

A Computation of the scaled score in the univariate models

A.1 χ^2 density

We compute the scaled score appearing in the dynamic of the log-variance $\lambda_t^{(i)}$ in Eq. (2.13) in the case of the χ^2 density. To simplify the notation, we suppress the subscript i . The conditional log-likelihood is:

$$\log p_{W_1}(x_t; v_t, \nu) = \frac{1}{2}c(\nu) + \left(\frac{\nu}{2} - 1\right) \log(x_t) - \frac{\nu}{2} \log(v_t) - \frac{\nu}{2} \left(\frac{x_t}{v_t}\right) \quad (\text{A.1})$$

where $c(\nu) = \nu \log(\nu/2) - 2 \log \Gamma(\nu/2)$. We now prove the following result (recall that $v_t = e^{\lambda_t}$):

Proposition A.1. *For the density in Eq. (A.1), the score $\nabla_t^{W_1} = \frac{\partial \log p_{W_1}(x_t; \lambda_t, \nu)}{\partial \lambda_t}$ is given by:*

$$\nabla_t^{W_1} = \frac{\nu}{2e^{\lambda_t}} [x_t - e^{\lambda_t}] \quad (\text{A.2})$$

Proof.

$$\begin{aligned} \nabla_t^{W_1} &= \frac{\partial \log p_{W_1}(x_t; \lambda_t, \nu)}{\partial \lambda_t} = \frac{\partial \log p_{W_1}(x_t; \lambda_t, \nu)}{\partial v_t} \times \frac{\partial v_t}{\partial \lambda_t} \\ &= \frac{\nu}{2v_t^2} [x_t - v_t] \times v_t \\ &= \frac{\nu}{2e^{\lambda_t}} [x_t - e^{\lambda_t}] \end{aligned}$$

□

Then, we compute the information quantity:

Proposition A.2. *For the density in Eq. (A.1), the Fisher information $\mathcal{I}_{t|t-1}^{W_1} = \mathbb{E}_{t|t-1}[\nabla_t^2]$ is given by:*

$$\mathcal{I}_{t|t-1}^{W_1} = \frac{\nu}{2} \quad (\text{A.3})$$

Proof.

$$\begin{aligned} \mathcal{I}_{t|t-1}^{W_1} &= \mathbb{E}_{t-1} \left[(\nabla_t^{W_1})^2 \right] = \mathbb{E}_{t-1} \left[\frac{\nu^2}{4e^{2\lambda_t}} (x_t - e^{\lambda_t})^2 \right] \\ &= \frac{\nu^2}{4e^{2\lambda_t}} \text{Var}[x_t] \stackrel{*}{=} \frac{\nu^2}{4e^{2\lambda_t}} \frac{2e^{2\lambda_t}}{\nu} = \frac{\nu}{2} \end{aligned}$$

where (*) follows from $\text{Var}[x] = \text{Var}[(v_t/\nu)k_\nu] = 2\frac{(v_t)^2}{\nu}$ if k_ν is distributed as a χ_ν^2 . □

Finally, it is immediate to compute the scaled score:

Proposition A.3. *For the density in Eq. (A.1), the scaled score $s_t^{W_1} = (\mathcal{I}_{t|t-1}^{W_1})^{-1} \nabla_t^{W_1}$ is given by:*

$$s_t^{W_1} = \frac{1}{e^{\lambda_t}} [x_t - e^{\lambda_t}] \quad (\text{A.4})$$

A.2 F density

In the case of the univariate F density, the conditional log-likelihood is:

$$\log p_F(x_t; v_t, \nu_1, \nu_2) = d(\nu_1, \nu_2) - \frac{\nu_1}{2} \log(v_t) + \left(\frac{\nu_1}{2} - 1\right) \log(x_t) - \frac{\nu_1 + \nu_2}{2} \log(\tilde{w}_t) \quad (\text{A.5})$$

where:

$$\tilde{w}_t = 1 + \frac{\nu_1 x_t}{(\nu_2 - 2)v_t} \quad (\text{A.6})$$

$$d(\nu_1, \nu_2) = \frac{\nu_1}{2} \log\left(\frac{\nu_1}{\nu_2 - 2}\right) + \log \Gamma\left(\frac{\nu_1 + \nu_2}{2}\right) - \log \Gamma\left(\frac{\nu_1}{2}\right) - \log \Gamma\left(\frac{\nu_2}{2}\right) \quad (\text{A.7})$$

We compute now the score of the conditional log-likelihood.

