2}{2\alpha_2\omega_n^2+1}\Big)\cdot \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-y^2/2}\, dy \end{aligned}$$

where A' and B' are the corresponding values of y in (3.43) as $x = A_1$ and B_1, respectively. This combining with (3.42) implies

$$\begin{aligned} & E\big[e^{-\alpha_2(V_n-s_p)^2} I(A_1 < V_n < B_1)\big] \\ \le\ & e^{-\alpha_2(A_1-s_p)^2} + \sqrt{4\pi\alpha_2 s_p^2}\cdot \exp\Big(-\frac{s_p^2}{2\omega_n^2 + \alpha_2^{-1}}\Big), \end{aligned}$$

where the inequality $\alpha_2(2\alpha_2+\omega_n^{-2})^{-1/2} \le \sqrt{\alpha_2/2}$ is used. Take $\alpha_2 = \frac{1-\delta}{1-\omega_n^2}$. Then $1-\delta < \alpha_2 < \frac{4}{3}$ by (3.39). Note

$$2\omega_n^2 + \alpha_2^{-1} \;=\; 2\omega_n^2 + \frac{1-\omega_n^2}{1-\delta} \le \frac{1+\omega_n^2}{1-\delta} \le \frac{1+\omega^2}{1-\delta},$$

where $\omega^2 := \sup_{n\ge 1}\omega_n^2 \le \frac{1}{4}$. From (3.39), we know $A_1 \le \frac{1}{10}s_p$. This concludes

$$\begin{aligned} & E\Big\{I_{K_n''}\cdot \exp\Big[-\frac{1-\delta}{1-\omega_n^2}(V_n-s_p)^2\Big]\Big\} \\ \le\;& \exp\Big[-(1-\delta)(\frac{1}{10}s_p-s_p)^2\Big] + 2\sqrt{6\pi(\log p)}\cdot\exp\Big(-\frac{1-\delta}{1+\omega^2}s_p^2\Big). \end{aligned}$$

The first term on the right hand side is $o(p^{-3})$ if $(1-\delta)(\frac{9}{10})^2\cdot 4 > 3$, which is true if $0<\delta<\frac{2}{27}$; the second term is $o(p^{-3})$ as long as $\frac{1-\delta}{1+\omega^2} > \frac{3}{4}$, which is equivalent to that $0<\delta<1-\frac{3}{4}(1+\omega^2)$. The desired conclusion then follows from the fact $\omega^2\le\frac{1}{4}$. ■

Let us continue to use the notations before Lemma 3.13. Set $m=n-1$ and

$$\begin{aligned} \eta'_{kij} &= a'_n\Big[\xi_{ki}\xi_{kj} - \frac{\rho_n}{2}(\xi_{ki}^2+\xi_{kj}^2-2)\Big] + b'_n\xi_k(\xi_{ki}+\xi_{kj}); \\ M'_{nij} &= \frac{1}{\sqrt{m}}\sum_{k=1}^m \eta'_{kij} \end{aligned}$$

for $k=1,2\cdots,m$.

The main result of this section is given below.

Proposition 3.2 *Set $M'_n = \max_{1\le i<j\le p} M'_{nij}$. Let $\rho_n\in(0,1)$ for each $n\ge 1$. Let s_p be as in (3.10). If $p\to\infty$ and $\log p = o(n^{1/3})$, then*

$$\lim_{n\to\infty} P\big(M'_n \le s_p\big) = e^{-Ke^{-x/2}}$$

for any $x\in\mathbb{R}$, where $K = \frac{1}{4\sqrt{2\pi}}$.

Proof. The strategy of the proof is similar to that of Proposition 3.1. However, the technical details are more involved. Let I, s_p and B_α be as in the proof of Proposition 3.1. For $\alpha=(i,j)\in I$, define $X_\alpha = M'_{nij}$. Let P_2 and E_2 stand for the conditional probability and the conditional expectation given $\{\xi_k;\, 1\le k\le m\}$, respectively. Again, the key observation is that, given $\{\xi_k;\, 1\le k\le m\}$, random variable X_α is independent of $\{X_\beta;\, \beta\notin B_\alpha\}$. Since $\{X_\alpha, \alpha\in I\}$ are identically distributed under P_2, by Lemma 3.3, we have

$$\Big|P_2(\max_{\alpha\in I} X_\alpha \le s_p) - e^{-\lambda_{p2}}\Big| \le w'_1 + w'_2, \tag{3.44}$$

where

$$\lambda_{p2} \;=\; \frac{p(p-1)}{2}P_2\Big(\frac{1}{\sqrt{m}}\sum_{k=1}^m \eta'_{k12} > s_p\Big)$$

and

$$\begin{aligned} w_1' &= \sum_{\alpha\in I}\sum_{\beta\in B_\alpha} P_2(X_\alpha > s_p)P_2(X_\beta > s_p) \\ &\leq \frac{p(p-1)}{2}\cdot(2p)\cdot P_2\Big(\frac{1}{\sqrt{m}}\sum_{k=1}^m \eta_{k12}' > s_p\Big)^2 \end{aligned}$$

and

$$\begin{aligned} w_2' &= \sum_{\alpha\in I}\sum_{\beta\in B_\alpha} P_2(X_\alpha > s_p,\, X_\beta > s_p) \\ &\leq \frac{p(p-1)}{2}\cdot(2p)\cdot P_2\Big(\frac{1}{\sqrt{m}}\sum_{k=1}^m \eta_{k12}' > s_p,\, \frac{1}{\sqrt{m}}\sum_{k=1}^m \eta_{k13}' > s_p\Big). \end{aligned}$$

Note that $P(\max_{\alpha\in I} X_\alpha \leq s_p) = EP_2(\max_{\alpha\in I} X_\alpha \leq s_p)$. From (3.44),

$$\begin{aligned} \big|P(\max_{\alpha\in I} X_\alpha \leq s_p) - Ee^{-\lambda_{p2}}\big| &\leq E\big|P_2(\max_{\alpha\in I} X_\alpha \leq s_p) - e^{-\lambda_{p2}}\big| \\ &\leq Ew_1' + Ew_2'. \end{aligned}$$

Obviously,

$$Ee^{-\lambda_{p2}} = E\exp\Big[-\frac{p(p-1)}{2}P_2\Big(\frac{1}{\sqrt{m}}\sum_{k=1}^m \eta_{k12}' > s_p\Big)\Big];$$

$$Ew_1' \leq p^3\cdot E\Big[P_2\Big(\frac{1}{\sqrt{m}}\sum_{k=1}^m \eta_{k12}' > s_p\Big)^2\Big];$$

$$Ew_2' \leq p^3\cdot P\Big(\frac{1}{\sqrt{m}}\sum_{k=1}^m \eta_{k12}' > s_p,\, \frac{1}{\sqrt{m}}\sum_{k=1}^m \eta_{k13}' > s_p\Big).$$

The following three lemmas say that $Ee^{-\lambda_{p2}} \to \exp\big(-\frac{1}{4\sqrt{2\pi}}e^{-x/2}\big)$, $Ew_1' \to 0$ and $Ew_2' \to 0$. The proof is then completed. ■

LEMMA **3.14** *Let the assumptions in Proposition 3.2 hold. Review $m = n-1$ and P_2 stands for the conditional probability given $\{\xi_k;\ 1\leq k\leq m\}$. Then*

$$\begin{aligned} &E\exp\Big[-\frac{p(p-1)}{2}P_2\Big(\frac{1}{\sqrt{m}}\sum_{k=1}^m \eta_{k12}' > s_p\Big)\Big] \\ &\to \exp\Big(-\frac{1}{4\sqrt{2\pi}}e^{-x/2}\Big) \end{aligned} \tag{3.45}$$

as $n\to\infty$ for all $x\in\mathbb{R}$.

LEMMA **3.15** *Let the assumptions in Proposition 3.2 hold. Review $m = n-1$ and P_2 stands for the conditional probability given $\{\xi_k;\ 1\leq k\leq m\}$. Then*

$$E\Big[P_2\Big(\frac{1}{\sqrt{m}}\sum_{k=1}^m \eta_{k12}' > s_p\Big)^2\Big] = o\Big(\frac{1}{p^3}\Big)$$

as $n\to\infty$.

LEMMA **3.16** *Let the assumptions in Proposition 3.2 hold. Review $m = n-1$. Then*

$$P\Big(\frac{1}{\sqrt{m}}\sum_{k=1}^{m}\eta'_{k12} > s_p,\ \frac{1}{\sqrt{m}}\sum_{k=1}^{m}\eta'_{k13} > s_p\Big) = o\Big(\frac{1}{p^3}\Big)$$

as $n \to \infty$.

Now we start to prove the three results one by one.

Proof of Lemma 3.14. We will get a sharp estimate on $P_2(\frac{1}{\sqrt{m}}\sum_{k=1}^{m}\eta'_{k12} > s_p)$ first by using Lemma 3.5. To carry on this, we have to check the required conditions.

Step 1: the behaviors of η'_{k12}. Write

$$\sum_{k=1}^{m}\eta'_{k12} = \sum_{k=1}^{m}\Big\{a'_n\Big[\xi_{k1}\xi_{k2} - \frac{\rho_n}{2}(\xi_{k1}^2+\xi_{k2}^2-2)\Big] + b'_n\xi_k(\xi_{k1}+\xi_{k2})\Big\}.$$

Given $\{\xi_k;\ 1 \le k \le m\}$, it is the sum of independent random variables. It is easy to check that

$$E_2\eta'_{k12} = 0, \quad \mathrm{Var}_2(\eta'_{kij}) = a_n'^2(1+\rho_n^2) + 2b_n'^2\xi_k^2.$$

So the conditional variance

$$\mathrm{Var}_2(\sum_{k=1}^{m}\eta'_{k12}) = m(1+\rho_n^2)a_n'^2 + 2b_n'^2\sum_{k=1}^{m}\xi_k^2. \tag{3.46}$$

Set

$$F_n = \Big\{\max_{1\le k\le n}|\xi_k| \le \sqrt{m} \text{ and } \frac{6}{7} \le \frac{1}{m}\sum_{k=1}^{m}\xi_k^2 \le \frac{15}{14}\Big\}.$$

Recall the notation $\tau = E(|\xi_1|^3)+1$ defined earlier. For $v > 0$, define

$$G_n(v) = \Big\{\frac{1}{m}\sum_{k=1}^{m}(1+|\xi_k|^3)e^{v\xi_k^2(\log p)/m} \le 2\tau\Big\}. \tag{3.47}$$

