

# Supplementary Material

For notational simplicity, the proofs below assume that in the case  $p < n$ , the support of  $F$  is a single compact interval  $[a, b] \subset (0, +\infty)$ . But they generalize easily to the case where  $\text{Supp}(F)$  is the union of a finite number  $\kappa$  of such intervals, as maintained in Assumptions 3.2 and 3.4. On the same grounds, we make a similar assumption on the support of  $\underline{F}$  in the case  $p > n$ ; see Section 6.

When there is no ambiguity, the first subscript,  $n$ , can be dropped from the notation of the eigenvalues and eigenvectors.

## 11 Proofs of Mathematical Results in Section 3.2

### 11.1 Proof of Theorem 3.1

**Definition 11.1.** For any integer  $k$ , define  $\forall x \in \mathbb{R}$ ,  $\Delta_n^{(k)}(x) := p^{-1} \sum_{i=1}^p u_i' \Sigma_n^k u_i \times \mathbb{1}_{[\lambda_i, +\infty)}(x)$ .

**Lemma 11.1.** Under Assumptions 3.1–3.3, there exists a nonrandom function  $\Delta^{(-1)}$  defined on  $\mathbb{R}$  such that  $\Delta_n^{(-1)}(x)$  converges almost surely to  $\Delta^{(-1)}(x)$ , for all  $x \in \mathbb{R}$ . Furthermore,  $\Delta^{(-1)}$  is continuously differentiable on  $\mathbb{R}$  and satisfies  $\forall x \in \mathbb{R}$ ,  $\Delta^{(-1)}(x) = \int_{-\infty}^x \delta^{(-1)}(\lambda) dF(\lambda)$ , where

$$\forall \lambda \in \mathbb{R} \quad \delta^{(-1)}(\lambda) := \begin{cases} 0 & \text{if } \lambda \leq 0, \\ \frac{1 - c - 2c\lambda \text{Re}[\check{m}_F(\lambda)]}{\lambda} & \text{if } \lambda > 0. \end{cases}$$

**Proof of Lemma 11.1.** The proof of Lemma 11.1 follows directly from [Ledoit and Péché \(2011, Theorem 5\)](#) and the corresponding proof, bearing in mind that we are in the case  $c < 1$  because of Assumption 3.1. ■

**Lemma 11.2.** Under Assumptions 3.1–3.4,

$$\frac{1}{p} \text{Tr}(\Sigma_n^{-1} \tilde{S}_n) \xrightarrow{\text{a.s.}} \int_a^b \tilde{\varphi}(x) d\Delta^{(-1)}(x).$$

**Proof of Lemma 11.2.** Restrict attention to the set  $\Omega_1$  of probability one on which  $\Delta_n^{(-1)}(x)$  converges to  $\Delta^{(-1)}(x)$ , for all  $x$ , and on which also the almost sure uniform convergence and the uniform boundedness of Assumption 3.4 hold for all rational, small  $\eta > 0$ . Wherever necessary, the results in the proof are understood to hold true on this set  $\Omega_1$ .

Note that

$$\frac{1}{p} \text{Tr}(\Sigma_n^{-1} \tilde{S}_n) = \frac{1}{p} \sum_{i=1}^p (u_i' \Sigma_n^{-1} u_i) \tilde{\varphi}_n(\lambda_i) = \int \tilde{\varphi}_n(x) d\Delta_n^{(-1)}(x). \quad (11.1)$$

Since  $\tilde{\varphi}$  is continuous and  $\Delta_n^{(-1)}$  converges weakly to  $\Delta^{(-1)}$ ,

$$\int_a^b \tilde{\varphi}(x) d\Delta_n^{(-1)}(x) \longrightarrow \int_a^b \tilde{\varphi}(x) d\Delta^{(-1)}(x). \quad (11.2)$$

Since  $|\tilde{\varphi}|$  is continuous on  $[a, b]$ , it is bounded above by a finite constant  $\tilde{K}_1$ . Fix  $\varepsilon > 0$ . Since  $\Delta^{(-1)}$  is continuous, there exists a rational  $\eta_1 > 0$  such that

$$|\Delta^{(-1)}(a + \eta_1) - \Delta^{(-1)}(a)| + |\Delta^{(-1)}(b) - \Delta^{(-1)}(b - \eta_1)| \leq \frac{\varepsilon}{6 \tilde{K}_1}. \quad (11.3)$$

Since  $\Delta_n^{(-1)}(x) \rightarrow \Delta^{(-1)}(x)$ , for all  $x \in \mathbb{R}$ , there exists  $N_1 \in \mathbb{N}$  such that

$$\forall n \geq N_1 \quad \max_{x \in \{a, a+\eta_1, b-\eta_1, b\}} |\Delta_n^{(-1)}(x) - \Delta^{(-1)}(x)| \leq \frac{\varepsilon}{24 \tilde{K}_1}. \quad (11.4)$$

Putting Equations (11.3)–(11.4) together yields

$$\forall n \geq N_1 \quad |\Delta_n^{(-1)}(a + \eta_1) - \Delta_n^{(-1)}(a)| + |\Delta_n^{(-1)}(b) - \Delta_n^{(-1)}(b - \eta_1)| \leq \frac{\varepsilon}{3 \tilde{K}_1}. \quad (11.5)$$

Therefore, for all  $n \geq N_1$ ,

$$\begin{aligned} & \left| \int_{a+\eta_1}^{b-\eta_1} \tilde{\varphi}(x) d\Delta_n^{(-1)}(x) - \int_a^b \tilde{\varphi}(x) d\Delta_n^{(-1)}(x) \right| \\ & \leq \tilde{K}_1 \left[ |\Delta_n^{(-1)}(a + \eta_1) - \Delta_n^{(-1)}(a)| + |\Delta_n^{(-1)}(b) - \Delta_n^{(-1)}(b - \eta_1)| \right] \\ & \leq \frac{\varepsilon}{3}. \end{aligned} \quad (11.6)$$

Since  $\tilde{\varphi}_n(x) \rightarrow \tilde{\varphi}(x)$  uniformly over  $x \in [a + \eta_1, b - \eta_1]$ , there exists  $N_2 \in \mathbb{N}$  such that

$$\forall n \geq N_2 \quad \forall x \in [a + \eta_1, b - \eta_1] \quad |\tilde{\varphi}_n(x) - \tilde{\varphi}(x)| \leq \frac{\varepsilon h}{3}.$$

By Assumption 3.2, there exists  $N_3 \in \mathbb{N}$  such that, for all  $n \geq N_3$ ,  $\max_{x \in \mathbb{R}} |\Delta_n^{(-1)}(x)| = \text{Tr}(\Sigma_n^{-1})/p$  is bounded by  $1/h$ . Therefore for all  $n \geq \max(N_2, N_3)$

$$\left| \int_{a+\eta_1}^{b-\eta_1} \tilde{\varphi}_n(x) d\Delta_n^{(-1)}(x) - \int_{a+\eta_1}^{b-\eta_1} \tilde{\varphi}(x) d\Delta_n^{(-1)}(x) \right| \leq \frac{\varepsilon h}{3} \times \frac{1}{h} = \frac{\varepsilon}{3}. \quad (11.7)$$

Arguments analogous to those justifying Equations (11.3)–(11.5) show there exists  $N_4 \in \mathbb{N}$  such that

$$\forall n \geq N_4 \quad |\Delta_n^{(-1)}(a + \eta_1) - \Delta_n^{(-1)}(a - \eta_1)| + |\Delta_n^{(-1)}(b + \eta_1) - \Delta_n^{(-1)}(b - \eta_1)| \leq \frac{\varepsilon}{3 \tilde{K}},$$

for the finite constant  $\tilde{K}$  of Assumption 3.4. Therefore, for all  $n \geq N_4$ ,

$$\left| \int_{a-\eta_1}^{b+\eta_1} \tilde{\varphi}_n(x) d\Delta_n^{(-1)}(x) - \int_{a+\eta_1}^{b-\eta_1} \tilde{\varphi}_n(x) d\Delta_n^{(-1)}(x) \right| \leq \frac{\varepsilon}{3}. \quad (11.8)$$

Putting together Equations (11.6)–(11.8) implies that, for all  $n \geq \max(N_1, N_2, N_3, N_4)$ ,

$$\left| \int_{a-\eta_1}^{b+\eta_1} \tilde{\varphi}_n(x) d\Delta_n^{(-1)}(x) - \int_a^b \tilde{\varphi}(x) d\Delta_n^{(-1)}(x) \right| \leq \varepsilon.$$

Since  $\varepsilon$  can be chosen arbitrarily small,

$$\int_{a-\eta_1}^{b+\eta_1} \tilde{\varphi}_n(x) d\Delta_n^{(-1)}(x) - \int_a^b \tilde{\varphi}(x) d\Delta_n^{(-1)}(x) \rightarrow 0.$$

By using Equation (11.2) we get

$$\int_{a-\eta_1}^{b+\eta_1} \tilde{\varphi}_n(x) d\Delta_n^{(-1)}(x) \longrightarrow \int_a^b \tilde{\varphi}(x) d\Delta^{(-1)}(x) .$$

Theorem 1.1 of Bai and Silverstein (1998) shows that on a set  $\Omega_2$  of probability one, there are no sample eigenvalues outside the interval  $[a - \eta_1, a + \eta_1]$ , for all  $n$  large enough. Therefore, on the set  $\Omega := \Omega_1 \cap \Omega_2$  of probability one,

$$\int \tilde{\varphi}_n(x) d\Delta_n^{(-1)}(x) \longrightarrow \int_a^b \tilde{\varphi}(x) d\Delta^{(-1)}(x) .$$

Together with Equation (11.1), this proves Lemma 11.2. ■

**Lemma 11.3.**

$$\frac{1}{p} \log \left[ \det (\Sigma_n^{-1} \tilde{S}_n) \right] \xrightarrow{\text{a.s.}} \int_a^b \log [\tilde{\varphi}(x)] dF(x) - \int \log(t) dH(t) .$$

**Proof of Lemma 11.3.**

$$\begin{aligned} \frac{1}{p} \log \left[ \det (\Sigma_n^{-1} \tilde{S}_n) \right] &= \frac{1}{p} \log \left[ \det (\Sigma_n^{-1}) \det (\tilde{S}_n) \right] \\ &= \frac{1}{p} \log \left[ \det (\Sigma_n^{-1}) \prod_{i=1}^p \tilde{\varphi}_n(\lambda_i) \right] \\ &= \int \log [\tilde{\varphi}_n(x)] dF_n(x) - \int \log(t) dH_n(t) . \end{aligned} \quad (11.9)$$

A reasoning analogous to that conducted in the proof of Lemma 11.2 shows that the first term on the right-hand side of Equation (11.9) converges almost surely to  $\int_a^b \log [\tilde{\varphi}(x)] dF(x)$ . Given that  $H_n$  converges weakly to  $H$ , Lemma 11.3 follows. ■

We are now ready to tackle Theorem 3.1. Lemma 11.1 and Lemma 11.2 imply that

$$\frac{1}{p} \text{Tr}(\Sigma_n^{-1} \tilde{S}_n) \xrightarrow{\text{a.s.}} \int_a^b \tilde{\varphi}(x) \frac{1 - c - 2cx \text{Re}[\check{m}_F(x)]}{x} dF(x) .$$

Lemma 11.3 implies that

$$-\frac{1}{p} \log \left[ \det (\Sigma_n^{-1} \tilde{S}_n) \right] - 1 \xrightarrow{\text{a.s.}} \int \log(t) dH(t) - \int_a^b \log [\tilde{\varphi}(x)] dF(x) - 1 .$$

Putting these two results together completes the proof of Theorem 3.1. ■

## 11.2 Proof of Proposition 3.1

We start with the simpler case where  $\forall n \in \mathbb{N}, \forall x \in \mathbb{R}, \tilde{\psi}_n(x) \equiv \tilde{\psi}(x)$ . We make implicitly use of Theorem 1.1 of Bai and Silverstein (1998), which states that, for any fixed  $\eta > 0$ , there are no eigenvalues outside the interval  $[a - \eta, b + \eta]$  with probability one, for all  $n$  large enough.

