

1 Eigenvalue matrix $V_{j,k}$

This section will be dedicated to providing a characterization of the eigenvalue matrix obtained from the eigendecomposition of the CEWS matrix (and the estimator of the CEWS) in terms of the factor model component.

1.1 Covariance matrix of F_k

In this section we will analyse an estimator of the covariance matrix of F_k . Define the wavelet estimator by,

$$\hat{\Sigma}_{j,k}^F = \frac{1}{2M+1} \sum_{s=-M}^M \sum_{m=0}^{T-1} \mathbf{F}_m \mathbf{F}_m' \psi_{j,k+s}^2(m) \quad (1.1)$$

The estimator is an average of random variables. This allows us to use a law of large number to show the convergence. In other words, under some conditions on $Y_{j,k+s} := \sum_{m=0}^{T-1} \mathbf{F}_m \mathbf{F}_m' \psi_{j,k+s}^2(m)$ the estimator converges to $\Sigma_{j,k}$. The expectation of the random variables $Y_{j,k+s}$ is,

$$\begin{aligned} \mathbb{E} \left[\sum_{m=0}^{T-1} \mathbf{F}_m \mathbf{F}_m' \psi_{j,k+s}^2(m) \right] &= \sum_{m=0}^{T-1} \mathbb{E} [\mathbf{F}_m \mathbf{F}_m'] \psi_{j,k+s}^2(m) \\ &= \mathbb{E} [\mathbf{F}_m \mathbf{F}_m'] \sum_{m=0}^{T-1} \psi_{j,k+s}^2(m) \quad (\text{iid factors}) \\ &= \mathbb{E} [\mathbf{F}_m \mathbf{F}_m'] \end{aligned}$$

by definition of wavelets.

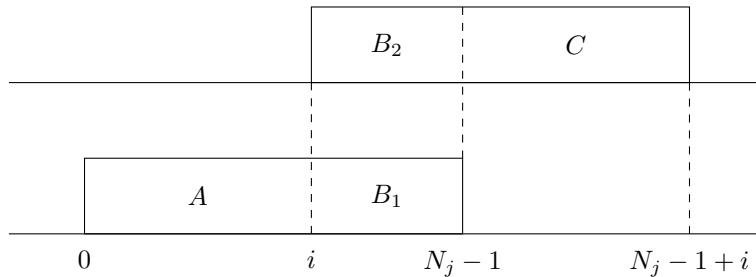
The random variables $Y_{j,k+s}$ are identically distributed but not independent. Therefore, it is not sufficient to only consider their variances. By Chebyshev inequality, a sufficient condition for convergence is $|\text{Cov}[Y_{j,k+s}, Y_{j,k+s+i}]| \rightarrow 0$ when $i \rightarrow \infty$. The latter condition is true for this estimator thanks to the finite support of wavelets : $N_j = (2^{-j} - 1)(N_{-1} - 1) + 1$. From now on, we suppose that $\psi_{j,k}(t)$ lives on $[k, k + N_j - 1]$.

$$\begin{aligned} \text{Cov}[Y_{j,k+s}, Y_{j,k+s+i}] &= \mathbb{E} \left[\sum_{m=0}^{T-1} \mathbf{F}_m \mathbf{F}_m' \psi_{j,k+s}^2(m) \sum_{m'=0}^{T-1} \mathbf{F}_{m'} \mathbf{F}_{m'}' \psi_{j,k+s+i}^2(m') \right] - \mathbb{E} \left[\sum_{m=0}^{T-1} \mathbf{F}_m \mathbf{F}_m' \psi_{j,k+s}^2(m) \right]^2 \\ &= \mathbb{E} \left[\sum_{m=0}^{T-1} \mathbf{F}_m \mathbf{F}_m' \psi_{j,k+s}^2(m) \sum_{m'=0}^{T-1} \mathbf{F}_{m'} \mathbf{F}_{m'}' \psi_{j,k+s}^2(m' - i) \right] - (\Sigma_{j,k}^F)^2 \\ &= \mathbb{E} \left[\sum_{m=0}^{T-1} \mathbf{F}_{m+k+s} \mathbf{F}_{m+k+s}' \psi_{j,0}^2(m) \sum_{m'=0}^{T-1} \mathbf{F}_{m'+k+s} \mathbf{F}_{m'+k+s}' \psi_{j,0}^2(m' - i) \right] - (\Sigma_{j,k}^F)^2 \\ &= \mathbb{E} \left[\sum_{m=0}^{N_j-1} \mathbf{F}_{m+k+s} \mathbf{F}_{m+k+s}' \psi_{j,0}^2(m) \sum_{m'=0}^{N_j-1} \mathbf{F}_{m'+k+s} \mathbf{F}_{m'+k+s}' \psi_{j,0}^2(m' - i) \right] - (\Sigma_{j,k}^F)^2 \quad (\text{finite support}) \end{aligned}$$