The parameter v will be chosen later. The inequality (3.21) says that

$$P\big((F_n \cap G_n(v))^c\big) \le 3\exp\Big(-\frac{1}{4}n^{1/2}(\log n)^{-2}\Big) \tag{3.48}$$

as $n \ge n_v$, where $n_v \ge 1$ is a constant depending on v only. Define

$$\sigma_{n2}^2 = (1+\rho_n^2)a_n'^2 + 2b_n'^2\frac{1}{m}\sum_{k=1}^{m}\xi_k^2. \tag{3.49}$$

Note (3.38). Then, on F_n,

$$\frac{1}{2} = \frac{1}{2}[1+\rho_n^2)a_n'^2 + 2b_n'^2] \le \sigma_{n2}^2 \le (1+\rho_n^2)a_n'^2 + 2b_n'^2\cdot\frac{15}{14} \le \frac{15}{14}. \tag{3.50}$$

Next we will use Lemma 3.5 to get a precise estimate on $P_2(\frac{1}{\sqrt{m}}\sum_{k=1}^m \eta'_{k12} > s_p)$. To do so, set

$$a' = c' = -\frac{a'_n\rho_n}{2\sqrt{m}\,\sigma_{n2}}; \quad b' = \frac{a'_n}{\sqrt{m}\,\sigma_{n2}};$$
$$d' = e' = \frac{b'_n\xi_k}{\sqrt{m}\,\sigma_{n2}}; \quad f' = \frac{a'_n\rho_n}{\sqrt{m}\,\sigma_{n2}}$$

and $\eta'_k = a'\xi_{k1}^2 + b'\xi_{k1}\xi_{k2} + c'\xi_{k2}^2 + d'\xi_{k1} + e'\xi_{k2} + f'$. Then, it follows from (3.46) that

$$E_2\eta'_k = 0 \text{ for each } 1 \le k \le n \text{ and } \sum_{k=1}^n \mathrm{Var}_2(\eta'_k) = 1. \tag{3.51}$$

Furthermore, from (3.49), $\sigma_{n2} \ge \max\{a'_n, b'_n\}$ on F_n. Then

$$\max\{|a'|, |b'|, |c'|, |f'|\} \le \frac{1}{\sqrt{m}} \quad \text{and} \quad |d'| = |e'| \le \frac{|\xi_k|}{\sqrt{m}} \le 1 \tag{3.52}$$

on F_n. Hence, on F_n, $|\eta'_k| \le \frac{2}{\sqrt{m}}(\xi_{k1}^2 + \xi_{k2}^2) + |\xi_{k1} + \xi_{k2}| + \frac{1}{\sqrt{m}}$. By the fact $\xi_{k1} + \xi_{k2} \sim \sqrt{2}\,N(0,1)$ and independence,

$$\begin{aligned} Ee^{h|\eta'_k|} &\le e^{h/\sqrt{m}} \cdot E\exp\Big(\frac{2h}{\sqrt{m}}(\xi_{k1}^2 + \xi_{k2}^2) + h|\xi_{11} + \xi_{12}|\Big) \\ &\le e^{1/16} \cdot \Big[E\exp\Big(\frac{4h}{\sqrt{m}}(\xi_{k1}^2 + \xi_{k2}^2)\Big)\Big]^{1/2} \cdot \big[E\exp(2\sqrt{2}hN(0,1)\big]^{1/2} \\ &= 2 \cdot E\exp\Big(\frac{4h}{\sqrt{m}}N(0,1)^2\Big) \cdot e^{2h^2} < \infty \end{aligned} \tag{3.53}$$

for all h, k, n satisfying $0 < h \le h_n := \frac{1}{16}\sqrt{m}$ and $1 \le k \le m$. Now, on F_n, by Lemma 3.6, (3.50) and (3.52) we have

$$\begin{aligned} E_2\big(|\eta'_k|^3 e^{x|\eta'_k|}\big) &\le \frac{C}{m^{3/2}}(1 + |\xi_k|^3)e^{4x^2\xi_k^2/m} \cdot e^{x/\sqrt{m}} \\ &\le \frac{C}{m^{3/2}}(1 + |\xi_k|^3)e^{4x^2\xi_k^2/m} \end{aligned} \tag{3.54}$$

if $0 < x \le \frac{1}{12(|a'|+|b'|+|c'|)} \wedge \sqrt{m}$, where C here and later in the proof is a constant not depending on ξ_k's and may be different from line to line. Observe that $\big(0, \frac{\sqrt{m}}{36}\big) \subset (0, \frac{1}{12(|a'|+|b'|+|c'|)})$ on F_n by (3.52). Thus, (3.54) particularly holds for all $x \in (0, \frac{\sqrt{m}}{36})$. Now we take $x_1 = \frac{s_p}{\sigma_{n2}}$. Then, by (3.50),

$$x_1 \le 2s_p < \frac{\sqrt{m}}{36} \tag{3.55}$$

on F_n by the assumption $\log p = o(n^{1/3})$. We then have

$$\begin{aligned}\gamma : &= \sum_{k=1}^{m} E_2\big(|\eta_k'|^3 e^{x_1|\eta_k'|}\big)\\ &\le \frac{C}{m^{3/2}}\sum_{k=1}^{m}(1+|\xi_k|^3)e^{4x_1^2\xi_k^2/m}\\ &\le \frac{C}{m^{3/2}}\sum_{k=1}^{m}(1+|\xi_k|^3)e^{64\xi_k^2(\log p)/m}\end{aligned}$$

on F_n as n is sufficiently large. Thus, $\gamma \le \frac{2C\tau}{\sqrt{m}}$ on $F_n \cap G_n(64) := H_n$ by (3.47). The inequality in (3.48) implies

$$P(H_n^c) = o\Big(\frac{1}{p^3}\Big) \tag{3.56}$$

as n is sufficiently large since $\log p = o(n^{1/3})$ by assumption.

Step 2: a sharp estimate on $P_2(\frac{1}{\sqrt{m}}\sum_{k=1}^{m}\eta_{k12}' > s_p)$ by Lemma 3.5. By (3.55), we see that $x_1 < \frac{1}{36}\sqrt{m} < \frac{1}{16}\sqrt{m} = h_n$. From (3.51), (3.53) and Lemma 3.5, we conclude

$$\begin{aligned}&P_2\Big(\frac{1}{\sqrt{m}}\sum_{k=1}^{m}\eta_{k12}' > s_p\Big)\\ = \;& P_2\Big(\sum_{k=1}^{m}\eta_k' > \frac{s_p}{\sigma_{n2}}\Big)\\ = \;& [1-\Phi(x_1)]\cdot\big[1+O(1)(1+x_1^3)\gamma e^{4x_1^3\gamma}\big]\end{aligned}$$

on H_n. Just notice $|O(1)|$ is bounded by an absolute constant. Finally, by (3.55), $x_1^3\gamma = O(s_p^3 m^{-1/2}) \to 0$ on H_n. Reviewing (3.50), we have $s_p/2 \le x_1 \le 2s_p$ on H_n. Hence, from the formula $P(N(0,1)\ge x) = \frac{1}{\sqrt{2\pi}\,x}e^{-x^2/2}(1+o(1))$ as $x\to\infty$ we obtain that, on H_n,

$$\begin{aligned}P_2\Big(\frac{1}{\sqrt{m}}\sum_{k=1}^{m}\eta_{k12}' > s_p\Big) &= \Big[1-\Phi\big(\frac{s_p}{\sigma_{n2}}\big)\Big]\cdot(1+o(1))\\ &= \frac{\sigma_{n2}}{\sqrt{2\pi}\,s_p}\cdot e^{-s_p^2/(2\sigma_{n2}^2)}\cdot(1+o(1))\end{aligned} \tag{3.57}$$

as $n\to\infty$, where $o(1)$ does not depend on ξ_k's.

Step 3: proof of (3.45) by (3.57). By the bounded convergence theorem, to prove the lemma, it is enough to show that

$$\frac{p^2}{2}\cdot P_2\Big(\frac{1}{\sqrt{m}}\sum_{k=1}^{m}\eta_{k12}' > s_p\Big) \to \frac{1}{4\sqrt{2\pi}}e^{-x/2}$$

in probability as $n\to\infty$. Since $P(H_n)\to 1$, to complete the proof, it is enough to prove

$$\frac{p^2}{2}\cdot P_2\Big(\frac{1}{\sqrt{m}}\sum_{k=1}^{m}\eta_{k12}' > s_p\Big)\cdot I_{H_n} \to \frac{1}{4\sqrt{2\pi}}e^{-x/2}$$

in probability as $n \to \infty$. Recalling (3.38) and (3.49), it is trivial to see $\sigma_{n2} \to 1$ in probability as $n \to \infty$. Also, $s_p \sim 2\sqrt{\log p}$, comparing this with (3.57), it is enough to prove

$$\frac{p^2}{4\sqrt{2\pi \log p}} \cdot e^{-s_p^2/(2\sigma_{n2}^2)} \cdot I_{H_n} \to \frac{1}{4\sqrt{2\pi}} e^{-x/2} \tag{3.58}$$

in probability. By the central limit theorem for i.i.d. random variables, we know $\sigma_{n2}^2 = 1 + O_p(\frac{1}{\sqrt{n}})$ from (3.38) and (3.49). Hence $\sigma_{n2}^{-2} = 1 + O_p(\frac{1}{\sqrt{n}})$. This leads to that

$$\begin{aligned} \frac{s_p^2}{2\sigma_{n2}^2} &= (2\log p - \frac{1}{2}\log\log p + \frac{1}{2}x) \cdot \Big[1 + O_p(\frac{1}{\sqrt{n}})\Big] \\ &= 2\log p - \frac{1}{2}\log\log p + \frac{1}{2}x + o_p(1) \end{aligned}$$

by the condition $(\log p)/n^{1/3} \to 0$. We then get (3.58). ■

Proof of Lemma 3.15. Review the proof of Lemma 3.14. Let H_n be defined as above (3.56). By (3.57), there exists a constant $n_1 \geq 1$ not depending on ξ_k's such that

$$P_2\Big(\frac{1}{\sqrt{m}}\sum_{k=1}^m \eta'_{k12} > s_p\Big) \cdot I_{H_n} \leq \frac{\sigma_{n2}}{\sqrt{2\pi}\, s_p} \cdot e^{-s_p^2/(2\sigma_{n2}^2)} \cdot I_{H_n}$$

as $n \geq n_1$. Then

$$\begin{aligned} \Big[P_2\Big(\frac{1}{\sqrt{m}}\sum_{k=1}^m \eta'_{k12} > s_p\Big)\Big]^2 \cdot I_{H_n} &\leq C \cdot \frac{\sigma_{n2}^2}{s_p^2} \cdot e^{-s_p^2/\sigma_{n2}^2} \cdot I_{H_n} \\ &\leq \frac{C}{\log p} \cdot e^{-7s_p^2/8} \end{aligned}$$

on H_n as $n \geq n_2$ by (3.50), where n_2 is a constant not depending on ξ_k's. Therefore, combining this with (3.56), we see

$$\begin{aligned} & E\Big[P_2\Big(\frac{1}{\sqrt{m}}\sum_{k=1}^m \eta'_{k12} > s_p\Big)^2\Big] \\ \leq\ & E\Big[P_2\Big(\frac{1}{\sqrt{m}}\sum_{k=1}^m \eta'_{k12} > s_p\Big)^2 \cdot I_{H_n}\Big] + P(H_n^c) \\ \leq\ & p^{-3.4} + o\Big(\frac{1}{p^3}\Big) \end{aligned}$$

as n is sufficiently large. This proves the lemma. ■

Proof of Lemma 3.16. Let P_3 and E_3 stand for the conditional probability and the conditional expectation given $\{\xi_k, \xi_{k1};\, 1 \leq k \leq n\}$, respectively. By independence,

$$\begin{aligned} & P\Big(\frac{1}{\sqrt{m}}\sum_{k=1}^m \eta'_{k12} > s_p,\ \frac{1}{\sqrt{m}}\sum_{k=1}^m \eta'_{k13} > s_p\Big) \\ =\ & E\Big[P_3\Big(\frac{1}{\sqrt{m}}\sum_{k=1}^m \eta'_{k12} > s_p\Big)^2\Big]. \end{aligned} \tag{3.59}$$

