A Proof of Theorem 2.2

A.1 Derivation of the self-consistent equation

We start from (16) and rely on the following power counting principles: Each derivative provides a smallness-factor of $1/\sqrt{m}$ because G is a function of $Y/\sqrt{m}$ and $Y^*/\sqrt{m}$, while each independent summation costs a factor of $n_1 \sim m$. However, we cannot have too many independent summations for if any index appears only once in the cumulant, then the latter vanishes identically by the independence property of cumulants. For example, if $i_2, \dots, i_{2k} \neq i_1$, then the random variables $Y_{i_3 i_4}, \dots, Y_{i_{2k-1} i_{2k}}$ are independent of $Y_{i_1 i_2}$ in the probability space of the random variables $\{w_{i_1 a}\}_{a=1}^{n_0}$ conditioned on the remaining random variables. By the law of total expectation and the independence property it follows that

$$\kappa(Y_{i_1 i_2}, \dots, Y_{i_{2k-1} i_{2k}}) = 0$$

in this case. Thus we only need to sum over those cumulants in which each W- and X-index appears at least twice (we call i the W-index of Y_{ij}, Y^*_{ji} and j the X-index). In the extreme case where each W- and X-index appears exactly twice, we either have a single cycle, or a union of cycles on disjoint index sets. In the latter case the cumulant vanishes identically by the independence property. In the former case, for a cycle of length $2k$ there are k indices each, we obtain a factor of n_1^{-1} from the normalised sum, a factor of $m^{-2k/2} = m^{-k}$ from the derivatives, a factor of $n_1^k m^k$ from the summations, and finally a factor of n_0^{1-k} from the cumulant in Proposition 3.2, i.e.

$$\frac{1}{n_1} \frac{1}{m^k} n_1^k m^k n_0^{1-k} \sim 1$$

and the power counting is neutral. On the contrary, when some index appears three times, the overall power counting described above is smaller by a factor of $1/\sqrt{m}$, and thus negligible to leading order. In particular this argument shows that cycles of odd length only negligible as they cannot arise on indices in which each W- and X-index appears exactly twice.

Thus, together with Proposition 3.2 we have (recalling that the shorthand notation $\approx$ indicates equalities up to an error of $n_0^{-1/2}$)

$$\begin{aligned}
1 + z\,\mathbf{E}g &= \frac{1}{n_1 m} \sum_{k \geq 1} \sum_{i_1, \dots, i_{2k}} \frac{\kappa(Y_{i_1 i_2}, Y_{i_3 i_4}, Y_{i_5 i_6}, \dots, Y_{i_{2k-1} i_{2k}})}{(k-1)!} \mathbf{E} \partial_{Y_{i_3 i_4}} \cdots \partial_{Y_{i_{2k-1} i_{2k}}} (Y^* G)_{i_2 i_1} \\
&\approx \frac{1}{n_1 m} \sum_{k \geq 1} \sum_{i_1, \dots, i_{2k}}^{*} \kappa(Y_{i_1 i_2}, Y^*_{i_2 i_3}, Y_{i_3 i_4}, \dots, Y^*_{i_{2k} i_1}) \mathbf{E} \partial_{Y_{i_3 i_4}} \cdots \partial_{Y_{i_{2k-1} i_{2k}}} (Y^* G)_{i_2 i_1} \\
&= \frac{1}{n_1 m} \sum_{i_1, i_2}^{*} \kappa(Y_{i_1 i_2}, Y^*_{i_2 i_1}) \mathbf{E} \partial_{Y^*_{i_2 i_1}} (Y^* G)_{i_2 i_1} \\
&\quad + \frac{1}{n_1 m} \sum_{k \geq 2} \sum_{i_1, \dots, i_{2k}}^{*} \kappa(Y_{i_1 i_2}, Y^*_{i_2 i_3}, Y_{i_3 i_4}, \dots, Y^*_{i_{2k} i_1}) \mathbf{E} \partial_{Y^*_{i_2 i_3}} \cdots \partial_{Y^*_{i_{2k} i_1}} (Y^* G)_{i_2 i_1} \\
&\approx \frac{\theta_1}{n_1 m} \sum_{i_1, i_2}^{*} \mathbf{E} \partial_{Y^*_{i_2 i_1}} (Y^* G)_{i_2 i_1} + \frac{1}{n_1 m} \sum_{k \geq 2} \frac{\theta_2^k}{n_0^{k-1}} \sum_{i_1, \dots, i_{2k}}^{*} \mathbf{E} \partial_{Y^*_{i_2 i_3}} \cdots \partial_{Y^*_{i_{2k} i_1}} (Y^* G)_{i_2 i_1},
\end{aligned} \tag{21}$$

where the summations $\sum^*$ are understood over pairwise distinct indices. Here in the second line the factorial $(k-1)!$ disappears since there are exactly $(k-1)!$ ways to map the variables $Y_{i_3 i_4}, Y_{i_5 i_6} \dots, Y_{i_{2k-1} i_{2k}}$ into $Y^*_{i_2 i_3}, Y_{i_3 i_4}, \dots, Y^*_{i_{2k} i_1}$ with distinct $i_1, \dots, i_{2k}$. From this point onwards, we will omit reference to $\mathbf{E}$ to simplify notation slightly.

We now need to compute the partial derivatives in (21). The proof of the following lemma is included in Appendix C.

Lemma A.1. *Let $G(z) = (M - z)^{-1}$, $z \in \mathbb{H}$, be the resolvent of the random matrix $M = \frac{1}{m}YY^* \in \mathbb{R}^{n_1 \times n_1}$. Then, it holds that*

$$\partial_{Y^*_{i_2 i_1}} (Y^*G)_{i_2 i_1} = G_{i_1 i_1} \left(1 - \left(\frac{Y^*GY}{m}\right)_{i_2 i_2}\right), \tag{22a}$$

$$\partial_{Y^*_{i_2 i_3}} \cdots \partial_{Y^*_{i_{2k} i_1}} (Y^*G)_{i_2 i_1} \approx -\partial_{Y_{i_3 i_4}} \cdots \partial_{Y_{i_{2k-1} i_{2k}}} \left(\frac{GY}{m}\right)_{i_3 i_{2k}} G_{i_1 i_1} \left(1 - \left(\frac{Y^*GY}{m}\right)_{i_2 i_2}\right). \tag{22b}$$

Thus, using Lemma A.1 in (21) we have

$$\begin{aligned}
1 + zg &\approx \frac{\theta_1}{n_1 m} \sum_{i_1, i_2}^{*} G_{i_1 i_1} \left(1 - \left(\frac{Y^*GY}{m}\right)_{i_2 i_2}\right) \\
&\quad - \frac{1}{n_1 m} \sum_{k \geq 2} \frac{\theta_2^k}{n_0^{k-1}} \sum_{i_1, \ldots, i_{2k}}^{*} \partial_{Y_{i_3 i_4}} \cdots \partial_{Y_{i_{2k-1} i_{2k}}} \left(\frac{GY}{m}\right)_{i_3 i_{2k}} G_{i_1 i_1} \left(1 - \left(\frac{Y^*GY}{m}\right)_{i_2 i_2}\right) \\
&= \theta_1 g - \theta_1 \frac{n_1}{m} g \left\langle \frac{Y^*GY}{m} \right\rangle \\
&\quad - \left(g - \frac{n_1}{m} g \left\langle \frac{Y^*GY}{m} \right\rangle\right) \frac{1}{m} \sum_{k \geq 2} \frac{\theta_2^k}{n_0^{k-1}} \sum_{i_3, \ldots, i_{2k}}^{*} \partial_{Y_{i_3 i_4}} \cdots \partial_{Y_{i_{2k-1} i_{2k}}} (GY)_{i_3 i_{2k}},
\end{aligned} \tag{23}$$