Proposition A.4. *For the density in Eq. (A.5), the score $\nabla_t^F = \frac{\partial \log p_F(x_t; v_t, \nu_1, \nu_2)}{\partial \lambda_t}$ is given by:*

$$\nabla_t^F = \frac{\nu_1}{2e^{\lambda_t}} \left[\frac{\nu_1 + \nu_2}{\nu_2 - 2} \frac{x_t}{\tilde{w}_t} - e^{\lambda_t} \right] \quad (\text{A.8})$$

Proof.

$$\begin{aligned} \nabla_t^F &= \frac{\partial \log p_F(x_t; v_t, \nu_1, \nu_2)}{\partial \lambda_t} = \frac{\partial \log p_F(x_t; v_t, \nu_1, \nu_2)}{\partial v_t} \times \frac{\partial v_t}{\partial \lambda_t} \\ &= -\frac{\nu_1}{2v_t} + \frac{\nu_1 + \nu_2}{2} \left[\tilde{w}_t \frac{\nu_1 x_t}{(\nu_2 - 2)(v_t)^2} \right] \times v_t \\ &= \frac{\nu_1}{2e^{2\lambda_t}} \left[\frac{\nu_1 + \nu_2}{\nu_2 - 2} \frac{x_t}{\tilde{w}_t} - e^{\lambda_t} \right] \times e^{\lambda_t} \\ &= \frac{\nu_1}{2e^{\lambda_t}} \left[\frac{\nu_1 + \nu_2}{\nu_2 - 2} \frac{x_t}{\tilde{w}_t} - e^{\lambda_t} \right] \end{aligned}$$

□

As in the correlation model (cf. Section 2.2.2), we scale the score by the inverse of the Fisher information of the χ^2 density. Thus, we get:

Proposition A.5. *For the density in Eq. (A.5), the scaled score $s_t^F = (\mathcal{I}_{t|t-1}^{W_1})^{-1} \nabla_t^F$ is given by:*

$$s_t^F = \frac{1}{e^{\lambda_t}} \left[\frac{\nu_1 + \nu_2}{\nu_2 - 2} \frac{x_t}{\tilde{w}_t} - e^{\lambda_t} \right] \quad (\text{A.9})$$

B Proposition 2.1

Proof. We need to compute $\frac{\partial l(X_t)}{\partial f_t'} = \frac{\partial l(X_t)}{\partial \text{vech}(Q_t)}$, where l is given by Eq. (2.17)

$$l(X_t) = \frac{1}{2} d_X(k, \nu) + \frac{\nu - k - 1}{2} \log |X_t| - \frac{\nu}{2} \log |V_t| - \frac{\nu}{2} \text{tr}(V_t^{-1} X_t).$$

Thanks to the chain rule, we can split our equation as:

$$\frac{\partial l(X_t)}{\partial \text{vech}(Q_t)'} = \frac{\partial l(X_t)}{\partial \text{vec}(V_t)'} \frac{\partial \text{vec}(V_t)}{\partial \text{vec}(R_t)'} \frac{\partial \text{vec}(R_t)}{\partial \text{vec}(Q_t)'} \frac{\partial \text{vec}(Q_t)}{\partial \text{vech}(Q_t)'}$$

Then, starting with the first term and considering $d \log |X| = \text{tr}(X^{-1}) dX$ and $d(X^{-1}) = -X^{-1}(dX)X^{-1}$, see Magnus and Neudecker (1999),

$$\begin{aligned} \frac{\partial l(X_t)}{\partial \text{vec}(V_t)'} &= -\frac{\nu}{2} \left[\text{vec}(V_t^{-1})' - \text{vec}(X_t)' (V_t^{-1} \otimes V_t^{-1}) \right] \\ &= \frac{\nu}{2} [\text{vec}(X_t) - \text{vec}(V_t)]' (V_t^{-1} \otimes V_t^{-1}). \end{aligned}$$

The second term is, thanks to the fact that $\text{vec}(AXB) = (B' \otimes A) \text{vec}(X)$

$$\frac{\partial \text{vec}(V_t)}{\partial \text{vec}(R_t)'} = \frac{\partial \text{vec}(D_t R_t D_t)}{\partial \text{vec}(R_t)'} = (D_t \otimes D_t).$$

