Internet Appendix

A Duan's Risk Neutralization

Consider the following model:

$$R_{t+1} = r + \lambda\sqrt{h_{t+1}} - \frac{1}{2}h_{t+1} + \sqrt{h_{t+1}}\varepsilon_{t+1}\,, \tag{A-1}$$

$$h_{t+1} = f\left(\{h_s, \varepsilon_s\}_{s\leq t} \;\middle|\; \Theta_h\right), \tag{A-2}$$

where the ε_t are i.i.d. $\mathcal{N}(0,1)$ under $\mathbb{P}$.

The risk-neutralization of Duan (1995) is a special case of Christoffersen, Elkamhi, Feunou, and Jacobs (CEFJ) (2010) in which the equivalent martingale measure (EMM) obtains by assuming that the Radon-Nikodym derivative is linear in stock return innovations. That is

$$\xi_\tau \equiv \left.\frac{\mathrm{d}\mathbb{Q}}{\mathrm{d}\mathbb{P}}\right|\mathcal{F}_\tau = \exp\left\{-\sum_{t=1}^{\tau}\left(\eta_t\varepsilon_t + \Psi_t^{\varepsilon}(\eta_t)\right)\right\}\,, \tag{A-3}$$

where Ψ_t^{ε} is the natural logarithm of the moment-generating function of the $\{\varepsilon_t\}$ innovations: that is, $\Psi_t^{\varepsilon}(\eta) = \frac{1}{2}\eta^2$.

For the $\mathbb{Q}$ measure defined by equation (A-3) to be an EMM, it must be that

$$\begin{aligned} 1 &= \mathbb{E}_{\text{t-1}}^{\mathbb{Q}}\left[\frac{S_t}{S_{t-1}}\Big/\frac{B_t}{B_{t-1}}\right] = \mathbb{E}_{\text{t-1}}^{\mathbb{P}}\left[\frac{\xi_t}{\xi_{t-1}}\frac{S_t}{S_{t-1}}\Big/\frac{B_t}{B_{t-1}}\right] \\ &= \mathbb{E}_{\text{t-1}}^{\mathbb{P}}\left[\exp\{-\eta_t\varepsilon_t - \Psi_t^{\varepsilon}(\eta_t)\}\exp\left\{\lambda\sqrt{h_t} - \tfrac{1}{2}h_t + \sqrt{h_t}\varepsilon_t\right\}\right] \\ \Leftrightarrow 0 &= \Psi_t^{\varepsilon}\left(\eta_t - \sqrt{h_t}\right) - \Psi_t^{\varepsilon}(\eta_t) + \lambda\sqrt{h_t} - \tfrac{1}{2}h_t\,, \end{aligned} \tag{A-4}$$

which implies that $\eta_t = \lambda, \forall t$. Hence, $\varepsilon_t^* = \varepsilon_t + \lambda \overset{\mathbb{Q}}{\sim} \mathcal{N}(0,1)$.

Replacing ε_t by $\varepsilon_t^* - \lambda$ in equations (A-1) and (A-2) yields

$$R_{t+1} = r - \frac{1}{2}h_{t+1} + \sqrt{h_{t+1}}\varepsilon_{t+1}^* , \tag{A-5}$$

$$h_{t+1} = f(\{h_s, \varepsilon_s^* - \lambda\}_{s \le t} \mid \Theta_h) . \tag{A-6}$$

A.1 Risk-Neutral Form of the NGARCH Model

Replacing ε_t by $\varepsilon_t^* - \lambda$ in the NGARCH model yields

$$h_{t+1} = \sigma^2 + \alpha h_t((\varepsilon_t^* - \lambda)^2 - 1 - 2\gamma(\varepsilon_t^* - \lambda)) + \beta(h_t - \sigma^2) . \tag{A-7}$$

Letting $\gamma^* = \gamma + \lambda$, I obtain

$$h_{t+1} = \sigma^2 + \alpha h_t(\varepsilon_t^{*2} - 1 - 2\gamma^*\varepsilon_t^*) + \alpha h_t(\gamma^{*2} - \gamma^2) + \beta(h_t - \sigma^2) . \tag{A-8}$$

Then, letting $\beta^* = \beta + \alpha(\gamma^{*2} - \gamma^2)$

$$h_{t+1} = (1-\beta)\sigma^2 + +\alpha h_t(\varepsilon_t^{*2} - 1 - 2\gamma^*\varepsilon_t^*) + \beta^* h_t . \tag{A-9}$$