where $\left\langle \frac{Y^*GY}{m} \right\rangle := \frac{1}{n_1} \operatorname{Tr} \frac{Y^*GY}{m} = 1 + zg$ from (15). Again, we stress that the equalities are meant in expectation. Moreover, shifting the index in the above summation, we get

$$\begin{aligned}
&\frac{1}{m} \sum_{k \geq 2} \frac{\theta_2^k}{n_0^{k-1}} \sum_{i_3, \ldots, i_{2k}}^{*} \partial_{Y_{i_3 i_4}} \cdots \partial_{Y_{i_{2k-1} i_{2k}}} (GY)_{i_3 i_{2k}} \\
&= \theta_2 \frac{n_1}{n_0} \frac{1}{m} \sum_{k \geq 1} \frac{\theta_2^k}{n_1 n_0^{k-1}} \sum_{i_3, \ldots, i_{2k+2}}^{*} \partial_{Y_{i_3 i_4}} \cdots \partial_{Y_{i_{2k+1} i_{2k+2}}} (GY)_{i_3 i_{2k+2}} \\
&= \theta_2^2 \frac{n_1}{n_0} \frac{1}{n_1 m} \sum_{i_3, i_4}^{*} \partial_{Y_{i_3 i_4}} (GY)_{i_3 i_4} \\
&\quad + \theta_2 \frac{n_1}{n_0} \frac{1}{n_1 m} \sum_{k \geq 2} \frac{\theta_2^k}{n_0^{k-1}} \sum_{i_3, \ldots, i_{2k+2}}^{*} \partial_{Y_{i_3 i_4}} \cdots \partial_{Y_{i_{2k+1} i_{2k+2}}} (GY)_{i_3 i_{2k+2}} \\
&\approx \theta_2^2 \frac{n_1}{n_0} \left(g - \frac{n_1}{m} g \left\langle \frac{Y^*GY}{m} \right\rangle\right) + \theta_2 \frac{n_1}{n_0} \left(1 + zg - \theta_1 g + \theta_1 \frac{n_1}{m} g \left\langle \frac{Y^*GY}{m} \right\rangle\right) \\
&= \theta_2 \frac{n_1}{n_0} (1 + zg) - \theta_2 (\theta_1 - \theta_2) \frac{n_1}{n_0} g \left(1 - \frac{n_1}{m} (1 + zg)\right),
\end{aligned}$$

where in the third step we used (21). Finally, together with (23), we have

$$\begin{aligned}
1 + zg &\approx \theta_1 g \left(1 - \frac{n_1}{m}(1 + zg)\right) - \theta_2 \frac{n_1}{n_0} g (1 + zg) \left(1 - \frac{n_1}{m}(1 + zg)\right) \\
&\quad + \theta_2 (\theta_1 - \theta_2) \frac{n_1}{n_0} g^2 \left(1 - \frac{n_1}{m}(1 + zg)\right)^2,
\end{aligned} \tag{24}$$

which corresponds to the desired equation (6) as $n_0, n_1, m \to \infty$. Thus, (24) combined with the concentration inequality given in Lemma 3.4 completes the proof of Theorem 2.2.

Proof of Theorem 2.2. We need to show the concentration w.r.t. $\mathbf{E}_{W,X} \equiv \mathbf{E}$. By the triangle and Jensen inequality we have

$$\begin{aligned}
\mathbf{E}|g(z) - \mathbf{E}g(z)|^4 &\lesssim \mathbf{E}|g(z) - \mathbf{E}_W g(z)|^4 + \mathbf{E}_X |\mathbf{E}_W g(z) - \mathbf{E}g(z)|^4 \\
&\leq \mathbf{E}_X \left(\mathbf{E}_W |g(z) - \mathbf{E}_W g(z)|^4\right) + \mathbf{E}_W \left(\mathbf{E}_X |g(z) - \mathbf{E}_X g(z)|^4\right) \lesssim \frac{2}{n_1^2 (\Im z)^4}
\end{aligned}$$

and thus the almost sure convergence follows from the Borel-Cantelli Lemma, completing the proof of Theorem 2.2 together with (24). ☐

A.2 Proof of Proposition 3.2

In light of the central limit theorem, we have that in the asymptotic limit the random variables

$$\left(\frac{WX}{\sqrt{n_0}}\right)_{ij} = \frac{1}{\sqrt{n_0}} \sum_{k=1}^{n_0} W_{ik} X_{kj},$$

are approximately $\mathcal{N}(0, \sigma_w^2 \sigma_x^2)$-normally distributed. Our next goal is to compute their cumulants. The first cumulant or expectation vanishes identically. For the second cumulant we obtain:

Lemma A.2. *The cumulant of* $\frac{(WX)_{i_1 i_2}}{\sqrt{n_0}}$ *and* $\frac{(WX)_{i_3 i_4}}{\sqrt{n_0}}$ *is nonzero only if* $i_1 = i_3$ *and* $i_2 = i_4$*, and in this case it holds that*

$$\kappa\left(\frac{(WX)_{i_1 i_2}}{\sqrt{n_0}}, \frac{(WX)^*_{i_2 i_1}}{\sqrt{n_0}}\right) = \sigma_w^2 \sigma_x^2.$$

Proof. We have

$$\begin{aligned}
\kappa\left(\frac{(WX)_{i_1 i_2}}{\sqrt{n_0}}, \frac{(WX)_{i_3 i_4}}{\sqrt{n_0}}\right) &= \frac{1}{n_0} \mathbf{E}(WX)_{i_1 i_2} (WX)_{i_3 i_4} \\
&= \frac{1}{n_0} \sum_{k_1, k_2 = 1}^{n_0} \mathbf{E} W_{i_1 k_1} X_{k_1 i_2} W_{i_3 k_2} X_{k_2 i_4} \\
&= \frac{1}{n_0} \sum_{k_1 = 1}^{n_0} \delta_{i_1 i_3} \delta_{i_2 i_4}\, \mathbf{E} W_{i_1 k_1}^2 X_{k_1 i_2}^2 = \delta_{i_1 i_3} \delta_{i_2 i_4} \sigma_w^2 \sigma_x^2.
\end{aligned}$$

Thus, the second cumulant is nonzero if $i_1 = i_3$ and $i_2 = i_4$, and in this case it is exactly the variance of the random variable $\frac{(WX)_{ij}}{\sqrt{n_0}}$. ☐

We now consider four random entries, and we compute

$$\frac{1}{n_0^2} \kappa\Big((WX)_{i_1 i_2}, (WX)_{i_3 i_4}, (WX)_{i_5 i_6}, (WX)_{i_7 i_8}\Big).$$

We observe that the cumulant vanishes identically if any index appears exactly once by the independence property, and thus each W- and X-index must appear exactly twice. This is only possible if we have two cycles on two indices each, or a single four-cycle. The cumulant of the former vanishes identically by independence ant thus the only non-vanishing 4-cumulant is

$$\begin{aligned}
&\kappa\left(\frac{(WX)_{i_1 i_2}}{\sqrt{n_0}}, \frac{(WX)^*_{i_2 i_3}}{\sqrt{n_0}}, \frac{(WX)_{i_3 i_4}}{\sqrt{n_0}}, \frac{(WX)^*_{i_4 i_1}}{\sqrt{n_0}}\right) \\
&= \frac{1}{n_0^2} \mathbf{E}(WX)_{i_1 i_2} (WX)^*_{i_2 i_3} (WX)_{i_3 i_4} (WX)^*_{i_4 i_1} \\
&= \frac{1}{n_0^2} \sum_{k_1, k_2, k_3, k_4 = 1}^{n_0} \mathbf{E} W_{i_1 k_1} X_{k_1 i_2} W_{i_3 k_2} X_{k_2 i_2} W_{i_3 k_3} X_{k_3 i_4} W_{i_1 k_4} X_{k_4 i_4} \\
&= \frac{1}{n_0^2} \sum_{k_1 = 1}^{n_0} \mathbf{E} W_{i_1 k_1}^2 X_{k_1 i_2}^2 W_{i_3 k_1}^2 X_{k_1 i_4}^2 = \frac{\left(\sigma_w^2 \sigma_x^2\right)^2}{n_0}
\end{aligned}$$

