

Proofs to

”Least Squares Inference on Integrated Volatility and the Relationship between Efficient Prices and Noise”

1 Preliminaries

Under Assumptions 1, 2 and 3, we have that

$$\mathbb{E} [RV^{h,s}(N_{h,s})] = IV + 2N_{h,s}\omega^2,$$

and hence we have the regression

$$y_{h,s} = c + \beta_0 N_{h,s} + \varepsilon_{h,s}, \quad s = 1, \dots, S, \quad h = 1, \dots, s,$$

where $y_{h,s} = RV^{h,s}(N_{h,s})$ and the total number of observations in the regression is $N_{tot} = S(S+1)/2$. Set $N_{h,s} = N_s$ as $N_{h,s} \approx \frac{N}{s}$, $s = 1, \dots, S$ up to a rounding error. The above regression can be written in a matrix form as

$$Y = X\theta + \varepsilon,$$

where $\theta = (c, \beta_0)'$. From now on, we condition on the trading times t_j , $j = 1, \dots, N$, which is equivalent to conditioning on the regressor matrix X .

Set $\text{Var}[\varepsilon] = \Xi = \Xi(N, S)$ (we will usually suppress the dependence on N and S). Hansen & Lunde (2006) (Equation 2) show that¹

$$\text{Var}[y_{h,s}] = \text{Var}[\varepsilon_{h,s}] = 12\kappa\omega^4 N_s + 8\omega^2 \int_0^1 \sigma_s^2 ds - (6\kappa - 2)\omega^4 + \frac{2}{N_s} \int_0^1 \sigma_s^4 H'(s) ds + o\left(\frac{1}{N_s}\right), \quad (1)$$

¹In their case with regular sampling $H'(t) = 1$, here we combine their result with a result contained in Equation (25) of Zhang, Mykland & Ait-Sahalia (2005). Alternatively, our expression follows directly from Equation (27) in Zhang et al. (2005) after accounting for the difference in notation.

which is a diagonal element of Ξ . Denoting the OLS estimator $\hat{\theta} = (\hat{c}, \hat{\beta}_0)'$, we have that

$$\text{Var}[\hat{\theta}] = (X'X)^{-1}X'\Xi X(X'X)^{-1}.$$

Denote by X_1 the first row of $(X'X)^{-1}X'$. Then

$$\text{Var}[\hat{c}] = X_1\Xi X_1'.$$

2 Auxiliary Lemma

Lemma 1. *Under Assumptions 1, 2 and 3, it holds that for any s, s', h, h' for which $s = s'$ and $h = h'$ are not simultaneously fulfilled,²*

$$\text{Cov}[RV^{h,s}(N_{h,s}), RV^{h',s'}(N_{h',s'})] = \begin{cases} \frac{2IQ \min(s,s')}{N}, & \text{if } (\star) \\ \frac{2IQ \min(s,s')}{N} + 4\omega^2 \int_{\mathcal{O}} \sigma_s^2 ds + \frac{N\omega^4(12\kappa-4)}{\text{lcm}(s,s')}, & \text{otherwise} \end{cases},$$

where $(\star) : \{t_{js+h}\}_{j=1,\dots,N_{h,s}} \cap \{t_{is'+h'}\}_{i=1,\dots,N_{h',s'}} = \emptyset$ and the set \mathcal{O} is defined in the following proof. $\text{lcm}(s, s')$ stands for the least common multiplier of s and s' .³

Proof. Write the covariance $\text{Cov}[RV^{h,s}(N_{h,s}), RV^{h',s'}(N_{h',s'})]$ explicitly as

$$\text{Cov}[RV^{h,s}(N_{h,s}), RV^{h',s'}(N_{h',s'})] = \text{Cov} \left[\sum_{j=1}^{N_{h,s}} r_{js+h}^2, \sum_{i=1}^{N_{h',s'}} r_{is'+h'}^2 \right].$$

²The case $s = s'$ and $h = h'$ corresponds to the variance of $RV^{h,s}(N_{h,s})$, which is given in Equation (1).

³It holds that $\max(s, s') \leq \text{lcm}(s, s') \leq ss'$. For coprime s and s' , $\text{lcm}(s, s') = ss'$.