Finally, letting $\sigma^{*2} = (1-\beta)\sigma^2/(1-\beta^*)$

$$h_{t+1} = (1-\beta^*)\sigma^{*2} + \alpha h_t(\varepsilon_t^{*2} - 1 - 2\gamma^*\varepsilon_t^*) + \beta^* h_t \tag{A-10}$$

$$= \sigma^{*2} + \alpha h_t(\varepsilon_t^{*2} - 1 - 2\gamma^*\varepsilon_t^*) + \beta^*(h_t - \sigma^{*2}) . \tag{A-11}$$

A.2 Risk-Neutral Form of the NGARCH(C) Model

Replacing ε_t by $\varepsilon_t^* - \lambda$ in the NGARCH(C) model yields

$$\text{(A-12)} \qquad h_{t+1} = q_{t+1} + \alpha_1 h_t((\varepsilon_t^* - \lambda)^2 - 1 - 2\gamma_1(\varepsilon_t^* - \lambda)) + \beta_1(h_t - q_t)\,,$$

$$\text{(A-13)} \qquad q_{t+1} = \sigma^2 + \alpha_2 h_t((\varepsilon_t^* - \lambda)^2 - 1 - 2\gamma_2(\varepsilon_t^* - \lambda)) + \beta_2(q_t - \sigma^2)\,.$$

Letting $\gamma_i^* = \gamma_i + \lambda$, I obtain

$$\text{(A-14)} \qquad h_{t+1} = q_{t+1} + \alpha_1 h_t(\varepsilon_t^{*2} - 1 - 2\gamma_1^*\varepsilon_t^*) + \alpha_1 h_t(\gamma_1^{*2} - \gamma_1^2) + \beta_1(h_t - q_t)\,,$$

$$\text{(A-15)} \qquad q_{t+1} = \sigma^2 + \alpha_2 h_t(\varepsilon_t^{*2} - 1 - 2\gamma_2^*\varepsilon_t^*) + \alpha_2 h_t(\gamma_2^{*2} - \gamma_2^2) + \beta_2(q_t - \sigma^2)\,.$$

By replacing q in h

$$\begin{aligned}
\text{(A-16)} \quad h_{t+1} &= \sigma^2 + \alpha_2 h_t(\varepsilon_t^{*2} - 1 - 2\gamma_2^*\varepsilon_t^*) + \alpha_2 h_t(\gamma_2^{*2} - \gamma_2^2) + \beta_2(q_t - \sigma^2) \\
&\qquad + \alpha_1 h_t(\varepsilon_t^{*2} - 1 - 2\gamma_1^*\varepsilon_t^*) + \alpha_1 h_t(\gamma_1^{*2} - \gamma_1^2) + \beta_1(h_t - q_t)\,, \\
&= \sigma^2 + \alpha_2 h_t(\varepsilon_t^{*2} - 1 - 2\gamma_2^*\varepsilon_t^*) + \alpha_1 h_t(\varepsilon_t^{*2} - 1 - 2\gamma_1^*\varepsilon_t^*) + \beta_2(q_t - \sigma^2) - \beta_1 q_t \\
&\qquad + [\beta_1 + \alpha_1(\gamma_1^{*2} - \gamma_1^2) + \alpha_2(\gamma_2^{*2} - \gamma_2^2))]h_t\,.
\end{aligned}$$

Then, letting $\beta_i^* = \beta_i + \alpha_1(\gamma_1^{*2} - \gamma_1^2) + \alpha_2(\gamma_2^{*2} - \gamma_2^2)$

$$\begin{aligned}
\text{(A-17)} \quad h_{t+1} &= (1 - \beta_2)\sigma^2 + \alpha_2 h_t(\varepsilon_t^{*2} - 1 - 2\gamma_2^*\varepsilon_t^*) + \alpha_1 h_t(\varepsilon_t^{*2} - 1 - 2\gamma_1^*\varepsilon_t^*) + \beta_1^* h_t \\
&\qquad + [\beta_2^* - \alpha_1(\gamma_1^{*2} - \gamma_1^2) + \alpha_2(\gamma_2^{*2} - \gamma_2^2)]q_t - [\beta_1^* - \alpha_1(\gamma_1^{*2} - \gamma_1^2) + \alpha_2(\gamma_2^{*2} - \gamma_2^2)]q_t \\
&= (1 - \beta_2)\sigma^2 + \alpha_1 h_t(\varepsilon_t^{*2} - 1 - 2\gamma_1^*\varepsilon_t^*) + \beta_1^*(h_t - q_t) + \alpha_2 h_t(\varepsilon_t^{*2} - 1 - 2\gamma_2^*\varepsilon_t^*) + \beta_2^* q_t\,.
\end{aligned}$$