Here for the first equality we used (14) where all but the trivial partition vanish identically since in some expectation a single index appears. This result can be generalised:

Lemma A.3. *For* $k \geq 2$ *and pairwise distinct indices we have*

$$\kappa\left(\frac{(WX)_{i_1 i_2}}{\sqrt{n_0}}, \frac{(WX)^*_{i_2 i_3}}{\sqrt{n_0}}, \frac{(WX)_{i_3 i_4}}{\sqrt{n_0}}, \ldots, \frac{(WX)^*_{i_{2k} i_1}}{\sqrt{n_0}}\right) = \frac{\left(\sigma_w^2 \sigma_x^2\right)^k}{n_0^{k-1}} + \mathcal{O}(n_0^{-k}).$$

Proof. As illustrated for the case with four random variables, to have a nonzero cumulant, we can encode the $2k$ random variables as a cycle graph of length $2k$. Then, the only contribution comes from

$$\kappa\left(\frac{(WX)_{i_1 i_2}}{\sqrt{n_0}}, \ldots, \frac{(WX)^*_{i_{2k} i_1}}{\sqrt{n_0}}\right) = \frac{1}{n_0^k}\,\mathbf{E}(WX)_{i_1 i_2}\cdots(WX)^*_{i_{2k} i_1} = \frac{\left(\sigma_w^2\sigma_x^2\right)^k}{n_0^{k-1}} + \mathcal{O}(n_0^{-k}),$$

which completes the proof. □

Finally, we compute the cumulants of the entries of the random matrix Y. Since the activation function f is applied component-wise, it follows from the previous results that the only contribution comes from $\kappa(Y_{i_1 i_2}, Y^*_{i_2 i_3}, Y_{i_3 i_4}, \ldots, Y^*_{i_{2k} i_1})$ for $k \geq 1$ and $i_1, \ldots, i_{2k}$ distinct, thus proving that Y has cycle correlations.

Proof of Proposition 3.2. From the Berry-Esséen Theorem it follows that

$$\begin{aligned}\kappa(Y_{ij}) = \mathbf{E}Y_{ij} &= \int_{\mathbb{R}} f(x)\frac{e^{-x^2/2\sigma_w^2\sigma_x^2}}{\sigma_w\sigma_x\sqrt{2\pi}}\,\mathrm{d}x + \mathcal{O}(n_0^{-1/2}) \\ &= \int_{\mathbb{R}} f(\sigma_w\sigma_x x)\frac{e^{-x^2/2}}{\sqrt{2\pi}}\,\mathrm{d}x + \mathcal{O}(n_0^{-1/2}) = \mathcal{O}(n_0^{-1/2}),\end{aligned}$$

and

$$\kappa(Y_{ij}, Y^*_{ji}) = (1+\mathcal{O}(n_0^{-1/2}))\int_{\mathbb{R}} f^2(\sigma_w\sigma_x x)\frac{e^{-x^2/2}}{\sqrt{2\pi}}\mathrm{d}x = \theta_1(f)(1+\mathcal{O}(n_0^{-1/2})),$$

since the random variables $(WX)_{ij}/\sqrt{n_0}$ are approximately centred Gaussian with variance $\sigma_w^2\sigma_x^2$. Let $k > 1$. Then, since f is a smooth function with compact support, we have that f is in C^l for some integer $l > 1 + \frac{2k^2}{k-1}$. Using the Fourier inversion theorem, it follows that

$$\begin{aligned}f(x_1) &= \frac{1}{2\pi}\int_{\mathbb{R}} \hat{f}(t_1)\,e^{it_1x_1}\mathrm{d}t_1 \\ &= \frac{1}{2\pi}\int_{|t_1|\leq n_0^{\frac{k-1}{2k}}} \hat{f}(t_1)\,e^{it_1x_1}\mathrm{d}t_1 + \frac{1}{2\pi}\int_{|t_1|> n_0^{\frac{k-1}{2k}}} \hat{f}(t_1)\,e^{it_1x_1}\mathrm{d}t_1 \\ &= \frac{1}{2\pi}\int_{|t_1|\leq n_0^{\frac{k-1}{2k}}} \hat{f}(t_1)\,e^{it_1x_1}\mathrm{d}t_1 + \mathcal{O}\left((n_0^{\frac{k-1}{2k}})^{1-l}\right),\end{aligned}$$

where we used $|\hat{f}(t_1)| \leq \frac{c}{(1+|t_1|)^l}$, for some positive constant c. For notational simplicity we work in the case $k = 2$, but the argument when $k > 2$ is the same. We compute

$$\begin{aligned}&\kappa(Y_{i_1i_2}, Y^*_{i_2i_3}, Y_{i_3i_4}, Y^*_{i_4i_1}) \\ &= \frac{1}{(2\pi)^4}\int_{\forall i,\,|t_i|\leq n_0^{\frac{1}{4}}} \hat{f}(t_1)\hat{f}(t_2)\hat{f}(t_3)\hat{f}(t_4)\kappa(e^{it_1Z_{i_1i_2}}, e^{it_2Z^*_{i_2i_3}}, e^{it_3Z_{i_3i_4}}, e^{it_4Z^*_{i_4i_1}})\,\mathrm{d}\boldsymbol{t} + \mathcal{O}(n_0^{-2}), \\ &= \frac{1}{(2\pi)^4}\sum_{l_1,\ldots,l_4\geq 1}\int_{\forall i,\,|t_i|\leq n_0^{\frac{1}{4}}}\prod_{i=1}^4\Big(\hat{f}(t_i)\frac{(it_i)^{l_i}}{l_i!}\Big)\kappa((Z_{i_1i_2})^{l_1}, (Z^*_{i_2i_3})^{l_2}, (Z_{i_3i_4})^{l_3}, (Z^*_{i_4i_1})^{l_4})\,\mathrm{d}\boldsymbol{t} + \mathcal{O}(n_0^{-2})\end{aligned}$$

where we introduced $Z := WX/\sqrt{n_0}$ and in the second equality used that any cumulant involving the deterministic 1 vanishes identically. We now expand the cumulant involving powers of Z via the well known formula [21, Theorem 11.30] in terms of partitions of the set $\{1, \ldots, l_1 + l_2 + l_3 + l_4\}$ whose joint with the partition $\{\{1, \ldots, l_1\}, \ldots, \{l_1 + l_2 + l_3 + 1, \ldots, +l_1 + l_2 + l_3 + l_4\}\}$ is the trivial partition. By the independence property it is clear that the leading contribution comes from those partitions with one block connecting one copy of each of $Z_{i_1i_2}, Z^*_{i_2i_3}, Z_{i_3i_4}, Z^*_{i_4i_1}$ and the remaining blocks being internal pairings. Since for odd l_i there are $l_1!! \cdots l_4!!$ such partitions it follows that