By definition of duplication matrix, see Abadir and Magnus (2005), we have that

$$\frac{\partial \text{vec}(Q_t)}{\partial \text{vech}(Q_t)'} = \mathcal{D}_k.$$

The third term is a little bit more complicated, indeed defining $\Delta_t = (\text{diag}(Q_t)^{1/2})$,

$$\begin{aligned} d\text{vec}(R_t) &= d\text{vec}(\Delta_t^{-1} Q_t \Delta_t^{-1}) \\ &= \Delta_t^{-1} \otimes \Delta_t^{-1} d\text{vec}(Q_t) + \text{vec}(d(\Delta_t^{-1}) Q_t \Delta_t^{-1}) + \text{vec}(\Delta_t^{-1} Q_t d(\Delta_t^{-1})) \\ &= \Delta_t^{-1} \otimes \Delta_t^{-1} d\text{vec}(Q_t) + [(\Delta_t^{-1} Q_t \otimes I) + (I \otimes \Delta_t^{-1} Q_t)] d\text{vec}(\Delta_t^{-1}) \\ &= \Delta_t^{-1} \otimes \Delta_t^{-1} d\text{vec}(Q_t) - [(\Delta_t^{-1} Q_t \otimes I) + (I \otimes \Delta_t^{-1} Q_t)] \Delta_t^{-1} \otimes \Delta_t^{-1} d\text{vec}(\Delta_t) \\ &= \Delta_t^{-1} \otimes \Delta_t^{-1} d\text{vec}(Q_t) - [(\Delta_t^{-1} Q_t \otimes I) + (I \otimes \Delta_t^{-1} Q_t)] \Delta_t^{-1} \otimes \Delta_t^{-1} W_Q d\text{vec}(Q_t), \end{aligned}$$

where $q_t = \text{vec}(\Delta_t)$ and W_Q is a diagonal matrix with its i th diagonal elements equal to $1/2\sqrt{q_t^{(i)}}$ if $q_t^{(i)} \neq 0$ and zero otherwise.

Given these four results combined with the fact that $(D_t \otimes D_t)$ and $(V_t^{-1} \otimes V_t^{-1})$ are symmetric, we get

$$\begin{aligned} \frac{\partial l(X_t)}{\partial \text{vec}(V_t)'} &= \frac{\nu}{2} [\text{vec}(X_t) - \text{vec}(V_t)]' (V_t^{-1} \otimes V_t^{-1}) (D_t \otimes D_t) (\Delta_t^{-1} \otimes \Delta_t^{-1}) \\ &\quad \times [I - (Q_t \Delta_t^{-1} \otimes I) + (I \otimes Q_t \Delta_t^{-1})] W_Q \mathcal{D}_k \\ &= \frac{\nu}{2} [\text{vec}(X_t) - \text{vec}(V_t)]' (D_t^{-1} \Delta_t Q_t^{-1} \otimes D_t^{-1} \Delta_t Q_t^{-1}) \Psi_t \mathcal{D}_k, \end{aligned}$$

where $\Psi_t = [I - [(\Delta_t^{-1} Q_t \otimes I) + (I \otimes \Delta_t^{-1} Q_t)] W_Q]$. □

C Proposition 2.2

Proof. Starting with the definition of Fisher information matrix:

$$\begin{aligned}
E \left[\nabla_t^W \nabla_t^{W'} | \mathcal{F}_{t-1} \right] &= E \left[\frac{\nu^2}{4} \mathcal{D}'_k \Psi'_t (D_t^{-1} \Delta_t Q_t^{-1} \otimes D_t^{-1} \Delta_t Q_t^{-1}) [\text{vec}(X_t) - \text{vec}(V_t)] \right. \\
&\quad \times [\text{vec}(X_t) - \text{vec}(V_t)]' (D_t^{-1} \Delta_t Q_t^{-1} \otimes D_t^{-1} \Delta_t Q_t^{-1}) \Psi_t \mathcal{D}_k | \mathcal{F}_{t-1} \left. \right] \\
&= \frac{\nu^2}{4} \mathcal{D}'_k \Psi'_t (D_t^{-1} \Delta_t Q_t^{-1} \otimes D_t^{-1} \Delta_t Q_t^{-1}) \times \\
&\quad \times \text{Var}(\text{vec}(X_t) - \text{vec}(V_t) | \mathcal{F}_{t-1}) (D_t^{-1} \Delta_t Q_t^{-1} \otimes D_t^{-1} \Delta_t Q_t^{-1}) \Psi_t \mathcal{D}_k \\
&=^* \frac{\nu^2}{4} \mathcal{D}'_k \Psi'_t (D_t^{-1} \Delta_t Q_t^{-1} \otimes D_t^{-1} \Delta_t Q_t^{-1}) \frac{1}{\nu} (I_{k^2} + K_k) \times \\
&\quad \times (V_t \otimes V_t) (D_t^{-1} \Delta_t Q_t^{-1} \otimes D_t^{-1} \Delta_t Q_t^{-1}) \Psi_t \mathcal{D}_k \\
&=^{**} \frac{\nu}{2} \mathcal{D}'_k \Psi'_t (D_t^{-1} \Delta_t Q_t^{-1} D_t \Delta_t^{-1} \otimes D_t^{-1} \Delta_t Q_t^{-1} D_t \Delta_t^{-1}) \mathcal{D}_k \mathcal{D}_k^+ \Psi_t \mathcal{D}_k
\end{aligned}$$

where * is thank to the vech formulation of the Wishart variance in Abadir and Magnus (2005) and ** is given by $2\mathcal{D}_k \mathcal{D}_k^+ = (I_k + K_k)$ (recall that $V_t = (D_t \Delta_t^{-1} Q_t \Delta_t^{-1} D_t)$)

$$\begin{aligned}
A &= (D_t^{-1} \Delta_t Q_t^{-1} \otimes D_t^{-1} \Delta_t Q_t^{-1}) (V_t \otimes V_t) (D_t^{-1} \Delta_t Q_t^{-1} \otimes D_t^{-1} \Delta_t Q_t^{-1}) \\
&= (D_t^{-1} \Delta_t Q_t^{-1} \otimes D_t^{-1} \Delta_t Q_t^{-1}) (D_t \Delta_t^{-1} Q_t \Delta_t^{-1} D_t D_t^{-1} \Delta_t Q_t^{-1} \otimes D_t \Delta_t^{-1} Q_t \Delta_t^{-1} D_t D_t^{-1} \Delta_t Q_t^{-1}) \\
&= (D_t^{-1} \Delta_t Q_t^{-1} \otimes D_t^{-1} \Delta_t Q_t^{-1}) (D_t \Delta_t^{-1} \otimes D_t \Delta_t^{-1}) \\
&= (D_t^{-1} \Delta_t Q_t^{-1} D_t \Delta_t^{-1} \otimes D_t^{-1} \Delta_t Q_t^{-1} D_t \Delta_t^{-1}) \\
&= (H_t^{-1} Q_t^{-1} H_t \otimes H_t^{-1} Q_t^{-1} H_t)
\end{aligned}$$

□

D Proposition 2.3

Proof. Multiplying the inverse of 2.19 with the 2.18 we get

$$\begin{aligned}
s_t^W &= (\mathcal{D}_k' \Psi'_t (H_t^{-1} Q_t^{-1} H_t \otimes H_t^{-1} Q_t^{-1} H_t) \mathcal{D}_k \mathcal{D}_k^+ \Psi_t \mathcal{D}_k)^{-1} \mathcal{D}_k' \Psi'_t \\
&\quad \times (H_t^{-1} Q_t^{-1} \otimes H_t^{-1} Q_t^{-1}) [\text{vec}(X_t) - \text{vec}(V_t)] \\
&= (\mathcal{D}_k' \Psi'_t (H_t^{-1} Q_t^{-1} H_t \otimes H_t^{-1} Q_t^{-1} H_t) \mathcal{D}_k \mathcal{D}_k^+ \Psi_t \mathcal{D}_k)^{-1} \mathcal{D}_k' \Psi'_t \\
&\quad \times (H_t^{-1} Q_t^{-1} H_t \otimes H_t^{-1} Q_t^{-1} H_t) (H_t^{-1} \otimes H_t^{-1}) [\text{vec}(X_t) - \text{vec}(V_t)] \\
&= (\mathcal{D}_k' \Psi'_t (H_t^{-1} Q_t^{-1} H_t \otimes H_t^{-1} Q_t^{-1} H_t) \mathcal{D}_k \mathcal{D}_k^+ \Psi_t \mathcal{D}_k)^{-1} \mathcal{D}_k' \Psi'_t \\
&\quad \times (H_t^{-1} Q_t^{-1} H_t \otimes H_t^{-1} Q_t^{-1} H_t) (H_t^{-1} \otimes H_t^{-1}) \mathcal{D}_k \mathcal{D}_k^+ [\text{vec}(X_t) - \text{vec}(V_t)] \\
&= (\mathcal{D}_k' \Psi'_t (H_t^{-1} Q_t^{-1} H_t \otimes H_t^{-1} Q_t^{-1} H_t) \mathcal{D}_k \mathcal{D}_k^+ \Psi_t \mathcal{D}_k)^{-1} \mathcal{D}_k' \Psi'_t \\
&\quad \times (H_t^{-1} Q_t^{-1} H_t \otimes H_t^{-1} Q_t^{-1} H_t) \mathcal{D}_k \mathcal{D}_k^+ (H_t^{-1} \otimes H_t^{-1}) [\text{vec}(X_t) - \text{vec}(V_t)]
\end{aligned}$$