For any given estimator  $\tilde{S}_n$  with limiting shrinkage function  $\tilde{\varphi}$ , define the univariate function  $\forall x, y \in [a, b]$ ,  $\tilde{\psi}(x) := \tilde{\varphi}(x)/x$  and the bivariate function

$$\forall x, y \in [a, b] \quad \tilde{\psi}^\sharp(x, y) := \begin{cases} \frac{x\tilde{\psi}(x) - y\tilde{\psi}(y)}{x - y} & \text{if } x \neq y \\ x\tilde{\psi}'(x) + \tilde{\psi}(x) & \text{if } x = y. \end{cases}$$

Since  $\tilde{\psi}$  is continuously differentiable on  $[a, b]$ ,  $\tilde{\psi}^\sharp$  is continuous on  $[a, b] \times [a, b]$ . Consequently, there exists  $K > 0$  such that,  $\forall x, y \in [a, b]$ ,  $|\tilde{\psi}^\sharp(x, y)| \leq K$ .

**Lemma 11.4.**

$$\frac{2}{p^2} \sum_{j=1}^p \sum_{i>j} \frac{\lambda_j \tilde{\psi}(\lambda_j) - \lambda_i \tilde{\psi}(\lambda_i)}{\lambda_j - \lambda_i} \xrightarrow{\text{a.s.}} \int_a^b \int_a^b \tilde{\psi}^\sharp(x, y) dF(x) dF(y). \quad (11.10)$$

**Proof of Lemma 11.4.**

$$\begin{aligned} \frac{2}{p^2} \sum_{j=1}^p \sum_{i>j} \frac{\lambda_j \tilde{\psi}(\lambda_j) - \lambda_i \tilde{\psi}(\lambda_i)}{\lambda_j - \lambda_i} &= \frac{1}{p^2} \sum_{j=1}^p \sum_{i=1}^p \tilde{\psi}^\sharp(\lambda_i, \lambda_j) - \frac{1}{p^2} \sum_{j=1}^p \tilde{\psi}^\sharp(\lambda_j, \lambda_j) \\ &= \int_a^b \int_a^b \tilde{\psi}^\sharp(x, y) dF_n(x) dF_n(y) - \frac{1}{p^2} \sum_{j=1}^p \tilde{\psi}^\sharp(\lambda_j, \lambda_j). \end{aligned}$$

Given Equation (3.1), the first term converges almost surely to the right-hand side of Equation (11.10). The absolute value of the second term is bounded by  $K/p$ ; therefore, it vanishes asymptotically. ■

**Lemma 11.5.**

$$\int_a^b \int_a^b \tilde{\psi}^\sharp(x, y) dF(x) dF(y) = -2 \int_a^b x \tilde{\psi}(x) \operatorname{Re} [\check{m}_F(x)] dF(x). \quad (11.11)$$

**Proof of Lemma 11.5.** Fix any  $\varepsilon > 0$ . Then there exists  $\eta_1 > 0$  such that, for all  $v \in (0, \eta_1)$ ,

$$\left| 2 \int_a^b x \tilde{\psi}(x) \operatorname{Re} [\check{m}_F(x)] dF(x) - 2 \int_a^b x \tilde{\psi}(x) \operatorname{Re} [\check{m}_F(x + iv)] dF(x) \right| \leq \frac{\varepsilon}{4}.$$

The definition of the Stieltjes transform implies

$$-2 \int_a^b x \tilde{\psi}(x) \operatorname{Re} [\check{m}_F(x + iv)] dF(x) = 2 \int_a^b \int_a^b \frac{x \tilde{\psi}(x)(x - y)}{(x - y)^2 + v^2} dF(x) dF(y).$$

There exists  $\eta_2 > 0$  such that, for all  $v \in (0, \eta_1)$ ,

$$\begin{aligned} &\left| 2 \int_a^b \int_a^b \frac{x \tilde{\psi}(x)(x - y)}{(x - y)^2 + v^2} dF(x) dF(y) - 2 \int_a^b \int_a^b \frac{x \tilde{\psi}(x)(x - y)}{(x - y)^2 + v^2} \mathbb{1}_{\{|x-y| \geq \eta_2\}} dF(x) dF(y) \right| \leq \frac{\varepsilon}{4} \\ \text{and} \quad &\left| \int_a^b \int_a^b \tilde{\psi}^\sharp(x, y) dF(x) dF(y) - \int_a^b \int_a^b \tilde{\psi}^\sharp(x, y) \mathbb{1}_{\{|x-y| \geq \eta_2\}} dF(x) dF(y) \right| \leq \frac{\varepsilon}{4}. \end{aligned}$$

We have

$$\begin{aligned}
\int_a^b \int_a^b \tilde{\psi}^\sharp(x, y) \mathbb{1}_{\{|x-y| \geq \eta_2\}} dF(x) dF(y) &= \int_a^b \int_a^b \frac{x\tilde{\psi}(x) - y\tilde{\psi}(y)}{x-y} \mathbb{1}_{\{|x-y| \geq \eta_2\}} dF(x) dF(y) \\
&= \int_a^b \int_a^b \frac{x\tilde{\psi}(x)}{x-y} \mathbb{1}_{\{|x-y| \geq \eta_2\}} dF(x) dF(y) \\
&\quad + \int_a^b \int_a^b \frac{y\tilde{\psi}(y)}{y-x} \mathbb{1}_{\{|y-x| \geq \eta_2\}} dF(y) dF(x) \\
&= 2 \int_a^b \int_a^b \frac{x\tilde{\psi}(x)}{x-y} \mathbb{1}_{\{|x-y| \geq \eta_2\}} dF(x) dF(y) .
\end{aligned}$$

Note that

$$\begin{aligned}
2 \int_a^b \int_a^b \frac{x\tilde{\psi}(x)}{x-y} \mathbb{1}_{\{|x-y| \geq \eta_2\}} dF(x) dF(y) &- 2 \int_a^b \int_a^b \frac{x\tilde{\psi}(x)(x-y)}{(x-y)^2 + v^2} \mathbb{1}_{\{|x-y| \geq \eta_2\}} dF(x) dF(y) \\
&= 2 \int_a^b \int_a^b \frac{x\tilde{\psi}(x)}{x-y} \frac{v^2}{(x-y)^2 + v^2} \mathbb{1}_{\{|x-y| \geq \eta_2\}} dF(x) dF(y) ,
\end{aligned}$$

and that

$$\forall(x, y) \text{ such that } |x-y| \geq \eta_2 \quad \frac{v^2}{(x-y)^2 + v^2} \leq \frac{v^2}{\eta_2^2 + v^2} .$$

The quantity on the right-hand side can be made arbitrarily small for fixed  $\eta_2$  by bringing  $v$  sufficiently close to zero. This implies that there exists  $\eta_3 \in (0, \eta_1)$  such that, for all  $v \in (0, \eta_3)$ ,

$$\left| 2 \int_a^b \int_a^b \frac{x\tilde{\psi}(x)}{x-y} \mathbb{1}_{\{|x-y| \geq \eta_2\}} dF(x) dF(y) - 2 \int_a^b \int_a^b \frac{x\tilde{\psi}(x)(x-y)}{(x-y)^2 + v^2} \mathbb{1}_{\{|x-y| \geq \eta_2\}} dF(x) dF(y) \right| \leq \frac{\varepsilon}{4} .$$

Putting these results together yields

$$\left| \int_a^b \int_a^b \tilde{\psi}^\sharp(x, y) dF(x) dF(y) + 2 \int_a^b x\tilde{\psi}(x) \operatorname{Re}[\check{m}_F(x)] dF(x) \right| \leq \varepsilon .$$

Since this holds for any  $\varepsilon > 0$ , Equation (11.11) follows. ■

Putting together Lemmas 11.4 and 11.5 yields

$$\frac{2}{p^2} \sum_{j=1}^p \sum_{i>j} \frac{\lambda_j \tilde{\psi}(\lambda_j) - \lambda_i \tilde{\psi}(\lambda_i)}{\lambda_j - \lambda_i} \xrightarrow{\text{a.s.}} -2 \int_a^b x\tilde{\psi}(x) \operatorname{Re}[\check{m}_F(x)] dF(x) .$$

**Lemma 11.6.** *As  $n$  and  $p$  go to infinity with their ratio  $p/n$  converging to the concentration  $c$ ,*

$$\log(n) - \frac{1}{p} \sum_{j=1}^p \mathbb{E}[\log(\chi_{n-j+1}^2)] \longrightarrow 1 + \frac{1-c}{c} \log(1-c) .$$

**Proof of Lemma 11.6.** It is well known that, for every positive integer  $\nu$ ,

$$\mathbb{E}[\log(\chi_\nu^2)] = \log(2) + \frac{\Gamma'(\nu/2)}{\Gamma(\nu/2)} ,$$

where  $\Gamma(\cdot)$  denotes the gamma function. Thus,

$$\frac{1}{p} \sum_{j=1}^p \mathbb{E}[\log(\chi_{n-j+1}^2)] = \log(2) + \frac{1}{p} \sum_{j=1}^p \frac{\Gamma'((n-j+1)/2)}{\Gamma((n-j+1)/2)}.$$

Formula 6.3.21 of [Abramowitz and Stegun \(1965\)](#) states that

$$\forall x \in (0, +\infty) \quad \frac{\Gamma'(x)}{\Gamma(x)} = \log(x) - \frac{1}{2x} - 2 \int_0^\infty \frac{t dt}{(t^2 + x^2)(e^{2\pi t} - 1)}.$$

It implies that

$$\begin{aligned} \log(n) - \frac{1}{p} \sum_{j=1}^p \mathbb{E}[\log(\chi_{n-j+1}^2)] &= -\frac{1}{p} \sum_{j=1}^p \log\left(1 - \frac{j-1}{n}\right) + \frac{1}{p} \sum_{k=n-p+1}^n \frac{1}{k} \\ &\quad + \frac{1}{p} \sum_{k=n-p+1}^n \int_0^\infty \frac{t dt}{[t^2 + (k/2)^2](e^{2\pi t} - 1)} \\ &=: -\frac{1}{p} \sum_{j=1}^p \log\left(1 - \frac{j-1}{n}\right) + A_n + B_n. \end{aligned}$$

It is easy to verify that

$$-\frac{1}{p} \sum_{j=1}^p \log\left(1 - \frac{j-1}{n}\right) \longrightarrow -\frac{1}{c} \int_0^c \log(1-x) dx = 1 + \frac{1-c}{c} \log(1-c).$$

Therefore, all that remains to be proven is that the two terms  $A_n$  and  $B_n$  vanish. Using formulas 6.3.2 and 6.3.18 of [Abramowitz and Stegun \(1965\)](#), we see that

$$A_n := \frac{1}{p} \sum_{k=n-p+1}^n \frac{1}{k} = \frac{1}{p} \left[ \frac{\Gamma'(n)}{\Gamma(n)} - \frac{\Gamma'(n-p+1)}{\Gamma(n-p+1)} \right] = \frac{1}{p} \log\left(\frac{n}{n-p+1}\right) + O\left(\frac{1}{p(n-p+1)}\right),$$

which vanishes indeed. As for the term  $B_n$ , it admits the upper bound

$$B_n := \frac{1}{p} \sum_{k=n-p+1}^n \int_0^\infty \frac{t dt}{[t^2 + (k/2)^2](e^{2\pi t} - 1)} \leq \int_0^\infty \frac{t dt}{[t^2 + ((n-p+1)/2)^2](e^{2\pi t} - 1)},$$

which also vanishes. ■

Going back to Equation (2.2), we notice that the term

$$\frac{2}{p} \sum_{j=1}^p \lambda_j \tilde{\psi}'(\lambda_j)$$

remains bounded asymptotically with probability one, since  $\tilde{\psi}'$  is bounded over a compact set.