Write

$$\eta'_{k12} = \alpha_n(U_k^2 - 1) + \beta_k U_k + \gamma_k$$

where $U_k = \xi_{k2}$,

$$\begin{aligned}
\alpha_n &= -\frac{1}{2}\rho_n a'_n, \\
\beta_k &= (a'_n \xi_{k1} + b'_n \xi_k),
\end{aligned}$$

and γ_k is defined in (3.36). Now,

$$\begin{aligned}
& P_3\Big(\frac{1}{\sqrt{m}}\sum_{k=1}^m \eta'_{k12} > s_p\Big) \\
= \ & P_3\Big(\frac{1}{\sqrt{m}}\sum_{k=1}^m \big[\alpha_n(U_k^2-1) + \beta_k U_k\big] > s_p - \frac{1}{\sqrt{m}}\sum_{k=1}^m \gamma_k\Big). \qquad (3.60)
\end{aligned}$$

We will finish the proof with a couple of steps.

Step 1: the size of $\frac{1}{\sqrt{m}}\sum_{k=1}^m \gamma_k$. Unconditionally, $\{\gamma_k;\ 1 \le k \le m\}$ are i.i.d. with mean zero and variance $\omega_n^2 = \frac{1}{2}\rho_n^2 a_n'^2 + b_n'^2$ mentioned below (3.38). By (3.39), $\omega_n^2 < \frac{1}{4}$. From (3.40) and the fact $P(N(0,1) \ge t) \le \frac{1}{\sqrt{2\pi}\, t} e^{-t^2/2}$ for all $t > 0$,

$$\begin{aligned}
P\Big(\frac{1}{\sqrt{m}}\sum_{k=1}^m \gamma_k \ge \theta\omega_n s_p\Big) &\le 2e^{-(\theta s_p)^2/2} \\
&\le p^{-2\theta^2}(\log p)^{\theta^2}
\end{aligned}$$

as n is sufficiently large for all $\theta > 0$. Review the short argument as in getting (3.40), the above inequality also holds if "γ_k" is replaced by "$-\gamma_k$". It follows that

$$P\Big(\frac{1}{\sqrt{m}}\Big|\sum_{k=1}^m \gamma_k\Big| \ge \theta\omega_n s_p\Big) \le 2p^{-2\theta^2}(\log p)^{\theta^2}$$

as n is sufficiently large for all $\theta > 0$. Set

$$\tilde{K}_n = \Big\{\frac{1}{\sqrt{m}}\Big|\sum_{k=1}^m \gamma_k\Big| < \frac{\sqrt{7}}{2}\omega_n s_p\Big\}.$$

Then

$$P(\tilde{K}_n^c) = o\Big(\frac{1}{p^3}\Big) \qquad (3.61)$$

as $n \to \infty$. Let

$$s'_p = s_p - \frac{1}{\sqrt{m}}\sum_{k=1}^m \gamma_k.$$

Set $W_k = \alpha_n(U_k^2 - 1) + \beta_k U_k$ for $1 \leq k \leq m$. Now we consider

$$P_3\Big(\frac{1}{\sqrt{m}}\sum_{k=1}^m \big[\alpha_n(U_k^2-1)+\beta_k U_k\big] > s_p'\Big) = P_3\Big(\frac{1}{\sqrt{m}}\sum_{k=1}^m W_k > s_p'\Big).$$

Step 2: the behaviors of W_k's on typical sets. Observe

$$E_3(W_k) = 0; \tag{3.62}$$
$$\mathrm{Var}_3(W_k) = 2\alpha_n^2 + \beta_k^2 = \frac{1}{2}(\rho_n a_n')^2 + (a_n'\xi_{k1} + b_n'\xi_k)^2.$$

It follows that

$$\begin{aligned}\sigma_{n3}^2 : &= \mathrm{Var}_3\Big(\frac{1}{\sqrt{m}}\sum_{k=1}^m W_k\Big)\\ &= \frac{1}{2}(\rho_n a_n')^2 + \frac{1}{m}\sum_{k=1}^m (a_n'\xi_{k1} + b_n'\xi_k)^2\\ &\overset{d}{=} \frac{1}{2}(\rho_n a_n')^2 + (a_n'^2 + b_n'^2)\frac{1}{m}\sum_{k=1}^m \xi_k^2. \end{aligned} \tag{3.63}$$

Set

$$F_n(\delta) = \Big\{\max_{1\leq k\leq n} |\xi_k| \leq \sqrt{n} \text{ and } 1-\delta \leq \frac{1}{n}\sum_{k=1}^n \xi_k^2 \leq 1+\delta\Big\}$$

for $n \geq 1$ and $\delta \in (0,1)$. By the fact $P(N(0,1)\geq t) \leq \frac{1}{\sqrt{2\pi}\,t}e^{-t^2/2}$ for all $t > 0$ again and (3.34), for any $\delta > 0$, there is a constant $C_\delta > 0$ such that

$$P(F_n(\delta)^c) \leq e^{-nC_\delta} \tag{3.64}$$

as n is sufficiently large. Review $m = n-1$. Under $F_m(\delta)$, it is easy to see from (3.38) that

$$\big|\sigma_{n3}^2 - \sigma_{03}^2\big| \leq \delta \tag{3.65}$$

where $\sigma_{03}^2 := (\frac{1}{2}\rho_n^2 + 1)a_n'^2 + b_n'^2$. Evidently,

$$\frac{1}{2} \leq \sigma_{03}^2 \leq 1 \tag{3.66}$$

by (3.38). Now, review the notation $\tau = E(|\xi_1|^3) + 1$ defined earlier. For $v > 0$, define

$$G_m(v) = \Big\{\frac{1}{m}\sum_{k=1}^m (1+|\beta_k|^3)e^{v\beta_k^2(\log p)/m} \leq 2\tau\Big\}.$$

The parameter v will be chosen later. Now $(\beta_1, \cdots, \beta_m)' \stackrel{d}{=} \sqrt{a_n'^2 + b_n'^2}\,(\xi_1, \cdots, \xi_m)$. From (3.38) we know $a_n'^2 + b_n'^2 \leq 1$. Then, by Lemma 3.7, for all $v > 0$, there exists $n_v > 0$ such that

$$\begin{aligned} P(G_m(v)^c) &\leq P\Big(\frac{1}{m}\sum_{k=1}^m (1+|\xi_k|^3)e^{v\xi_k^2(\log p)/m} > 2\tau\Big) \\ &\leq \exp\Big(-\frac{1}{4}m^{1/2}(\log m)^{-2}\Big) \end{aligned}$$

for all $n \geq n_v$. Define $H_n(\delta, v) := F_m(\delta) \cap G_m(v) \cap \tilde{K}_n$. Join the above with (3.61) and (3.64) to see

$$P(H_n(\delta, v)^c) = o\Big(\frac{1}{p^3}\Big) \tag{3.67}$$

as $n \to \infty$ for all $\delta \in (0, 1)$ and $v > 0$. By Hölder's inequality,

$$\begin{aligned} & E_3 e^{h|W_k|/\sqrt{m}} \\ \leq\ & e^{h|\alpha_n|/\sqrt{m}} \cdot E_3 \exp\Big(hm^{-1/2}|\alpha_n|U_k^2 + hm^{-1/2}|\beta_k||U_k|\Big) \\ \leq\ & e^{|\alpha_n|h} \cdot \big[E_3 \exp\big(2hm^{-1/2}|\alpha_n|U_1^2\big)\big]^{1/2} \cdot \big[E_3 \exp\big(2hm^{-1/2}|\beta_k||U_1|\big)\big]^{1/2} \\ <\ & \infty \end{aligned} \tag{3.68}$$

as long as $0 < h \leq \frac{\sqrt{m}}{8|\alpha_n|}$. From (3.38) we see $|\alpha_n| \leq 1$. Therefore, (3.68) holds for all $0 < h \leq h_n := \frac{1}{8}\sqrt{m}$. Furthermore, by taking $a = \frac{\alpha_n}{\sqrt{m}}$, $d = \frac{\beta_k}{\sqrt{m}}$, $f = -\frac{\alpha_n}{\sqrt{m}}$ and $b = c = e = 0$, we have from Lemma 3.6 that

$$\begin{aligned} E_3\Big(\frac{|W_k|^3}{\sqrt{m^3}}e^{x|W_k|/\sqrt{m}}\Big) &\leq \frac{C}{m^{3/2}}(|\alpha_n|^3 + |\beta_k|^3) \cdot \exp\Big(\frac{2\beta_k^2}{m}x^2\Big) \cdot e^{|\alpha_n|x/\sqrt{m}} \\ &\leq \frac{Ce}{m^{3/2}} \cdot (1 + |\beta_k|^3) \cdot \exp\Big(\frac{2\beta_k^2}{m}x^2\Big) \end{aligned} \tag{3.69}$$

for all $0 < x \leq \frac{1}{12}\sqrt{m}$ since $\frac{1}{12|\alpha_n|}\sqrt{m} \geq \frac{1}{12}\sqrt{m}$. Now take $x_3 = \frac{s_p'}{\sigma_{n3}}$. The assertions (3.65) and (3.66) imply that $\frac{1}{4} \leq \sigma_{n3}^2 \leq 2$ on $F_m(\delta)$ for all $\delta \in (0, \frac{1}{4}]$. Then $x_3 \leq 2s_p'$ on $H_n(\delta, v)$ for all $\delta \in (0, \frac{1}{4}]$ and all $v > 0$. Moreover, due to the fact $0 \leq \omega_n < \frac{1}{2}$ we see that