This expression can be decomposed as

$$\begin{aligned}
& \text{Cov} \left[\sum_{j=1}^{N_{h,s}} r_{js+h}^2, \sum_{i=1}^{N_{h',s'}} r_{is'+h'}^2 \right] \\
&= \text{Cov} \left[\sum_{j=1}^{N_{h,s}} r_{js+h}^{*2}, \sum_{i=1}^{N_{h',s'}} r_{is'+h'}^{*2} \right] + 2 \text{Cov} \left[\sum_{j=1}^{N_{h,s}} r_{js+h}^{*2}, \sum_{i=1}^{N_{h',s'}} r_{is'+h'}^* e_{is'+h'} \right] + \text{Cov} \left[\sum_{j=1}^{N_{h,s}} r_{js+h}^{*2}, \sum_{i=1}^{N_{h',s'}} e_{is'+h'}^2 \right] \\
&+ 2 \text{Cov} \left[\sum_{j=1}^{N_{h,s}} r_{js+h}^* e_{js+h}, \sum_{i=1}^{N_{h',s'}} r_{is'+h'}^{*2} \right] + 4 \text{Cov} \left[\sum_{j=1}^{N_{h,s}} r_{js+h}^* e_{js+h}, \sum_{i=1}^{N_{h',s'}} r_{is'+h'}^* e_{is'+h'} \right] + 2 \text{Cov} \left[\sum_{j=1}^{N_{h,s}} r_{js+h}^* e_{js+h}, \sum_{i=1}^{N_{h',s'}} e_{is'+h'}^2 \right] \\
&+ \text{Cov} \left[\sum_{j=1}^{N_{h,s}} e_{js+h}^2, \sum_{i=1}^{N_{h',s'}} r_{is'+h'}^{*2} \right] + 2 \text{Cov} \left[\sum_{j=1}^{N_{h,s}} e_{js+h}^2, \sum_{i=1}^{N_{h',s'}} r_{is'+h'}^* e_{is'+h'} \right] + \text{Cov} \left[\sum_{j=1}^{N_{h,s}} e_{js+h}^2, \sum_{i=1}^{N_{h',s'}} e_{is'+h'}^2 \right] \\
&= \text{Cov} \left[\sum_{j=1}^{N_{h,s}} r_{js+h}^{*2}, \sum_{i=1}^{N_{h',s'}} r_{is'+h'}^{*2} \right] + 4 \text{Cov} \left[\sum_{j=1}^{N_{h,s}} r_{js+h}^* e_{js+h}, \sum_{i=1}^{N_{h',s'}} r_{is'+h'}^* e_{is'+h'} \right] + \text{Cov} \left[\sum_{j=1}^{N_{h,s}} e_{js+h}^2, \sum_{i=1}^{N_{h',s'}} e_{is'+h'}^2 \right],
\end{aligned}$$

where the last equation follows because all other terms are zero. The first term is a covariance between two estimators for IV in the absence of noise. Consider the case when the s' -mesh is a proper subgrid of the s -mesh (or vice versa), e.g., the $s = 2, h = 1$ (comprising the ticks t_1, t_3, t_5, \dots) and $s' = 4, h' = 1$ (comprising the ticks t_1, t_5, t_9, \dots) combination. In these cases, using Lemma 2.1 in Hausman (1978), it follows that the covariance between them is equal to the variance of the more efficient one, i.e.,

$$\begin{aligned}
\text{Cov} \left[\sum_{j=1}^{N_{h,s}} r_{js+h}^{*2}, \sum_{i=1}^{N_{h',s'}} r_{is'+h'}^{*2} \right] &= \begin{cases} \text{Var} \left[\sum_{j=1}^{N_{h,s}} r_{js+h}^{*2} \right] & , \text{ if } N_{h,s} \geq N_{h',s'} \\ \text{Var} \left[\sum_{i=1}^{N_{h',s'}} r_{is'+h'}^{*2} \right] & , \text{ otherwise.} \end{cases} \\
&= \frac{2}{\max(N_{h,s}, N_{h',s'})} \int_0^1 \sigma_s^4 H'(s) ds + o(1/N) = \frac{c^* \min(s, s')}{N} + o(1/N),
\end{aligned}$$

where the expression for the variance of a sparse realized variance under irregular sampling follows from Equation (25) in Zhang et al. (2005). In the remaining cases, when one of the subgrids does not represent a proper subset of the other one, the above result can be seen as a first order approximation. In these cases, the covariance is in fact smaller than the variance of the more efficient one, but the difference between the two terms is of a smaller order than the variance.

The second term vanishes if $\{t_{js+h}\}_{j=1, \dots, N_{h,s}} \cap \{t_{is'+h'}\}_{i=1, \dots, N_{h',s'}} = \emptyset$ since then the summands are uncorrelated. In the remaining cases we have $\{t_{js+h}\}_{j=1, \dots, N_{h,s}} \cap \{t_{is'+h'}\}_{i=1, \dots, N_{h',s'}} = \mathcal{A}$, which is a set with $\frac{N}{\text{lcm}(s, s')}$ elements. For $\{\{t_{js+h}\} \in \mathcal{A}\} \cup \{\{t_{is'+h'}\} \in \mathcal{A}\}$, denote $t^* = \max(t_{(j-1)s+h}, t_{(i-1)s'+h'})$ and $t_* = \min(t_{js+h}, t_{is'+h'})$, where the dependence on i, j, s, h, s', h' is deliberately suppressed. Since $e_{js+h} = u_{(j-1)s+h} - u_{js+h}$, we have that for each individual summand

in the second term, there are 3 possibilities:

$$\text{Cov} [r_{js+h}^* e_{js+h}, r_{is'+h'}^* e_{is'+h'}] = \begin{cases} 0, & \text{if } t_{js+h} \neq t_{is'+h'} \text{ and } t_{(j-1)s+h} \neq t_{(i-1)s'+h'} \\ \omega^2 \int_{t^*}^{t_{js+h}} \sigma_s^2 ds, & \text{if } t_{js+h} = t_{is'+h'} \\ \omega^2 \int_{t_{(j-1)s+h}}^{t^*} \sigma_s^2 ds, & \text{if } t_{(j-1)s+h} = t_{(i-1)s'+h'} \end{cases}.$$

It follows that

$$\begin{aligned} 4 \text{Cov} \left[\sum_{j=1}^{N_{h,s}} r_{js+h}^* e_{js+h}, \sum_{i=1}^{N_{h',s'}} r_{is'+h'}^* e_{is'+h'} \right] &= 4\omega^2 \sum_{\mathcal{A}} \left(\int_{t^*}^{t_{js+h}} \sigma_s^2 ds + \int_{t_{(j-1)s+h}}^{t^*} \sigma_s^2 ds \right) \\ &= 4\omega^2 \sum_{\mathcal{A}} \left(\int_{t^*}^{t^*} \sigma_s^2 ds \right) = 4\omega^2 \int_{\mathcal{O}} \sigma_s^2 ds, \end{aligned}$$

where $\mathcal{O} = \bigcup_{t_{js+h} \in \mathcal{A}, t_{is'+h'} \in \mathcal{A}} [t^*, t^*]$. Since the set \mathcal{A} has $\frac{N}{\text{lcm}(s, s')}$ elements and each of the integrals $\int_{t^*}^{t^*} \sigma_s^2 ds$ is of order $O\left(\frac{1}{\max(N_{h,s}, N_{h',s'})}\right)$ and $\frac{1}{\max(N_{h,s}, N_{h',s'})} = \frac{\min(s, s')}{N}$, it follows that $\int_{\mathcal{O}} \sigma_s^2 ds$ is of order $O\left(\frac{\min(s, s')}{\text{lcm}(s, s')}\right)$.