Putting all these results together shows that the unbiased estimator of risk  $\Theta_n(S_n, \widehat{\Sigma})$  converges almost surely to

$$\begin{aligned} (1-c) \int_a^b \tilde{\psi}(x) dF(x) - \int_a^b \log[\tilde{\psi}(x)] dF(x) - 2c \int_a^b x \tilde{\psi}(x) \operatorname{Re}[\check{m}_F(x)] dF(x) + \frac{1-c}{c} \log(1-c) \\ = \int_a^b \left\{ \frac{1-c - 2cx \operatorname{Re}[\check{m}_F(x)]}{x} \tilde{\varphi}(x) - \log[\tilde{\varphi}(x)] \right\} dF(x) + \int_a^b \log(x) dF(x) + \frac{1-c}{c} \log(1-c) \\ = \int_a^b \left\{ \frac{1-c - 2cx \operatorname{Re}[\check{m}_F(x)]}{x} \tilde{\varphi}(x) - \log[\tilde{\varphi}(x)] \right\} dF(x) + \int \log(t) dH(t) - 1, \end{aligned}$$

where the last equality comes from the following lemma.

**Lemma 11.7.**  $\int_a^b \log(x) dF(x) + \frac{1-c}{c} \log(1-c) = \int \log(t) dH(t) - 1$ .

**Proof of Lemma 11.7.** Setting  $\tilde{\varphi}(x) = x$  for all  $x \in \text{Supp}(F)$  in Lemma 11.3 yields

$$\frac{1}{p} \log \left[ \det (\Sigma_n^{-1} S_n) \right] \xrightarrow{\text{a.s.}} \int_a^b \log(x) dF(x) - \int \log(t) dH(t). \quad (11.12)$$

In addition, note that

$$\begin{aligned} \frac{1}{p} \log \left[ \det (\Sigma_n^{-1} S_n) \right] &= \frac{1}{p} \log \left[ \det \left( \Sigma_n^{-1} \frac{1}{n} \sqrt{\Sigma_n} X'_n X_N \sqrt{\Sigma_n} \right) \right] \\ &= \frac{1}{p} \log \left[ \det \left( \frac{1}{n} X'_n X_n \right) \right] \xrightarrow{\text{a.s.}} \frac{c-1}{c} \log(1-c) - 1, \end{aligned} \quad (11.13)$$

where the convergence comes from Equation (1.1) of [Bai and Silverstein \(2004\)](#). Comparing Equation (11.12) with Equation (11.13) proves the lemma. ■

It is easy to verify that these results carry through to the more general case where the function  $\tilde{\psi}_n$  can vary across  $n$ , as long as it is well behaved asymptotically in the sense of Assumption 3.4. ■

### 11.3 Proof of Proposition 3.2

We provide a proof by contradiction. Suppose that Proposition 3.2 does not hold. Then there exist  $\varepsilon > 0$  and  $x_0 \in \text{Supp}(F)$  such that

$$1 - c - 2c x_0 \text{Re}[\check{m}_F(x_0)] \leq \frac{a_1}{h} - 2\varepsilon. \quad (11.14)$$

Since  $\check{m}_F$  is continuous, there exist  $x_1, x_2 \in \text{Supp}(F)$  such that  $x_1 < x_2$ ,  $[x_1, x_2] \subset \text{Supp}(F)$ , and

$$\forall x \in [x_1, x_2] \quad 1 - c - 2c x \text{Re}[\check{m}_F(x)] \leq \frac{a_1}{h} - \varepsilon.$$

Define, for all  $n \in \mathbb{N}$  and  $x \in \mathbb{R}$ ,

$$\begin{aligned} \bar{\varphi}(x) &:= x \mathbb{1}_{[x_1, x_2]}(x) \\ \bar{\varphi}_n(x) &:= \bar{\varphi}(x) \\ \bar{D}_n &:= \text{Diag}(\bar{\varphi}_n(\lambda_{n,1}), \dots, \bar{\varphi}_n(\lambda_{n,p})) \\ \bar{S}_n &:= U_n \bar{D}_n U_n'. \end{aligned}$$

By Lemmas 11.1–11.2,

$$\frac{1}{p} \text{Tr} (\Sigma_n^{-1} \bar{S}_n) \xrightarrow{\text{a.s.}} \int \bar{\varphi}(x) \frac{1 - c - 2c x \text{Re}[\check{m}_F(x)]}{x} dF(x). \quad (11.15)$$

The left-hand side of Equation (11.15) is asymptotically bounded from below as follows.

$$\begin{aligned} \frac{1}{p} \text{Tr} (\Sigma_n^{-1} \bar{S}_n) &= \frac{1}{p} \sum_{i=1}^p u'_{n,i} \Sigma_n^{-1} u_{n,i} \times \lambda_{n,i} \mathbb{1}_{[x_1, x_2]}(\lambda_{n,i}) \\ &\geq \frac{\lambda_{n,1}}{h} [F_n(x_2) - F_n(x_1)] \xrightarrow{\text{a.s.}} \frac{a_1}{h} [F(x_2) - F(x_1)]. \end{aligned} \quad (11.16)$$

The right-hand side of Equation (11.15) is bounded from above as follows.

$$\int \bar{\varphi}(x) \frac{1 - c - 2cx \operatorname{Re}[\check{m}_F(x)]}{x} dF(x) \leq \left( \frac{a_1}{h} - \varepsilon \right) [F(x_2) - F(x_1)] . \quad (11.17)$$

Given that  $F(x_2) - F(x_1) > 0$ , Equations (11.15)–(11.17) form a logical contradiction. Therefore, the initial assumption (11.14) must be false, which proves Proposition 3.2. ■

### 11.4 Proof of Proposition 3.3

If we compare Equations (3.8) and (3.9), we see that the term  $\int \log(t) dH(t)$  appears in both, so it can be ignored. The challenge is then to prove that

$$\sum_{k=1}^{\kappa} \int_{a_k}^{b_k} \{c + 2cx \operatorname{Re}[\check{m}_F(x)] + \log(x)\} dF(x) < \sum_{k=1}^{\kappa} \int_{a_k}^{b_k} \log \left[ \frac{x}{1 - c - 2cx \operatorname{Re}[\check{m}_F(x)]} \right] dF(x) . \quad (11.18)$$

Rearranging terms, we can restate this inequality as

$$\sum_{k=1}^{\kappa} \int_{a_k}^{b_k} \{c + 2cx \operatorname{Re}[\check{m}_F(x)] + \log(1 - c - 2cx \operatorname{Re}[\check{m}_F(x)])\} dF(x) < 0 . \quad (11.19)$$

Setting  $y := c + 2cx \operatorname{Re}[\check{m}_F(x)]$  leads us to investigate the function  $y \mapsto y + \log(1 - y)$ . Elementary calculus shows that it is strictly negative over its domain of definition, except at  $y = 0$ , where it attains its maximum of zero. The condition  $y = 0$  is equivalent to  $x \operatorname{Re}[\check{m}_F(x)] = -1/2$ .

If we set the variable  $x$  equal to  $a_1$ , the lower bound of the leftmost interval of the support of the limiting sample spectral distribution  $F$ , we get

$$a_1 \operatorname{Re}[\check{m}_F(a_1)] = \operatorname{PV} \int_{-\infty}^{\infty} \frac{a_1}{\lambda - a_1} dF(\lambda) , \quad (11.20)$$

where PV denotes the Cauchy Principal Value (Henrici, 1988, pp. 259–262). The quantity in Equation (11.20) is nonnegative because  $\lambda \geq a_1$  for all  $\lambda \in \operatorname{Supp}(F)$ . By continuity, there exists some  $\beta_1 \in (a_1, b_1]$  such that  $x \operatorname{Re}[\check{m}_F(x)] > -1/2$  for all  $x \in [a_1, \beta_1]$ . This implies that the strict inequality (11.19) is true. ■

### 11.5 Proof of Proposition 3.4

Subtracting Equation (3.8) from Equation (3.14) shows that the difference between limiting losses  $\mathcal{M}_c^S(H, \varphi^M) - \mathcal{M}_c^S(H, \varphi^S)$  is equal to

$$\int \left\{ \frac{1 - c - 2cx \operatorname{Re}[\check{m}_F(x)]}{1 - c + 2cF(x)} - 1 - \log \left[ \frac{1 - c - 2cx \operatorname{Re}[\check{m}_F(x)]}{1 - c + 2cF(x)} \right] \right\} dF(x) . \quad (11.21)$$

The function  $y \mapsto y - 1 + \log(y)$  is strictly positive over its domain of definition, except at  $y = 1$ , where it attains its minimum of zero. Therefore

$$\forall x \in \operatorname{Supp}(F) \quad \frac{1 - c - 2cx \operatorname{Re}[\check{m}_F(x)]}{1 - c + 2cF(x)} - 1 - \log \left[ \frac{1 - c - 2cx \operatorname{Re}[\check{m}_F(x)]}{1 - c + 2cF(x)} \right] \geq 0 , \quad (11.22)$$



which implies that  $\mathcal{M}_c^S(H, \varphi^M) - \mathcal{M}_c^S(H, \varphi^S) \geq 0$ , as we already knew from Corollary 3.1. Elementary calculus shows that the inequality (11.22) is strict if and only if  $-x \operatorname{Re}[\check{m}_F(x)] \neq F(x)$ . As in the proof of Proposition 3.3, we use  $a_1$ , the lower bound of the leftmost interval of the support of the limiting sample spectral distribution  $F$ :

$$\forall x \in [0, a_1) \quad -x \operatorname{Re}[\check{m}_F(x)] = \int \frac{x}{x-\lambda} dF(\lambda) = 1 + \int \frac{\lambda}{x-\lambda} dF(\lambda), \quad (11.23)$$

which is a strictly decreasing function of  $x$ . Therefore, using the fact that  $\check{m}_F$  is continuous (Silverstein and Choi, 1995, Theorem 1.1),  $-a_1 \operatorname{Re}[\check{m}_F(a_1)]$  is strictly below the value that  $-x \operatorname{Re}[\check{m}_F(x)]$  takes at  $x = 0$ , which is itself zero. It implies  $-a_1 \operatorname{Re}[\check{m}_F(a_1)] \neq F(a_1)$ . By continuity, there exists some  $\beta'_1 \in (a_1, b_1]$  such that  $-x \operatorname{Re}[\check{m}_F(x)] \neq F(x)$  for all  $x \in [a_1, \beta'_1]$ . This in turn implies that the integral in Equation (11.21) is strictly positive. ■