$$\begin{aligned} 0 < s_p' &\leq s_p + \frac{1}{\sqrt{m}}\Big|\sum_{k=1}^m \gamma_k\Big| \\ &\leq s_p + \frac{\sqrt{7}}{2}\omega_n s_p \\ &\leq 2s_p \end{aligned} \tag{3.70}$$

on $\tilde{K}_n$. This says that $0 < x_3 \leq 2s_p' \leq 4s_p \leq \frac{1}{24}\sqrt{m}$ as $n \geq n_{v,\delta} \geq n_v$ for all $\delta \in (0, \frac{1}{4}]$

and all $v > 0$, where $n_{v,\delta} > 0$ is a constant depending on δ and v. This and (3.69) yield

$$\begin{aligned}
&\sum_{k=1}^{m} E_3\Big(\frac{|W_k|^3}{\sqrt{m^3}} e^{2x_3|W_k|/\sqrt{m}}\Big) \\
\leq\ & \frac{C}{m^{3/2}} \sum_{k=1}^{m} (1+|\beta_k|^3)\cdot \exp\Big(128 s_p^2 \cdot \frac{\beta_k^2}{m}\Big) \\
\leq\ & \frac{2\tau C}{\sqrt{m}} \qquad (3.71)
\end{aligned}$$

on $H_n(\delta, 128)$ as $n \geq n_\delta \geq n_{128,\delta}$ for all $\delta \in (0, \frac{1}{4}]$, where n_δ depends on δ. The last step follows from the definition of $G_m(v)$ and the fact $s_p^2 \leq 4\log p$ as n is sufficiently large.

Step 3: a bound on $P_3(\frac{1}{\sqrt{m}}\sum_{k=1}^m \eta'_{k12} > s_p)$. Review (3.60) and the definition of W_k, we see

$$P_3\Big(\frac{1}{\sqrt{m}}\sum_{k=1}^{m} \eta'_{k12} > s_p\Big) = P_3\Big(\frac{1}{\sqrt{m}}\sum_{k=1}^{m} \frac{W_k}{\sigma_{n3}} > x_3\Big) \qquad (3.72)$$

since $x_3 = \frac{s'_p}{\sigma_{n3}}$. Set $W'_k = \frac{W_k}{\sqrt{m}\sigma_{n3}}$ for $1 \leq k \leq m$. Then, (3.62) and (3.63) imply

$$EW'_k = 0 \ \text{ and } \ \mathrm{Var}_3\Big(\sum_{k=1}^{m} W'_k\Big) = 1$$

for each $1 \leq k \leq m$. Since $\frac{1}{4} \leq \sigma_{n3}^2 \leq 2$ on $F_m(\delta)$ for all $\delta \in (0, \frac{1}{4}]$, we see from (3.68) that $E_3 e^{h|W'_k|} \leq E_3 e^{2h|W_k|/\sqrt{m}} < \infty$ for all $0 < h \leq h_n := \frac{\sqrt{m}}{16}$. Moreover, by (3.71),

$$\begin{aligned}
\gamma :\ &= \sum_{k=1}^{m} E\big(|W'_k|^3 e^{x_3|W'_k|}\big) \\
&= \sum_{k=1}^{m} E_3\Big[\frac{|W_k|^3}{\sigma_{n3}^3\sqrt{m^3}} \exp\Big(x_3 \frac{|W_k|}{\sqrt{m}\sigma_{n3}}\Big)\Big] \\
&\leq 8\sum_{k=1}^{m} E_3\Big(\frac{|W_k|^3}{\sqrt{m^3}} e^{2x_3|W_k|/\sqrt{m}}\Big) \\
&\leq \frac{16\tau C}{\sqrt{m}}
\end{aligned}$$

on $H_n(\delta, 128)$ for all $n \geq n_\delta$ and $\delta \in (0, \frac{1}{4}]$. Trivially, $0 < x_3 \leq \frac{1}{24}\sqrt{m} < h_n$. The inequality from (3.70) says that $x_3^3\gamma = O(s_p^3/\sqrt{m}) \to 0$ on $H_n(\delta, 128)$ by the condition $\log p = o(n^{1/3})$. After verifying all conditions required in Lemma 3.5, we conclude

$$P_3\Big(\sum_{k=1}^{m} W'_k > x_3\Big) \leq 2[1 - \Phi(x_3)]$$

on $H_n(\delta, 128)$ for all $n \geq n_\delta$ and $\delta \in (0, \frac{1}{4}]$. The definition of s_p' and (3.72) yield that

$$P_3\Big(\frac{1}{\sqrt{m}}\sum_{k=1}^m \eta_{k12}' > s_p\Big) \leq 2\Big[1 - \Phi\Big(\frac{s_p}{\sigma_{n3}} - \frac{1}{\sigma_{n3}\sqrt{m}}\sum_{k=1}^m \gamma_k\Big)\Big]$$

on $H_n(\delta, 128)$ for all $n \geq n_\delta$ and $\delta \in (0, \frac{1}{4}]$. On $\tilde{K}_n$,

$$\frac{1}{\sqrt{m}\sigma_{n3}}\Big|\sum_{k=1}^m \gamma_k\Big| \leq \frac{\sqrt{7}\omega_n s_p}{2\sigma_{n3}} \leq \frac{\sqrt{7}}{4} \cdot \frac{s_p}{\sigma_{n3}}$$

since $0 \leq \omega_n < \frac{1}{2}$ by (3.39). By the fact $\frac{1}{4} \leq \sigma_{n3}^2 \leq 2$ on $H_n(\delta, 128)$ with $\delta \in (0, \frac{1}{4}]$. Therefore, $\frac{s_p}{\sigma_{n3}} - \frac{1}{\sigma_{n3}\sqrt{m}}\sum_{k=1}^m \gamma_k \to \infty$ on $H_n(\delta, 128)$ as $n \to \infty$. Since $P(N(0,1) \geq x) \leq e^{-x^2/2}$ for $x \geq 1$, we obtain that, given $\delta \in (0, \frac{1}{4}]$,

$$P_3\Big(\frac{1}{\sqrt{m}}\sum_{k=1}^m \eta_{k12}' > s_p\Big)^2 \leq 4 \cdot \exp\Big[-\Big(\frac{s_p}{\sigma_{n3}} - \frac{1}{\sigma_{n3}\sqrt{m}}\sum_{k=1}^m \gamma_k\Big)^2\Big]$$

on $H_n(\delta, 128)$ as n is sufficiently large. By (3.65) and (3.67), given $\delta \in (0, \frac{1}{4}]$,

$$\begin{aligned} & E\Big[P_3\Big(\frac{1}{\sqrt{m}}\sum_{k=1}^m \eta_{k12}' > s_p\Big)^2\Big] \\ \leq\ & 4 \cdot E\Big\{I_{H_n(\delta,128)} \cdot \exp\Big[-\frac{1}{\sigma_{n3}^2}\Big(s_p - \frac{1}{\sqrt{m}}\sum_{k=1}^m \gamma_k\Big)^2\Big]\Big\} + o\Big(\frac{1}{p^3}\Big) \\ \leq\ & 4 \cdot E\Big\{I_{\tilde{K}_n} \cdot \exp\Big[-\frac{1}{(\sigma_{03}^2 + \delta)}(s_p - V_n)^2\Big]\Big\} + o\Big(\frac{1}{p^3}\Big) \end{aligned}$$

as n is sufficiently large, where $V_n = \frac{1}{\sqrt{m}}\sum_{k=1}^m \gamma_k$. Now

$$\begin{aligned} & E\Big\{I(V_n \leq 0) \cdot \exp\Big[-\frac{1}{(\sigma_{03}^2 + \frac{1}{5})}(s_p - V_n)^2\Big]\Big\} \\ \leq\ & \exp\Big[-\frac{s_p^2}{(\sigma_{03}^2 + \frac{1}{5})}\Big] = o\Big(\frac{1}{p^3}\Big) \end{aligned}$$

since $\frac{1}{2} \leq \sigma_{03}^2 \leq 1$ by (3.66). Denote

$$K_n' = \Big\{0 < \frac{1}{\sqrt{m}}\sum_{k=1}^m \gamma_k < \frac{\sqrt{7}}{2}\omega_n s_p\Big\}.$$

Then, for given $\delta \in (0, \frac{1}{5}]$,

$$\begin{aligned} & E\Big[P_3\Big(\frac{1}{\sqrt{m}}\sum_{k=1}^m \eta_{k12}' > s_p\Big)^2\Big] \\ \leq\ & 4 \cdot E\Big\{I_{K_n'} \cdot \exp\Big[-\frac{1}{(\sigma_{03}^2 + \delta)}(s_p - V_n)^2\Big]\Big\} + o\Big(\frac{1}{p^3}\Big) \end{aligned}$$

as n is sufficiently large. By (3.38) and (3.39), $\sigma_{03}^2 + \omega_n^2 = 1$. The desired conclusion then follows from Lemma 3.13 and (3.59). ■

3.5 Proofs of Theorems 2.1 and 2.2

Review the notations (3.8)-(3.11). Let J_n and L_n be as in (2.1). Define $W_n = nJ_n$ for all $n \geq 2$. To make a summary, we have

$$W_n = \max_{1\leq i<j\leq p} \sum_{k=1}^{n} x_{ki}x_{kj} \quad \text{and} \quad L_n = \max_{1\leq i<j\leq p} \hat{\rho}_{ij}. \tag{3.73}$$

The statistics W_n and L_n will be reduced to a sum of two random variables, each of which has a limiting distribution. The lemma below, which is a coupling result, enables us to prove that the two random variables are actually asymptotically independent.

LEMMA **3.17** *Assume $p = p_n \to \infty$ as $n \to \infty$. Set $C_{nij} = n^{-1/2}\sum_{k=1}^{n} \xi_k(\xi_{ki} + \xi_{kj})$ for all $1 \leq i < j \leq p$. For any real numbers $\{\lambda_n;\, n \geq 1\}$ and any set of random variables $\{H_{ij};\, 1 \leq i < j \leq p\}$, we have*

$$\max_{1\leq i<j\leq p} \big\{H_{i,j} + \lambda_n C_{nij}\big\} = \max_{1\leq i<j\leq p} \Big\{H_{i,j} + \lambda_n \cdot \frac{\sqrt{n}}{\|\xi\|} C_{nij}\Big\} + O_p\Big(\frac{\lambda_n\sqrt{\log p}}{\sqrt{n}}\Big)$$

as $n \to \infty$. The above also holds if "C_{nij}" is replaced by "C_{mij}" with $m = n - 1$.