Now let us simplify $\mathcal{I}_t^W = \frac{\nu}{2} \mathcal{D}'_k \Psi'_t (H_t^{-1} Q_t^{-1} H_t \otimes H_t^{-1} Q_t^{-1} H_t) \mathcal{D}_k$. This simplification is not restrictive because the matrix Ψ_t is very sparse, moreover using the approximation $\Psi_t = I$ allows us to define the inverse of \mathcal{I}_t which is not full-rank with the original representation.

We get

$$\begin{aligned} s_t &= \mathcal{D}_k^+ (H_t^{-1} \otimes H_t^{-1}) [\text{vec}(X_t) - \text{vec}(V_t)] \\ &= \mathcal{D}_k^+ (H_t^{-1} \otimes H_t^{-1}) \text{vec}(X_t) - \mathcal{D}_k^+ (H_t^{-1} \otimes H_t^{-1}) (H_t \otimes H_t) \text{vec}(Q_t) \\ &= \mathcal{D}_k^+ (H_t^{-1} \otimes H_t^{-1}) \text{vec}(X_t) - \text{vech}(Q_t) \end{aligned}$$

□

E Proposition 2.4

Proof. As in the Wishart case, we can split

$$\frac{\partial l(X_t)}{\partial \text{vech}(Q_t)'} = \frac{\partial l(X_t)}{\partial \text{vec}(V_t)'} \frac{\partial \text{vec}(V_t)}{\partial \text{vec}(R_t)'} \frac{\partial \text{vec}(R_t)}{\partial \text{vec}(Q_t)'} \frac{\partial \text{vec}(Q_t)}{\partial \text{vech}(Q_t)'}$$

The only terms which is different from the previous model is the first one. The log-likelihood function is and get, using again $d \log |X| = \text{tr}(X^{-1}) dX$ and $d(X^{-1}) = -X^{-1} (dX) X^{-1}$

$$\begin{aligned} dl_{X_t} &= -\frac{\nu_1}{2} \text{tr}(V_t^{-1} dV_t) - \frac{\nu_1 + \nu_2}{2} \text{tr}(\tilde{W}_t^{-1} d\tilde{W}_t) \\ &=^* -\frac{\nu_1}{2} (\text{vec} V_t^{-1})' d\text{vec} V_t + \frac{\nu_1 + \nu_2}{2} \text{tr} \left(\tilde{W}_t^{-1} \frac{\nu_1}{\nu_2 - k - 1} V_t^{-1} dV_t V_t^{-1} X_t \right) \\ &= -\frac{\nu_1}{2} (\text{vec} V_t^{-1})' d\text{vec} V_t + \frac{\nu_1 + \nu_2}{2} \text{tr} \left(\frac{\nu_1}{\nu_2 - k - 1} V_t^{-1} X_t \tilde{W}_t^{-1} V_t^{-1} dV_t \right) \\ &= -\frac{\nu_1}{2} (\text{vec} V_t^{-1})' d\text{vec} V_t + \frac{\nu_1 + \nu_2}{2} \text{vec} \left(\frac{\nu_1}{\nu_2 - k - 1} V_t^{-1} X_t \tilde{W}_t^{-1} V_t^{-1} \right)' d\text{vec} V_t \end{aligned}$$