## 11.6 Proof of Proposition 3.5

The linear shrinkage estimator in Equation (14) of Ledoit and Wolf (2004) is of the form

$$S_n^L := m_n \mathbb{I}_n + \frac{a_n^2}{d_n^2} (S_n - m_n \mathbb{I}_n), \quad (11.24)$$

where

$$m_n := \int \lambda dF_n(\lambda) \xrightarrow{\text{a.s.}} \int \lambda dF(\lambda) \quad (11.25)$$

$$a_n^2 := \int t^2 dH_n(t) - \left[ \int t dH_n(t) \right]^2 \longrightarrow \int t^2 dH(t) - \left[ \int t dH(t) \right]^2 \quad (11.26)$$

$$d_n^2 := \int \lambda^2 dF_n(\lambda) - \left[ \int \lambda dF_n(\lambda) \right]^2 \xrightarrow{\text{a.s.}} \int \lambda^2 dF(\lambda) - \left[ \int \lambda dF(\lambda) \right]^2. \quad (11.27)$$

Thus, the linear shrinkage function is  $\varphi_n^L : x \mapsto m_n + (a_n^2/d_n^2)(x - m_n)$ . Under Assumptions 3.1–3.3,

$$\forall x \in \operatorname{Supp}(F) \quad \varphi_n^L(x) \xrightarrow{\text{a.s.}} \int \lambda dF(\lambda) + \frac{\int t^2 dH(t) - \left[ \int t dH(t) \right]^2}{\int \lambda^2 dF(\lambda) - \left[ \int \lambda dF(\lambda) \right]^2} \left[ x - \int \lambda dF(\lambda) \right]. \quad (11.28)$$

Since the support of  $F$  is compact, the convergence is uniform. ■

## 12 Proofs of Theorems in Section 4

### 12.1 Proof of Theorem 4.1

**Lemma 12.1.** *Under Assumptions 3.1–3.3, there exists a nonrandom function  $\Delta^{(1)}$  defined on  $\mathbb{R}$  such that the random function  $\Delta_n^{(1)}(x)$  converges almost surely to  $\Delta^{(1)}(x)$ , for all  $x \in \mathbb{R}$ . Furthermore,  $\Delta^{(1)}$  is continuously differentiable on  $\mathbb{R}$  and can be expressed as*

$$\forall x \in \mathbb{R} \quad \Delta^{(1)}(x) = \begin{cases} 0 & \text{if } x < a, \\ \int_a^x \delta^{(1)}(\lambda) dF(\lambda) & \text{if } x \geq a, \end{cases}$$

where  $\forall \lambda \in [a, +\infty)$ ,  $\delta^{(1)}(\lambda) := \lambda/|1 - c - c\lambda\check{m}_F(\lambda)|^2$ .

**Proof of Lemma 12.1.** Follows directly from Theorem 4 of [Ledoit and P ech e \(2011\)](#). ■

**Lemma 12.2.** Under Assumptions 3.1–3.4,

$$\frac{1}{p} \text{Tr}(\Sigma_n \tilde{S}_n^{-1}) \xrightarrow{\text{a.s.}} \int_a^b \frac{1}{\tilde{\varphi}(x)} d\Delta^{(1)}(x) .$$

**Proof of Lemma 12.2.** Note that

$$\frac{1}{p} \text{Tr}(\Sigma_n \tilde{S}_n^{-1}) = \frac{1}{p} \sum_{i=1}^p \frac{u_i' \Sigma_n u_i}{\tilde{\varphi}_n(\lambda_i)} = \int \frac{1}{\tilde{\varphi}_n(x)} d\Delta_n^{(1)}(x) .$$

The remainder of the proof is similar to the proof of Lemma 11.2 and is thus omitted. ■

Lemma 12.1 and Lemma 12.2 imply that

$$\frac{1}{p} \text{Tr}(\Sigma_n \tilde{S}_n^{-1}) \xrightarrow{\text{a.s.}} \int_a^b \frac{x}{\tilde{\varphi}(x) |1 - c - cx\check{m}_F(x)|^2} dF(x) . \quad (12.1)$$

Lemma 11.3 implies that

$$-\frac{1}{p} \log \left[ \det(\Sigma_n \tilde{S}_n^{-1}) \right] - 1 \xrightarrow{\text{a.s.}} \int_a^b \log[\tilde{\varphi}(x)] dF(x) - \int \log(t) dH(t) - 1 .$$

Putting these two results together completes the proof of Theorem 4.1. ■

## 12.2 Proof of Theorem 4.2

Note that

$$\begin{aligned} \frac{1}{p} \text{Tr} \left[ \left( \Sigma_n - \tilde{S}_n \right)^2 \right] &= \frac{1}{p} \sum_{i=1}^p \left[ \tau_{n,i}^2 - 2u_{n,i}' \Sigma_n u_{n,i} \tilde{\varphi}_n(\lambda_{n,i}) + \tilde{\varphi}_n(\lambda_{n,i})^2 \right] \\ &= \int x^2 dH_n(x) - 2 \int \tilde{\varphi}_n(x) d\Delta_n^{(1)}(x) + \int \tilde{\varphi}_n(x)^2 dF_n(x) . \end{aligned}$$

The remainder of the proof is similar to the proof of Lemma 11.2 and is thus omitted. ■

## 12.3 Proof of Theorem 4.3

Note that

$$\begin{aligned} \frac{1}{p} \text{Tr} \left[ \left( \Sigma_n^{-1} - \tilde{S}_n^{-1} \right)^2 \right] &= \frac{1}{p} \sum_{i=1}^p \left[ \frac{1}{\tau_{n,i}^2} - 2 \frac{u_{n,i}' \Sigma_n^{-1} u_{n,i}}{\tilde{\varphi}_n(\lambda_{n,i})} + \frac{1}{\tilde{\varphi}_n(\lambda_{n,i})^2} \right] \\ &= \int \frac{1}{x^2} dH_n(x) - 2 \int \frac{1}{\tilde{\varphi}_n(x)} d\Delta_n^{(-1)}(x) + \int \frac{1}{\tilde{\varphi}_n(x)^2} dF_n(x) . \end{aligned}$$

The remainder of the proof is similar to the proof of Lemma 11.2 and is thus omitted. ■

## 13 Proof of Theorem 5.2

Define the shrinkage function

$$\forall x \in \text{Supp}(F_{\widehat{\tau}_n}) \quad \widehat{\varphi}_n^*(x) := \frac{x}{1 - \frac{p}{n} - 2 \frac{p}{n} x \text{Re}[\check{m}_{n,p}^{\widehat{\tau}_n}(x)]}.$$

Theorem 2.2 of [Ledoit and Wolf \(2015\)](#) and Proposition 4.3 of [Ledoit and Wolf \(2012\)](#) imply that  $\forall x \in \text{Supp}(F)$ ,  $\widehat{\varphi}_n^*(x) \xrightarrow{\text{a.s.}} \varphi^*(x)$ , and that this convergence is uniform over  $x \in \text{Supp}(F)$ , apart from arbitrarily small boundary regions of the support. Theorem 5.2 then follows from Corollary 3.1. ■

## 14 Proofs of Theorems in Section 6

### 14.1 Proof of Theorem 6.1

**Lemma 14.1.** *Under Assumptions 3.2, 3.3, and 6.1, there exists a nonrandom function  $\Delta^{(-1)}$  defined on  $\mathbb{R}$  such that  $\Delta_n^{(-1)}(x)$  converges almost surely to  $\Delta^{(-1)}(x)$ , for all  $x \in \mathbb{R} - \{0\}$ . Furthermore,  $\Delta^{(-1)}$  is continuously differentiable on  $\mathbb{R} - \{0\}$  and can be expressed as  $\forall x \in \mathbb{R}$ ,  $\Delta^{(-1)}(x) = \int_{-\infty}^x \delta^{(-1)}(\lambda) dF(\lambda)$ , where*

$$\forall \lambda \in \mathbb{R} \quad \delta^{(-1)}(\lambda) := \begin{cases} 0 & \text{if } \lambda < 0, \\ \frac{c}{c-1} \cdot \check{m}_H(0) - \check{m}_F(0) & \text{if } \lambda = 0, \\ \frac{1 - c - 2c\lambda \text{Re}[\check{m}_F(\lambda)]}{\lambda} & \text{if } \lambda > 0. \end{cases}$$

**Proof of Lemma 14.1.** The proof of Lemma 14.1 follows directly from [Ledoit and P ech e \(2011, Theorem 5\)](#) and the corresponding proof, bearing in mind that we are in the case  $c > 1$  because of Assumption 6.1. ■

The proof of Theorem 6.1 proceeds as the proof of Theorem 3.1, except that Lemma 14.1 replaces Lemma 11.1. ■

### 14.2 Proof of Theorem 6.2

Define the shrinkage function

$$\widehat{\varphi}_n^*(0) := \left( \frac{p/n}{p/n - 1} \cdot \widehat{\check{m}}_H(0) - \widehat{\check{m}}_F(0) \right)^{-1},$$

$$\text{and } \forall x \in \text{Supp}(F_{\widehat{\tau}_n}) \quad \widehat{\varphi}_n^*(x) := \frac{x}{1 - \frac{p}{n} - 2 \frac{p}{n} x \text{Re}[\check{m}_{n,p}^{\widehat{\tau}_n}(x)]}.$$

First, since both  $\widehat{\check{m}}_H(0)$  and  $\widehat{\check{m}}_F(0)$  are strongly consistent estimators,  $\widehat{\varphi}_n^*(0) \xrightarrow{\text{a.s.}} \varphi^*(0)$ . Second, Theorem 2.2 of [Ledoit and Wolf \(2015\)](#) and Proposition 4.3 of [Ledoit and Wolf \(2012\)](#) applied to  $\underline{F}$  imply that  $\forall x \in \text{Supp}(\underline{F})$ ,  $\widehat{\varphi}_n^*(x) \xrightarrow{\text{a.s.}} \varphi^*(x)$ , and that this convergence is uniform over  $x \in \text{Supp}(\underline{F})$ , apart from arbitrarily small boundary regions of the support. Theorem 6.2 then follows from Corollary 6.1. ■

## 15 Proofs of Propositions in Section 7

### 15.1 Common Notation

Let  $V_n$  denote a matrix of eigenvectors of  $\Sigma_n$  arranged to match the ascending order of the eigenvalues vector  $\boldsymbol{\tau}_n = (\tau_{n,1}, \dots, \tau_{n,p})$ . Let  $v_{n,p}$  denote the  $p$ th column vector of the matrix  $V_n$ . We can decompose the population covariance matrix  $\Sigma_n$  into its bulk and arrow components according to  $\Sigma_n = \Sigma_n^B + \Sigma_n^A$ , where

$$\Sigma_n^B := V_n \times \text{Diag}(\tau_{n,1}, \dots, \tau_{n,p-1}, 0) \times V_n' \quad (15.1)$$

$$\Sigma_n^A := V_n \times \text{Diag}(\underbrace{0, \dots, 0}_{p-1 \text{ times}}, \tau_{n,p}) \times V_n' . \quad (15.2)$$

Note that the  $\min(n, p)$  largest eigenvalues of  $S_n$  are the same as those of  $T_n := n^{-1}X_n\Sigma_nX_n'$ , so in many instances we will be able to simply investigate the spectral decomposition of the latter matrix. Equations (15.1)–(15.2) enable us to write  $T_n = T_n^B + T_n^A$ , where  $T_n^B := n^{-1}X_n\Sigma_n^B X_n'$  and  $T_n^A := n^{-1}X_n\Sigma_n^A X_n'$ .

### 15.2 Proof of Proposition 7.1

Given that the bulk population eigenvalues are below  $\bar{h}$ , Theorem 1.1 of [Bai and Silverstein \(1998\)](#) shows that there exists a constant  $\bar{B}$  such that the largest eigenvalue of  $T_n^B$  is below  $\bar{B}$  almost surely for all  $n$  sufficiently large. Furthermore, due to the fact that the rank of the matrix  $T_n^A$  is one, its second largest eigenvalue is zero. Therefore the Weyl inequalities (e.g., see Theorem 1 in Section 6.7 of [Franklin \(2000\)](#) for a textbook treatment) imply that  $\lambda_{n,p-1} \leq \bar{B} + 0 = \bar{B}$  a.s. for sufficiently large  $n$ . This establishes the first part of the proposition.