Let's focus the analysis in the first term. Define,

$$\alpha = \min\{i - 1, N_j - 1\} \quad (1.2)$$

$$\gamma = \max\{i - 1, N_j - 1\} \quad (1.3)$$



Given the graph above, the first term can be decomposed in several sums which are non-overlapping for some.

$$\begin{aligned} \mathbb{E} \left[\left(\sum_{m=0}^{\alpha} \mathbf{F}_{m+k+s} \mathbf{F}_{m+k+s}' \psi_{j,0}^2(m) + \sum_{m=\alpha+1}^{\gamma} \mathbf{F}_{m+k+s} \mathbf{F}_{m+k+s}' \psi_{j,0}^2(m) \right) \right. \\ \left. \left(\sum_{m'=\alpha+1}^{\gamma} \mathbf{F}_{m'+k+s} \mathbf{F}_{m'+k+s}' \psi_{j,0}^2(m' - i) + \sum_{m'=\gamma+1}^{i+N_j-1} \mathbf{F}_{m'+k+s} \mathbf{F}_{m'+k+s}' \psi_{j,0}^2(m' - i) \right) \right] \end{aligned}$$

In order to simplify notations and before distributing the product, define :

$$\begin{array}{l|l}
A := \sum_{m=0}^{\alpha} \mathbf{F}_{m+k+s} \mathbf{F}'_{m+k+s} \psi_{j,0}^2(m) & a := \sum_{m=0}^{\alpha} \psi_{j,0}^2(m) \\
B_1 := \sum_{m=\alpha+1}^{\gamma} \mathbf{F}_{m+k+s} \mathbf{F}'_{m+k+s} \psi_{j,0}^2(m) & b_1 := \sum_{m=\alpha+1}^{\gamma} \psi_{j,0}^2(m) \\
B_2 := \sum_{\substack{m'=\alpha+1 \\ i+N_j-1}}^{\gamma} \mathbf{F}_{m'+k+s} \mathbf{F}'_{m'+k+s} \psi_{j,0}^2(m'-i) & b_2 := \sum_{\substack{m'=\alpha+1 \\ i+N_j-1}}^{\gamma} \psi_{j,0}^2(m'-i) \\
C := \sum_{m'=\gamma+1}^{\gamma} \mathbf{F}_{m'+k+s} \mathbf{F}'_{m'+k+s} \psi_{j,0}^2(m'-i) & c := \sum_{m'=\gamma+1}^{\gamma} \psi_{j,0}^2(m'-i)
\end{array}$$

Therefore, the decomposition becomes,

$$\mathbb{E}[(A+B_1)(B_2+C)] = \mathbb{E}[AB_2] + \mathbb{E}[AC] + \mathbb{E}[B_1B_2] + \mathbb{E}[B_2C]$$

Note that by construction all sums in the expectations except the third one are independent. Therefore,

$$\mathbb{E}[A] \mathbb{E}[B_2] + \mathbb{E}[A] \mathbb{E}[C] + \mathbb{E}[B_1B_2] + \mathbb{E}[B_2] \mathbb{E}[C]$$