hence we obtain

$$\begin{aligned} \frac{\partial l(X_t)}{\partial \text{vec}(V_t)'} &= -\frac{\nu_1}{2} (\text{vec} V_t^{-1})' + \frac{\nu_1 + \nu_2}{2} \text{vec} \left(\frac{\nu_1}{\nu_2 - k - 1} V_t^{-1} X_t \tilde{W}_t^{-1} V_t^{-1} \right)' \\ &= \frac{\nu_1}{2} \left[(V_t^{-1} \otimes V_t^{-1}) \left(\frac{\nu_1 + \nu_2}{\nu_2 - k - 1} \text{vec} (X_t \tilde{W}_t^{-1}) - \text{vec}(V_t) \right) \right]'. \end{aligned}$$

Combining all the formulas together we get

$$\begin{aligned}
\frac{\partial l(X_t)}{\partial \text{vech}(Q_t)'} &= \frac{\nu_1}{2} \left(\frac{\nu_1 + \nu_2}{\nu_2 - k - 1} \text{vec} \left(X_t \tilde{W}_t^{-1} \right) - \text{vec} (V_t) \right)' (V_t^{-1} \otimes V_t^{-1}) (D_t \otimes D_t) \\
&\quad \times (\Delta_t^{-1} \otimes \Delta_t^{-1}) \Psi_t \mathcal{D}_k \\
&= \frac{\nu_1}{2} \left(\frac{\nu_1 + \nu_2}{\nu_2 - k - 1} \text{vec} \left(X_t \tilde{W}_t^{-1} \right) - \text{vec} (V_t) \right)' \\
&\quad \times (D_t^{-1} \Delta_t Q_t^{-1} \Delta_t D_t^{-1} \otimes D_t^{-1} \Delta_t Q_t^{-1} \Delta_t D_t^{-1}) (D_t \Delta_t^{-1} \otimes D_t \Delta_t^{-1}) \Psi_t' \mathcal{D}_k' \\
&= \frac{\nu_1}{2} \left(\frac{\nu_1 + \nu_2}{\nu_2 - k - 1} \text{vec} \left(X_t \tilde{W}_t^{-1} \right) - \text{vec} (V_t) \right)' (H_t^{-1} Q_t^{-1} \otimes H_t^{-1} Q_t^{-1})
\end{aligned}$$

□

F Proposition 2.5

Proof. Consider the multiplication $\mathcal{I}_t^W \nabla_t^F$, considering the same approximation of \mathcal{I}_t^W we used in D,

$$\begin{aligned}
s_t^F &= (\mathcal{D}_k' (H_t^{-1} Q_t^{-1} H_t \otimes H_t^{-1} Q_t^{-1} H_t) \mathcal{D}_k)^{-1} \mathcal{D}_k' \\
&\quad \times (H_t^{-1} Q_t^{-1} \otimes H_t^{-1} Q_t^{-1}) \left[\frac{\nu_1 + \nu_2}{\nu_2 - k - 1} \text{vec} \left(X_t \tilde{W}_t^{-1} \right) - \text{vec} (V_t) \right] \\
&= (\mathcal{D}_k' (H_t^{-1} Q_t^{-1} H_t \otimes H_t^{-1} Q_t^{-1} H_t) \mathcal{D}_k)^{-1} \mathcal{D}_k' (H_t^{-1} Q_t^{-1} H_t \otimes H_t^{-1} Q_t^{-1} H_t) \\
&\quad \times \mathcal{D}_k \mathcal{D}_k^+ (H_t^{-1} \otimes H_t^{-1}) \left[\frac{\nu_1 + \nu_2}{\nu_2 - k - 1} \text{vec} \left(X_t \tilde{W}_t^{-1} \right) - \text{vec} (V_t) \right] \\
&= \frac{\nu_1 + \nu_2}{\nu_2 - k - 1} \text{vech} \left(H_t^{-1} X_t \tilde{W}_t^{-1} H_t^{-1} \right) - \text{vech} (Q_t)
\end{aligned}$$

□

G Proposition 2.6

Proof. The proof is straightforward:

$$\begin{aligned}
\lim_{\nu_2 \rightarrow \infty} s_t^F &= \lim_{\nu_2 \rightarrow \infty} \frac{\nu_1 + \nu_2}{\nu_2 - k - 1} \text{vech} \left(H_t^{-1} X_t \tilde{W}_t^{-1} H_t^{-1} \right) - \text{vech} (Q_t) \\
&= \text{vech} \left(H_t^{-1} X_t \tilde{W}_t^{-1} H_t^{-1} \right) - \text{vech} (V_t) = s_t^W
\end{aligned}$$

since $\tilde{W}_t = I_k + \frac{\nu_1}{\nu_2 - k - 1} V_t^{-1} X_t$

□

H Figures of Section (3.2)