The third term is also zero whenever $\{t_{js+h}\}_{j=1, \dots, N_{h,s}} \cap \{t_{is'+h'}\}_{i=1, \dots, N_{h',s'}} = \emptyset$. In the remaining cases we have that for each $j, i : t_{js+h} \in \mathcal{A}, t_{is'+h'} \in \mathcal{A}$ there are four correlated pairs of noise terms, e.g., if $t_{js+h} = t_{is'+h'}$, then the following four pairs are correlated: $e_{js+h}^2, e_{is'+h'}^2$; $e_{(j-1)s+h}^2, e_{is'+h'}^2$; $e_{js+h}^2, e_{(i-1)s'+h'}^2$ and $e_{(j-1)s+h}^2, e_{(i-1)s'+h'}^2$. Take, for example, the first pair and consider its covariance:

$$\begin{aligned} \text{Cov} [e_{js+h}^2, e_{is'+h'}^2] &= \text{E} [e_{js+h}^2 e_{is'+h'}^2] - \text{E} [e_{js+h}^2] \text{E} [e_{is'+h'}^2] \\ &= \text{E} [u_{js+h}^2 u_{is'+h'}^2] + \text{E} [u_{(j-1)s+h}^2 u_{is'+h'}^2] + \text{E} [u_{js+h}^2 u_{(i-1)s'+h'}^2] \\ &\quad + \text{E} [u_{(j-1)s+h}^2 u_{(i-1)s'+h'}^2] - \text{E} [e_{js+h}^2] \text{E} [e_{is'+h'}^2] \\ &= \mu_4 + 3\omega^4 - 4\omega^4 = \mu_4 - \omega^4 = (3\kappa - 1)\omega^4. \end{aligned}$$

The remaining three pairs can be similarly shown to have the same covariance. Thus, it follows

$$\text{Cov} \left[\sum_{j=1}^{N_{h,s}} e_{js+h}^2, \sum_{i=1}^{N_{h',s'}} e_{is'+h'}^2 \right] = \frac{N\omega^4(12\kappa - 4)}{\text{lcm}(s, s')}.$$

□

3 Proof of Theorem 1

Calculating X_1

We have

$$X'X = \begin{pmatrix} N_{tot} & \sum_{s,h} N_s \\ \sum_{s,h} N_s & \sum_{s,h} N_s^2 \end{pmatrix},$$

and in the following we suppress the double summation indices s, h when unambiguous. Then

$$\det(X'X) = N_{tot} \sum N_s^2 - \left(\sum N_s \right)^2,$$

and

$$(X'X)^{-1} = \frac{1}{\det(X'X)} \begin{pmatrix} \sum N_s^2 & -\sum N_s \\ -\sum N_s & N_{tot} \end{pmatrix}.$$

The first row of $(X'X)^{-1}$ is

$$\left(\frac{\sum N_s^2}{N_{tot} \sum N_s^2 - (\sum N_s)^2} \quad -\frac{\sum N_s}{N_{tot} \sum N_s^2 - (\sum N_s)^2} \right).$$

Set

$$A = \frac{1}{N_{tot}B - C^2}, \quad \text{with } B = \sum N_s^2 \text{ and } C = \sum N_s.$$

We then have:

$$X_1 = \begin{pmatrix} AB - ACN_1 \\ \left. \begin{matrix} AB - ACN_2 \\ AB - ACN_2 \\ \vdots \\ AB - ACN_S \\ \vdots \\ AB - ACN_S \end{matrix} \right\} \begin{matrix} 2 \text{ times} \\ \\ \\ S \text{ times} \end{matrix} \end{pmatrix}'.$$

Calculating $\text{Var}[\hat{c}]$

Given the block structure of X_1 and Ξ , we can write

$$X_1 \Xi X_1' = \sum_{s=1}^S \sum_{r=1}^S \sum_{i=1}^s \sum_{j=1}^r X_1^{(s)} X_1^{(r)} \xi_{ij}^{(s,r)}.$$

where $\xi_{ij}^{(s,r)}$ is the ij element in the (s,r) -block of Ξ . Let us look at the terms A , B and C .