From the iid assumption on the factors, the expectations have the same form, $\Sigma_F x$ where $x \in \{a; b_2; c\}$. Concerning the expectation $\mathbb{E}[B_1B_2]$,

$$\begin{aligned}
\mathbb{E}[B_1B_2]^2 &= \mathbb{E} \left[\sum_{m=\alpha+1}^{\gamma} \mathbf{F}_{m+k+s} \mathbf{F}'_{m+k+s} \psi_{j,0}^2(m) \sum_{m'=\alpha+1}^{\gamma} \mathbf{F}_{m'+k+s} \mathbf{F}'_{m'+k+s} \psi_{j,0}^2(m'-i) \right]^2 \\
&\leq \mathbb{E} \left[\left(\sum_{m=\alpha+1}^{\gamma} \mathbf{F}_{m+k+s} \mathbf{F}'_{m+k+s} \psi_{j,0}^2(m) \right)^2 \right] \mathbb{E} \left[\left(\sum_{m'=\alpha+1}^{\gamma} \mathbf{F}_{m'+k+s} \mathbf{F}'_{m'+k+s} \psi_{j,0}^2(m'-i) \right)^2 \right]
\end{aligned}$$

Let's analyse the second factor which "generalizes" the first one.

$$\begin{aligned}
\mathbb{E} \left[\left(\sum_{m'=\alpha+1}^{\gamma} \mathbf{F}_{m'+k+s} \mathbf{F}'_{m'+k+s} \psi_{j,0}^2(m'-i) \right)^2 \right] &= \text{Var} \left[\sum_{m'=\alpha+1}^{\gamma} \mathbf{F}_{m'+k+s} \mathbf{F}'_{m'+k+s} \psi_{j,0}^2(m'-i) \right] + \Sigma_F^2 \\
&= \sum_{m'=\alpha+1}^{\gamma} \text{Var} [\mathbf{F}_{m'+k+s} \mathbf{F}'_{m'+k+s}] \psi_{j,0}^4(m'-i) \\
&= \text{Var} [\mathbf{F}_{m'+k+s} \mathbf{F}'_{m'+k+s}] \sum_{m'=\alpha+1}^{\gamma} \psi_{j,0}^4(m'-i)
\end{aligned}$$

The last sum can further be decomposed,

$$\begin{aligned}
\sum_{m'=\alpha+1}^{\gamma} [\psi_{j,0}^2(m'-i)]^2 &= \left(\sum_{m'=\alpha+1}^{\gamma} \psi_{j,0}^2(m'-i) \right)^2 - \sum_{p=\alpha+1}^{\gamma} \sum_{\substack{q=\alpha+1 \\ q \neq p}}^{\gamma} \psi_{j,0}^2(p-i) \psi_{j,0}^2(q-i) \\
&\leq \left(\sum_{m'=\alpha+1}^{\gamma} \psi_{j,0}^2(m'-i) \right)^2 \\
&= \begin{cases} \left(\sum_{m'=i}^{N_j-1} \psi_{j,0}^2(m'-i) \right)^2 & \text{if } i \in [0, N_j - 1] \\ \left(\sum_{m'=N_j}^i \psi_{j,0}^2(m'-i) \right)^2 & \text{if } i \notin [0, N_j - 1] \end{cases} \\
&= \begin{cases} \left(\sum_{m'=0}^{N_j-1-i} \psi_{j,0}^2(m') \right)^2 & \text{if } i \in [0, N_j - 1] \\ \left(\sum_{m'=N_j-i}^0 \psi_{j,0}^2(m') \right)^2 & \text{if } i \notin [0, N_j - 1] \end{cases} \\
&\begin{cases} \leq 1 & \text{if } i \in [0, N_j - 1] \\ = 0 & \text{if } i \notin [0, N_j - 1] \end{cases}
\end{aligned}$$

since $\psi_{j,0}^2(t)$ is supported on $t \in [0, N_j - 1]$.