$$\begin{aligned}
&\kappa(Y_{i_1i_2}, Y^*_{i_2i_3}, Y_{i_3i_4}, Y^*_{i_4i_1}) \\
&\quad = \frac{1}{(2\pi)^4} \sum_{\substack{l_1,\ldots,l_4\geq 1 \\ l_i \text{ odd}}} \int_{\forall i,\, |t_i|\leq n_0^{\frac{1}{4}}} \prod_{i=1}^4 \Big(\hat{f}(t_i) \frac{(it_i)^{l_i}}{(l_i-1)!!} \Big) \kappa(Z_{i_1i_2}, Z^*_{i_2i_3}, Z_{i_3i_4}, Z^*_{i_4i_1}) \\
&\qquad\qquad \times \operatorname{Var}(Z_{i_1i_2})^{(l_1-1)/2} \cdots \operatorname{Var}(Z^*_{i_4i_1})^{(l_4-1)/2} \, \mathrm{d}\boldsymbol{t} + \mathcal{O}(n_0^{-3/2}) \\
&\quad = \frac{\sigma_w^4\sigma_x^4}{n_0} \frac{1}{(2\pi)^4} \sum_{k_1,\ldots,k_4\geq 0} \int_{\forall i,\, |t_i|\leq n_0^{\frac{1}{4}}} t_1t_2t_3t_4 \prod_{i=1}^4 \Big(\hat{f}(t_i) \frac{(-\sigma_w^2\sigma_x^2 t_i^2/2)^{k_i}}{k_i!} \Big) \, \mathrm{d}\boldsymbol{t} + \mathcal{O}(n_0^{-3/2}) \\
&\quad = \frac{1}{n_0} \left(\sigma_w\sigma_x \frac{1}{2\pi} \int \widehat{f'}(t) e^{-\sigma_w^2\sigma_x^2\, t^2/2} \, \mathrm{d}t \right)^4 + \mathcal{O}(n_0^{-3/2}),
\end{aligned}$$

where in the penultimate step we used Lemmata A.2–A.3 and in the ultimate step we used the Fourier property $\widehat{f'}(t) = it\hat{f}(t)$. Together with

$$\begin{aligned}
\frac{\sigma_w\sigma_x}{2\pi} \int \widehat{f'}(t) e^{-\sigma_w^2\sigma_x^2\, t^2/2} \, \mathrm{d}t &= \frac{1}{\sqrt{2\pi}} \int f'(x) e^{-x^2/2\sigma_w^2\sigma_x^2} \, \mathrm{d}x \\
&= \sigma_w\sigma_x \int f'(\sigma_w\sigma_x x) \frac{e^{-x^2/2}}{\sqrt{2\pi}} \, \mathrm{d}x = \theta_2(f)^{1/2}.
\end{aligned}$$

we conclude

$$\kappa(Y_{i_1i_2}, Y^*_{i_2i_3}, Y_{i_3i_4}, Y^*_{i_4i_1}) = \theta_2(f)^2 n_0^{-1} \Big(1 + \mathcal{O}(n_0^{-1/2}) \Big),$$

just as claimed. □

B Proof of Theorem 2.5

B.1 Derivation of the self-consistent equation

We proceed as in Subsection A.1. We know from (15) that

$$\frac{1}{m} \sum_{i=1}^m \left(\frac{Y^*GY}{m} \right)_{ii} = \frac{n_1}{m} \left\langle \frac{YY^*G}{m} \right\rangle = \frac{n_1}{m}(1+zg). \tag{25}$$

We further claim the following.

Lemma B.1. *It holds that*

$$\frac{1}{m} \sum_{i=1}^m \sum_{j=1}^{n_1} \left(\frac{Y^*GY}{m} \right)_{ij} = 1 + \mathcal{O}\left((\theta_{1,b}(f)\, n_1)^{-1} \right). \tag{26}$$

Together with (25), Lemma B.1 implies

$$\frac{1}{m} \sum_{i\neq j} \left(\frac{Y^*GY}{m} \right)_{ij} \approx 1 - \frac{n_1}{m}(1+zg). \tag{27}$$

Proof. Using the Woodbury matrix identity[3], we have

$$\frac{1}{m} \left(\frac{Y^*GY}{m} \right) = \frac{1}{m^2} Y^* \left(\frac{YY^*}{m} - z \right)^{-1} Y = \frac{1}{m} + \frac{z}{m} \left(\frac{Y^*Y}{m} - z \right)^{-1},$$

[3]For $A \in \mathbb{R}^{n\times n}$, $C \in \mathbb{R}^{r\times r}$, $U \in \mathbb{R}^{n\times r}$ and $V \in \mathbb{R}^{r\times n}$ the *Woodbury matrix identity* is given by

$$(A + UCV)^{-1} = A^{-1} - A^{-1}U\left(C^{-1} + VA^{-1}U\right)^{-1} VA^{-1}.$$

which implies

$$\sum_{i,j}\frac{1}{m}\left(\frac{Y^*GY}{m}\right)_{ij}=\sum_{i,j}\frac{1}{m}\delta_{ij}+\sum_{i,j}\frac{z}{m}\left(\frac{Y^*Y}{m}-z\right)^{-1}_{ij}=1+\sum_{i,j}\frac{z}{m}\left(\frac{Y^*Y}{m}-z\right)^{-1}_{ij}.$$

So, we need to show that $\sum_{i,j}\frac{z}{m}\left(\frac{Y^*Y}{m}-z\right)^{-1}_{ij}$ is approximately zero. Let $e:=\frac{1}{\sqrt{m}}[1\ \cdots\ 1]^T$ be a normalized vector in $\mathbb{R}^m$. We then write

$$\sum_{i,j}\frac{z}{m}\left(\frac{Y^*Y}{m}-z\right)^{-1}_{ij}=z\,\langle e,\left(\frac{Y^*Y}{m}-z\right)^{-1}e\rangle.$$

It turns out that e is approximately an eigenvector of $\frac{1}{m}Y^*Y$. Indeed, it holds that

$$\mathbf{E}\left(\frac{Y^*Y}{m}e\right)_i=\frac{1}{m\sqrt{m}}\sum_{j=1}^{m}\sum_{k=1}^{n_1}\mathbf{E}\,Y^*_{ik}Y_{kj}\approx m^{-1/2}n_1\,\theta_{1,b}(f)=(n_1\,\theta_{1,b}(f))e_i.$$

Moreover, the variance is approximately $\mathcal{O}(n_1/m)$, which means that the standard deviation is of order 1, while the expectation of order n_1. Thus, e is approximately an eigenvector of $\frac{1}{m}Y^*Y$ with eigenvalue $n_1\theta_{1,b}(f)$. Since $\theta_{1,b}(f)$ is nonzero by assumption, we have that e is approximately an eigenvector of the matrix $\left(\frac{Y^*Y}{m}-z\mathbf{1}_m\right)^{-1}$ with eigenvalue $(n_1\theta_{1,b}(f)-z)^{-1}$, from which the result follows:

$$\left|\langle e,\left(\frac{Y^*Y}{m}-z\right)^{-1}e\rangle\right|\approx\left|(n_1\,\theta_{1,b}(f)-z)^{-1}\right|\ll 1.\qquad\square$$

Given Lemma B.1 and Proposition 3.3, we can now prove the global law for the random matrix M with the cycle correlations.

Proof of Theorem 2.5. Applying Proposition 3.3 to (16) and using the same power counting argument as in (21) we obtain

$$\begin{aligned}1+zg&\approx\frac{1}{n_1m}\sum^{*}_{i_1,i_2}\kappa(Y_{i_1i_2},Y^*_{i_2i_1})\,\partial_{Y^*_{i_2i_1}}(Y^*G)_{i_2i_1}+\frac{1}{n_1m}\sum^{*}_{i_1,i_2,i_3}\kappa(Y_{i_1i_2},Y^*_{i_3i_1})\,\partial_{Y^*_{i_3i_1}}(Y^*G)_{i_2i_1}\\&\quad+\frac{1}{n_1m}\sum_{k\geq2}\sum^{*}_{i_1,\ldots,i_{2k}}\kappa(Y_{i_1i_2},\ldots,Y^*_{i_{2k}i_1})\,\partial_{Y^*_{i_2i_3}}\cdots\partial_{Y^*_{i_{2k}i_1}}(Y^*G)_{i_2i_1}\\&\approx\frac{\theta_1(f)}{n_1m}\sum^{*}_{i_1,i_2}\partial_{Y^*_{i_2i_1}}(Y^*G)_{i_2i_1}+\frac{\theta_{1,b}(f)}{n_1m}\sum_{i_1}\sum^{*}_{i_2,i_3}\partial_{Y^*_{i_3i_1}}(Y^*G)_{i_2i_1}\\&\quad+\frac{1}{n_1m}\sum_{k\geq2}\frac{\theta_2^k(f)}{n_0^{k-1}}\sum^{*}_{i_1,\ldots,i_{2k}}\partial_{Y^*_{i_2i_3}}\cdots\partial_{Y^*_{i_{2k}i_1}}(Y^*G)_{i_2i_1},\end{aligned}\tag{28}$$

