

SUPPLEMENT TO “SPOT VOLATILITY ESTIMATION FOR HIGH-FREQUENCY DATA: ADAPTIVE ESTIMATION IN PRACTICE”

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In this supplement, we recall the proof of Lemma 3.1 in “Spot volatility estimation for high-frequency data: adaptive estimation in practice” as it is given in Schmidt-Hieber (2010), Lemma 6, p. 65.

APPENDIX A: PROOF OF LEMMA 3.1

To keep notation simple, we use the following quantities in the spirit of the definitions of Section 2.3: For any process $(A_{i,n}) \in \{(Y_{i,n}), (\epsilon_{i,n}), (X)_{i,n}\}$, define

$$\bar{A}_{i,m} = \bar{A}_{i,m}(\lambda) := \frac{m}{n} \sum_{\frac{j}{n} \in [\frac{i-2}{m}, \frac{i}{m}]} \lambda(m\frac{j}{n} - (i-2)) A_{j,n}.$$

$$\mathfrak{b}(A)_{i,m} = \mathfrak{b}(\lambda, A)_{i,m} := \frac{m^2}{2n^2} \sum_{\frac{j}{n} \in [\frac{i-2}{m}, \frac{i}{m}]} \lambda^2(m\frac{j}{n} - (i-2)) (A_{j,n} - A_{j-1,n})^2.$$

Further, recall that our estimator for the integrated volatility is given by $\widehat{\langle 1, \sigma^2 \rangle} = \sum_{i=2}^m \bar{Y}_{i,m}^2 - \mathfrak{b}(Y)_{i,m}$.

To prove the lemma, let us first show that the bias is of smaller order than $n^{-1/4}$. In fact, note that $\mathbb{E}[\bar{Y}_{i,m}^2] = \mathbb{E}[\bar{X}_{i,m}^2] + \mathbb{E}[\bar{\epsilon}_{i,m}^2]$. Clearly, one can bound

$$\left| \mathbb{E}[\bar{\epsilon}_{i,m}^2] - \mathbb{E}[\mathfrak{b}(\lambda, Y)_{i,m}] \right| = O\left(\frac{1}{n}\right).$$

Further, Lipschitz continuity of λ together with a Riemann approximation argument gives us

$$\left| \mathbb{E}[\bar{X}_{i,m}^2] - \frac{\sigma^2}{m} \right| = \left| \frac{\sigma^2}{m} \int_0^2 \int_0^2 \lambda(s) \lambda(t) (s \wedge t) dt ds - \frac{\sigma^2}{m} \right| + O\left(\frac{1}{n}\right) = O\left(\frac{1}{n}\right).$$

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Here, the last equation is due to partial integration and the definition of a pre-average function (cf. Definition 2.1). Since both approximations are uniformly in i , this shows that the bias is of order $O(n^{-1/2})$.

For the asymptotic variance, first observe that $\text{Var}(\sum_{i=2}^m \mathbf{b}(\lambda, Y)_{i,m}) = o(n^{-1/2})$. Hence,

$$\text{Var}(\widehat{\langle 1, \sigma^2 \rangle}) = \text{Var}\left(\sum_{i=2}^m \bar{Y}_{i,m}^2\right) + o\left(n^{-1/4} \left(\text{Var}\left(\sum_{i=2}^m \bar{Y}_{i,m}^2\right)\right)^{1/2} + n^{-1/2}\right),$$

by Cauchy-Schwarz inequality. Recall that for centered Gaussian random variables U, V , $\text{Cov}(U^2, V^2) = 2(\text{Cov}(U, V))^2$. Therefore, it suffices to compute $\text{Cov}(\bar{Y}_{i,m}, \bar{Y}_{k,m}) = \mathbb{E}[\bar{Y}_{i,m} \bar{Y}_{k,m}]$.

By the same arguments as above, that is Riemann summation and partial integration, we find

$$\mathbb{E}\left[\left|\bar{X}_{i,m} \bar{X}_{k,m} - \int_0^1 \Lambda(ms - (i-2))dX_s \int_0^1 \Lambda(ms - (k-2))dX_s\right|\right] \lesssim n^{-1}.$$

Therefore,

$$\mathbb{E}[\bar{X}_{i,m} \bar{X}_{k,m}] = \sigma^2 \int_0^1 \Lambda(ms - (i-2))\Lambda(ms - (k-2))ds + O(n^{-1}),$$

where the last two arguments hold uniformly in i, k .