Proof. Recall $\|\xi\| = (\xi_1^2 + \cdots + \xi_n^2)^{1/2}$. Then,

$$\begin{aligned}\Big|\frac{\sqrt{n}}{\|\xi\|} - 1\Big| &= \frac{|\,\|\xi\|^2 - n|}{\|\xi\| + \sqrt{n}} \cdot \frac{1}{\|\xi\|} \\ &\leq \frac{1}{\sqrt{n}} \cdot \frac{\sqrt{n}}{\|\xi\|} \cdot \Big|\frac{1}{\sqrt{n}}\sum_{k=1}^{n}(\xi_k^2 - 1)\Big| = O_p\big(n^{-1/2}\big) \end{aligned} \tag{3.74}$$

as $n \to \infty$ since $\frac{\sqrt{n}}{\|\xi\|} \to 1$ in probability and $\frac{1}{\sqrt{n}}\sum_{k=1}^{n}(\xi_k^2 - 1)$ converges to $N(0,2)$ weakly. For any real numbers $\{\lambda_n;\, n \geq 1\}$ and any set of random variables $\{H_{ij};\, 1 \leq i < j \leq p\}$, by a triangle inequality,

$$\begin{aligned} &\Big|\max_{1\leq i<j\leq p} \big\{H_{i,j} + \lambda_n C_{nij}\big\} - \max_{1\leq i<j\leq p} \Big\{H_{i,j} + \lambda_n \cdot \frac{\sqrt{n}}{\|\xi\|} C_{nij}\Big\}\Big| \\ \leq\ & \lambda_n \cdot \Big|\frac{\sqrt{n}}{\|\xi\|} - 1\Big| \cdot \max_{1\leq i<j\leq p} |C_{nij}|. \end{aligned} \tag{3.75}$$

Note that

$$\max_{1\leq i<j\leq p} |C_{nij}| \leq 2 \cdot \max_{1\leq i\leq p} \frac{1}{\sqrt{n}}\Big|\sum_{k=1}^{n} \xi_k\xi_{ki}\Big|.$$

Observe $E(\xi_1\xi_{11}) = 0$, $\text{Var}(\xi_1\xi_{11}) = 1$ and $E\exp(\frac{1}{2}|\xi_1\xi_{11}|) < \infty$. By Lemma 3.4 and assumption $\log p = o(n^{1/3})$ we have

$$\begin{aligned} & P\Big(\max_{1\leq i<j\leq p} |C_{nij}| \geq 2A\sqrt{\log p}\Big) \\ \leq\ & p \cdot P\Big(\frac{1}{\sqrt{n}}\Big|\sum_{k=1}^{n} \xi_k\xi_{k1}\Big| \geq A\sqrt{\log p}\Big) \\ \leq\ & p \cdot e^{-A^2(\log p)/3} \to 0 \end{aligned} \tag{3.76}$$

as long as $A > \sqrt{3}$. So $\max_{1\le i<j\le p} |C_{nij}| = O_p(\sqrt{\log p}\,)$. This joining with (3.74) and (3.75) implies the desired result. Reviewing the arguments above, we see the assertion is still true if "n" is replaced by "m". ■

Proof of Theorem 2.1. By assumption, $\mu = \mathbf{0}$. Let $\{\xi_k, \xi_{ki}, k, i = 1, 2, \cdots\}$, ρ_n', $\|\xi\|$ be as in (3.8)-(3.11). Write

$$x_{ki} = \sqrt{\rho_n}\xi_k + \sqrt{\rho_n'}\xi_{ki}, \quad 1 \le k \le n,\ 1 \le i \le p. \tag{3.77}$$

It is easy to check the n rows of the matrix $(x_{ij})_{n\times p}$ are i.i.d. random vectors, $x_{1i} \sim N(0,1)$ for each $1 \le i \le p$ and $Cov(x_{1i}, x_{1j}) = \rho_n$ for $1 \le i < j \le p$. That is, each row follows $N_p(\mathbf{0}, \mathbf{R})$. As a result, $\mathbf{X}$ and $(x_{ij})_{n\times p}$ have the same distribution. So we assume $\mathbf{X} = (x_{ij})_{n\times p}$ in the next. Denote

$$A_n = \frac{1}{\sqrt{n}}\sum_{k=1}^n \xi_k^2, \quad B_{nij} = \frac{1}{\sqrt{n}}\sum_{k=1}^n \xi_{ki}\xi_{kj}, \quad C_{nij} = \frac{1}{\sqrt{n}}\sum_{k=1}^n \xi_k(\xi_{ki} + \xi_{kj})$$

for all $1 \le i \le j \le p$. Then it follows from the expression (3.77) that

$$\frac{1}{\sqrt{n}}\sum_{k=1}^n x_{ki}x_{kj} = \rho_n A_n + \rho_n' B_{nij} + \sqrt{\rho_n\rho_n'}C_{nij}. \tag{3.78}$$

First, by the central limit theorem, we are able to write

$$A_n = \sqrt{n} + \sqrt{2}U_{n1},$$

where $U_{n1} := \frac{1}{\sqrt{2n}}\sum_{k=1}^n(\xi_k^2 - 1) \xrightarrow{d} N(0,1)$. Define

$$M_{nij} := \frac{\rho_n' B_{nij} + \sqrt{\rho_n\rho_n'}C_{nij}}{\sqrt{1-\rho_n^2}} = \frac{1}{\sqrt{n}}\sum_{k=1}^n \big[a_n\xi_{ki}\xi_{kj} + b_n\xi_k(\xi_{ki} + \xi_{kj})\big],$$

where $a_n = \sqrt{\frac{1-\rho_n}{1+\rho_n}}$ and $b_n = \sqrt{\frac{\rho_n}{1+\rho_n}}$. Denote $M_n = \max_{1\le i<j\le p} M_{nij}$. From these notations we have

$$\frac{1}{\sqrt{n}}\sum_{k=1}^n x_{ki}x_{kj} = \rho_n\sqrt{n} + \sqrt{2}\rho_n U_{n1} + \sqrt{1-\rho_n^2}\, M_{nij}, \tag{3.79}$$

and hence

$$\max_{1\le i<j\le p}\frac{1}{\sqrt{n}}\sum_{k=1}^n x_{ki}x_{kj} = \sqrt{n}\rho_n + \sqrt{2}\rho_n U_{n1} + \sqrt{1-\rho_n^2}M_n. \tag{3.80}$$

Review the notation $\xi = (\xi_1, \cdots, \xi_n)'$. Define

$$\begin{aligned}\tilde{M}_n &= \max_{1\le i<j\le p}\frac{1}{\sqrt{n}}\sum_{k=1}^n \Big[a_n\xi_{ki}\xi_{kj} + b_n\frac{\sqrt{n}}{\|\xi\|}\xi_k(\xi_{ki} + \xi_{kj})\Big] \\ &= \max_{1\le i<j\le p}\Big\{H_{i,j} + b_n \cdot \frac{\sqrt{n}}{\|\xi\|}C_{nij}\Big\}\end{aligned}$$

where $H_{i,j} = n^{-1/2} \sum_{k=1}^{n} a_n \xi_{ki} \xi_{kj}$. By Lemma 3.17 and the fact $0 \le b_n \le 1$,

$$M_n = \tilde{M}_n + O_p\Big(\frac{\sqrt{\log p}}{\sqrt{n}}\Big). \tag{3.81}$$

This and (3.80) imply that

$$\begin{aligned} & \max_{1\le i<j\le p} \frac{1}{\sqrt{n}} \sum_{k=1}^{n} x_{ki} x_{kj} \\ = \ & \sqrt{n}\rho_n + \sqrt{2}\rho_n U_{n1} + \sqrt{1-\rho_n^2}\tilde{M}_n + O_p\Big(\frac{\sqrt{\log p}}{\sqrt{n}}\Big). \end{aligned} \tag{3.82}$$

Since $\|\xi\|$ and $\frac{\xi}{\|\xi\|}$ are independent [see the discussion above (3.13)], $U_{n1} = \frac{1}{\sqrt{2n}}(\|\xi\|^2 - n)$ and $\tilde{M}_n$, which is a function of $\frac{\xi}{\|\xi\|}$ and ξ_{ki}'s, are also independent. This is a crucial observation in the following argument.

Now, it follows from Lemma 3.8 and Proposition 3.1 that

$$M_n = 2\sqrt{\log p} - \frac{\log\log p}{4\sqrt{\log p}} + \frac{1}{4\sqrt{\log p}} U_{n2},$$

where $U_{n2} \xrightarrow{d} \eta$ with distribution function $F_\eta(x) = e^{-\frac{1}{4\sqrt{2\pi}}e^{-\frac{x}{2}}}$ for all $x \in \mathbb{R}$. From (3.81),

$$\tilde{M}_n = 2\sqrt{\log p} - \frac{\log\log p}{4\sqrt{\log p}} + \frac{1}{4\sqrt{\log p}} U_{n2} + O_p\Big(\frac{\sqrt{\log p}}{\sqrt{n}}\Big).$$

Then

$$\tilde{U}_{n2} := 4\sqrt{\log p} \cdot \Big(\tilde{M}_n - 2\sqrt{\log p} + \frac{\log\log p}{4\sqrt{\log p}}\Big) \xrightarrow{d} \eta. \tag{3.83}$$

Since U_{n1} and $\tilde{M}_n$ are independent, U_{n1} and $\tilde{U}_{n2}$ are independent. Reviewing the definition of W_n as in (3.73). Solve $\tilde{M}_n$ from the first identity in (3.83) and then plug it into (3.82) to see

$$\begin{aligned} \frac{1}{\sqrt{n}} W_n - \mu_1 &= \sqrt{2}\rho_n U_{n1} + \frac{\sqrt{1-\rho_n^2}}{4\sqrt{\log p}} \tilde{U}_{n2} + O_p\Big(\frac{\sqrt{\log p}}{\sqrt{n}}\Big) \\ &= \sqrt{2}\rho_n U_{n1} + \frac{\sqrt{1-\rho_n^2}}{4\sqrt{\log p}} \tilde{U}_{n2} + o_p\Big(\frac{1}{\sqrt{\log p}}\Big) \end{aligned}$$

by the assumption $\log p = o(n^{1/3})$, where

$$\mu_1 = \sqrt{n}\rho_n + \Big(2\sqrt{\log p} - \frac{\log\log p}{4\sqrt{\log p}}\Big)\sqrt{1-\rho_n^2}.$$

We now derive the three conclusions by the above relation.