where we omitted reference to $\mathbf{E}$ to simplify notation. Given Lemma A.1, we only need to compute $\partial_{Y^*_{i_3i_1}}(Y^*G)_{i_2i_1}$:

$$\partial_{Y^*_{i_3i_1}}(Y^*G)_{i_2i_1}=\sum_{j=1}^{n_1}\partial_{Y^*_{i_3i_1}}\left(Y^*_{i_2j}G_{ji_1}\right)\approx-G_{i_1i_1}\left(\frac{Y^*GY}{m}\right)_{i_2i_3},$$

where we omitted the contribution of $\partial_{Y^*_{i_3 i_1}} Y^*_{i_2 j}$ since it is very small. Plugging the partial derivatives into (28), we get

$$
\begin{aligned}
1+zg &\approx \frac{\theta_1(f)}{n_1 m}\sum_{i_1,i_2}^{*} G_{i_1i_1}\left(1-\left(\frac{Y^*GY}{m}\right)_{i_2i_2}\right) - \frac{\theta_{1,b}(f)}{n_1 m}\sum_{i_1}\sum_{i_2,i_3}^{*} G_{i_1i_1}\left(\frac{Y^*GY}{m}\right)_{i_2i_3} \\
&\quad - \frac{1}{n_1 m}\sum_{k\geq 2}\frac{\theta_2^k(f)}{n_0^{k-1}}\sum_{i_1,\dots,i_{2k}}^{*}\partial_{Y_{i_3i_4}}\cdots\partial_{Y_{i_{2k-1}i_{2k}}}\left(\frac{GY}{m}\right)_{i_3i_{2k}} G_{i_1i_1}\left(1-\left(\frac{Y^*GY}{m}\right)_{i_2i_2}\right) \\
&\approx \theta_1(f)g\left(1-\frac{n_1}{m}(1+zg)\right) - \theta_{1,b}(f)g\left(1-\frac{n_1}{m}(1+zg)\right) \\
&\quad - g\left(1-\frac{n_1}{m}(1+zg)\right)\sum_{k\geq 2}\frac{\theta_2^k}{n_0^{k-1}}\sum_{i_3,\dots,i_{2k}}^{*}\partial_{Y_{i_3i_4}}\cdots\partial_{Y_{i_{2k-1}i_{2k}}}\left(\frac{GY}{m}\right)_{i_3i_{2k}},
\end{aligned}
$$

where in the second step we used (25) and (27). Finally, by shifting the index in the summation and doing some simple bookkeeping, we have

$$
\begin{aligned}
1+zg &\approx (\theta_1-\theta_{1,b})g\left(1-\frac{n_1}{m}(1+zg)\right) - \theta_2\frac{n_1}{n_0}g(1+zg)\left(1-\frac{n_1}{m}(1+zg)\right) \\
&\quad + \theta_2(\theta_1-\theta_{1,b}-\theta_2)\frac{n_1}{n_0}g^2\left(1-\frac{n_1}{m}(1+zg)\right)^2,
\end{aligned}
$$

which corresponds to the self-consistent equation (6) as $n_0, n_1, m \to \infty$, where θ_1 is replaced by $\theta_1 - \theta_{1,b}$. In the same way as in the bias-free case, the concentration inequality of Lemma 3.4 can also be applied here, thereby concluding that g is approximately equal to its mean with high probability. The first claim of Theorem 2.5 then follows. The second claim follows easily from Lemma B.1. Since $n_1\theta_{1,b}(f)$ is approximately an eigenvalue of the random matrix $\frac{1}{m}Y^*Y$, and since the nonzero eigenvalues of Y^*Y are the same as the one of YY^*, we have that $\lambda_{\max} \approx n_1\theta_{1,b}(f)$ is an eigenvalue of M located away from the rest of the spectrum (called *outlier*). This concludes the proof of Theorem 2.5. □

B.2 Proof of Proposition 3.3

In light of the central limit theorem, in the asymptotic limit the random variables $\frac{(WX)_{ij}}{\sqrt{n_0}} + B_i$ are approximately normally distributed with zero mean and variance $\sigma_w^2\sigma_x^2 + \sigma_b^2$. In contrast to the bias-free case, here we have two different nonzero second cumulants of the entries of the random matrix $\frac{WX}{\sqrt{n_0}} + B$, and therefore also of the Y_{ij}'s.

Proof of Proposition 3.3. The first identity follows in a straightforward manner by assumption (8):

$$
\kappa(Y_{ij}) = \mathbf{E}Y_{ij} = \int_{\mathbb{R}} f(x)\frac{e^{-x^2/2(\sigma_w^2\sigma_x^2+\sigma_b^2)}}{\sqrt{2\pi(\sigma_w^2\sigma_x^2+\sigma_b^2)}}\,\mathrm{d}x + \mathcal{O}(n_0^{-1/2}) = \mathcal{O}(n_0^{-1/2}).
$$

For the second cumulant, we first compute

$$
\begin{aligned}
\kappa\left(\frac{(WX)_{i_1i_2}}{\sqrt{n_0}} + B_{i_1}, \frac{(WX)_{i_3i_4}}{\sqrt{n_0}} + B_{i_3}\right) &= \mathbf{E}\left(\frac{(WX)_{i_1i_2}}{\sqrt{n_0}} + B_{i_1}\right)\left(\frac{(WX)_{i_3i_4}}{\sqrt{n_0}} + B_{i_3}\right) \\
&= \frac{1}{n_0}\mathbf{E}(WX)_{i_1i_2}(WX)_{i_3i_4} + \mathbf{E}B_{i_1}B_{i_3} \\
&= \delta_{i_1i_3}\delta_{i_2i_4}\,\sigma_w^2\sigma_x^2 + \delta_{i_1i_3}\sigma_b^2.
\end{aligned}
$$

For $i_1 = i_3$ and $i_2 = i_4$, the cumulant $\kappa(Y_{i_1i_2}, Y^*_{i_2i_1})$ follows easily:

$$
\kappa(Y_{i_1i_2}, Y^*_{i_2i_1}) = (1+\mathcal{O}(n_0^{-1/2}))\int_{\mathbb{R}} f^2(x)\frac{e^{-x^2/2(\sigma_w^2\sigma_x^2+\sigma_b^2)}}{\sqrt{2\pi(\sigma_w^2\sigma_x^2+\sigma_b^2)}}\,\mathrm{d}x = \theta_1(f)(1+\mathcal{O}(n_0^{-1/2})).
$$

On the other hand, for $i_1 = i_3$ and $i_2 \neq i_4$, to compute the cumulant $\kappa(Y_{i_1i_2}, Y^*_{i_4i_1})$, we need the characteristic function of $\frac{(WX)_{i_1i_2}}{\sqrt{n_0}} + B_{i_1}$ and $\frac{(WX)^*_{i_4i_1}}{\sqrt{n_0}} + B_{i_1}$ which turns out to be asymptotically equal to

$$\exp\left(-\frac{\sigma_w^2\sigma_x^2+\sigma_b^2}{2}(t_1^2+t_2^2)-\sigma_b^2 t_1 t_2\right).$$