As for the second part, it comes from

$$\frac{\lambda_{n,p}}{\tau_{n,p}} \geq \frac{v_{n,p}' S_n v_{n,p}}{\tau_{n,p}} = \frac{1}{\tau_{n,p}} v_{n,p}' \sqrt{\Sigma_n} \frac{X_n' X_n}{n} \sqrt{\Sigma_n} v_{n,p} = v_{n,p}' \frac{X_n' X_n}{n} v_{n,p} \xrightarrow{\text{a.s.}} 1. \blacksquare \quad (15.3)$$

### 15.3 Proof of Proposition 7.2

**Lemma 15.1.** *Under Assumptions 3.1, 3.2.a–c, and 3.2.f, there is spectral separation between the arrow and the bulk in the sense that*

$$\sup \left\{ t \in \mathbb{R} : F_{n,p}^{\boldsymbol{\tau}_n}(t) \leq \frac{p-1}{p} \right\} < \inf \left\{ t \in \mathbb{R} : F_{n,p}^{\boldsymbol{\tau}_n}(t) > \frac{p-1}{p} \right\} \quad (15.4)$$

for large enough  $n$ .

**Proof of Lemma 15.1.** From page 5356 of [Mestre \(2008\)](#), a necessary and sufficient condition for spectral separation to occur between the arrow and the bulk is that

$$\exists t \in (\tau_{n,p-1}, \tau_{n,p}) \quad \text{s.t.} \quad \Theta_n(t) := \frac{1}{p} \sum_{i=1}^p \frac{\tau_{n,i}^2}{(\tau_{n,i} - t)^2} - \frac{1}{c} < 0 . \quad (15.5)$$

This is equivalent to the condition that the function  $x_F(m)$  defined in Equation (1.6) of [Silverstein and Choi \(1995\)](#) is strictly increasing at  $m = -1/t$ . Section 4 of [Silverstein and Choi](#)

(1995) explains in detail how this enables us to determine the boundaries of the support of  $F_{n,p}^{\tau_n}$ . Assumption 3.2.f guarantees that

$$\forall i = 1, \dots, p-1, \quad \forall t \in (\tau_{n,p-1}, \tau_{n,p}), \quad \frac{\tau_{n,i}^2}{(\tau_{n,i} - t)^2} \leq \frac{\bar{h}^2}{(\bar{h} - t)^2}, \quad (15.6)$$

therefore a sufficient condition for arrow separation is that

$$\exists t \in (\tau_{n,p-1}, \tau_{n,p}) \quad \text{s.t.} \quad \theta_n(t) := \frac{p-1}{p} \frac{\bar{h}^2}{(\bar{h} - t)^2} + \frac{1}{p} \frac{\tau_{n,p}^2}{(\tau_{n,p} - t)^2} - \frac{1}{c} < 0. \quad (15.7)$$

The function  $\theta_n$  is strictly convex on  $(\bar{h}, \tau_{n,p})$  and goes to infinity as it approaches  $\bar{h}$  and  $\tau_{n,p}$ , therefore it admits a unique minimum on  $(\bar{h}, \tau_{n,p})$  characterized by the first-order condition

$$\begin{aligned} \theta_n'(t) = 0 &\iff 2 \frac{p-1}{p} \frac{\bar{h}^2}{(\bar{h} - t)^3} + 2 \frac{1}{p} \frac{\tau_{n,p}^2}{(\tau_{n,p} - t)^3} = 0 \\ &\iff \frac{p-1}{p} \frac{\bar{h}^2}{(t - \bar{h})^3} = \frac{1}{p} \frac{\tau_{n,p}^2}{(\tau_{n,p} - t)^3} \\ &\iff \left(\frac{p}{p-1}\right)^{1/3} \frac{t - \bar{h}}{\bar{h}^{2/3}} = p^{1/3} \frac{\tau_{n,p} - t}{\tau_{n,p}^{2/3}} \\ &\iff t = t_n^* := (\bar{h} \tau_{n,p})^{2/3} \frac{\left(\frac{p}{p-1}\right)^{1/3} \tau_{n,p}^{1/3} + \left(\frac{1}{p}\right)^{1/3} \bar{h}^{-1/3}}{\left(\frac{p}{p-1}\right)^{1/3} \bar{h}^{2/3} + \left(\frac{1}{p}\right)^{1/3} \tau_{n,p}^{2/3}}. \end{aligned}$$

Note that  $t_n^* \sim \bar{h}^{2/3} \beta_1^{1/3} p^{2/3}$ , therefore

$$\theta_n(t_n^*) \sim \frac{\bar{h}^2}{\bar{h}^{4/3} \beta_1^{2/3} p^{4/3}} + \frac{\beta_1^2 p^2}{\beta_1^2 p^3} - \frac{1}{c} \longrightarrow -\frac{1}{c} < 0, \quad (15.8)$$

which implies that condition (15.7) is satisfied for large enough  $n$ , and the arrow separates from the bulk. ■

Since the function  $\Theta_n$  from Equation (15.5) is strictly convex over the interval  $(\tau_{n,p-1}, t_n^*)$ ,  $\lim_{t \searrow \tau_{n,p-1}} \Theta_n(t) = +\infty$  and  $\Theta_n(t_n^*) \leq \theta_n(t_n^*) < 0$  by Lemma 15.1,  $\Theta_n$  admits a unique zero in  $(\tau_{n,p-1}, t_n^*)$ . Call it  $\bar{b}_n$ . An asymptotically valid bound for  $\bar{b}_n$  is given by the following lemma.

**Lemma 15.2.** *Under Assumptions 3.1, 3.2.a–c, and 3.2.f,*

$$\forall \varepsilon > 0 \quad \exists N \in \mathbb{N} \quad \text{s.t.} \quad \forall n \geq N \quad \bar{b}_n \leq (1 + \sqrt{c + \varepsilon}) \bar{h}. \quad (15.9)$$

**Proof of Lemma 15.2.**

$$\Theta(\bar{b}_n) = 0 \iff \frac{1}{p} \sum_{i=1}^{p-1} \frac{\tau_{n,i}^2}{(\tau_{n,i} - \bar{b}_n)^2} + \frac{1}{p} \frac{\tau_{n,p}^2}{(\tau_{n,p} - \bar{b}_n)^2} = \frac{1}{c}. \quad (15.10)$$

From  $\bar{b}_n \leq t_n^*$  and  $\tau_{n,p} \sim \beta_1 p$  we deduce

$$\frac{1}{p} \frac{\tau_{n,p}^2}{(\tau_{n,p} - \bar{b}_n)^2} \sim \frac{1}{p} \longrightarrow 0; \quad (15.11)$$

therefore,

$$\frac{1}{p} \sum_{i=1}^{p-1} \frac{\tau_{n,i}^2}{(\tau_{n,i} - \bar{b}_n)^2} \longrightarrow \frac{1}{c}. \quad (15.12)$$

This implies that  $\forall \varepsilon > 0 \exists N \in \mathbb{N}$  s.t.  $\forall n \geq N$

$$\begin{aligned} \frac{1}{p} \sum_{i=1}^{p-1} \frac{\tau_{n,i}^2}{(\tau_{n,i} - \bar{b}_n)^2} &\geq \frac{1}{c + \varepsilon} \\ \frac{p-1}{p} \frac{\bar{h}^2}{(\bar{h} - \bar{b}_n)^2} &\geq \frac{1}{c + \varepsilon} \\ \frac{(\bar{h} - \bar{b}_n)^2}{\bar{h}^2} &\leq c + \varepsilon \\ \bar{b}_n &\leq (1 + \sqrt{c + \varepsilon}) \bar{h}. \blacksquare \end{aligned} \quad (15.13)$$

Since the function  $\Theta_n$  from Equation (15.5) is strictly convex over the interval  $(t_n^*, \tau_{n,p})$ ,  $\lim_{t \nearrow \tau_{n,p}} \Theta_n(t) = +\infty$  and  $\Theta_n(t_n^*) \leq \theta_n(t_n^*) < 0$  by Lemma 15.1,  $\Theta_n$  admits a unique zero in  $(t_n^*, \tau_{n,p})$ . Call it  $\underline{t}_n$ . An asymptotically valid equivalency result for  $\underline{t}_n$  is given by the following lemma.

**Lemma 15.3.** *Under Assumptions 3.1, 3.2.a-c, and 3.2.f,*

$$\tau_{n,p} - \underline{t}_n \sim \frac{\tau_{n,p}}{\sqrt{n}}. \quad (15.14)$$

**Proof of Lemma 15.3.**

$$\Theta(\underline{t}_n) = 0 \iff \frac{1}{p} \sum_{i=1}^{p-1} \frac{\tau_{n,i}^2}{(\tau_{n,i} - \underline{t}_n)^2} + \frac{1}{p} \frac{\tau_{n,p}^2}{(\tau_{n,p} - \underline{t}_n)^2} = \frac{1}{c}. \quad (15.15)$$

From the inequalities  $\underline{t}_n \geq t_n^*$  and  $\tau_{n,i} \leq \bar{h}$  (for  $i = 1, \dots, p-1$ ) we deduce

$$\frac{1}{p} \sum_{i=1}^{p-1} \frac{\tau_{n,i}^2}{(\tau_{n,i} - \underline{t}_n)^2} \leq \frac{p-1}{p} \frac{\bar{h}^2}{(\bar{h} - t_n^*)^2} \sim \frac{\bar{h}^{-2/3}}{\beta_1^{2/3} p^{4/3}} \longrightarrow 0, \quad (15.16)$$

therefore

$$\begin{aligned} \frac{1}{p} \frac{\tau_{n,p}^2}{(\tau_{n,p} - \underline{t}_n)^2} &\longrightarrow \frac{1}{c} \\ \frac{1}{n} \frac{\tau_{n,p}^2}{(\tau_{n,p} - \underline{t}_n)^2} &\longrightarrow 1 \\ \frac{\tau_{n,p} - \underline{t}_n}{\tau_{n,p}/\sqrt{n}} &\longrightarrow 1. \blacksquare \end{aligned}$$

**Lemma 15.4.** *Define*

$$\underline{\lambda}_n := \inf \left\{ t \in \mathbb{R} : F_{n,p}^{\tau_n}(t) > \frac{p-1}{p} \right\}. \quad (15.17)$$

*Then under Assumptions 3.1, 3.2.a-c, and 3.2.f,*

$$\tau_{n,p} - \underline{\lambda}_n \sim 2 \frac{\tau_{n,p}}{\sqrt{n}}. \quad (15.18)$$

**Proof of Lemma 15.4.** Equation (13) of [Mestre \(2008\)](#) gives

$$\underline{\lambda}_n = \underline{t}_n - c \underline{t}_n \frac{1}{p} \sum_{i=1}^p \frac{\tau_{n,i}}{\tau_{n,i} - \underline{t}_n}. \quad (15.19)$$

This is equivalent to plugging  $m = -1/\underline{t}_n$  into Equation (1.6) of [Silverstein and Choi \(1995\)](#). These authors' Section 4 explains why method yields the boundary points of  $\text{Supp}(F_{n,p}^{\tau_n})$ . From Equation (15.19) we deduce

$$1 - \frac{\underline{\lambda}_n}{\underline{t}_n} = c \frac{1}{p} \frac{\tau_{n,p}}{\tau_{n,p} - \underline{t}_n} - c \frac{1}{p} \sum_{i=1}^{p-1} \frac{\tau_{n,i}}{\underline{t}_n - \tau_{n,i}}. \quad (15.20)$$

