Appendix – Proof of Theorem

We first prove statement *(i)*. Let $\omega \in \Omega$ and $x := \xi_i(\omega)$; we will omit the ω -dependence hereafter. Let $v := \Psi^h_{\theta,s}(Z_{i-s+1:i})$. It follows from [\(8\)](#page-0-0) that

$$
z = v + x = Z_i + h\left(\beta_{-1}f(v,\theta) + \sum_{j=0}^{s-1} \beta_j f(Z_{i-j},\theta)\right) + x.
$$
 (12)

It follows by rearranging the terms in (12) that

$$
\frac{1}{\beta_{-1}}\left(\frac{z-Z_i}{h}-\sum_{j=0}^{s-1}\beta_j f(Z_{i-j},\theta)\right)=f(v,\theta)+\frac{x}{\beta_{-1}h}.
$$

By subtracting $f(z, \theta)$ from both sides, taking the norm, and squaring, we obtain

$$
\left\|\frac{1}{\beta_{-1}}\left(\frac{z-Z_i}{h}-\sum_{j=0}^{s-1}\beta_j f(Z_{i-j},\theta)\right)-f(z,\theta)\right\|^2=\left\|f(v,\theta)-f(z,\theta)+\frac{x}{\beta_{-1}h}\right\|^2.
$$

We may thus rewrite (6) as

$$
p(v+x|v,\theta,\eta,h) = \frac{1}{K} \exp\left(-\frac{1}{2\eta^2} \left\| f(v,\theta) - f(v+x,\theta) + \frac{x}{\beta-1h} \right\|^2\right). \tag{13}
$$

and it follows that the normalising constant is given by

$$
K(v, \theta, \eta, h) = \int_{\mathbb{R}^d} \exp \left(-\frac{1}{2\eta^2} \left\| f(v, \theta) - f(v+x, \theta) + \frac{x}{\beta - 1h} \right\|^2 \right) dx.
$$

We now bound the function described in $\sqrt{13}$ from above and below by unnormalised Gaussian probability densities. First note that by the triangle inequality and the assumption of global Lipschitz continuity we have the lower bound

$$
\left\| f(v, \theta) - f(v + x, \theta) + \frac{x}{\beta - 1h} \right\| \ge \left\| \frac{x}{\beta - 1h} \right\| - \left\| f(v, \theta) - f(v + x, \theta) \right\|
$$

$$
\ge \left\| \frac{x}{\beta - 1h} \right\| - L_{f, \theta} \left\| x \right\| = \left\| x \right\| \left((\beta - 1h)^{-1} - L_{f, \theta} \right).
$$

Similar reasoning yields the upper bound

$$
\left\| f(v, \theta) - f(v+x, \theta) + \frac{x}{\beta - 1h} \right\| \leq \|x\| \left(L_{f, \theta} + (\beta - 1h)^{-1} \right).
$$

Thus for $h > 0$, there exist constants c_h , $C_h > 0$ that do not depend on ω such that

$$
c_h ||x||^2 \le ||f(v, \theta) - f(v + x, \theta) + \frac{x}{\beta - 1}||^2 \le C_h ||x||^2
$$

where we have defined $c_h := \left((\beta - 1/h)^{-1} - L_f \theta \right)^2$ and $C_h := \left((\beta - 1/h)^{-1} + L_f \theta \right)^2$. Recall that by the definition of the AM method $\beta_{-1} > 0$. [\(13\)](#page-0-1) now gives

$$
\exp\left(-(2\eta^2)^{-1}C_h \|x\|^2\right) \le K(v,\theta,\eta,h) \cdot p\left(v+x|v,\theta,\eta,h\right) \le \exp\left(-(2\eta^2)^{-1}c_h \|x\|^2\right) \tag{14}
$$

where we note that the lower and upper bounds in (14) do not depend on *v*. In what follows, we will omit the dependence of p and K on v and θ , and write $p_h(\cdot) := p(\cdot|v, \theta, \eta, h)$ and $K_h :=$ $K(v, \theta, \eta, h)$, in order to emphasise the dependence of these quantities on *h*.

The interpretation of $\sqrt{14}$ is that, up to normalisation, the random variable ξ_i has a Lebesgue density that lies between the densities of two centred Gaussian random variables.

Integrating each of the three terms in $\sqrt{14}$ with respect to x and using the formula for the normalising constant of a Gaussian measure on \mathbb{R}^d , we obtain from the hypotheses $\eta = kh^\rho$ and $1 - L_{f,\theta}\beta_{-1}h > 0$ that

$$
\left(\frac{\sqrt{2\pi}kh^{\rho+1}\beta_{-1}}{1+L_{f,\theta}\beta_{-1}h}\right)^{d} = \left(\frac{2\pi\eta^{2}}{C_{h}}\right)^{d/2} =: K_{C,h} \le K_{h} \le K_{c,h} := \left(\frac{2\pi\eta^{2}}{c_{h}}\right)^{d/2} = \left(\frac{\sqrt{2\pi}kh^{\rho+1}\beta_{-1}}{1-L_{f,\theta}\beta_{-1}h}\right)^{d} \tag{15}
$$

Note that $K_{C,h}$ and $K_{c,h}$ are the normalising constants for the Gaussian random variables $\zeta_{C,h} \sim$ $N(0, (\eta^2/C_h)I_d)$ and $\zeta_{c,h} \sim N(0, (\eta^2/c_h)I_d)$ respectively, where I_d denotes the $d \times d$ identity matrix.