Therefore, the second factor becomes,

$$\mathbb{E} \left[\left(\sum_{m'=\alpha+1}^{\gamma} \mathbf{F}_{m'+k+s} \mathbf{F}'_{m'+k+s} \psi_{j,0}^2(m'-i) \right)^2 \right] \begin{cases} \leq \text{Var} [\mathbf{F}_{m'+k+s} \mathbf{F}'_{m'+k+s}] & \text{if } i \in [0, N_j - 1] \\ = 0 & \text{if } i \notin [0, N_j - 1] \end{cases}$$

Finally we obtain,

$$\mathbb{E} [B_1 B_2]^2 \begin{cases} \leq \text{Var} [\mathbf{F}_{m'+k+s} \mathbf{F}'_{m'+k+s}]^2 \sum_{m'=i}^{N_j-1} \psi_{j,0}^4(m') \sum_{m'=i}^{N_j-1} \psi_{j,0}^4(m'-i) & \text{if } i \in [0, N_j - 1] \\ = 0 & \text{if } i \notin [0, N_j - 1] \end{cases}$$

$$\begin{cases} \leq \text{Var} [\mathbf{F}_{m'+k+s} \mathbf{F}'_{m'+k+s}]^2 \sum_{m'=i}^{N_j-1} \psi_{j,0}^4(m') \sum_{m'=0}^{N_j-1-i} \psi_{j,0}^4(m') & \text{if } i \in [0, N_j - 1] \\ = 0 & \text{if } i \notin [0, N_j - 1] \end{cases}$$

, which is a decreasing function of i .

Equipped with those simplification we can analyse the decomposition of the covariance of $Y_{j,k+s}$,

$$\begin{aligned} \text{Cov} [Y_{j,k+s}, Y_{j,k+s+i}] &= \mathbb{E} \left[\sum_{m=0}^{N_j-1} \mathbf{F}_{m+k+s} \mathbf{F}'_{m+k+s} \psi_{j,0}^2(m) \sum_{m'=0}^{N_j-1} \mathbf{F}_{m'+k+s} \mathbf{F}'_{m'+k+s} \psi_{j,0}^2(m'-i) \right] - (\Sigma_{j,k}^F)^2 \\ &= \mathbb{E} [A] \mathbb{E} [B_2] + \mathbb{E} [A] \mathbb{E} [A] + \mathbb{E} [B_1 B_2] + \mathbb{E} [B_2] \mathbb{E} [C] \\ &= (\Sigma_{j,k}^F)^2 (ab_2 + ac + \mathbb{E} [B_1 B_2] + b_1 c - 1) \\ &= (\Sigma_{j,k}^F)^2 \left(\underbrace{a(b_2 + c)}_{=1} + \mathbb{E} [B_1 B_2] + b_1 c - 1 \right) \quad \text{by def. of wavelets} \\ &= (\Sigma_{j,k}^F)^2 \left(\sum_{m=0}^{\alpha} \psi_{j,0}^2(m) + \mathbb{E} [B_1 B_2] + \sum_{m=\alpha+1}^{\gamma} \psi_{j,0}^2(m) \sum_{m'=\gamma+1}^{i+N_j-1} \psi_{j,0}^2(m'-i) - 1 \right) \\ &= (\Sigma_{j,k}^F)^2 \left(\sum_{m=0}^{\alpha} \psi_{j,0}^2(m) + \mathbb{E} [B_1 B_2] + \left(1 - \sum_{m=0}^{\alpha} \psi_{j,0}^2(m) \right) \left(1 - \sum_{m'=0}^{N_j-1-i} \psi_{j,0}^2(m') \right) - 1 \right) \\ &= (\Sigma_{j,k}^F)^2 \left(\sum_{m=0}^{\alpha} \psi_{j,0}^2(m) + \mathbb{E} [B_1 B_2] - \sum_{m'=0}^{N_j-1-i} \psi_{j,0}^2(m') - \sum_{m=0}^{\alpha} \psi_{j,0}^2(m) + \sum_{m=0}^{\alpha} \psi_{j,0}^2(m) \sum_{m'=0}^{N_j-1-i} \psi_{j,0}^2(m') \right) \\ &= (\Sigma_{j,k}^F)^2 \left(\mathbb{E} [B_1 B_2] - \sum_{m'=0}^{N_j-1-i} \psi_{j,0}^2(m') + \sum_{m=0}^{\alpha} \psi_{j,0}^2(m) \sum_{m'=0}^{N_j-1-i} \psi_{j,0}^2(m') \right) \\ &= (\Sigma_{j,k}^F)^2 \left(\mathbb{E} [B_1 B_2] + \sum_{m'=0}^{N_j-1-i} \psi_{j,0}^2(m') \left(\sum_{m=0}^{\alpha} \psi_{j,0}^2(m) - 1 \right) \right) \\ &= (\Sigma_{j,k}^F)^2 \left(\mathbb{E} [B_1 B_2] - \sum_{m'=0}^{N_j-1-i} \psi_{j,0}^2(m') \sum_{m=\alpha+1}^{\gamma} \psi_{j,0}^2(m) \right) \end{aligned}$$