In order to calculate $\mathbb{E}[\bar{Y}_{i,m} \bar{Y}_{k,m}]$, we must treat three different cases, $|i - k| \geq 2$, $|i - k| = 1$ and $i = k$, denoted by *I*, *II* and *III*.

I.: In this case $(\frac{i-2}{m}, \frac{i}{m}]$ and $(\frac{k-2}{m}, \frac{k}{m}]$ do not overlap. By the equalities above, it follows $\text{Cov}(\bar{Y}_{i,m}, \bar{Y}_{k,m}) = O(n^{-1})$.

II.: Without loss of generality, we set $k = i + 1$. Then, we obtain

$$\begin{aligned} \text{Cov}(\bar{Y}_{i,m}, \bar{Y}_{i+1,m}) &= \mathbb{E}[\bar{X}_{i,m} \bar{X}_{i+1,m}] + \mathbb{E}[\bar{\epsilon}_{i,m} \bar{\epsilon}_{i+1,m}] \\ &= \sigma^2 \int_0^1 \Lambda(ms - (i-2))\Lambda(ms - (i-1))ds + O(n^{-1}) \\ &\quad + \tau^2 \frac{m^2}{n^2} \sum_{\frac{j}{n} \in (\frac{i-2}{m}, \frac{i}{m}]} \lambda(m\frac{j}{n} - (i-2))\lambda(m\frac{j}{n} - (i-1)) \\ &= \frac{\sigma^2}{m} \int_0^1 \Lambda(u)\Lambda(1+u)du + \tau^2 \frac{m}{n} \int_0^1 \lambda(u)\lambda(1+u)du + O(n^{-1}), \end{aligned}$$

where the last inequality can be verified by Riemann summation. Noting that λ is a pre-average function, we obtain $\lambda(1+u) = -\lambda(1-u)$ and

$$\begin{aligned} & \text{Cov}(\bar{Y}_{i,m}, \bar{Y}_{i+1,m}) \\ &= \frac{\sigma^2}{m} \int_0^1 \Lambda(u) \Lambda(1-u) du - \frac{\tau^2 m}{n} \int_0^1 \lambda(u) \lambda(1-u) du + O(n^{-1}). \end{aligned}$$

III.: It can be shown by redoing the arguments in *II* that

$$\begin{aligned} \text{Var}(\bar{Y}_{i,m}) &= \text{Var}(\bar{X}_{i,m}) + \text{Var}(\bar{\epsilon}_{i,m}) \\ &= \frac{\sigma^2}{m} \int_0^2 \Lambda^2(u) du + \tau^2 \frac{m}{n} \int_0^2 \lambda^2(u) du + O(n^{-1}). \end{aligned}$$

Note that $\|\Lambda\|_{L^2[0,2]} = 1$. Since the above results hold uniformly in i, k , it follows directly that

$$\begin{aligned} & \text{Var}\left(\sum_{i=2}^m \bar{Y}_{i,m}^2\right) \\ &= \sum_{i,k=2, |i-k|\geq 2}^m 2(\text{Cov}(\bar{Y}_{i,m}, \bar{Y}_{k,m}))^2 \\ & \quad + 2 \sum_{i=2}^{m-1} 2(\text{Cov}(\bar{Y}_{i,m}, \bar{Y}_{i+1,m}))^2 + \sum_{i=2}^m 2(\text{Var}(\bar{Y}_{i,m}))^2 \\ &= O(n^{-1}) + 4\left(\frac{\sigma^2}{\sqrt{c}} \int_0^1 \Lambda(u) \Lambda(1-u) du - \tau^2 c^{3/2} \int_0^1 \lambda(u) \lambda(1-u) du\right)^2 n^{-1/2} \\ & \quad + 2\left(\frac{\sigma^2}{\sqrt{c}} + 2\tau^2 c^{3/2} \|\lambda\|_{L^2[0,1]}^2\right)^2 n^{-1/2}. \quad \square \end{aligned}$$

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