Since $\rho + 1 \ge 0$, the upper and lower bounds in $\sqrt{15}$ are respectively finite and strictly positive. This proves *(i)*.

To prove *(ii)*, observe that $(\sqrt{15})$ yields that, for all $0 < h < (L_{f,\theta}\beta_{-1})^{-1}$ and $v \in \mathbb{R}^d$, we have

$$
1 \le \frac{K_{c,h}}{K_{C,h}} = \left(\frac{C_h}{c_h}\right)^{d/2} = \left(\frac{1 + L_{f,\theta}\beta_{-1}h}{1 - L_{f,\theta}\beta_{-1}h}\right)^d
$$
(16)

The upper bound decreases to 1 as *h* decreases to zero, since $L_{f,\theta}$, β_{-1} and *h* are all strictly positive. By the second inequality in (14) ,

$$
\mathbb{E}[\|v + \xi_i\|^2] = \mathbb{E}[\|Z_{i+1}\|^2] \n= \int_{\mathbb{R}^d} \|z\|^2 p(z|v, \theta, \eta, h) dz \n\le K_{c,h} K_h^{-1} \int_{\mathbb{R}^d} \|z\|^2 \exp\left(-\frac{c_h \|x\|^2}{2\eta^2}\right) (dx) \n= K_{c,h} K_h^{-1} \mathbb{E}[\|v + \zeta_{c,h}\|^2].
$$
\n(17)

Since the preceding inequalities hold for arbitrary $v \in \mathbb{R}^d$, we may set $v = 0$ in [\(13\)](#page-0-1). Using this fact and the fact that (16) implies that $\lim_{h\to 0} K_{c,h} K_h^{-1} = 1$, we only need to show $\mathbb{E}[\|\zeta_{c,h}\|^r] \leq$ $C_r h^{(\rho+1)r}$ for some $C_r > 0$ that does not depend on *h*. Consider the change of variables $x \mapsto$ $x' := x(\eta^2/c_h)^{-1/2}$. Since this is just a scaling, we have by the change of variables formula that $dx = (\eta^2/c_h)^{d/2} dx'$, and hence

$$
K_{c,h}^{-1} \int_{\mathbb{R}^d} ||x||^r \exp\left(-\frac{||x||^2}{2\eta^2/c_h}\right) dx
$$

= $\left(\frac{2\pi\eta^2}{c_h}\right)^{-d/2} \int_{\mathbb{R}^d} \left[\left(\frac{\eta^2}{c_h}\right)^{r/2} ||x'||^r \exp\left(-\frac{||x'||^2}{2}\right) \left(\frac{\eta^2}{c_h}\right)^{d/2} \right] dx'$
= $C_r \left(\frac{\eta^2}{c_h}\right)^{r/2}$
 $\leq C'_r h^{(\rho+1)r}.$ (18)

where we have used (15) in the first equation, and where C_r , $C'_r > 0$ do not depend on *h*.

To prove *(iii)*, we set $r = 2$ and $\rho \ge s + \frac{1}{2}$ in *(ii)* to obtain $\mathbb{E}[\|\xi_i\|^2] \le ch^{(2s+3)}$. Since *s* is the number of steps of the Adams–Moulton method of order $s + 1$, the random variable ξ_i^h satisfies the assumption in the statement of Theorem 3 in $Teymur$ et al. (2016) . It then follows from that result that

$$
\sup_{0 \le i h \le T} \mathbb{E} \|Z_i - x(t_i)\| \le c h^{2(s+1)}
$$

(Note: the *s* used here is different to *s* in the referenced paper, since we follow the usual convention in numerical analysis texts where the implicit multistep method of order s has $s - 1$ steps.) П

Appendix – MCMC Psuedo-code

Algorithm for sampling $p(\theta, Z|Y)$

```
1 INPUT \theta^{[1]}2 \xi^{[1]} \sim p(\xi)<br>3 FOR 1 \leq k3 FOR 1 \leq k \leq K<br>4 \phi^{[k,k]} \leftarrow p\phi^{[k,k]} \leftarrow p(Y|Z,\sigma)p(Z|\theta^{[k]},\xi^{[k]})p(\theta^{[k]})5 \theta^* \sim q(\cdot|\theta^{[k]})6 \phi^{[*,k]} \leftarrow p(Y|Z,\sigma)p(Z|\theta^*,\xi^{[k]})p(\theta^*)\alpha^{[k]} \leftarrow \min(1, \phi^{[*, k]}/\phi^{[k, k]})8 r^{[k]} \sim \mathcal{U}[0, 1]<br>9 IF r^{[k]} < a^{[k]}\sum_{k=1}^{\infty} r^{k} if \sum_{k=1}^{\infty} r^{k}10 \theta^{[k+1]} \leftarrow \theta^*<br>
11 \xi^{[k+1]} \sim \mathbb{P}_{\xi}11 \xi^{[k+1]} \sim \mathbb{P}_{\xi}<br>12 k \leftarrow k+112 k \leftarrow k + 1<br>13 ELSE
                   {\rm ELSE}14 \theta^{[k+1]} \leftarrow \theta^{[k]}<br>15 k \leftarrow k+115 k \leftarrow k + 1<br>16 END
                   \ensuremath{\mathrm{END}}17 END
18 OUTPUT \theta^{[2]}, \ldots, \theta^{[K]}
```