For B we have

$$\lim_{S \rightarrow \infty} B = \lim_{S \rightarrow \infty} \sum N_s^2 = \lim_{S \rightarrow \infty} \sum_{s=1}^S \sum_{h=1}^s N_s^2 = \lim_{S \rightarrow \infty} \sum_{s=1}^S s N_s^2 = N^2 \lim_{S \rightarrow \infty} \sum_{s=1}^S \frac{1}{s} = N^2 \lim_{S \rightarrow \infty} (\ln(S) + \gamma_0)$$

with γ_0 the Euler-Mascheroni constant. Similarly, we can derive $C = NS$. It follows that

$$\begin{aligned} \lim_{S \rightarrow \infty} A &= \lim_{S \rightarrow \infty} \frac{1}{\frac{S(S+1)}{2} N^2 (\ln(S) + \gamma_0) - N^2 S^2} \\ &= \lim_{S \rightarrow \infty} \frac{2}{N^2 (S^2 \ln(S) + S^2 (\gamma_0 - 2) + S \ln(S) + S \gamma_0)} \end{aligned}$$

The expression

$$\text{Var}[\hat{c}] = X_1 \Xi X_1' = \sum_{s=1}^S \sum_{r=1}^S \sum_{i=1}^s \sum_{j=1}^r X_1^{(s)} X_1^{(r)} \xi_{ij}^{(s,r)}$$

can be decomposed as

$$\begin{aligned}
& \sum_{s=1}^S \sum_{r=1}^S \sum_{i=1}^s \sum_{j=1}^r X_1^{(s)} X_1^{(r)} \xi_{ij}^{(s,r)} \\
&= \sum_{s=1}^S \sum_{i=1}^s \sum_{j=1}^s \left(X_1^{(s)} \right)^2 \xi_{ij}^{(s,s)} + \sum_{s=1}^S \sum_{r \neq s}^S \sum_{i=1}^s \sum_{j=1}^r X_1^{(s)} X_1^{(r)} \xi_{ij}^{(s,r)} \\
&= \sum_{s=1}^S \sum_{i=1}^s \left(X_1^{(s)} \right)^2 \xi_{ii}^{(s,s)} + \sum_{s=1}^S \sum_{i=1}^s \sum_{j \neq i}^s \left(X_1^{(s)} \right)^2 \xi_{ij}^{(s,s)} + \sum_{s=1}^S \sum_{r \neq s}^S \sum_{i=1}^s \sum_{j=1}^r X_1^{(s)} X_1^{(r)} \xi_{ij}^{(s,r)} \quad (2)
\end{aligned}$$

The term $\sum_{s=1}^S \sum_{i=1}^s \left(X_1^{(s)} \right)^2 \xi_{ii}^{(s,s)}$

Since $X_1^{(s)}$ does not depend on i , we have

$$\sum_{s=1}^S \sum_{i=1}^s \left(X_1^{(s)} \right)^2 \xi_{ii}^{(s,s)} = \sum_{s=1}^S \left(X_1^{(s)} \right)^2 \sum_{i=1}^s \xi_{ii}^{(s,s)}$$

We have that (ignoring the $o\left(\frac{1}{N_s}\right)$ term)

$$\xi_{ii}^{(s,s)} = \underbrace{aN_s + b}_{\text{noise error}} + \underbrace{\frac{c}{N_s}}_{\text{discretization error}},$$

where, by comparing to Equation (1), we see that

$$a = 12\kappa\omega^4, \quad b = 8\omega^2 \int_0^1 \sigma_s^2 ds - (6\kappa - 2)\omega^4, \quad c = 2 \int_0^1 \sigma_s^4 H'(s) ds$$

The inner sum is

$$\sum_{i=1}^s \xi_{ii}^{(s,s)} = \sum_{i=1}^s \left(a\frac{N}{s} + b + \frac{cs}{N} \right) = aN + bs + \frac{cs^2}{N}.$$

Further

$$\left(X_1^{(s)} \right)^2 = \left(AB - AC\frac{N}{s} \right)^2 = A^2B^2 - 2A^2BC\frac{N}{s} + A^2C^2\frac{N^2}{s^2}$$

Finally, we have

$$\sum_{s=1}^S \sum_{i=1}^s \left(X_1^{(s)}\right)^2 \xi_{ii}^{(s,s)} = \sum_{s=1}^S \left(aN + bs + \frac{cs^2}{N}\right) \left(A^2B^2 - 2A^2BC\frac{N}{s} + A^2C^2\frac{N^2}{s^2}\right)$$

Since

$$\begin{aligned} \sum_{s=1}^S s^2 &= \frac{1}{6}(2S^3 + 3S^2 + S), & \sum_{s=1}^S s &= \frac{1}{2}(S^2 + S), \\ \lim_{S \rightarrow \infty} \left(\sum_{s=1}^S \frac{1}{s} - \ln(S)\right) &= \gamma_0, & \lim_{S \rightarrow \infty} \left(\sum_{s=1}^S \frac{1}{s^2} - \frac{\pi^2}{6}\right) &= 0, \\ A^2B^2 &\in O\left(\frac{1}{S^4}\right), & A^2BC &\in O\left(\frac{1}{NS^3 \ln(S)}\right), \\ A^2C^2 &\in O\left(\frac{1}{N^2S^2(\ln(S))^2}\right) \end{aligned}$$

we obtain that as $S \rightarrow \infty$ and $N \rightarrow \infty$, $\sum_{s=1}^S \sum_{i=1}^s \left(X_1^{(s)}\right)^2 \xi_{ii}^{(s,s)}$ is dominated by $\frac{2\pi^2 aN}{3(S(\ln(S)+\gamma_0)+(\ln(S)+\gamma_0)-2S)^2}$ which is of order $O\left(\frac{N}{S^2(\ln(S))^2}\right)$.