In this section, we report the figures of the experiment based on the misspecified DGP's presented in Section (3.2)

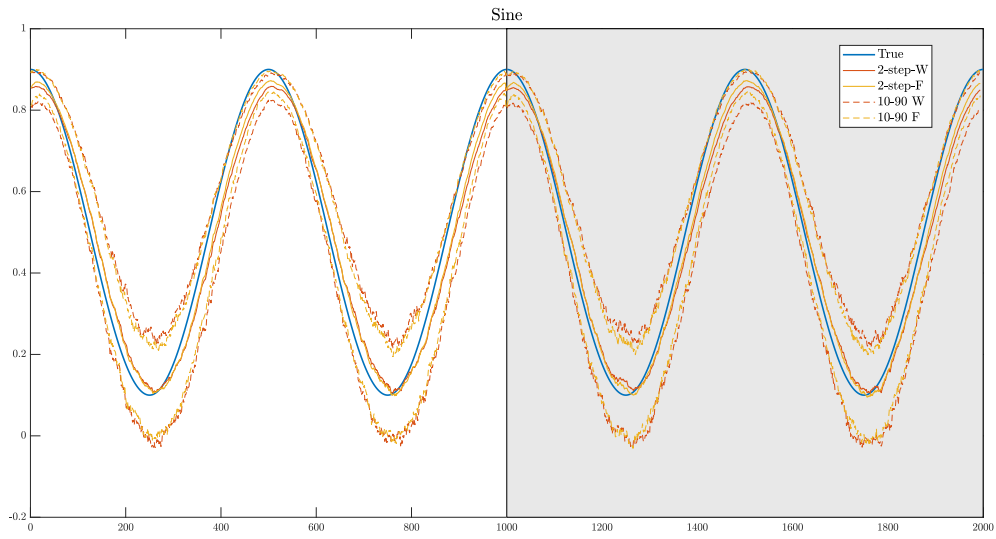


Figure 8: In-sample and out-of-sample filtered estimates of $\rho_t^{(1)}$ from both the 2-step-W and 2-step-F models. Estimates are averaged over the 1000 simulations. Confidence bands are constructed by computing the 10% and 90% empirical quantiles.

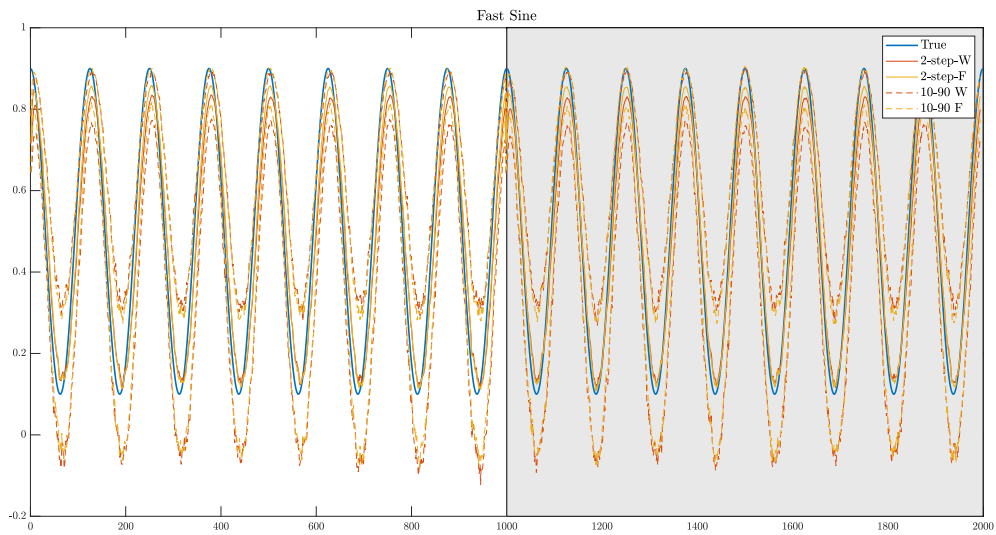


Figure 9: In-sample and out-of-sample filtered estimates of $\rho_t^{(2)}$ from both the 2-step-W and 2-step-F models. Estimates are averaged over the 1000 simulations. Confidence bands are constructed by computing the 10% and 90% empirical quantiles.