Now, we can compute the cumulant of $Y_{i_1 i_2}$ and $Y^*_{i_4 i_1}$:

$$\begin{aligned}\kappa(Y_{i_1 i_2}, Y^*_{i_4 i_1}) &\approx \frac{1}{(2\pi)^2}\int_{\mathbb{R}^2} f(x_1)f(x_2)e^{-i\boldsymbol{t}\cdot\boldsymbol{x}}\exp\left(-\frac{\sigma_w^2\sigma_x^2+\sigma_b^2}{2}(t_1^2+t_2^2)-\sigma_b^2 t_1 t_2\right)\mathrm{d}\boldsymbol{t}\,\mathrm{d}\boldsymbol{x}\\ &= \frac{1}{(2\pi)^2}\int_{\mathbb{R}^2}\hat{f}(t_1)\hat{f}(t_2)\exp\left(-\frac{\sigma_w^2\sigma_x^2+\sigma_b^2}{2}(t_1^2+t_2^2)-\sigma_b^2 t_1 t_2\right)\mathrm{d}t_1\,\mathrm{d}t_2,\end{aligned}$$

where in the second step we applied the Fourier inversion theorem. We denote the covariance matrix Σ by

$$\Sigma := \begin{pmatrix}\sigma_w^2\sigma_x^2+\sigma_b^2 & \sigma_b^2\\ \sigma_b^2 & \sigma_w^2\sigma_x^2+\sigma_b^2\end{pmatrix} \tag{29}$$

with determinant $\det(\Sigma)=\sigma_w^2\sigma_x^2(\sigma_w^2\sigma_x^2+2\sigma_b^2)$ and inverse matrix

$$\Sigma^{-1} = \frac{1}{\det(\Sigma)}\begin{pmatrix}\sigma_w^2\sigma_x^2+\sigma_b^2 & -\sigma_b^2\\ -\sigma_b^2 & \sigma_w^2\sigma_x^2+\sigma_b^2\end{pmatrix}.$$

Again applying the Fourier inversion formula, we obtain

$$\begin{aligned}\kappa(Y_{i_1 i_2}, Y^*_{i_4 i_1}) &\approx \frac{1}{(2\pi)^2}\int_{\mathbb{R}^2}\hat{f}(t_1)\hat{f}(t_2)e^{-\frac{1}{2}\langle\boldsymbol{t},\Sigma\boldsymbol{t}\rangle}\mathrm{d}\boldsymbol{t}\\ &= \frac{1}{(2\pi)^2}\int_{\mathbb{R}^2} f(x_1)f(x_2)\frac{2\pi}{\sqrt{\det(\Sigma)}}e^{-\frac{1}{2}\langle\boldsymbol{x},\Sigma^{-1}\boldsymbol{x}\rangle}\mathrm{d}\boldsymbol{x}\\ &= \frac{1}{2\pi\sqrt{\sigma_w^2\sigma_x^2(\sigma_w^2\sigma_x^2+2\sigma_b^2)}}\int_{\mathbb{R}^2} f(x_1)f(x_2)e^{-\frac{1}{2}\langle\boldsymbol{x},\Sigma^{-1}\boldsymbol{x}\rangle}\mathrm{d}\boldsymbol{x} = \theta_{1,b}(f),\end{aligned}$$

where

$$e^{-\frac{1}{2}\langle\boldsymbol{x},\Sigma^{-1}\boldsymbol{x}\rangle} = \exp\left(-\frac{(\sigma_w^2\sigma_x^2+\sigma_b^2)(x_1^2+x_2^2)-2\sigma_b^2 x_1 x_2}{2\sigma_w^2\sigma_x^2(\sigma_w^2\sigma_x^2+2\sigma_b^2)}\right).$$

To complete the proof, it remains to compute the joint cumulant of $Y_{i_1 i_2}, Y^*_{i_2 i_3}, Y_{i_3 i_4}, \ldots, Y^*_{i_{2k} i_1}$ for $k>1$ and $i_1,\ldots,i_{2k}$ distinct. For notational simplicity, we prove the statement for $k=2$. First, we use the cumulant asymptotics in order to asymptotically compute the characteristic function. The cumulants have match those of the bias-free case, except for

$$\kappa\left(\frac{(WX)_{i_1 i_2}}{\sqrt{n_0}}+B_{i_1}, \frac{(WX)_{i_1 i_2}}{\sqrt{n_0}}+B_{i_1}\right) = \sigma_w^2\sigma_x^2+\sigma_b^2.$$

In addition to all these cumulants, we also have

$$\kappa\left(\frac{(WX)_{i_1 i_2}}{\sqrt{n_0}}+B_{i_1}, \frac{(WX)^*_{i_4 i_1}}{\sqrt{n_0}}+B_{i_1}\right) = \kappa\left(\frac{(WX)^*_{i_2 i_3}}{\sqrt{n_0}}+B_{i_3}, \frac{(WX)_{i_3 i_4}}{\sqrt{n_0}}+B_{i_3}\right) = \sigma_b^2.$$

Therefore, the $\log$-characteristic function is given by

$$\begin{aligned}&-\frac{\sigma_w^2\sigma_x^2+\sigma_b^2}{2}\sum_{i=1}^4 t_i^2 - \sigma_b^2(t_1t_4+t_2t_3) + \sum_{n\geq 1}\frac{(-1)^{n-1}}{n}\left(\frac{(\sigma_w^2\sigma_x^2)^2}{n_0}\prod_{i=1}^4 t_i + \mathcal{O}(n_0^{-2})\right)^n\\ &= -\frac{\sigma_w^2\sigma_x^2+\sigma_b^2}{2}\sum_{i=1}^4 t_i^2 - \sigma_b^2(t_1t_4+t_2t_3) + \log\left(1+\frac{(\sigma_w^2\sigma_x^2)^2}{n_0}\prod_{i=1}^4 t_i + \mathcal{O}(n_0^{-2})\right),\end{aligned}$$

for $t_1,t_2,t_3,t_4\in\mathbb{R}$ such that $|t_i| < n_0^{1/4}$. We obtain the characteristic function by taking the exponential of the above expression. By the same argument as in the proof of Proposition 3.2, we have

$$
\begin{aligned}
&\kappa(Y_{i_1i_2}, Y^*_{i_2i_3}, Y_{i_3i_4}, Y^*_{i_4i_1}) \\
&= \frac{1}{n_0}\left(\frac{\sigma_w^2\sigma_x^2}{(2\pi)^2}\int \widehat{f'}(t_1)\widehat{f'}(t_2)\exp\left(-\frac{\sigma_w^2\sigma_x^2+\sigma_b^2}{2}(t_1^2+t_2^2)-\sigma_b^2 t_1t_2\right)\mathrm{d}t_1\mathrm{d}t_2\right)^2 + \mathcal{O}(n_0^{-3/2}) \\
&= \left(\frac{1}{2\pi\sqrt{\sigma_w^2\sigma_x^2(\sigma_w^2\sigma_x^2+2\sigma_b^2)}}\int f(x_1)f(x_2)e^{-\frac{1}{2}\langle \boldsymbol{x},\Sigma^{-1}\boldsymbol{x}\rangle}\mathrm{d}\boldsymbol{x}\right)^2 \\
&\quad + \frac{1}{n_0}\left(\frac{\sigma_w^2\sigma_x^2}{2\pi\sqrt{\sigma_w^2\sigma_x^2(\sigma_w^2\sigma_x^2+2\sigma_b^2)}}\int f'(x_1)f'(x_2)e^{-\frac{1}{2}\langle \boldsymbol{x},\Sigma^{-1}\boldsymbol{x}\rangle}\mathrm{d}\boldsymbol{x}\right)^2 + \mathcal{O}(n_0^{-3/2}),
\end{aligned}
$$