By taking the absolute value and considering the above formula for lags $i \notin [0, N_j - 1]$,

$$|\text{Cov} [Y_{j,k+s}, Y_{j,k+s+i}]| = |(\Sigma_{j,k}^F)^2| |0 - 0 \cdot 0| = 0$$

This last relation confirms the sufficient condition to apply the needed law of large numbers. However if $i \in [0, N_j - 1]$ we get the upperbound,

$$|\text{Cov} [Y_{j,k+s}, Y_{j,k+s+i}]| \leq |(\Sigma_{j,k}^F)^2| \left| \text{Var} [\mathbf{F}_{m'+k+s} \mathbf{F}'_{m'+k+s}]^2 \sum_{m'=i}^{N_j-1} \psi_{j,0}^4(m') \sum_{m'=0}^{N_j-1-i} \psi_{j,0}^4(m') - \sum_{m'=0}^{N_j-1-i} \psi_{j,0}^2(m') \sum_{m=0}^{N_j-1} \psi_{j,0}^2(m) \right|_{=1}$$

From this eigendecomposition of the CEWS estimator and (??) we get,

$$[K_{j,k} + \Theta_{j,k} + \Theta'_{j,k} + \Upsilon_{j,k}] \hat{\Lambda}_{j,k} = \hat{\Lambda}_{j,k} \hat{\mathbf{V}}_{j,k}$$

Define,

$$Q_{j,k} = \left[\hat{\Sigma}_{j,k}^F \right]^{\frac{1}{2}} \frac{\Lambda'_{j,k} \hat{\Lambda}_{j,k}}{N} \quad (1.4)$$

$$P_{j,k} = \left[\hat{\Sigma}_{j,k}^F \right]^{\frac{1}{2}} \frac{\Lambda'_{j,k} \Lambda_{j,k}}{N} \left[\hat{\Sigma}_{j,k}^F \right]^{\frac{1}{2}} \quad (1.5)$$

Therefore we can write,

$$\begin{aligned} \left[\widehat{\Sigma}_{j,k}^F \right]^{\frac{1}{2}} \frac{\Lambda'_{j,k}}{N} [K_{j,k} + \Theta_{j,k} + \Theta'_{j,k} + \Upsilon_{j,k}] \widehat{\Lambda}_{j,k} &= \left[\widehat{\Sigma}_{j,k}^F \right]^{\frac{1}{2}} \frac{\Lambda'_{j,k}}{N} \widehat{\Lambda}_{j,k} \widehat{V}_{j,k} \\ \left[\widehat{\Sigma}_{j,k}^F \right]^{\frac{1}{2}} \frac{\Lambda'_{j,k}}{N} [K_{j,k} + \Theta_{j,k} + \Theta'_{j,k} + \Upsilon_{j,k}] \widehat{\Lambda}_{j,k} &= Q_{j,k} \widehat{V}_{j,k} \end{aligned} \quad (1.6)$$