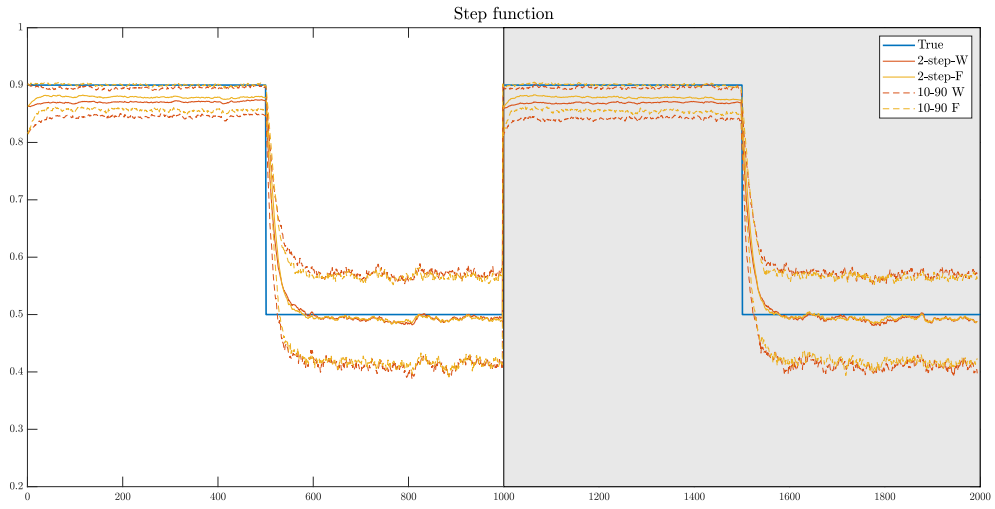


Figure 10: In-sample and out-of-sample filtered estimates of $\rho_t^{(3)}$ from both the 2-step-W and 2-step-F models. Estimates are averaged over the 1000 simulations. Confidence bands are constructed by computing the 10% and 90% empirical quantiles.

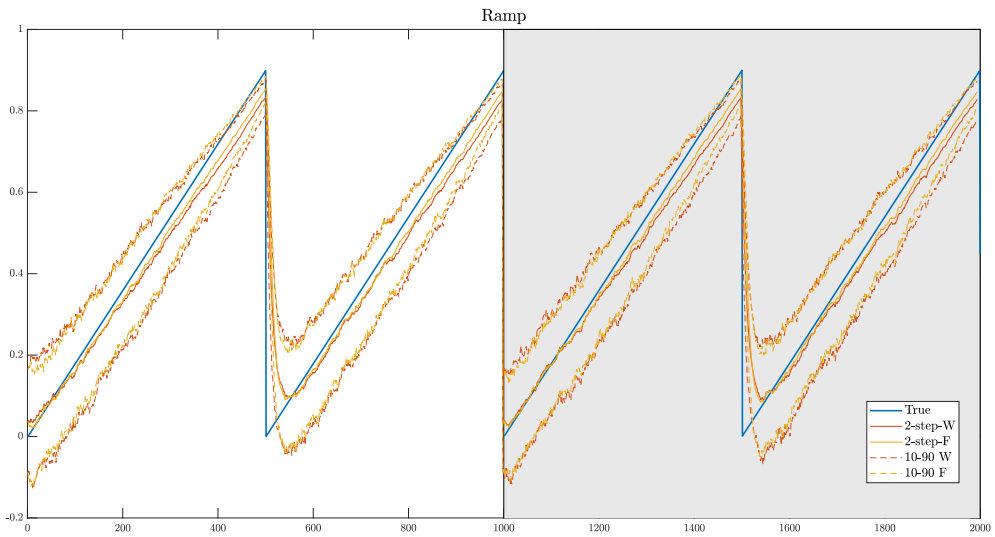


Figure 11: In-sample and out-of-sample filtered estimates of $\rho_t^{(4)}$ from both the 2-step-W and 2-step-F models. Estimates are averaged over the 1000 simulations. Confidence bands are constructed by computing the 10% and 90% empirical quantiles.