Finally, letting $\sigma^{*2} = (1-\beta_2)\sigma^2/(1-\beta_2^*)$

$$
\begin{aligned}
\text{(A-18)} \quad h_{t+1} &= (1-\beta_2^*)\sigma^{*2} + \alpha_2 h_t(\varepsilon_t^{*2} - 1 - 2\gamma_2^*\varepsilon_t^*) + \beta_2^* q_t + \alpha_1 h_t(\varepsilon_t^{*2} - 1 - 2\gamma_1^*\varepsilon_t^*) + \beta_1^*(h_t - q_t) \\
&= \sigma^{*2} + \alpha_2 h_t(\varepsilon_t^{*2} - 1 - 2\gamma_2^*\varepsilon_t^*) + \beta_2^*(q_t - \sigma^{*2}) + \alpha_1 h_t(\varepsilon_t^{*2} - 1 - 2\gamma_1^*\varepsilon_t^*) + \beta_1^*(h_t - q_t) \\
\Leftrightarrow h_{t+1} &= q_{t+1} + \alpha_1 h_t(\varepsilon_t^{*2} - 1 - 2\gamma_1^*\varepsilon_t^*) + \beta_1^*(h_t - q_t)\,, \\
q_{t+1} &= \sigma^{*2} + \alpha_2 h_t(\varepsilon_t^{*2} - 1 - 2\gamma_2^*\varepsilon_t^*) + \beta_2^*(q_t - \sigma^{*2})\,.
\end{aligned}
$$

B Risk Neutralization with Macro-Finance Variables

Assume that the macro-finance variable under consideration follows a dynamics of the form

$$
\text{(B-1)} \qquad x_{t+1} = \varphi\left(\{x_s, u_s\}_{s\le t} \middle| \Theta_x\right) + \sigma_x\, u_{t+1}
$$

where $u_t \overset{\mathbb{P}}{\sim} \mathcal{N}(0,1)$ are serially uncorrelated macroeconomic innovations.[21]

Given that asset returns are potentially correlated with macroeconomic innovations, I consider a GARCH model of the form

$$
\begin{aligned}
\text{(B-2)} \qquad R_{t+1} &= r + \lambda_{t+1}\sqrt{h_{t+1}} - \tfrac{1}{2}h_{t+1} + \sqrt{h_{t+1}}(\rho u_{t+1} + \sqrt{1-\rho^2}z_{t+1}) \\
\text{(B-3)} \qquad h_{t+1} &= f(\,\cdot \mid \Theta, \mathcal{F}_t)\,,
\end{aligned}
$$

[21]The volatility of the series could follow a GARCH process, i.e. $\sigma_{x,t+1} = \varphi_\sigma\left(\{\sigma_{x,s}, u_s\}_{s\le t} \middle| \Theta_{\sigma_x}\right)$. For simplicity, I here assume constant volatility.

where λ_{t+1} and h_{t+1} are $\mathcal{F}_t$-measurable and $z_t \overset{\mathbb{P}}{\sim} \mathcal{N}(0,1)$ may be seen as a "pure-market" innovation process, independent of u_t. To formally demonstrate the risk neutralization of u_t and z_t, I here draw on CEFJ (2010) for the treatment of two-shock stochastic volatility models (see CEFJ's (2010) Section 7). Note that my model is, however, fundamentally different from a stochastic volatility model because in my case the "second" shock, u_{t+1}, does not contemporaneously impact the variance; instead, it impacts the mean of the return process. I will return to the implications of this fundamental difference shortly.