The term $\sum_{s=1}^S \sum_{i=1}^s \sum_{j \neq i}^s \left(X_1^{(s)}\right)^2 \xi_{ij}^{(s,s)}$

For this term we need the covariance between two realized variances computed at the same sampling frequency (within an (s, s) -block) but with non-overlapping grids. As we are working under an iid noise framework, this covariance is not affected by the noise. Using the same arguments as Barndorff-Nielsen & Shephard (2002), it follows that this covariance is equal to

$$\xi_{ij}^{(s,s)} = \text{Cov} \left[RV^{h,s}(N_{h,s}), RV^{h',s}(N_{h',s}) \right] = \frac{2}{N_s} \int_0^1 \sigma_s^4 H'(s) ds + o\left(\frac{1}{N_s}\right) = \frac{c}{N_s} + o\left(\frac{1}{N_s}\right).$$

Then we have

$$\sum_{s=1}^S \sum_{i=1}^s \sum_{j \neq i}^s \left(X_1^{(s)}\right)^2 \xi_{ij}^{(s,s)} = \sum_{s=1}^S \left(X_1^{(s)}\right)^2 \sum_{i=1}^s \sum_{j \neq i}^s \frac{cs}{N} = \sum_{s=1}^S \left(X_1^{(s)}\right)^2 \frac{s^2(s-1)c}{N}$$

Substituting in $(X_1^{(s)})^2$ yields

$$\begin{aligned} \sum_{s=1}^S (X_1^{(s)})^2 \frac{s^2(s-1)c}{N} &= \sum_{s=1}^S \left(A^2 B^2 - 2A^2 BC \frac{N}{s} + A^2 C^2 \frac{N^2}{s^2} \right) \frac{s^2(s-1)c}{N} \\ &= \sum_{s=1}^S cA^2 B^2 \frac{s^2(s-1)}{N} - 2cA^2 BC s(s-1) + cA^2 C^2 N(s-1). \end{aligned}$$

This sum is of order $O\left(\frac{1}{N}\right)$ and thus negligible.

The term $\sum_{s=1}^S \sum_{r \neq s}^S \sum_{i=1}^s \sum_{j=1}^r X_1^{(s)} X_1^{(r)} \xi_{ij}^{(s,r)}$

For this term we use Lemma 1. The covariance $\xi_{ij}^{(s,r)}$ is affected by whether the numbers s and r are coprime or not. Consider first the case (I) when s and r are coprime. This implies that the number of common observations in an s -subgrid and r -subgrid is $\frac{N}{sr}$ for all s -subgrids and r -subgrids. From Lemma 1, it follows that in this case the covariance $\xi_{ij}^{(s,r)}$ can be written as

$$\xi_{ij}^{(s,r)} = a^* \frac{N}{sr} + b^* \int_{\mathcal{O}} \sigma_s^2 ds + \frac{c^* \min(s,r)}{N},$$

where

$$a^* = 12\kappa\omega^4 - 4\omega^4, \quad b^* = 4\omega^2, \quad c^* = 2 \int_0^1 \sigma_s^4 H'(s) ds.$$

In the second case (II) s and r are not coprime. In such an (s,r) -block there are two possibilities: (II.1) in $\text{lcm}(s,r)$ out of the sr elements in the block, the number of common points on both subgrids is $\frac{N}{\text{lcm}(s,r)}$, (II.2) in the remaining $sr - \text{lcm}(s,r)$ cases the subgrids do not share observations. In case (II.1) we have

$$\xi_{ij}^{(s,r)} = a^* \frac{N}{\text{lcm}(s,r)} + b^* \int_{\mathcal{O}} \sigma_s^2 ds + \frac{c^* \min(s,r)}{N},$$

while in case (II.2) it holds that

$$\xi_{ij}^{(s,r)} = \frac{c^* \min(s, r)}{N}.$$

As in all cases (I, II.1 and II.2), $\xi_{ij}^{(s,r)}$ does not depend on i and j , and because for coprime s and r , $\text{lcm}(s, r) = sr$, we can write in general that

$$\begin{aligned} \sum_{i=1}^s \sum_{j=1}^r \xi_{ij}^{(s,r)} &= \left(a^* \frac{N}{\text{lcm}(s, r)} + b^* \int_{\mathcal{O}} \sigma_s^2 ds + \frac{c^* \min(s, r)}{N} \right) \text{lcm}(s, r) + \frac{c^* \min(s, r)}{N} (sr - \text{lcm}(s, r)) \\ &= a^* N + b^* \int_{\mathcal{O}} \sigma_s^2 ds \text{lcm}(s, r) + \frac{c^* sr \min(s, r)}{N} \\ &\approx a^* N + b^* \min(s, r) + \frac{c^* sr \min(s, r)}{N} \end{aligned}$$

where the last approximation is employed for operational reasons in the sense that $\int_{\mathcal{O}} \sigma_s^2 ds$ term is of order $O\left(\frac{\min(s,r)}{\text{lcm}(s,r)}\right)$ (and as we show in the sequel, terms involving b^* are asymptotically negligible). As the matrix Ξ is symmetric, we express

$$\sum_{s=1}^S \sum_{r \neq s}^S X_1^{(s)} X_1^{(r)} \sum_{i=1}^s \sum_{j=1}^r \xi_{ij}^{(s,r)} = 2 \sum_{s=1}^S \sum_{r>s}^S X_1^{(s)} X_1^{(r)} \sum_{i=1}^s \sum_{j=1}^r \xi_{ij}^{(s,r)}.$$