Lemma 15.3 enables us to approximate the first term on the right-hand side by

$$c \frac{1}{p} \frac{\tau_{n,p}}{\tau_{n,p} - \underline{t}_n} \sim \frac{p}{n} \times \frac{1}{p} \times \sqrt{n} = \frac{1}{\sqrt{n}}. \quad (15.21)$$

Since  $\tau_{n,i} \leq \bar{h} < \underline{t}_n$ , the second term is bounded by

$$0 \leq c \frac{1}{p} \sum_{i=1}^{p-1} \frac{\tau_{n,i}}{\underline{t}_n - \tau_{n,i}} \leq c \frac{\bar{h}}{\underline{t}_n - \bar{h}} \sim c \frac{\bar{h}}{\beta_1 p}, \quad (15.22)$$

therefore it is negligible with respect to the first term. We conclude by remarking that

$$\begin{aligned} 1 - \frac{\underline{\lambda}_n}{\underline{t}_n} &\sim \frac{1}{\sqrt{n}} \\ \underline{t}_n - \underline{\lambda}_n &\sim \frac{\underline{t}_n}{\sqrt{n}} \sim \frac{\tau_{n,p}}{\sqrt{n}} \\ \tau_{n,p} - \underline{\lambda}_n &= (\tau_{n,p} - \underline{t}_n) + (\underline{t}_n - \underline{\lambda}_n) \sim 2 \frac{\tau_{n,p}}{\sqrt{n}}. \blacksquare \end{aligned}$$

**Lemma 15.5.** *Define*

$$\bar{\mu}_n := \sup \left\{ t \in \mathbb{R} : F_{n,p}^{\tau_n}(t) \leq \frac{p-1}{p} \right\}. \quad (15.23)$$

Then under Assumptions 3.1, 3.2.a-c, and 3.2.f,

$$\forall \varepsilon > 0 \quad \exists N \in \mathbb{N} \quad \text{s.t.} \quad \forall n \geq N \quad \bar{\mu}_n \leq (1 + \sqrt{c + \varepsilon})^2 \bar{h}. \quad (15.24)$$

**Proof of Lemma 15.5.** Equation (13) of [Mestre \(2008\)](#) gives

$$\bar{\mu}_n = \bar{b}_n - c \bar{b}_n \frac{1}{p} \sum_{i=1}^p \frac{\tau_{n,i}}{\tau_{n,i} - \bar{b}_n}. \quad (15.25)$$

This is equivalent to plugging  $m = -1/\bar{b}_n$  into Equation (1.6) of [Silverstein and Choi \(1995\)](#). Fix any  $i \in \{1, 2, \dots, p-2\}$  and hold  $(\tau_{n,j})_{j \neq i}$  constant. Define the function

$$\forall b \in (\tau_{n,p-1}, t_n^*), \quad \forall t \leq \tau_{n,i+1} \quad F_i(b, t) := b - c b \frac{1}{p} \frac{t}{t-b} - c b \frac{1}{p} \sum_{\substack{j=1 \\ j \neq i}}^p \frac{\tau_{n,j}}{\tau_{n,j} - b}. \quad (15.26)$$

Then clearly  $\bar{\mu}_n = F_i(\bar{b}_n, \tau_{n,i})$ . Viewing  $\bar{\mu}_n$  and  $\bar{b}_n$  as two univariate functions of  $\tau_{n,i}$ , we can write:

$$\frac{d\bar{\mu}_n}{d\tau_{n,i}} = \frac{\partial F_i}{\partial b}(\bar{b}_n, \tau_{n,i}) \times \frac{d\bar{b}_n}{d\tau_{n,i}} + \frac{\partial F_i}{\partial t}(\bar{b}_n, \tau_{n,i}) . \quad (15.27)$$

But notice that

$$\forall b \in (\tau_{n,p-1}, t_n^*), \quad \forall t \leq \tau_{n,i+1} \quad \frac{\partial F_i}{\partial b}(b, t) = 1 - c \frac{1}{p} \frac{t^2}{(t-b)^2} - c \frac{1}{p} \sum_{\substack{j=1 \\ j \neq i}}^p \frac{\tau_{n,j}^2}{(\tau_{n,j} - b)^2} ; \quad (15.28)$$

therefore,

$$\frac{\partial F_i}{\partial b}(\bar{b}_n, \tau_{n,i}) = -c \Theta_n(\bar{b}_n) , \quad (15.29)$$

which is identically equal to zero by Equation (15.5). By the envelope theorem, Equation (15.27) simplifies into

$$\frac{d\bar{\mu}_n}{d\tau_{n,i}} = \frac{\partial F_i}{\partial t}(\bar{b}_n, \tau_{n,i}) = c \frac{1}{p} \frac{\bar{b}_n^2}{(\tau_{n,i} - \bar{b}_n)^2} > 0 . \quad (15.30)$$

We can thus obtain an upper bound on  $\bar{\mu}_n$  by setting  $\tau_{n,1}, \dots, \tau_{n,p-2}$  equal to  $\tau_{n,p-1}$ . In this particular case,  $\bar{b}_n$  verifies

$$\frac{p-1}{p} \frac{\tau_{n,p-1}^2}{(\tau_{n,p-1} - \bar{b}_n)^2} + \frac{1}{p} \frac{\tau_{n,p}^2}{(\tau_{n,p} - \bar{b}_n)^2} = \frac{1}{c} . \quad (15.31)$$

From Equation (15.13) and  $\tau_{n,p} \sim \beta_1 p$  we deduce

$$\frac{p-1}{p} \frac{\tau_{n,p-1}^2}{(\tau_{n,p-1} - \bar{b}_n)^2} \longrightarrow \frac{1}{c} \quad (15.32)$$

$$\frac{\tau_{n,p-1}}{\tau_{n,p-1} - \bar{b}_n} \longrightarrow -\frac{1}{\sqrt{c}} . \quad (15.33)$$

Thus, in the particular case where  $\tau_{n,1}, \dots, \tau_{n,p-2}$  are all equal to  $\tau_{n,p-1}$ ,  $\bar{\mu}_n$  verifies

$$\frac{\bar{\mu}_n}{\bar{b}_n} = 1 - c \frac{p-1}{p} \frac{\tau_{n,p-1}}{\tau_{n,p-1} - \bar{b}_n} - c \frac{1}{p} \frac{\tau_{n,p}}{\tau_{n,p} - \bar{b}_n} \longrightarrow 1 + \sqrt{c} . \quad (15.34)$$

Remember that, by Equation (15.30), the particular case  $\tau_{n,1} = \dots = \tau_{n,p-2} = \tau_{n,p-1}$  yields an upper bound on  $\bar{\mu}_n$  that holds in the general case  $\tau_{n,1} \leq \dots \leq \tau_{n,p-2} \leq \tau_{n,p-1}$ , therefore putting together Equations (15.13) and (15.34) yields the conclusion

$$\forall \varepsilon > 0 \quad \exists N \in \mathbb{N} \quad \text{s.t.} \quad \forall n \geq N \quad \bar{\mu}_n \leq (1 + \sqrt{c + \varepsilon})^2 \bar{h} . \blacksquare \quad (15.35)$$

The first part of Proposition 7.2 follows from Lemma 15.5 and from the observation that  $q_{n,p}^{p-1}(\tau_n)$  is no greater than  $\bar{\mu}_n$  as defined in Equation (15.23). The second part of Proposition 7.2 follows from Lemma 15.4 and from the observation that  $q_{n,p}^p(\tau_n)$  is no smaller than  $\underline{\lambda}_n$  as defined in Equation (15.17). ■



## 15.4 Proof of Proposition 7.3

The eigenvalues of  $T_n^B$  are bounded from below by zero. Given that the bulk population eigenvalues are below  $\bar{h}$ , Theorem 1.1 of [Bai and Silverstein \(1998\)](#) shows that there exists a constant  $\bar{B}$  such that the largest eigenvalue of  $T_n^B$  is below  $\bar{B}$  almost surely for all  $n$  sufficiently large. Therefore the Weyl inequalities imply that

$$\lambda_{n,p}^A \leq \lambda_{n,p} \leq \lambda_{n,p}^A + \bar{B} \quad (15.36)$$

almost surely for sufficiently large  $n$ , where  $\lambda_{n,p}^A$  denotes the largest eigenvalue of  $T_n^A$ . Furthermore, we have

$$\frac{\lambda_{n,p}^A}{\tau_{n,p}} = v_{n,p}' \frac{X_n' X_n}{n} v_{n,p} \xrightarrow{\text{a.s.}} 1. \quad (15.37)$$

Putting together Equations (15.36) and (15.37) yields  $\lambda_{n,p}/\tau_{n,p} \xrightarrow{\text{a.s.}} 1$ , as desired. ■

## 15.5 Proof of Proposition 7.4

Since the function  $\Theta_n$  from Equation (15.5) is strictly convex over the interval  $(\tau_{n,p}, +\infty)$ ,  $\lim_{t \searrow \tau_{n,p}} \Theta_n(t) = +\infty$  and  $\lim_{t \searrow +\infty} \Theta_n(t) = -1/c < 0$ ,  $\Theta_n$  admits a unique zero in  $(\tau_{n,p}, +\infty)$ . Call it  $\bar{t}_n$ . An asymptotically valid equivalency result for  $\bar{t}_n$  is given by the following lemma.

**Lemma 15.6.** *Under Assumptions 3.1, 3.2.a–c, and 3.2.f,*

$$\bar{t}_n - \tau_{n,p} \sim \frac{\tau_{n,p}}{\sqrt{n}}. \quad (15.38)$$

**Proof of Lemma 15.6.**

$$\Theta(\bar{t}_n) = 0 \iff \frac{1}{p} \sum_{i=1}^{p-1} \frac{\tau_{n,i}^2}{(\tau_{n,i} - \bar{t}_n)^2} + \frac{1}{p} \frac{\tau_{n,p}^2}{(\tau_{n,p} - \bar{t}_n)^2} = \frac{1}{c}. \quad (15.39)$$

From  $\bar{t}_n \sim \beta_1 p$  and  $\tau_{n,i} \leq \bar{h}$  (for  $i = 1, \dots, p-1$ ) we deduce

$$\frac{1}{p} \sum_{i=1}^{p-1} \frac{\tau_{n,i}^2}{(\tau_{n,i} - \bar{t}_n)^2} \sim \frac{\bar{h}^2}{\beta_1^2 p^2} \longrightarrow 0; \quad (15.40)$$

therefore,

$$\begin{aligned} \frac{1}{p} \frac{\tau_{n,p}^2}{(\tau_{n,p} - \bar{t}_n)^2} &\longrightarrow \frac{1}{c} \\ \frac{1}{n} \frac{\tau_{n,p}^2}{(\tau_{n,p} - \bar{t}_n)^2} &\longrightarrow 1 \\ \frac{\bar{t}_n - \tau_{n,p}}{\tau_{n,p}/\sqrt{n}} &\longrightarrow 1. \quad \blacksquare \end{aligned}$$

**Lemma 15.7.** *Define*

$$\bar{\lambda}_n := \sup \{t \in \mathbb{R} : F_{n,p}^{\tau_n}(t) < 1\}. \quad (15.41)$$

*Then under Assumptions 3.1, 3.2.a–c, and 3.2.f,*

$$\bar{\lambda}_n - \tau_{n,p} \sim 2 \frac{\tau_{n,p}}{\sqrt{n}}. \quad (15.42)$$