Let's decompose the LHS of this relation and analyze its convergence. First take,

$$\begin{aligned} \left\| \left[\widehat{\Sigma}_{j,k}^F \right]^{\frac{1}{2}} \frac{\Lambda'_{j,k}}{N} [K_{j,k} + \Upsilon_{j,k}] \widehat{\Lambda}_{j,k} - P_{j,k} Q_{j,k} \right\| &\leq \left\| \left[\widehat{\Sigma}_{j,k}^F \right]^{\frac{1}{2}} \frac{\Lambda'_{j,k}}{N} [K_{j,k} + \Upsilon_{j,k}] \widehat{\Lambda}_{j,k} - \left[\widehat{\Sigma}_{j,k}^F \right]^{\frac{1}{2}} \frac{\Lambda'_{j,k}}{N} N^{-1} \mathbf{S}_j(k/T) \widehat{\Lambda}_{j,k} \right\| \\ &\quad + \left\| \left[\widehat{\Sigma}_{j,k}^F \right]^{\frac{1}{2}} \frac{\Lambda'_{j,k}}{N} N^{-1} \mathbf{S}_j(k/T) \widehat{\Lambda}_{j,k} - \left[\widehat{\Sigma}_{j,k}^F \right]^{\frac{1}{2}} \frac{\Lambda'_{j,k} \Lambda_{j,k}}{N} \widehat{\Sigma}_{j,k}^F \frac{\Lambda'_{j,k} \widehat{\Lambda}_{j,k}}{N} \right\| \end{aligned}$$

The first term converges asymptotically to zero. To see this note that we can write :

$$\left\| \left[\widehat{\Sigma}_{j,k}^F \right]^{\frac{1}{2}} \frac{\Lambda'_{j,k}}{N} [K_{j,k} + \Upsilon_{j,k} - N^{-1} \mathbf{S}_j(k/T)] \widehat{\Lambda}_{j,k} \right\| \leq \left\| \left[\widehat{\Sigma}_{j,k}^F \right]^{\frac{1}{2}} \right\| \left\| \frac{\Lambda'_{j,k}}{\sqrt{N}} \right\| \left\| [K_{j,k} + \Upsilon_{j,k} - N^{-1} \mathbf{S}_j(k/T)] \right\| \left\| \frac{\widehat{\Lambda}_{j,k}}{\sqrt{N}} \right\|$$

All factors except the third one are bounded by assumption. The third term converges to zero since it is sufficient in L_2 space that its expectation along its variance converges to zero :

$$\begin{aligned} \mathbb{E} [K_{j,k} + \Upsilon_{j,k} - N^{-1} \mathbf{S}_j(k/T)] &= \mathbb{E} [K_{j,k} + \Upsilon_{j,k}] - N^{-1} \\ &= N^{-1} \mathbf{S}_j(k/T) - \mathbb{E} [\Upsilon_{j,k}] + \mathbb{E} [\Upsilon_{j,k}] - N^{-1} \mathbf{S}_j(k/T) + O(T^{-1}) \quad \text{from theorem ??} \\ &= O(T^{-1}) \rightarrow 0 \end{aligned}$$

$$\text{Var} [K_{j,k} + \Upsilon_{j,k} - N^{-1} \mathbf{S}_j(k/T)] = \text{Var} [K_{j,k} + \Upsilon_{j,k}] \rightarrow 0 \quad \text{from lemma ??}$$

It is a bit more difficult to show the convergence of the second term.