Case (i): $\rho_n\sqrt{\log p} \to 0$. For this case, by the Slutsky lemma,

$$\frac{4\sqrt{\log p}}{\sqrt{1-\rho_n^2}}\big(n^{-1/2}W_n - \mu_1\big) \xrightarrow{d} \phi$$

where ϕ is the extreme-value distribution $F(x) = e^{-Ke^{-\frac{x}{2}}}$ with $K = \frac{1}{4\sqrt{2\pi}}$. The conclusion then follows by the assumption $\rho_n \to 0$ and the Slutsky lemma again.

Case (ii): $\rho_n\sqrt{\log p} \to \lambda \in (0, +\infty)$. By using the independence between U_{n1} and $\tilde{U}_{n2}$ and the Slutsky lemma again, we have

$$\frac{n^{-1/2}W_n - \mu_1}{\sqrt{2}\rho_n} \xrightarrow{d} \xi + \lambda_0\phi,$$

where $\xi \sim N(0,1)$, $\lambda_0 = \frac{1}{4\sqrt{2}\lambda}$ and ϕ is as in case (i) and ϕ is independent of ξ.

Case (iii): $\rho_n\sqrt{\log p} \to \infty$. In this situation, by the Slutsky lemma,

$$\frac{n^{-1/2}W_n - \mu_1}{\sqrt{2}\rho_n} \xrightarrow{d} N(0,1).$$

The proof is completed by using (3.73). ■

The major contribution of L_n in Theorem 2.2 comes from (3.84) next, which will be represented as a sum of two random variables well understood from earlier sections.

LEMMA **3.18** *Let $\rho_n \in [0,1)$ for all $n \geq 1$. Review the notations in (3.8)-(3.9). Define $x_{ki} = \sqrt{\rho_n}\xi_k + \sqrt{1-\rho_n}\xi_{ki}$ for $1 \leq k \leq m$ and $1 \leq i \leq p$, where $m = n-1$. Assume $\log p = o(n^{\frac{1}{3}})$ as $n \to \infty$. Then*

$$\begin{aligned}&\Big(\frac{1}{\sqrt{m}}\sum_{k=1}^m x_{ki}x_{kj}\Big)\cdot\Big[1 - \frac{1}{4m}\sum_{k=1}^m (x_{ki}^2 + x_{kj}^2)\Big]\\ =\ & \frac{1}{2}\rho_n\sqrt{m} + \frac{1}{\sqrt{2}}\rho_n(1-\rho_n)U_{m1} + \frac{1}{2}\sqrt{1-\rho_n^2}\cdot\frac{1}{\sqrt{m}}\sum_{k=1}^m \psi_{kij} + \Delta_{nij}\end{aligned} \tag{3.84}$$

where $U_{m1} = \frac{1}{\sqrt{2m}}\sum_{k=1}^m(\xi_k^2 - 1)$,

$$\psi_{kij} = a_n\Big[\xi_{ki}\xi_{kj} - \frac{\rho_n}{2}(\xi_{ki}^2 + \xi_{kj}^2 - 2)\Big] + (1-\rho_n)b_n\xi_k(\xi_{ki} + \xi_{kj})$$

and

$$\max_{1\leq i<j\leq p}|\Delta_{nij}| = O_p\Big(\frac{\log p}{\sqrt{m}}\Big) \tag{3.85}$$

as $n \to \infty$.

Proof. Define

$$M_{mij} = \frac{1}{\sqrt{m}} \sum_{k=1}^{m} \eta_{kij}, \quad 1 \le i \le j \le p,$$

where $\eta_{kij} = a_n \xi_{ki}\xi_{kj} + b_n \xi_k(\xi_{ki} + \xi_{kj})$, $a_n = \sqrt{\frac{1-\rho_n}{1+\rho_n}}$ and $b_n = \sqrt{\frac{\rho_n}{1+\rho_n}}$. From (3.79) we have

$$\frac{1}{\sqrt{m}} \sum_{k=1}^{m} x_{ki}x_{kj} = \rho_n\sqrt{m} + \sqrt{2}\rho_n U_{m1} + \sqrt{1-\rho_n^2}\, M_{mij}; \tag{3.86}$$

$$\frac{1}{\sqrt{m}} \sum_{k=1}^{m} x_{ki}^2 = \rho_n\sqrt{m} + \sqrt{2}\rho_n U_{m1} + \sqrt{1-\rho_n^2}\, M_{mii}$$

where $U_{m1} = \frac{1}{\sqrt{2m}} \sum_{k=1}^{m} (\xi_k^2 - 1)$. In particular,

$$M_{mii} = \frac{1}{\sqrt{m}} \sum_{k=1}^{m} (a_n \xi_{ki}^2 + 2b_n \xi_k \xi_{ki}).$$

We can write

$$\begin{aligned}
& \frac{1}{4m} \sum_{k=1}^{m} (x_{ki}^2 + x_{kj}^2) \\
= \; & \frac{1}{4\sqrt{m}} \big(2\rho_n\sqrt{m} + 2\sqrt{2}\rho_n U_{m1}\big) + \frac{1}{4\sqrt{m}} \sqrt{1-\rho_n^2} (M_{mii} + M_{mjj}) \\
= \; & \frac{1}{2}\rho_n + \frac{1}{2} a_n \sqrt{1-\rho_n^2} + \frac{\rho_n}{\sqrt{2m}} U_{m1} + \frac{1}{4\sqrt{m}} \sqrt{1-\rho_n^2}\, T_{mij} \\
= \; & \frac{1}{2} + \frac{\rho_n}{\sqrt{2m}} U_{m1} + \frac{1}{4\sqrt{m}} \sqrt{1-\rho_n^2}\, T_{mij}
\end{aligned}$$

where

$$T_{mij} = \frac{1}{\sqrt{m}} \sum_{k=1}^{m} \big[a_n(\xi_{ki}^2 + \xi_{kj}^2 - 2) + 2b_n \xi_k(\xi_{ki} + \xi_{kj})\big]. \tag{3.87}$$

So the product in (3.84) is equal to

$$\begin{aligned}
& \big(\rho_n\sqrt{m} + \sqrt{2}\rho_n U_{m1} + \sqrt{1-\rho_n^2}\, M_{mij}\big) \cdot \\
& \qquad \Big(\frac{1}{2} - \frac{\rho_n}{\sqrt{2m}} U_{m1} - \frac{1}{4\sqrt{m}} \sqrt{1-\rho_n^2}\, T_{mij}\Big) \\
= \; & \frac{1}{2}\rho_n\sqrt{m} + \frac{1}{\sqrt{2}}\rho_n(1-\rho_n)U_{m1} + \frac{1}{2}\sqrt{1-\rho_n^2}\, M_{mij} - \frac{\rho_n}{4}\sqrt{1-\rho_n^2}\, T_{mij} \\
& \qquad + \Delta_{nij}
\end{aligned}$$

where

$$\begin{aligned}
\Delta_{nij} \; = \; & -\frac{\rho_n^2}{\sqrt{m}} U_{m1}^2 - \frac{\rho_n\sqrt{1-\rho_n^2}}{\sqrt{2m}} (U_{m1}M_{mij}) \\
& -\frac{1}{4\sqrt{m}} \sqrt{1-\rho_n^2}\, T_{mij}\big(\sqrt{2}\rho_n U_{m1} + \sqrt{1-\rho_n^2}\, M_{mij}\big).
\end{aligned}$$

Observe that

$$\begin{aligned}
& \frac{1}{2}\sqrt{1-\rho_n^2} M_{mij} - \frac{\rho_n}{4}\sqrt{1-\rho_n^2}\, T_{mij} \\
= & \ \frac{1}{2}\sqrt{1-\rho_n^2}\cdot \frac{1}{\sqrt{m}}\sum_{k=1}^{n}\psi_{kij},
\end{aligned}$$

where

$$\psi_{kij} = a_n\Big[\xi_{ki}\xi_{kj} - \frac{\rho_n}{2}(\xi_{ki}^2+\xi_{kj}^2-2)\Big] + (1-\rho_n)b_n\xi_k(\xi_{ki}+\xi_{kj}).$$

Use the trivial bound $1-\rho_n^2 \le 1$ to see

$$\begin{aligned}
& \max_{1\le i<j\le p}|\Delta_{nij}| \\
\le & \ \frac{\rho_n^2}{\sqrt{m}}U_{m1}^2 + \frac{\rho_n}{\sqrt{m}}(M_m+T_m)|U_{m1}| + \frac{1}{\sqrt{m}}(M_m T_m)
\end{aligned} \tag{3.88}$$

where

$$M_m = \max_{1\le i<j\le p}|M_{mij}| \text{ and } T_m = \max_{1\le i<j\le p}|T_{mij}|.$$

From Proposition 3.1, we know

$$\frac{M_m}{\sqrt{\log p}} \to 2 \tag{3.89}$$

in probability. Now, from (3.87) we have

$$\begin{aligned}
T_m \ \le & \ \max_{1\le i<j\le p}\frac{1}{\sqrt{m}}\Big|\sum_{k=1}^{m}(\xi_{ki}^2+\xi_{kj}^2-2)\Big| + \max_{1\le i<j\le p}\frac{1}{\sqrt{m}}\Big|\sum_{k=1}^{m}\xi_k(\xi_{ki}+\xi_{kj})\Big| \\
\le & \ 2\max_{1\le i\le p}\frac{1}{\sqrt{m}}\Big|\sum_{k=1}^{m}(\xi_{ki}^2-1)\Big| + 2\max_{1\le i<j\le p}\frac{1}{\sqrt{m}}\Big|\sum_{k=1}^{m}\xi_k\xi_{ki}\Big| \\
:= & \ 2I_n + 2I_n'.
\end{aligned} \tag{3.90}$$

Let $\zeta_k = (\xi_{k1}^2-1)/\sqrt{2}$ for $1\le k\le m$. Then $E\zeta_k=0$, $\mathrm{Var}(\zeta_k)=1$ and $Ee^{|\zeta_1|/2}<\infty$. By Lemma 3.4, from assumption $\sqrt{\log p} = o(n^{1/3})$ we see that

$$\begin{aligned}
& P\Big(I_n \ge 2A_2\sqrt{\log p}\Big) \\
\le & \ p\cdot P\Big(\frac{1}{\sqrt{m}}\Big|\sum_{k=1}^{m}\zeta_k\Big| \ge A_2\sqrt{\log p}\Big) \\
\le & \ p\cdot e^{-A_2^2(\log p)/3} \to 0
\end{aligned} \tag{3.91}$$

as long as $A_2 > \sqrt{3}$. So $I_n = O_p(\sqrt{\log p}\,)$. Furthermore, notice $E(\xi_1\xi_{11}) = 0$, $\mathrm{Var}(\xi_1\xi_{11}) = 1$ and $E\exp(\frac{1}{2}|\xi_1\xi_{11}|) < \infty$. By the same argument as obtaining (3.91), we have $I'_n = O_p(\sqrt{\log p})$. In summary, $T_m = O_p(\sqrt{\log p})$. This together with (3.89) and the fact $U_{m1} \to N(0,1)$ implies that

$$\max_{1\le i<j\le p} |\Delta_{nij}| = O_p\Big(\frac{\log p}{\sqrt{m}}\Big)$$

by using (3.88). We then get (3.85). ■

Now we prove the last result in this paper.