Substituting in the above derived equation for $\sum_{i=1}^s \sum_{j=1}^r \xi_{ij}^{(s,r)}$, $X_1^{(s)}$ and $X_1^{(r)}$ results in

$$\begin{aligned} 2 \sum_{s=1}^S \sum_{r>s}^S X_1^{(s)} X_1^{(r)} \sum_{i=1}^s \sum_{j=1}^r \xi_{ij}^{(s,r)} &= 2 \sum_{s=1}^S \sum_{r>s}^S A^2 \left(B - C \frac{N}{s} \right) \left(B - C \frac{N}{r} \right) \left(a^* N + b^* s + \frac{c^* s^2 r}{N} \right) \\ &= 2 \left(\frac{S(S-1)}{2} a^* A^2 B^2 N + b^* A^2 B^2 \sum_{s=1}^S \sum_{r>s}^S s + \frac{c^* A^2 B^2}{N} \sum_{s=1}^S \sum_{r>s}^S s^2 r \right. \\ &\quad - a^* A^2 B C N^2 \sum_{s=1}^S \sum_{r>s}^S \left(\frac{1}{r} + \frac{1}{s} \right) - b^* A^2 B C N \sum_{s=1}^S \sum_{r>s}^S \left(1 + \frac{s}{r} \right) - c^* A^2 B C \sum_{s=1}^S \sum_{r>s}^S (s^2 + sr) \\ &\quad \left. + a^* A^2 C^2 N^3 \sum_{s=1}^S \sum_{r>s}^S \frac{1}{rs} + b^* A^2 C^2 N^2 \sum_{s=1}^S \sum_{r>s}^S \frac{1}{r} + c^* A^2 C^2 N \sum_{s=1}^S \sum_{r>s}^S s \right). \end{aligned}$$

We first show that the terms involving b^* are asymptotically negligible. This can be confirmed by considering that $\sum_{s=1}^S \sum_{r>s}^S s \in O(S^3)$, $\sum_{s=1}^S \sum_{r>s}^S \left(1 + \frac{s}{r} \right) \in O(S^2)$ and $\sum_{s=1}^S \sum_{r>s}^S \frac{1}{r} \in$

$O(S)$. The term $b^* A^2 B^2 \sum_{s=1}^S \sum_{r>s}^S s$ is dominant and of order $O\left(\frac{1}{S}\right)$ and hence asymptotically negligible. Next, we look at limits of terms involving a^* . To this end consider the sums

$$\begin{aligned} \sum_{s=1}^S \sum_{r>s}^S \left(\frac{1}{r} + \frac{1}{s}\right) &= \sum_{s=1}^S \left(\sum_{r=1}^S \frac{1}{r} - \sum_{r=1}^s \frac{1}{r} \right) + \sum_{s=1}^S \frac{1}{s} (S-s) \\ &= 2 \sum_{s=1}^S (\ln(S) + \gamma_0) - \sum_{s=1}^S (\ln(s) + \gamma_0) - S = S(\ln(S) + \gamma_0) - 0.5 \ln(S) - 0.5 \ln(2\pi) + o(1). \\ \sum_{s=1}^S \sum_{r>s}^S \frac{1}{rs} &= \sum_{s=1}^S \frac{1}{s} \left(\sum_{r=1}^S \frac{1}{r} - \sum_{r=1}^s \frac{1}{r} \right) = \sum_{s=1}^S \frac{1}{s} (\ln(S) + \gamma_0) - \sum_{s=1}^S \frac{1}{s} (\ln(s) + \gamma_0) \\ &= (\ln(S) + \gamma_0)^2 - 0.5 (\ln(S))^2 - \gamma_1 - \gamma_0 (\ln(S) + \gamma_0) = 0.5 (\ln(S))^2 + \gamma_0 \ln(S) - \gamma_1 + o(1). \end{aligned}$$

where we have used that $\lim_{S \rightarrow \infty} \left(\sum_{s=1}^S \ln(s) - \ln \left(\sqrt{2\pi S} \left(\frac{S}{e}\right)^S \right) \right) = 0$ by Sterling's approximation and $\lim_{S \rightarrow \infty} \left(\sum_{s=1}^S \frac{\ln(s)}{s} - 0.5 (\ln(S))^2 \right) = \gamma_1$, where γ_1 is the first Stieltjes constant equal to approximately -0.0728 (see, e.g., Havil (2003)). Thus, we obtain

$$\begin{aligned} \frac{S(S-1)}{2} A^2 B^2 N &= \frac{1}{2} \frac{4N(S^2 - S)(\ln(S) + \gamma_0)^2}{(S^2(\ln(S) + \gamma_0) + S(\ln(S) + \gamma_0) - 2S^2)^2} \\ &= \frac{2N(S^2 - S)}{\left(S^2 + S - \frac{2S^2}{\ln(S) + \gamma_0}\right)^2} = \frac{2N}{\left(S + 1 - \frac{2S}{\ln(S) + \gamma_0}\right)^2} + O\left(\frac{N}{S^3}\right). \end{aligned}$$

$$\begin{aligned} -A^2 BC N^2 \sum_{s=1}^S \sum_{r>s}^S \left(\frac{1}{r} + \frac{1}{s}\right) &= -\frac{4NS(\ln(S) + \gamma_0) (S(\ln(S) + \gamma_0) - 0.5 \ln(S) - 0.5 \ln(2\pi))}{(S^2(\ln(S) + \gamma_0) + S(\ln(S) + \gamma_0) - 2S^2)^2} \\ &= -\frac{4N}{\left(S + 1 - \frac{2S}{\ln(S) + \gamma_0}\right)^2} + O\left(\frac{N}{S^3}\right). \end{aligned}$$

$$\begin{aligned} A^2 C^2 N^3 \sum_{s=1}^S \sum_{r>s}^S \frac{1}{rs} &= \frac{4NS^2 (0.5 (\ln(S))^2 + \gamma_0 \ln(S) - \gamma_1)}{(S^2(\ln(S) + \gamma_0) + S(\ln(S) + \gamma_0) - 2S^2)^2} \\ &= \frac{NS^2 (2 (\ln(S) + \gamma_0)^2 - 2\gamma_0^2 - 4\gamma_1)}{(S^2(\ln(S) + \gamma_0) + S(\ln(S) + \gamma_0) - 2S^2)^2} \\ &= \frac{2N}{\left(S + 1 - \frac{2S}{\ln(S) + \gamma_0}\right)^2} - \frac{N(2\gamma_0^2 + 4\gamma_1)}{(S(\ln(S) + \gamma_0) + (\ln(S) + \gamma_0) - 2S)^2}. \end{aligned}$$