$$\left\| \left[\widehat{\Sigma}_{j,k}^F \right]^{\frac{1}{2}} \frac{\Lambda'_{j,k}}{N} N^{-1} \mathbf{S}_j(k/T) \widehat{\Lambda}_{j,k} - \left[\widehat{\Sigma}_{j,k}^F \right]^{\frac{1}{2}} \frac{\Lambda'_{j,k} \Lambda_{j,k}}{N} \widehat{\Sigma}_{j,k}^F \frac{\Lambda'_{j,k} \widehat{\Lambda}_{j,k}}{N} \right\| \leq \left\| \left[\widehat{\Sigma}_{j,k}^F \right]^{\frac{1}{2}} \right\| \left\| \frac{\Lambda'_{j,k}}{\sqrt{N}} \right\| \left\| N^{-1} \mathbf{S}_j(k/T) - \frac{\Lambda_{j,k}}{\sqrt{N}} \widehat{\Sigma}_{j,k}^F \frac{\Lambda'_{j,k}}{\sqrt{N}} \right\| \left\| \frac{\widehat{\Lambda}_{j,k}}{\sqrt{N}} \right\|$$

All factors are bounded by assumption except the third one. The latter convergence to zero asymptotically. To see this, by (1.1),

$$\begin{aligned} \left\| N^{-1} \mathbf{S}_j(k/T) - \frac{\Lambda_{j,k}}{\sqrt{N}} \widehat{\Sigma}_{j,k}^F \frac{\Lambda'_{j,k}}{\sqrt{N}} \right\| &= \left\| \frac{\Lambda_{j,k}}{\sqrt{N}} \widehat{\Sigma}_{j,k}^F \frac{\Lambda'_{j,k}}{\sqrt{N}} - N^{-1} \mathbf{S}_j(k/T) \right\| \\ &= \left\| \frac{1}{2M+1} \sum_{s=-M}^M \sum_{m=0}^{T-1} \frac{\Lambda_{j,k}}{\sqrt{N}} \mathbf{F}_m \mathbf{F}_m' \frac{\Lambda'_{j,k}}{\sqrt{N}} \psi_{j,k+s}^2(m) - N^{-1} \mathbf{S}_j(k/T) \right\| \\ &= \left\| \frac{1}{2M+1} \sum_{s=-M}^M \underbrace{\left[\sum_{m=0}^{T-1} \frac{\Lambda_{j,k}}{\sqrt{N}} \mathbf{F}_m \mathbf{F}_m' \frac{\Lambda'_{j,k}}{\sqrt{N}} \psi_{j,k+s}^2(m) - N^{-1} \mathbf{S}_j(k/T) \right]}_{e_{j,k+s}} \right\| \end{aligned}$$

This reorganization allows us to use a law of large number to show the convergence. The expectation of $e_{j,k+s}$ is given by :

$$\begin{aligned} \mathbb{E} [e_{j,k+s}] &= \frac{\Lambda_{j,k}}{\sqrt{N}} \left[\sum_{m=0}^{T-1} \mathbb{E} [\mathbf{F}_m \mathbf{F}_m'] \psi_{j,k+s}^2(m) - \mathbb{E} [\mathbf{F}_m \mathbf{F}_m'] \right] \frac{\Lambda'_{j,k}}{\sqrt{N}} - N^{-1} \mathbb{E} [\boldsymbol{\epsilon}_{j,k+s} \boldsymbol{\epsilon}_{j,k+s}'] \\ &= \frac{\Lambda_{j,k}}{\sqrt{N}} \left[\mathbb{E} [\mathbf{F}_m \mathbf{F}_m'] \sum_{m=0}^{T-1} \psi_{j,k+s}^2(m) - \mathbb{E} [\mathbf{F}_m \mathbf{F}_m'] \right] \frac{\Lambda'_{j,k}}{\sqrt{N}} - N^{-1} \mathbb{E} [\boldsymbol{\epsilon}_{j,k+s} \boldsymbol{\epsilon}_{j,k+s}'] \end{aligned}$$

By definition of wavelets we know that $\sum_{m=0}^{T-1} \psi_{j,k+s}^2(m) \rightarrow 1$ when $M(T) \rightarrow \infty$. Finally since the covariance of the idiosyncratic has bounded eigenvalues by assumption on the factor model, the last term converges to zero when $N \rightarrow \infty$.