where Σ is the matrix defined by (29). It then follows that

$$
\begin{aligned}
\kappa(Y_{i_1i_2}, Y^*_{i_2i_3}, Y_{i_3i_4}, Y^*_{i_4i_1}) &\approx \mathbf{E}Y_{i_1i_2}Y^*_{i_2i_3}Y_{i_3i_4}Y^*_{i_4i_1} - \mathbf{E}Y_{i_1i_2}Y^*_{i_4i_1}\,\mathbf{E}\,Y^*_{i_2i_3}Y_{i_3i_4} \\
&= \theta_2(f)^2 n_0^{-1}\left(1+\mathcal{O}(n_0^{-1/2})\right),
\end{aligned}
$$

as desired. The proof for $k > 2$ is similar. □

C Proofs of auxiliary results

Proof of Lemma 3.1. By applying the Fourier inversion theorem, we have

$$
\mathbf{E}X_1 f(\boldsymbol{X}) = \frac{1}{(2\pi)^n}\int_{\mathbb{R}^n}\int_{\mathbb{R}^n} x_1 f(\boldsymbol{x})e^{-i\boldsymbol{t}\cdot\boldsymbol{x}}\varphi_{\boldsymbol{X}}(\boldsymbol{t})\mathrm{d}\boldsymbol{x}\,\mathrm{d}\boldsymbol{t},
$$

where $\varphi_{\boldsymbol{X}}(\boldsymbol{t})$ is the characteristic function of the n-dimensional random vector $\boldsymbol{X}$. It holds that $\int_{\mathbb{R}^n}(-ix_1)f(\boldsymbol{x})e^{-i\boldsymbol{t}\cdot\boldsymbol{x}}\mathrm{d}\boldsymbol{x} = \partial_{t_1}\hat{f}(\boldsymbol{t})$. Then, it follows that

$$
\begin{aligned}
\mathbf{E}X_1 f(\boldsymbol{X}) &= \frac{i}{(2\pi)^n}\int_{\mathbb{R}^n}\left(\partial_{t_1}\hat{f}(\boldsymbol{t})\right)\varphi_{\boldsymbol{X}}(\boldsymbol{t})\mathrm{d}\boldsymbol{t} \\
&= -\frac{i}{(2\pi)^n}\int_{\mathbb{R}^n}\hat{f}(\boldsymbol{t})\left(\partial_{t_1}\varphi_{\boldsymbol{X}}(\boldsymbol{t})\right)\mathrm{d}\boldsymbol{t} \\
&= -\frac{i}{(2\pi)^n}\int_{\mathbb{R}^n}\hat{f}(\boldsymbol{t})\left(\partial_{t_1}e^{\log\varphi_{\boldsymbol{X}}(\boldsymbol{t})}\right)\mathrm{d}\boldsymbol{t} \\
&= -\frac{i}{(2\pi)^n}\int_{\mathbb{R}^n}\hat{f}(\boldsymbol{t})\left(\partial_{t_1}\log\varphi_{\boldsymbol{X}}(\boldsymbol{t})\right)\varphi_{\boldsymbol{X}}(\boldsymbol{t})\mathrm{d}\boldsymbol{t}.
\end{aligned}
$$

Cumulants can also be defined in an analytical way as the coefficients of the log-characteristic function

$$
\log\mathbf{E}e^{i\boldsymbol{t}\cdot\boldsymbol{X}} = \sum_{\boldsymbol{l}}\kappa_{\boldsymbol{l}}\frac{(i\boldsymbol{t})^{\boldsymbol{l}}}{\boldsymbol{l}!}, \tag{30}
$$

where $\sum_{\boldsymbol{l}}$ is the sum over all multi-indices $\boldsymbol{l} = (l_1,\dots,l_n)\in\mathbb{N}^n$. We note that $\kappa_{\boldsymbol{l}}(X_1,\dots,X_n) = \kappa(\{X_1\}^{l_1},\dots,\{X_n\}^{l_n})$ means that X_i appears l_i times. One can prove that this definition of cumulants is equivalent to the combinatorial one given by 14 (see [24] for a proof). Using definition (30) results in

$$
\partial_{t_1}\log\varphi_{\boldsymbol{X}}(\boldsymbol{t}) = i\sum_{\boldsymbol{l}}\kappa_{\boldsymbol{l}+\boldsymbol{e_1}}\frac{(i\boldsymbol{t})^{\boldsymbol{l}}}{\boldsymbol{l}!},
$$

where $\boldsymbol{l}+\boldsymbol{e_1} = (l_1+1, l_2,\dots,l_n)$. Since $(i\boldsymbol{t})^{\boldsymbol{l}}\hat{f}(\boldsymbol{t}) = \widehat{f^{(\boldsymbol{l})}}(\boldsymbol{t})$, we finally obtain

$$
\mathbf{E}X_1 f(\boldsymbol{X}) = \sum_{\boldsymbol{l}}\frac{\kappa_{\boldsymbol{l}+\boldsymbol{e_1}}}{\boldsymbol{l}!}\frac{1}{(2\pi)^n}\int_{\mathbb{R}^n}\widehat{f^{(\boldsymbol{l})}}(\boldsymbol{t})\varphi_{\boldsymbol{X}}(\boldsymbol{t})\mathrm{d}\boldsymbol{t} = \sum_{\boldsymbol{l}}\frac{\kappa_{\boldsymbol{l}+\boldsymbol{e_1}}}{\boldsymbol{l}!}\mathbf{E}\,f^{(\boldsymbol{l})}(\boldsymbol{X}),
$$

where we again applied the Fourier inversion formula. □

Proof of Lemma A.1. Let $\Delta^{i,j}$ denote a $m \times n_1$ matrix such that $\Delta^{i,j}_{kl} = \mathbf{1}_{\{(i,j)=(k,l)\}}$. Then, applying the resolvent identity, we get

$$\frac{\partial G}{\partial Y^*_{ij}} = \lim_{\epsilon \to 0} \frac{\left(\frac{Y(Y^* + \epsilon \Delta^{i,j})}{m} - z\right)^{-1} - \left(\frac{YY^*}{m} - z\right)^{-1}}{\epsilon} = -\frac{GY\Delta^{i,j}G}{m}.$$

It follows that $\partial_{Y^*_{ij}} G_{ab} = -\left(\frac{GY}{m}\right)_{ai} G_{jb}$ for $1 \le a, b \le n_1$, $1 \le i \le m$, and $1 \le j \le n_1$. Therefore, we have

$$\partial_{Y^*_{i_2 i_1}} (Y^*G)_{i_2 i_1} = \sum_{j=1}^{n_1} \partial_{Y^*_{i_2 i_1}} \left(Y^*_{i_2 j} G_{j i_1}\right) = G_{i_1 i_1} \left(1 - \left(\frac{Y^*GY}{m}\right)_{i_2 i_2}\right),$$

which proves (3.6a). We now compute

$$\begin{aligned}\sum_{j=1}^{n_1} \partial_{Y^*_{i_2 i_3}} \partial_{Y^*_{i_{2k} i_1}} \left(Y^*_{i_2 j} G_{j i_1}\right) &\approx -\sum_{j=1}^{n_1} \partial_{Y^*_{i_2 i_3}} \left(Y^*_{i_2 j} \left(\frac{GY}{m}\right)_{j i_{2k}} G_{i_1 i_1}\right) \\ &\approx -\left(\frac{GY}{m}\right)_{i_3 i_{2k}} G_{i_1 i_1} + \left(\frac{Y^*GY}{m}\right)_{i_2 i_2} \left(\frac{GY}{m}\right)_{i_3 i_{2k}} G_{i_1 i_1},\end{aligned}$$

where the approximation in the first line comes from the fact that the contribution of $\partial_{Y^*_{i_{2k} i_1}} Y^*_{i_2 j}$ is very small and can therefore be neglected. Since the off-diagonals of the resolvent of random matrices are small if $\Im z \gg n_1^{-1}$, the partial derivative $\partial_{Y^*_{i_2 i_3}} G_{i_1 i_1}$ can be omitted. This justifies the second approximation. So, we obtain