Summing up the three terms, we obtain $-\frac{(2\gamma_0^2+4\gamma_1)N}{(S(\ln(S)+\gamma_0)+(\ln(S)+\gamma_0)-2S)^2} + O\left(\frac{N}{S^3}\right)$. It remains to calculate the terms with c^* . We have $\sum_{s=1}^S \sum_{r>s}^S s^2 r = 1/15S^5 + 1/24S^4 - 1/12S^3 - 1/24S^2 + 1/60S$, $\sum_{s=1}^S \sum_{r>s}^S (s^2 + sr) = 5/24S^4 + 1/12S^3 - 5/24S^2 - 1/12S$, and $\sum_{s=1}^S \sum_{r>s}^S s = 1/6S^3 - 1/6S$. Considering the order of the terms A^2B^2 , A^2BC and A^2C^2 , the leading term turns out to be

$$\frac{c^*A^2B^2}{N} \sum_{s=1}^S \sum_{r>s}^S s^2 r = \frac{4Sc^*}{15N \left(1 - \frac{2}{\ln(S)+\gamma_0} + \frac{1}{S}\right)^2} + O\left(\frac{1}{N}\right).$$

Final Result

Let $N \rightarrow \infty$ and $S = \alpha N^\beta$ for $\alpha > 0$ and $\beta \in [0.5, 1)$. Summing everything up together results in

$$\text{Var}[\hat{c}] = \frac{2(\pi^2 a - 6(\gamma_0^2 + 2\gamma_1)a^*)N}{3(S(\ln(S) + \gamma_0) + (\ln(S) + \gamma_0) - 2S)^2} + \frac{8Sc^*}{15N \left(1 - \frac{2}{\ln(S)+\gamma_0} + \frac{1}{S}\right)^2} + O(N^{-1/2}).$$

Let $\eta = \frac{2}{3}(\pi^2 a - 6(\gamma_0^2 + 2\gamma_1)a^*)$ and $\delta = \frac{8c^*}{15}$. Substituting $S = \alpha N^\beta$ we can rewrite

$$\text{Var}[\hat{c}] = \frac{\eta}{\beta^2 \alpha^2} N^{1-2\beta} (\ln(N))^{-2} + \delta \alpha N^{\beta-1} + o(N^{1-2\beta} (\ln(N))^{-2}) + o(N^{\beta-1}).$$

4 Proof of Corollary 1

The choice of β determines the speed of convergence and the dominating terms. The highest speed of convergence of the estimator is achieved when $N^{1-2\beta} (\ln(N))^{-2} = N^{\beta-1}$ which holds for $\beta_N = \frac{2}{3} \left(1 - \frac{\ln(\ln(N))}{\ln(N)}\right)$ converging to $\beta = 2/3$ from below. For $\beta_N = \frac{2}{3} \left(1 - \frac{\ln(\ln(N))}{\ln(N)}\right)$, we have that $N^{1-2\beta_N} (\ln(N))^{-2} = N^{\beta_N-1} = N^{-1/3} (\ln(N))^{-2/3}$. Thus, with $S = \alpha N^{\beta_N}$, the asymptotic variance can be expressed as

$$\lim_{N \rightarrow \infty} \text{Var} [N^{1/6} (\ln(N))^{1/3} \hat{c}] = \lim_{N \rightarrow \infty} \frac{\eta}{\beta_N^2 \alpha^2} + \delta \alpha = \frac{9\eta}{4\alpha^2} + \delta \alpha.$$

Minimizing this expression with respect to α gives

$$\alpha^* = \sqrt[3]{\frac{9\eta}{2\delta}}$$

for which $\text{Var} [N^{1/6}(\ln(N))^{1/3} \hat{c}] = 2.48\sqrt[3]{\delta^2\eta}$.

Recalling that $a = 12\kappa\omega^4$, $a^* = 12\kappa\omega^4 - 4\omega^4$, $c^* = 2 \int_0^1 \sigma_s^4 H'(s) ds$, denoting $IQ = \int_0^1 \sigma_s^4 H'(s) ds$ and setting $\kappa = 1$ (normal noise) we can write $\eta = 8\omega^4(\pi^2 - 4(\gamma_0^2 + 2\gamma_1))$ and $\delta = \frac{16IQ}{15}$ and thus

$$\alpha^* = \sqrt[3]{\frac{33.75\omega^4(\pi^2 - 4(\gamma_0^2 + 2\gamma_1))}{IQ}}.$$

5 Proof of Theorem 2

This proof follows closely the proof of Theorem 1. Denote by X_2 the second row of $(X'X)^{-1}X'$.