Proof of Theorem 2.2. As explained at the beginning of the proof of Lemma 3.2, without loss of generality, we assume $\mu = \mathbf{0}$.

Let $\{\xi_k, \xi_{ki}, k, i = 1, 2, \cdots\}$ and $\rho'_n = 1 - \rho_n$ be as in (3.8)-(3.9). As before, $p = p_n$. Define

$$x_{ki} = \sqrt{\rho_n}\xi_k + \sqrt{\rho'_n}\xi_{ki}, \quad 1 \le k \le n-1,\ 1 \le i \le p.$$

Review the beginning of the proof of Theorem 2.1, we know the $n-1$ rows of the matrix $(x_{ij})_{(n-1)\times p}$ are i.i.d. random vectors, each of which follows $N_p(\mathbf{0}, \mathbf{R})$. Write $(x_{ij})_{(n-1)\times p} = (V_1, \cdots, V_p)$ such that $V_j = (x_{1j}, \cdots, x_{n-1,j})'$ for each $1 \le j \le p$. By Lemma 3.2, we have

$$\sqrt{n-1}\max_{1\le i<j\le p} \hat{\rho}_{ij} \overset{d}{=} \max_{1\le i<j\le p} \frac{\frac{1}{\sqrt{n-1}}\sum_{k=1}^{n-1} x_{ki}x_{kj}}{\sqrt{\frac{1}{n-1}\sum_{k=1}^{n-1} x_{ki}^2}\sqrt{\frac{1}{n-1}\sum_{k=1}^{n-1} x_{kj}^2}}. \tag{3.92}$$

Denote $m = n-1$, $h_i = \sqrt{\frac{1}{m}\sum_{k=1}^m x_{ki}^2}$ and

$$\Lambda_{nij} = \frac{\frac{1}{\sqrt{m}}\sum_{k=1}^m x_{ki}x_{kj}}{h_ih_j}. \tag{3.93}$$

So it suffices to prove the statements (i), (ii) and (iii) with "$\sqrt{n-1}L_n$" replaced by "$\max_{1\le i<j\le p}\Lambda_{nij}$" in the following. The arguments are divided into a few of steps.

Step 1: Reduction of L_n to a simple form. Write $\frac{1}{h_i} = (1 + \frac{1}{\sqrt{m}}\zeta_{ni})^{-1/2}$ where $\zeta_{ni} := \frac{1}{\sqrt{m}}\sum_{k=1}^m(x_{ki}^2 - 1)$. By the Taylor expansion, there exists $\delta \in (0,1)$ such that $(1+x)^{-\frac{1}{2}} = 1 - \frac{x}{2} + \phi(x)$ where $|\phi(x)| \le x^2$ for all $x \in [-\delta, \delta]$. It follows that

$$\begin{aligned}\frac{1}{h_ih_j} &= \Big[1 - \frac{\zeta_{ni}}{2\sqrt{m}} + \phi\Big(\frac{\zeta_{ni}}{\sqrt{m}}\Big)\Big]\cdot\Big[1 - \frac{\zeta_{nj}}{2\sqrt{m}} + \phi\Big(\frac{\zeta_{nj}}{\sqrt{m}}\Big)\Big] \\ &= 1 - \frac{\zeta_{ni}}{2\sqrt{m}} - \frac{\zeta_{nj}}{2\sqrt{m}} + \epsilon_{ij} \end{aligned} \tag{3.94}$$

where

$$\begin{aligned}\epsilon_{ij} &= \frac{\zeta_{ni}\zeta_{nj}}{4m} + \Big(1 - \frac{\zeta_{ni}}{2\sqrt{m}}\Big)\cdot\phi\Big(\frac{\zeta_{nj}}{\sqrt{m}}\Big) \\ &\quad + \Big(1 - \frac{\zeta_{nj}}{2\sqrt{m}}\Big)\cdot\phi\Big(\frac{\zeta_{ni}}{\sqrt{m}}\Big) + \phi\Big(\frac{\zeta_{ni}}{\sqrt{m}}\Big)\phi\Big(\frac{\zeta_{nj}}{\sqrt{m}}\Big).\end{aligned}$$

Obviously, if $|\frac{\zeta_{ni}}{\sqrt{m}}| < \delta$ and $|\frac{\zeta_{nj}}{\sqrt{m}}| < \delta$, then $\max_{k=i,j} |1 - \frac{\zeta_{nk}}{2\sqrt{m}}| < 2$ because $\delta \in (0,1)$, and hence

$$\begin{aligned} |\epsilon_{ij}| &\leq \frac{|\zeta_{ni}|\cdot|\zeta_{nj}|}{4m} + \frac{2\zeta_{ni}^2}{m} + \frac{2\zeta_{nj}^2}{m} + \frac{\zeta_{ni}^2}{m}\cdot\frac{\zeta_{nj}^2}{m} \\ &\leq \frac{4(\zeta_{ni}^2+\zeta_{nj}^2)}{m}. \end{aligned}$$

This gives that

$$\max_{1\leq i<j\leq p} |\epsilon_{ij}| \leq \frac{8}{m}\cdot \max_{1\leq i\leq m}\zeta_{ni}^2 \tag{3.95}$$

provided $\max_{1\leq i\leq p}|\frac{\zeta_{ni}}{\sqrt{m}}| < \delta$. Let $\zeta_k = (\xi_{k1}^2-1)/\sqrt{2}$ for $1\leq k\leq m$. Then $E\zeta_k = 0$, $\mathrm{Var}(\zeta_k) = 1$ and $Ee^{|\zeta_1|/2} < \infty$. By assumption, $(x_{1i}, x_{2i}, \cdots, x_{mi}) \stackrel{d}{=} (\xi_1, \xi_2, \cdots, \xi_k)$ for each $1\leq i\leq p$. Set

$$\Omega_n = \big\{\max_{1\leq i\leq p}|\zeta_{ni}| < 3\sqrt{\log p}\big\}.$$

Then it follows by (3.91) that

$$\lim_{n\to\infty} P(\Omega_n) = 1. \tag{3.96}$$

Now we see from (3.93) and (3.94) that

$$\begin{aligned} \Lambda_{nij} &= \Big(\frac{1}{\sqrt{m}}\sum_{k=1}^m x_{ki}x_{kj}\Big)\cdot\Big(1 - \frac{\zeta_{ni}}{2\sqrt{m}} - \frac{\zeta_{nj}}{2\sqrt{m}} + \epsilon_{ij}\Big) \\ &= \Big(\frac{2}{\sqrt{m}}\sum_{k=1}^m x_{ki}x_{kj}\Big)\cdot\Big[1 - \frac{1}{4m}\big(\sum_{k=1}^m x_{ki}^2 + \sum_{k=1}^m x_{kj}^2\big)\Big] + \epsilon_{ij}' \end{aligned} \tag{3.97}$$

where

$$\epsilon_{ij}' := \Big(\frac{1}{\sqrt{m}}\sum_{k=1}^m x_{ki}x_{kj}\Big)\cdot\epsilon_{ij}.$$

Now we estimate the size of $\max_{1\leq i<j\leq p}\frac{1}{\sqrt{m}}|\sum_{k=1}^m x_{ki}x_{kj}|$. In fact, (3.86) implies that

$$\begin{aligned} &\max_{1\leq i<j\leq p}\frac{1}{\sqrt{m}}\Big|\sum_{k=1}^m x_{ki}x_{kj}\Big| \\ \leq\ & \sqrt{m} + |U_{m1}| + \max_{1\leq i<j\leq p}\frac{1}{\sqrt{m}}\Big|\sum_{k=1}^m\big[a_n\xi_{ki}\xi_{kj} + b_n\xi_k(\xi_{ki}+\xi_{kj})\big]\Big| \\ \leq\ & \sqrt{m} + |U_{m1}| + \max_{1\leq i<j\leq p}\frac{1}{\sqrt{m}}\Big|\sum_{k=1}^m \xi_{ki}\xi_{kj}\Big| + 2\max_{1\leq i\leq p}\frac{1}{\sqrt{m}}\Big|\sum_{k=1}^m\xi_k\xi_{ki}\Big| \end{aligned}$$

where $U_{m1} = \frac{1}{\sqrt{2m}}\sum_{k=1}^m(\xi_k^2-1)$. Observe that the last two maxima above have the same distribution. By the estimate of I_n' from (3.90), each of them has size $O_p(\sqrt{\log p})$. Using the assumption $\log p = o(n^{1/3})$, we see

$$\Upsilon_n := \max_{1\le i<j\le p}\frac{1}{\sqrt{m}}\Big|\sum_{k=1}^m x_{ki}x_{kj}\Big| = O_p(\sqrt{n})$$

as $n\to\infty$. Therefore, by (3.95),

$$\begin{aligned}\max_{1\le i<j\le p}|\epsilon_{ij}'| &\le \Upsilon_n\cdot\max_{1\le i<j\le p}|\epsilon_{ij}|\\ &\le \frac{8}{m}\cdot\Upsilon_n\cdot\max_{1\le i\le m}\zeta_{ni}^2\end{aligned}$$

provided $\max_{1\le i<j\le p}|\frac{\zeta_{ni}}{\sqrt{m}}|<\delta$. By assumption, $\frac{3\sqrt{\log p}}{\sqrt{m}}\to 0$. This enables us to see

$$I_{\Omega_n}\cdot\max_{1\le i<j\le p}|\epsilon_{ij}'| = \frac{8}{m}\cdot O_p(\sqrt{n})\cdot(3\sqrt{\log p})^2 = O\Big(\frac{\log p}{\sqrt{n}}\Big). \tag{3.98}$$