$$\partial_{Y^*_{i_2 i_3}} \cdots \partial_{Y^*_{i_{2k} i_1}} (Y^*G)_{i_2 i_1} \approx -\partial_{Y_{i_3 i_4}} \cdots \partial_{Y_{i_{2k-1} i_{2k}}} \left(\frac{GY}{m}\right)_{i_3 i_{2k}} G_{i_1 i_1} \left(1 - \left(\frac{Y^*GY}{m}\right)_{i_2 i_2}\right),$$

which completes the proof of Lemma A.1. □

D Concentration inequality

Proof of Lemma 3.4. Without loss of generality, it suffices to prove the statement w.r.t. $\mathbf{E}_X$ since by cyclicity the statement for $\mathbf{E}_W$ is analogous. We write $X = (\boldsymbol{x}_1, \ldots, \boldsymbol{x}_m)$ with $\boldsymbol{x}_k = (x_{1k}, \ldots, x_{n_0 k})'$, and similarly, $Y = (\boldsymbol{y}_1, \ldots, \boldsymbol{y}_m)$. We denote by $\mathcal{F}_k$, $1 \le k \le m$, the filtration generated by $\{\boldsymbol{x}_l,\ 1 \le l \le k\}$ and by $\mathbf{E}_k[\cdot] \coloneqq \mathbf{E}_X[\cdot \,|\, \mathcal{F}_k]$ the conditional expectation w.r.t. $\mathcal{F}_k$. Now, we decompose $g(z) - \mathbf{E}_X g(z)$ as a sum of martingale differences

$$D_k \coloneqq \mathbf{E}_k \operatorname{Tr}(M - z\mathbf{1}_{n_1})^{-1} - \mathbf{E}_{k-1} \operatorname{Tr}(M - z\mathbf{1}_{n_1})^{-1}, \quad \text{for } k = 1, \ldots, m.$$

By construction, we have $\mathbf{E}_m \operatorname{Tr}(M - z\mathbf{1}_{n_1})^{-1} = \operatorname{Tr}(M - z\mathbf{1}_{n_1})^{-1}$ and $\mathbf{E}_0 \operatorname{Tr}(M - z\mathbf{1}_{n_1})^{-1} = \mathbf{E}_X \operatorname{Tr}(M - z\mathbf{1}_{n_1})^{-1}$. It then follows that

$$g(z) - \mathbf{E}_X g(z) = \frac{1}{n_1} \sum_{k=1}^{m} \mathbf{E}_k \operatorname{Tr}(M - z\mathbf{1}_{n_1})^{-1} - \mathbf{E}_{k-1} \operatorname{Tr}(M - z\mathbf{1}_{n_1})^{-1} = \frac{1}{n_1} \sum_{k=1}^{m} D_k.$$

Next, we define $M_k \coloneqq M - \boldsymbol{y}_k \boldsymbol{y}_k^*$. We note that

$$\mathbf{E}_k \operatorname{Tr}(M_k - z\mathbf{1}_{n_1})^{-1} = \mathbf{E}_{k-1} \operatorname{Tr}(M_k - z\mathbf{1}_{n_1})^{-1},$$

since M_k is independent of $\boldsymbol{y}_k$ and therefore is also independent of $\boldsymbol{x}_k$. So, we have

$$D_k = (\mathbf{E}_k - \mathbf{E}_{k-1})[\operatorname{Tr}(M - z\mathbf{1}_{n_1})^{-1} - \operatorname{Tr}(M_k - z\mathbf{1}_{n_1})^{-1}].$$

Then, by the Shermann-Morrison formula, we have

$$\begin{aligned}\left|\operatorname{Tr}(M - z\mathbf{1}_{n_1})^{-1} - \operatorname{Tr}(M_k - z\mathbf{1}_{n_1})^{-1}\right| &= \left|\frac{\boldsymbol{y}_k^*(M_k - z\mathbf{1}_{n_1})^{-2}\boldsymbol{y}_{\boldsymbol{k}}}{1 + \boldsymbol{y}_k^*(M_k - z\mathbf{1}_{n_1})^{-1}\boldsymbol{y}_{\boldsymbol{k}}}\right| \\ &\le \frac{|\boldsymbol{y}_k^*(M_k - z\mathbf{1}_{n_1})^{-2}\boldsymbol{y}_{\boldsymbol{k}}|}{\Im(\boldsymbol{y}_k^*(M_k - z\mathbf{1}_{n_1})^{-1}\boldsymbol{y}_{\boldsymbol{k}})} \\ &\le \frac{1}{\Im z},\end{aligned}$$

where the last inequality follows from the resolvent identity:

$$\begin{aligned}|\boldsymbol{y}_k^*(M_k - z\mathbf{1}_{n_1})^{-2}\boldsymbol{y_k}| &\le \boldsymbol{y}_k^*(M_k - z\mathbf{1}_{n_1})^{-1}(M_k - \bar{z}\mathbf{1}_{n_1})^{-1}\boldsymbol{y_k} \\ &= \frac{\boldsymbol{y}_k^*\left((M_k - z\mathbf{1}_{n_1})^{-1} - (M_k - \bar{z}\mathbf{1}_{n_1})^{-1}\right)\boldsymbol{y}_k}{2i\,\Im z} \\ &= \frac{\Im(\boldsymbol{y}_k^*(M_k - z\mathbf{1}_{n_1})^{-1}\boldsymbol{y_k})}{\Im z}.\end{aligned}$$

Thus, $|D_k| \le 2(\Im z)^{-1}$, and so $g(z) - \mathbf{E}_X g(z)$ is a sum of bounded martingale differences. We can now apply the Burkholder's inequality which states that for $\{D_k, 1 \le k \le m\}$ being a complex-valued martingale difference sequence, for $p > 1$,

$$\mathbf{E}\left|\sum_{k=1}^{m} D_k\right|^p \le C\,\mathbf{E}\left(\sum_{k=1}^{n}|D_k|^2\right)^{p/2},$$

where C is a positive constant depending on p. We refer to [5, Lemma 2.12] for a proof of this inequality. By choosing $p = 4$, we get

$$\begin{aligned}\mathbf{E}_X\,|g(z) - \mathbf{E}_X g(z)|^4 &= \frac{1}{n_1^4}\,\mathbf{E}_X\left|\sum_{k=1}^{m} D_k\right|^4 \\ &\le \frac{1}{n_1^4}C\,\mathbf{E}_X\left(\sum_{k=1}^{m}|D_k|^2\right)^2 \\ &\le \frac{16\,C\,m^2}{n_1^4\,(\Im z)^4} = \mathcal{O}(n_1^{-2}(\Im z)^{-4}),\end{aligned}$$

just as claimed. □

E Complex case

Remark E.1. *We can also consider matrices $X \in \mathbb{C}^{n_0 \times m}$ and $W \in \mathbb{C}^{n_1 \times n_0}$ of complex random entries with zero mean and variance $\mathbf{E}|X_{ij}|^2 = \sigma_x^2$ and $\mathbf{E}|W_{ij}|^2 = \sigma_w^2$. Let $M = \frac{1}{m}YY^*$ with $Y = f\left(\frac{WX}{\sqrt{n_0}}\right)$, and let $f\colon \mathbb{C} \to \mathbb{R}$ be a real-differentiable function satisfying $\int_{\mathbb{C}} f(\sigma_w\sigma_x z)\frac{e^{-|z|^2}}{\pi}\mathrm{d}^2 z = 0$. Set $\theta_1(f) = \int_{\mathbb{C}} |f(\sigma_w\sigma_x z)|^2\,\frac{e^{-|z|^2}}{\pi}\mathrm{d}^2 z$. Then, it can be proved that the normalized trace of the resolvent of M satisfies equation* (7).