**Proof of Lemma 15.7.** Equation (13) of [Mestre \(2008\)](#) gives

$$\bar{\lambda}_n = \bar{t}_n - c\bar{t}_n \frac{1}{p} \sum_{i=1}^p \frac{\tau_{n,i}}{\tau_{n,i} - \bar{t}_n}. \quad (15.43)$$

This is equivalent to plugging  $m = -1/\bar{t}_n$  into Equation (1.6) of [Silverstein and Choi \(1995\)](#). From Equation (15.43) we deduce

$$\frac{\bar{\lambda}_n}{\bar{t}_n} - 1 = c \frac{1}{p} \frac{\tau_{n,p}}{\bar{t}_n - \tau_{n,p}} + c \frac{1}{p} \sum_{i=1}^{p-1} \frac{\tau_{n,i}}{\bar{t}_n - \tau_{n,i}}. \quad (15.44)$$

Lemma 15.6 enables us to approximate the first term on the right-hand side by

$$c \frac{1}{p} \frac{\tau_{n,p}}{\bar{t}_n - \tau_{n,p}} \sim \frac{p}{n} \times \frac{1}{p} \times \sqrt{n} = \frac{1}{\sqrt{n}}. \quad (15.45)$$

Since  $\tau_{n,i} \leq \bar{h} < \bar{t}_n$ , the second term is bounded by

$$0 \leq c \frac{1}{p} \sum_{i=1}^{p-1} \frac{\tau_{n,i}}{\bar{t}_n - \tau_{n,i}} \leq c \frac{\bar{h}}{\bar{t}_n - \bar{h}} \sim c \frac{\bar{h}}{\beta_1 p}; \quad (15.46)$$

therefore, it is negligible with respect to the first term. We conclude by remarking that

$$\begin{aligned} \frac{\bar{\lambda}_n}{\bar{t}_n} - 1 &\sim \frac{1}{\sqrt{n}} \\ \bar{\lambda}_n - \bar{t}_n &\sim \frac{\bar{t}_n}{\sqrt{n}} \sim \frac{\tau_{n,p}}{\sqrt{n}} \\ \bar{\lambda}_n - \tau_{n,p} &= (\bar{\lambda}_n - \bar{t}_n) + (\bar{t}_n - \tau_{n,p}) \sim 2 \frac{\tau_{n,p}}{\sqrt{n}}. \blacksquare \end{aligned}$$

The observation that  $\lambda_n \leq q_{n,p}^p(\tau_n) \leq \bar{\lambda}_n$  together with Lemmas 15.4 and 15.7 establishes Proposition 7.4.  $\blacksquare$

## 15.6 Proof of Lemma 7.1

For ease of notation, let us denote  $\tilde{\varphi}_n(\lambda_{n,i})$  by  $\tilde{\varphi}_{n,i}$  in this proof only.

$$\begin{aligned} \mathcal{L}_n^S(\Sigma_n, \tilde{S}_n) &= \frac{1}{p} \sum_{i=1}^p \tilde{\varphi}_{n,i} \cdot u_{n,i} \Sigma_n^{-1} u_{n,i} + \frac{1}{p} \sum_{i=1}^p \log(\tau_{n,i}) - \frac{1}{p} \sum_{i=1}^p \log(\tilde{\varphi}_{n,i}) - 1 \\ \frac{\partial \mathcal{L}_n^S(\Sigma_n, \tilde{S}_n)}{\partial \tilde{\varphi}_{n,i}} &= \frac{1}{p} u_{n,i} \Sigma_n^{-1} u_{n,i} - \frac{1}{p} \frac{1}{\tilde{\varphi}_{n,i}} \end{aligned}$$

The first-order condition is

$$\frac{\partial \mathcal{L}_n^S(\Sigma_n, \tilde{S}_n)}{\partial \tilde{\varphi}_{n,i}} = 0 \iff \tilde{\varphi}_{n,i} = \frac{1}{u_{n,i} \Sigma_n^{-1} u_{n,i}}. \blacksquare$$

## 15.7 Proof of Proposition 7.5

As in the proof of Proposition 7.3 above, let  $V_n$  denote a matrix of eigenvectors of  $\Sigma_n$  arranged to match the nondescending order of the eigenvalues  $\tau_n = (\tau_{n,1}, \dots, \tau_{n,p})$ , and let  $v_{n,i}$  denote its  $i$ th column vector ( $i = 1, \dots, p$ ). The matrix  $\Sigma_n^A$  defined in Equation (15.2) is a rank-degenerate version of the population covariance matrix where all bulk eigenvalues have been neglected. The sample covariance matrix that corresponds to  $\Sigma_n^A$  is

$$S_n^A := n^{-1} \sqrt{\Sigma_n^A} X_n' X_n \sqrt{\Sigma_n^A}. \quad (15.47)$$

It admits a spectral decomposition on the same orthonormal basis as  $\Sigma_n$  and  $\Sigma_n^A$ :

$$S_n^A = V_n \times \text{Diag}(\lambda_{n,1}^A, \dots, \lambda_{n,p}^A) \times V_n', \quad (15.48)$$

with all eigenvalues equal to zero except for  $\lambda_{n,p}^A = n^{-1} \tau_{n,p} \cdot v_{n,p}' X_n' X_n v_{n,p}$ . Viewing  $S_n$  as a perturbation of  $S_n^A$ , Equation (5.1) of Meyer and Stewart (1988) gives the approximation

$$\forall i = 1, \dots, p-1 \quad u_{n,p}' v_{n,i} = \frac{v_{n,i}' (S_n - S_n^A) v_{n,p}}{\lambda_{n,p}^A - \lambda_{n,i}^A} + O\left(\left(\frac{\tau_{n,i}}{\tau_{n,p}}\right)^2\right), \quad (15.49)$$

from which we deduce

$$\tau_{n,p} \sum_{i=1}^{p-1} \frac{(u_{n,p}' v_{n,i})^2}{\tau_{n,i}} = \sum_{i=1}^{p-1} \frac{\tau_{n,p}}{\tau_{n,i}} \left[ \frac{v_{n,i}' (S_n - S_n^A) v_{n,p}}{\lambda_{n,p}^A - \lambda_{n,i}^A} \right]^2 + O\left(\frac{1}{p}\right). \quad (15.50)$$

Note that  $\forall i = 1, \dots, p-1$ ,  $v_{n,i}' S_n^A v_{n,p} = 0$ , and  $v_{n,i}' S_n v_{n,p} = n^{-1} \sqrt{\tau_{n,i} \tau_{n,p}} \cdot v_{n,i}' X_n' X_n v_{n,p}$ , therefore this expression simplifies to

$$\tau_{n,p} \sum_{i=1}^{p-1} \frac{(u_{n,p}' v_{n,i})^2}{\tau_{n,i}} = \frac{1}{n} \sum_{i=1}^{p-1} \frac{(v_{n,i}' X_n' X_n v_{n,p})^2 / n}{(v_{n,p}' X_n' X_n v_{n,p} / n)^2} + O\left(\frac{1}{p}\right). \quad (15.51)$$

By the law of large numbers,  $(p-1)^{-1} \sum_{i=1}^{p-1} (v_{n,i}' X_n' X_n v_{n,p})^2 / n \xrightarrow{\text{a.s.}} 1$  and  $v_{n,p}' X_n' X_n v_{n,p} / n \xrightarrow{\text{a.s.}} 1$ ; therefore,

$$\tau_{n,p} \sum_{i=1}^{p-1} \frac{(u_{n,p}' v_{n,i})^2}{\tau_{n,i}} \xrightarrow{\text{a.s.}} c. \quad (15.52)$$

Given that  $\sum_{i=1}^p (u_{n,p}' v_{n,i})^2 = 1$ , we have  $(u_{n,p}' v_{n,p})^2 \xrightarrow{\text{a.s.}} 1$ . This enables us to conclude that

$$\tau_{n,p} \cdot u_{n,p}' \Sigma_n^{-1} u_{n,p} = (u_{n,p}' v_{n,p})^2 + \tau_{n,p} \sum_{i=1}^{p-1} \frac{(u_{n,p}' v_{n,i})^2}{\tau_{n,i}} \xrightarrow{\text{a.s.}} 1 + c. \blacksquare$$

## 15.8 Proof of Proposition 7.6

**Lemma 15.8.** *Let*

$$\tau_n^A := (\underbrace{0, \dots, 0}_{p-1 \text{ times}}, \tau_{n,p}). \quad (15.53)$$

*Then under Assumptions 3.1, 3.2.a-c, and 3.2.f,  $1 + \lambda_{n,p} \check{m}_{n,p}^{\tau_n^A}(\lambda_{n,p}) \xrightarrow{\text{a.s.}} 0$ .*

**Proof of Lemma 15.8.** By taking the limit of Equation (5.7) as  $m \in \mathbb{C}^+$  approaches the real line, we find that for all  $\lambda \in (0, +\infty)$ ,  $m := \check{m}_{n,p}^{\tau_n^A}(\lambda)$  is the unique solution in  $\mathbb{C}^+ \cup \mathbb{R}$  to the equation

$$m = -\frac{p-1}{p\lambda} + \frac{1}{p} \frac{1}{\tau_{n,p} \left(1 - \frac{p}{n} - \frac{p}{n} \lambda m\right) - \lambda}. \quad (15.54)$$

With the change of variables  $\tilde{m} := pm + (p-1)/\lambda$ , Equation (15.54) becomes

$$\tilde{m} = \frac{1}{\tau_{n,p} \left(1 - \frac{1}{n} - \frac{1}{n} \lambda \tilde{m}\right) - \lambda} \quad (15.55)$$

$$\tau_{n,p} \frac{1}{n} \lambda \tilde{m}^2 + \left(\tau_{n,p} \frac{1}{n} + \lambda - \tau_{n,p}\right) \tilde{m} + 1 = 0. \quad (15.56)$$

(15.56) is a classic quadratic equation whose discriminant is  $\Delta = (\tau_{n,p} n^{-1} + \lambda - \tau_{n,p})^2 - 4\tau_{n,p} n^{-1}$ . In turn, the Equation  $\Delta = 0$  is itself a quadratic equation in  $\lambda$ :

$$\lambda^2 - 2\tau_{n,p} \left(\frac{1}{n} + 1\right) \lambda + \tau_{n,p}^2 \left(\frac{1}{n} - 1\right)^2 = 0. \quad (15.57)$$

It admits two distinct real, positive solutions:  $\lambda = \tau_{n,p} (1 \pm n^{-1/2})^2$ . This enables us to factorize the discriminant  $\Delta$  into

$$\Delta = \left[ \lambda - \tau_{n,p} \left(1 + \frac{1}{\sqrt{n}}\right)^2 \right] \times \left[ \lambda - \tau_{n,p} \left(1 - \frac{1}{\sqrt{n}}\right)^2 \right]. \quad (15.58)$$

This factorization shows that Equation (15.56) admits a solution in  $\mathbb{C}^+$  if and only if  $\lambda \in (\tau_{n,p}(1 + n^{-1/2})^2, \tau_{n,p}(1 - n^{-1/2})^2)$ . Over this interval, the solution with positive imaginary part is

$$\tilde{m} = \frac{\tau_{n,p}(1 - n^{-1}) - \lambda + i \cdot \sqrt{[\lambda - \tau_{n,p}(1 - n^{-1/2})^2] \times [\tau_{n,p}(1 + n^{-1/2})^2 - \lambda]}}{2\tau_{n,p} \lambda/n}. \quad (15.59)$$