Then

$$\text{Var}[\hat{\beta}_0] = X_2 \Xi X_2'.$$

Since $\hat{\omega}^2 = \hat{\beta}_0/2$ it follows that

$$\text{Var}[\hat{\omega}^2] = \frac{1}{4}X_2 \Xi X_2'.$$

Using notation from above, X_2 is given by:

$$X_2 = \begin{pmatrix} -AC + N_{tot}AN_1 \\ \left. \begin{matrix} -AC + N_{tot}AN_2 \\ -AC + N_{tot}AN_2 \\ \vdots \\ -AC + N_{tot}AN_S \\ \vdots \\ -AC + N_{tot}AN_S \end{matrix} \right\} \begin{matrix} 2 \text{ times} \\ \\ \\ S \text{ times} \end{matrix} \end{pmatrix}'.$$

Calculating $\text{Var}[\hat{\beta}_0]$

Given the block structure of X_1 and Ξ , we can write

$$X_2 \Xi X_2' = \sum_{s=1}^S \sum_{r=1}^S \sum_{i=1}^s \sum_{j=1}^r X_2^{(s)} X_2^{(r)} \xi_{ij}^{(s,r)}.$$

Using the decomposition in Eq. (2), with $X_2^{(\cdot)}$ in the place of $X_1^{(\cdot)}$, we examine each term separately.

The term $\sum_{s=1}^S \sum_{i=1}^s \left(X_2^{(s)}\right)^2 \xi_{ii}^{(s,s)}$

Since $X_2^{(s)}$ does not depend on i , we have

$$\sum_{s=1}^S \sum_{i=1}^s \left(X_2^{(s)}\right)^2 \xi_{ii}^{(s,s)} = \sum_{s=1}^S \left(X_2^{(s)}\right)^2 \sum_{i=1}^s \xi_{ii}^{(s,s)}$$

where

$$\left(X_2^{(s)}\right)^2 = \left(-AC + N_{tot}A\frac{N}{s}\right)^2 = A^2C^2 - 2A^2CN_{tot}\frac{N}{s} + A^2N_{tot}^2\frac{N^2}{s^2}.$$

Thus, we obtain

$$\sum_{s=1}^S \sum_{i=1}^s \left(X_2^{(s)} \right)^2 \xi_{ii}^{(s,s)} = \sum_{s=1}^S \left(aN + bs + \frac{cs^2}{N} \right) \left(A^2 C^2 - 2A^2 C N_{tot} \frac{N}{s} + A^2 N_{tot}^2 \frac{N^2}{s^2} \right)$$

Using results from above, it follows that as $S \rightarrow \infty$ and $N \rightarrow \infty$, the leading term in the expression is given by $\frac{\pi^2 a}{6N(\ln(S))^2}$.

The term $\sum_{s=1}^S \sum_{i=1}^s \sum_{j \neq i}^s \left(X_2^{(s)} \right)^2 \xi_{ij}^{(s,s)}$

As in Theorem 1, this term is of smaller order than the previous term and thus asymptotically negligible.

The term $\sum_{s=1}^S \sum_{r \neq s}^S \sum_{i=1}^s \sum_{j=1}^r X_2^{(s)} X_2^{(r)} \xi_{ij}^{(s,r)}$

As above we examine the cases I: s and r coprime, II.1: s and r not coprime with number of common points on both subgrids $\frac{N}{\text{lcm}(s,r)}$ ($\text{lcm}(s,r)$ elements), and II.2: s and r not coprime with no common points on the subgrids ($sr - \text{lcm}(s,r)$ elements). Proceeding as in the proof of Theorem 1, it can be shown that terms involving b^* are asymptotically negligible. From the terms involving a^* , the dominating term can be shown to be $\frac{a^*}{N}$.

The three terms involving c^* are of the same order, so it becomes important to consider them in more detail. The first one, $2 \frac{c^* A^2 C^2}{N} \sum_{s=1}^S \sum_{r \neq s}^S s^2 r$ has a leading term given by $\frac{8c^* S^3}{15N^3(\ln(S))^2}$, the second one $-2c^* A^2 C N_{tot} \sum_{s=1}^S \sum_{r \neq s}^S (s^2 + sr)$ has a leading term given by $-\frac{5c^* S^3}{6N^3(\ln(S))^2}$, and the third one $2C^* A^2 N_{tot}^2 N \sum_{s=1}^S \sum_{r \neq s}^S s$ has a leading term given by $\frac{c^* S^3}{3N^3(\ln(S))^2}$. Summing up the three terms, we obtain $\frac{c^* S^3}{30N^3(\ln(S))^2}$.

Final Result

Let $N \rightarrow \infty$ and $S = \alpha N^\beta$ for $\alpha > 0$ and $\beta \in [0.5, 1)$. Summing everything up together results in

$$\text{Var}[\hat{\omega}^2] = \frac{1}{4} \text{Var}[\hat{\beta}_0] = \frac{1}{4} \left(\frac{a^*}{N} + \frac{c^* S^3}{30N^3(\ln(S))^2} \right) + o(N^{-1}).$$

Substituting $S = \alpha N^\beta$ in the above equation results in

$$\text{Var}[\hat{\omega}^2] = \frac{1}{4} \left(\frac{a^*}{N} + \frac{c^* \alpha^3 N^{3\beta}}{30N^3(\ln(\alpha) + \beta \ln(N))^2} \right) + o(N^{-1}).$$

The two terms in the brackets are of the same order, $O(N^{-1})$, if $\beta = \frac{2}{3} \left(\frac{\ln(\ln(N))}{\ln(N)} + 1 \right)$. It follows that for $\beta < \frac{2}{3} \left(\frac{\ln(\ln(N))}{\ln(N)} + 1 \right)$

$$\lim_{N \rightarrow \infty} \text{Var}[\hat{\omega}^2] = \frac{a^*}{4N} + o(N^{-1}).$$

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