By Lemma 3.18 and (3.97),

$$\begin{aligned}\Lambda_{nij} &= \rho_n\sqrt{m}+\sqrt{2}\rho_n(1-\rho_n)U_{m1}+\sqrt{1-\rho_n^2}\cdot\frac{1}{\sqrt{m}}\sum_{k=1}^n\psi_{kij}+2\Delta_{nij}+\epsilon_{ij}'\\ &= \rho_n\sqrt{m}+\sqrt{2}\rho_n(1-\rho_n)U_{m1}+\sigma_{n1}\sqrt{1-\rho_n^2}\cdot\frac{1}{\sigma_{n1}\sqrt{m}}\sum_{k=1}^n\psi_{kij}+\epsilon_{ij}''\end{aligned} \tag{3.99}$$

where ψ_{kij} and Δ_{nij} are defined as in the lemma, $\epsilon_{ij}''=2\Delta_{nij}+\epsilon_{ij}'$ and $\sigma_{n1}^2=(1-\rho_n)^2+2\rho_n a_n^2$. Easily

$$I_{\Omega_n}\cdot\max_{1\le i<j\le p}|\epsilon_{ij}''|\le 2\cdot\max_{1\le i<j\le p}|\Delta_{nij}|+I_{\Omega_n}\cdot\max_{1\le i<j\le p}|\epsilon_{ij}'| = O_p\Big(\frac{\log p}{\sqrt{n}}\Big)$$

by (3.85) and (3.98). Let $f(i,j)$ and $g(i,j)$ be real functions defined on $\{(i,j);\ 1\le i<j\le m\}$. It is easy to see that

$$|\max_{1\le i<j\le p}f(i,j)-\max_{1\le i<j\le p}g(i,j)|\le\max_{1\le i<j\le p}|f(i,j)-g(i,j)|.$$

Therefore, from (3.99) we have

$$\begin{aligned}&I_{\Omega_n}\cdot\max_{1\le i<j\le p}\Lambda_{nij}\\ =\ &I_{\Omega_n}\cdot\big[\rho_n\sqrt{m}+\sqrt{2}\rho_n(1-\rho_n)U_{m1}\big]\\ &\qquad+\sigma_{n1}\sqrt{1-\rho_n^2}\cdot\max_{1\le i<j\le p}\Big\{\frac{1}{\sigma_{n1}\sqrt{m}}\cdot\sum_{k=1}^n\psi_{kij}\Big\}\cdot I_{\Omega_n}+O_p\Big(\frac{\log p}{\sqrt{n}}\Big).\end{aligned}$$

Observe that the last maximum is exactly M_n' appeared in Proposition 3.2. Writing $I_{\Omega_n} = 1 - I_{\Omega_n^c}$, we eventually get

$$\begin{aligned}
& \max_{1\le i<j\le p} \Lambda_{nij} \\
= \ & \rho_n\sqrt{m} + \sqrt{2}\rho_n(1-\rho_n)U_{m1} + \sigma_{n1}\sqrt{1-\rho_n^2}M_n' + O_p\Big(\frac{\log p}{\sqrt{m}}\Big) + I_{\Omega_n^c}\cdot \Psi_n
\end{aligned} \tag{3.100}$$

for some random variable Ψ_n.

Step 2: Asymptotic independence between U_{m1} and M_n'. Review the definition of ψ_{kij} in Lemma 3.18. Set

$$\begin{aligned}
\tilde{\eta}_{kij}' &= a_n\Big[\xi_{ki}\xi_{kj} - \frac{\rho_n}{2}(\xi_{ki}^2 + \xi_{kj}^2 - 2)\Big] + (1-\rho_n)b_n\frac{\sqrt{m}}{\|\xi\|}\xi_k(\xi_{ki}+\xi_{kj});\\
\tilde{M}_n' &= \max_{1\le i<j\le p}\Big\{\frac{1}{\sigma_{n1}\sqrt{m}}\cdot\sum_{k=1}^m \tilde{\eta}_{kij}'\Big\}.
\end{aligned}$$

By (3.38), $(1+\rho_n^2)a_n'^2 + 2b_n'^2 = 1$. Since $b_n' = \frac{(1-\rho_n)b_n}{\sigma_{n1}}$, we get $|\frac{(1-\rho_n)b_n}{\sigma_{n1}}| \le \frac{1}{2}$. By Lemma 3.17,

$$\tilde{M}_n' - M_n' = O_p\Big(\frac{(1-\rho_n)b_n}{\sigma_{n1}}\cdot\frac{\sqrt{\log p}}{\sqrt{n}}\Big) = O_p\Big(\frac{\sqrt{\log p}}{\sqrt{n}}\Big). \tag{3.101}$$

By Lemma 3.8 and Proposition 3.2,

$$M_n' = 2\sqrt{\log p} - \frac{\log\log p}{4\sqrt{\log p}} + \frac{1}{4\sqrt{\log p}}V_n,$$

where $V_n \xrightarrow{d} \phi$ with distribution function $F(x) = e^{-Ke^{-\frac{x}{2}}}$ for all $x \in \mathbb{R}$, where $K = \frac{1}{4\sqrt{2\pi}}$. The above two assertions tell us that

$$\tilde{M}_n' = 2\sqrt{\log p} - \frac{\log\log p}{4\sqrt{\log p}} + \frac{1}{4\sqrt{\log p}}V_n + o_p\Big(\frac{1}{\sqrt{\log p}}\Big).$$

Then

$$\tilde{U}_{n2} := 4\sqrt{\log p}\cdot\Big(\tilde{M}_n' - 2\sqrt{\log p} + \frac{\log\log p}{4\sqrt{\log p}}\Big) \xrightarrow{d} \phi. \tag{3.102}$$

Since $U_{m1} = \frac{1}{\sqrt{2m}}\sum_{k=1}^m(\xi_k^2 - 1)$ and $\tilde{M}_n'$ are independent by the same argument as that after (3.82), U_{m1} and $\tilde{U}_{n2}$ are independent. Evidently,

$$\begin{aligned}
\sigma_{n1}\sqrt{1-\rho_n^2} &= \Big((1-\rho_n)^2 + 2\rho_n\cdot\frac{1-\rho_n}{1+\rho_n}\Big)^{1/2}\cdot\sqrt{1-\rho_n^2}\\
&= (1-\rho_n)\cdot\sqrt{1+2\rho_n-\rho_n^2}.
\end{aligned}$$

In particular, $\sigma_{n1}\sqrt{1-\rho_n^2} \le 2$. Combining (3.100), (3.101) and (3.102), we obtain

$$\begin{aligned}
&\max_{1\le i<j\le p} \Lambda_{nij} - \rho_n\sqrt{m} - \sqrt{2}\rho_n(1-\rho_n)U_{m1} \\
= \;& \sigma_{n1}\sqrt{1-\rho_n^2}\tilde{M}_n' + O_p\Big(\frac{\log p}{\sqrt{n}}\Big) + I_{\Omega_n^c}\cdot\Psi_n \\
= \;& \sigma_{n1}\sqrt{1-\rho_n^2}\Big(2\sqrt{\log p} - \frac{\log\log p}{4\sqrt{\log p}} + \frac{1}{4\sqrt{\log p}}\tilde{U}_{n2}\Big) + O_p\Big(\frac{\log p}{\sqrt{n}}\Big) + I_{\Omega_n^c}\cdot\Psi_n.
\end{aligned}$$

Set

$$\mu_2 = \rho_n\sqrt{m} + (1-\rho_n)\cdot\sqrt{1+2\rho_n-\rho_n^2}\cdot\Big(2\sqrt{\log p} - \frac{\log\log p}{4\sqrt{\log p}}\Big).$$

Then,

$$\begin{aligned}
&\max_{1\le i<j\le p} \Lambda_{nij} - \mu_2 \\
= \;& \sqrt{2}\rho_n(1-\rho_n)U_{m1} + (1-\rho_n)\cdot\sqrt{1+2\rho_n-\rho_n^2}\cdot\frac{\tilde{U}_{n2}}{4\sqrt{\log p}} + o_p\Big(\frac{1}{\sqrt{\log p}}\Big) + I_{\Omega_n^c}\cdot\Psi_n
\end{aligned}$$

where the equality $O_p(\frac{\log p}{\sqrt{m}}) = o_p(\frac{1}{\sqrt{\log p}})$ holds due to the assumption $\log p = o(n^{1/3})$. Notice that $P(|I_{\Omega_n^c}\cdot\Psi_n|\cdot\sqrt{\log p} \ge \epsilon) \le P(\Omega_n^c) \to 0$ for any $\epsilon > 0$ by (3.96), hence $I_{\Omega_n^c}\cdot\Psi_n = o_p(\frac{1}{\sqrt{\log p}})$. It follows that

$$\begin{aligned}
&\max_{1\le i<j\le p} \Lambda_{nij} - \mu_2 \\
= \;& \sqrt{2}\rho_n(1-\rho_n)U_{m1} + (1-\rho_n)\cdot\sqrt{1+2\rho_n-\rho_n^2}\cdot\frac{\tilde{U}_{n2}}{4\sqrt{\log p}} + o_p\Big(\frac{1}{\sqrt{\log p}}\Big).
\end{aligned}$$

Step 3: Derivation of conclusions (i), (ii) and (iii). Recall the assumption that $\rho_n \ge 0$ for each $n \ge 1$ and $\sup_{n\ge1}\rho_n < 1$.

Case (i): $\rho_n\sqrt{\log p} \to 0$. For this case, by the Slutsky lemma,

$$\frac{4}{(1-\rho_n)\cdot\sqrt{1+2\rho_n-\rho_n^2}}\cdot\sqrt{\log p}\cdot\big(\max_{1\le i<j\le p}\Lambda_{nij} - \mu_2\big) \xrightarrow{d} \phi,$$

where ϕ has distribution function $F(x) = e^{-Ke^{-\frac{x}{2}}}$ with $K = \frac{1}{4\sqrt{2\pi}}$. The conclusion follows by the assumption $\rho_n \to 0$ and the Slutsky lemma again.

Case (ii): $\rho_n\sqrt{\log p} \to \lambda \in (0,\infty)$. By the Slutsky lemma and independence,

$$\frac{\max_{1\le i<j\le p}\Lambda_{nij} - \mu_2}{\sqrt{2}\rho_n(1-\rho_n)} \xrightarrow{d} \xi + \lambda_0\phi,$$

where $\xi \sim N(0,1)$, $\lambda_0 = \frac{1}{4\sqrt{2}\lambda}$ and ϕ is the same as in case (i) and ϕ is independent of ξ. The conclusion is yielded by the assumption $\rho_n \to 0$ and the Slutsky lemma again.

Case (iii): $\rho_n\sqrt{\log p} \to \infty$. In this situation, by the Slutsky lemma,

$$\frac{\max_{1\le i<j\le p}\Lambda_{nij} - \mu_2}{\sqrt{2}\rho_n(1-\rho_n)} = U_{m1} + o_p(1) \xrightarrow{d} N(0,1).$$

The proof is completed. ∎

Acknowledgements

Fan's research was supported by NSF grants DMS-1406266 and DMS-1712591. Jiang's research was supported by NSF grant DMS-1406279. We thank Professor Junshan Xie very much for many discussions.

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