This is none other than the Stieltjes transform of the celebrated Marčenko-Pastur (1967) distribution with scale parameter  $\tau_{n,p}$  and concentration parameter  $1/n$ . Changing back to the original variable  $m$ , we obtain the following solution for Equation (15.54):

$$m = -\frac{p-1}{p\lambda} + \frac{\tau_{n,p}(1 - n^{-1}) - \lambda + i \cdot \sqrt{[\lambda - \tau_{n,p}(1 - n^{-1/2})^2] \times [\tau_{n,p}(1 + n^{-1/2})^2 - \lambda]}}{2\tau_{n,p} \lambda p/n}, \quad (15.60)$$

for all  $\lambda \in [\tau_{n,p}(1 - n^{-1/2})^2, \tau_{n,p}(1 + n^{-1/2})^2]$ . Note that this closed interval, along with zero, constitutes the support of  $F_{n,p}^{\tau_n^A}$ . The general solution for all  $\lambda > 0$  can be expressed concisely by introducing the function

$$\forall \lambda \in (0, +\infty) \quad u(\lambda) := \begin{cases} -1 & \text{if } 0 < \lambda < \tau_{n,p}(1 - n^{-1/2})^2, \\ i & \text{if } \tau_{n,p}(1 - n^{-1/2})^2 \leq \lambda \leq \tau_{n,p}(1 + n^{-1/2})^2, \\ 1 & \text{if } \tau_{n,p}(1 + n^{-1/2})^2 < \lambda. \end{cases} \quad (15.61)$$

It is

$$\check{m}_{n,p}^{\tau_n^A}(\lambda) = -\frac{p-1}{p\lambda} + \frac{\tau_{n,p}(1-n^{-1}) - \lambda + u(\lambda) \sqrt{|\lambda - \tau_{n,p}(1-n^{-1/2})^2| \times |\tau_{n,p}(1+n^{-1/2})^2 - \lambda|}}{2\tau_{n,p}\lambda p/n},$$

from which we deduce, after simplification,

$$1 + \lambda \check{m}_{n,p}^{\tau_n^A}(\lambda) = \frac{1}{2p} + \frac{n}{2p} \left(1 - \frac{\lambda}{\tau_{n,p}}\right) + \frac{nu(\lambda)}{2p} \sqrt{\left|\frac{\lambda}{\tau_{n,p}} - \left(1 - \frac{1}{\sqrt{n}}\right)^2\right| \times \left|\left(1 + \frac{1}{\sqrt{n}}\right)^2 - \frac{\lambda}{\tau_{n,p}}\right|}. \quad (15.62)$$

Lemma 15.8 then follows by setting  $\lambda = \lambda_{n,p}$  in Equation (15.62) and using Proposition 7.3. ■

**Lemma 15.9.**

$$\forall \lambda \in (0, +\infty) \quad \left|1 + \lambda \check{m}_{n,p}^{\tau_n}(\lambda)\right| \leq \sqrt{\frac{n}{p}}. \quad (15.63)$$

**Proof of Lemma 15.9.** Section 2.2 of Ledoit and Wolf (2012) defines the ancillary function

$$\underline{m}_{n,p}^{\tau_n}(z) := \frac{p-n}{nz} + \frac{p}{n} m_{n,p}^{\tau_n}(z), \quad \forall z \in \mathbb{C}^+. \quad (15.64)$$

Call its image  $\underline{m}_{n,p}^{\tau_n}(\mathbb{C}^+)$ . Equation (1.4) of Silverstein and Choi (1995) states that the function  $\underline{m}_{n,p}^{\tau_n}$  has a unique inverse on  $\mathbb{C}^+$  given by

$$\underline{z}_{n,p}^{\tau_n}(m) := -\frac{1}{m} + \frac{1}{n} \sum_{i=1}^p \frac{\tau_{n,i}}{1 + m\tau_{n,i}}, \quad \forall m \in \underline{m}_{n,p}^{\tau_n}(\mathbb{C}^+). \quad (15.65)$$

The change of variables  $m = \underline{m}_{n,p}^{\tau_n}(z) \iff z = \underline{z}_{n,p}^{\tau_n}(m)$  yields

$$\forall z \in \mathbb{C}^+ \quad 1 + z \underline{m}_{n,p}^{\tau_n}(z) = \frac{n}{p} [1 + z \underline{m}_{n,p}^{\tau_n}(z)] = \frac{n}{p} [1 + \underline{z}_{n,p}^{\tau_n}(m)m] = \frac{1}{p} \sum_{i=1}^p \frac{m\tau_{n,i}}{1 + m\tau_{n,i}}. \quad (15.66)$$

By Jensen's inequality,

$$\forall m \in \underline{m}_{n,p}^{\tau_n}(\mathbb{C}^+) \quad \left(\frac{1}{p} \sum_{i=1}^p \operatorname{Re} \left[ \frac{m\tau_{n,i}}{1 + m\tau_{n,i}} \right]\right)^2 \leq \frac{1}{p} \sum_{i=1}^p \left(\operatorname{Re} \left[ \frac{m\tau_{n,i}}{1 + m\tau_{n,i}} \right]\right)^2 \quad (15.67)$$

$$\left(\frac{1}{p} \sum_{i=1}^p \operatorname{Im} \left[ \frac{m\tau_{n,i}}{1 + m\tau_{n,i}} \right]\right)^2 \leq \frac{1}{p} \sum_{i=1}^p \left(\operatorname{Im} \left[ \frac{m\tau_{n,i}}{1 + m\tau_{n,i}} \right]\right)^2. \quad (15.68)$$

Adding these two equations, we obtain

$$\forall m \in \underline{m}_{n,p}^{\tau_n}(\mathbb{C}^+) \quad \left|\frac{1}{p} \sum_{i=1}^p \frac{m\tau_{n,i}}{1 + m\tau_{n,i}}\right|^2 \leq \frac{1}{p} \sum_{i=1}^p \left|\frac{m\tau_{n,i}}{1 + m\tau_{n,i}}\right|^2. \quad (15.69)$$

Since  $\underline{z}_{n,p}^{\tau_n}(m) \in \mathbb{C}^+$  for all  $m \in \underline{m}_{n,p}^{\tau_n}(\mathbb{C}^+)$ , we have:

$$\forall m \in \underline{m}_{n,p}^{\tau_n}(\mathbb{C}^+) \quad \operatorname{Im} [\underline{z}_{n,p}^{\tau_n}(m)] > 0. \quad (15.70)$$

Let  $m_1 := \operatorname{Re}[m]$  and  $m_2 := \operatorname{Im}[m]$ . Equation (1.3) of [Silverstein and Choi \(1995\)](#) implies that  $\underline{m}_{n,p}^{\tau_n}(\mathbb{C}^+) \subset \mathbb{C}^+$ ; therefore,  $m_2 > 0$ . This enables us to deduce from Equation (15.70) that

$$\begin{aligned} \forall m \in \underline{m}_{n,p}^{\tau_n}(\mathbb{C}^+) \quad \operatorname{Im} \left[ -\frac{1}{m_1 + im_2} + \frac{1}{n} \sum_{i=1}^p \frac{\tau_{n,i}}{1 + (m_1 + im_2)\tau_{n,i}} \right] &> 0 \\ \frac{m_2}{m_1^2 + m_2^2} - \frac{1}{n} \sum_{i=1}^p \frac{m_2 \tau_{n,i}^2}{(1 + m_1 \tau_{n,i})^2 + m_2 \tau_{n,i}^2} &> 0 \\ \frac{1}{p} \sum_{i=1}^p \frac{\tau_{n,i}^2 (m_1^2 + m_2^2)}{(1 + m_1 \tau_{n,i})^2 + m_2 \tau_{n,i}^2} &< \frac{n}{p} \\ \frac{1}{p} \sum_{i=1}^p \left| \frac{m \tau_{n,i}}{1 + m \tau_{n,i}} \right|^2 &< \frac{n}{p}. \end{aligned} \quad (15.71)$$

Putting together Equations (15.66), (15.69), and (15.71) yields  $\forall z \in \mathbb{C}^+ \quad |1 + z m_{n,p}^{\tau_n}(z)|^2 < n/p$ . Lemma 15.9 then follows from taking the limit as  $z \in \mathbb{C}^+$  goes to  $\lambda \in (0, +\infty)$ . ■

By taking the limit of Equation (5.7) as  $m \in \mathbb{C}^+$  approaches the real line, we find that for all  $\lambda \in (0, +\infty)$ ,  $m := \check{m}_{n,p}^{\tau_n}(\lambda)$  is the unique solution in  $\mathbb{C}^+ \cup \mathbb{R}$  to the equation

$$m = \frac{1}{p} \sum_{i=1}^{p-1} \frac{1}{\tau_{n,i} \left(1 - \frac{p}{n} - \frac{p}{n} \lambda m\right) - \lambda} + \frac{1}{p} \frac{1}{\tau_{n,p} \left(1 - \frac{p}{n} - \frac{p}{n} \lambda m\right) - \lambda}. \quad (15.72)$$

Comparing Equation (15.72) with Equation (15.54) yields

$$\forall \lambda \in (0, +\infty) \quad \lambda \left[ \check{m}_{n,p}^{\tau_n}(\lambda) - \check{m}_{n,p}^{\tau_n^A}(\lambda) \right] = \frac{1}{p} \sum_{i=1}^{p-1} \frac{\tau_{n,i} \left[1 - \frac{p}{n} - \frac{p}{n} \lambda \check{m}_{n,p}^{\tau_n}(\lambda)\right]}{\tau_{n,i} \left[1 - \frac{p}{n} - \frac{p}{n} \lambda \check{m}_{n,p}^{\tau_n}(\lambda)\right] - \lambda}. \quad (15.73)$$

Remember that by Assumption 3.2.f, there exists  $\bar{h} > 0$  such that  $0 \leq \tau_{n,1} \leq \dots \leq \tau_{n,p-1} \leq \bar{h}$  for all  $n$  large enough. Furthermore by Assumption 3.1 there exists  $\bar{c}$  such that  $p/n \leq \bar{c}$  for all  $n$  large enough. Lemma 15.9 then yields the following bound for sufficiently large  $n$ :

$$\forall \lambda \in \left(\bar{h} (1 + \sqrt{\bar{c}}), +\infty\right) \quad \lambda \left| \check{m}_{n,p}^{\tau_n}(\lambda) - \check{m}_{n,p}^{\tau_n^A}(\lambda) \right| \leq \frac{\bar{h} (1 + \sqrt{\bar{c}})}{\lambda - \bar{h} (1 + \sqrt{\bar{c}})}. \quad (15.74)$$

By Proposition 7.3, this implies

$$\lambda_{n,p} \left[ \check{m}_{n,p}^{\tau_n}(\lambda_{n,p}) - \check{m}_{n,p}^{\tau_n^A}(\lambda_{n,p}) \right] \xrightarrow{\text{a.s.}} 0. \quad (15.75)$$

Using Lemma 15.8, we obtain

$$1 + \lambda_{n,p} \check{m}_{n,p}^{\tau_n}(\lambda_{n,p}) \xrightarrow{\text{a.s.}} 0, \quad (15.76)$$

from which we can finally conclude that

$$\frac{\lambda_{n,p}}{1 - \frac{p}{n} - 2 \frac{p}{n} \lambda_{n,p} \operatorname{Re}[\check{m}_{n,p}^{\tau_n}(\lambda_{n,p})]} \underset{\text{a.s.}}{\sim} \frac{\lambda_{n,p}}{1 + \frac{p}{n}} \underset{\text{a.s.}}{\sim} \frac{\tau_{n,p}}{1 + \bar{c}}. \quad \blacksquare \quad (15.77)$$

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