First, I write the risk neutralization of my return process in terms of the risk neutralization of the bivariate, uncorrelated normal innovations $\{u_t, z_t\}$ using the following Radon-Nikodym derivative:

$$\text{(B-4)} \qquad \xi_\tau \equiv \left.\frac{\mathrm{d}\mathbb{Q}}{\mathrm{d}\mathbb{P}}\right| \mathcal{F}_\tau = \exp\left\{-\sum_{t=1}^{\tau}\left(\eta_{u,t}u_t + \eta_{z,t}z_t + \Psi_t^{u,z}\left(\eta_{u,t},\eta_{z,t}\right)\right)\right\} ,$$

where $\Psi_t^{u,z}$ is the natural logarithm of the moment-generating function of the $\{u_t, z_t\}$ pairs, that is,

$$\text{(B-5)} \qquad \Psi_t^{u,z}\left(\eta_u,\eta_z\right) = \tfrac{1}{2}\left(\eta_u^2 + \eta_z^2\right) .$$

For the probability measure $\mathbb{Q}$ defined by the Radon-Nikodym derivative of equation (B-4) to be an equivalent martingale measure (EMM), it must be the case that

$$\text{(B-6)} \quad \begin{aligned} 1 &= \mathbb{E}_{\text{t-1}}^{\mathbb{Q}}\left[\frac{S_t}{S_{t-1}}\Big/\frac{B_t}{B_{t-1}}\right] = \mathbb{E}_{\text{t-1}}^{\mathbb{P}}\left[\frac{\xi_t}{\xi_{t-1}}\frac{S_t}{S_{t-1}}\Big/\frac{B_t}{B_{t-1}}\right] \\ &= \mathbb{E}_{\text{t-1}}^{\mathbb{P}}\left[\exp\left\{-\eta_{u,t}u_t - \eta_{z,t}z_t - \Psi_t^{u,z}\left(\eta_{u,t},\eta_{z,t}\right)\right\}\exp\left\{\lambda_t\sqrt{h_t} - \tfrac{1}{2}h_t + \sqrt{h_t}(\rho u_t + \sqrt{1-\rho^2}z_t)\right\}\right] \end{aligned}$$

or, equivalently,

$$\text{(B-7)} \qquad 0 = \Psi_t^{u,z}\left(\eta_{u,t} - \rho\sqrt{h_t}\,, \eta_{z,t} - \sqrt{(1-\rho^2)h_t}\right) - \Psi_t^{u,z}\left(\eta_{u,t}, \eta_{z,t}\right) + \lambda_t\sqrt{h_t} - \tfrac{1}{2}h_t\,,$$

which boils down to

$$\text{(B-8)} \qquad \rho\eta_{u,t} + \sqrt{1-\rho^2}\eta_{z,t} = \lambda_t\,.$$

Equation (B-8) admits an infinite number of solutions. However, as highlighted above, my model has the specificity that both shocks affect the mean of the return process. Thus, the bivariate normal shocks may be seen as blending into a single stream of standard normal innovations $\{\varepsilon_t\}$ and equation (B-2) is equivalent to

$$\text{(B-9)} \qquad R_{t+1} = r + \lambda_{t+1}\sqrt{h_{t+1}} - \tfrac{1}{2}h_{t+1} + \sqrt{h_{t+1}}\varepsilon_{t+1}\,.$$

This last equation is that of Duan (1995), which is a special case of CEFJ (2010) for which the (linear) Radon-Nikodym derivative can be written as

$$\text{(B-10)} \qquad \xi_\tau \equiv \left.\frac{\mathrm{d}\mathbb{Q}}{\mathrm{d}\mathbb{P}}\right|\mathcal{F}_\tau = \exp\left\{-\sum_{t=1}^{\tau}\left(\eta_t\varepsilon_t + \Psi_t^{\varepsilon}\left(\eta_t\right)\right)\right\}\,,$$

where Ψ_t^{ε} is the natural logarithm of the moment-generating function of the $\{\varepsilon_t\}$ innovations: that is, $\Psi_t^{\varepsilon}(\eta) = \frac{1}{2}\eta^2$. Again, for the $\mathbb{Q}$ measure defined by equation (B-10) to be an EMM, it must be

that

$$\text{(B-11)} \qquad \begin{aligned} 1 &= \mathbb{E}^{\mathbb{Q}}_{\text{t-1}}\left[\frac{S_t}{S_{t-1}}\Big/\frac{B_t}{B_{t-1}}\right] = \mathbb{E}^{\mathbb{P}}_{\text{t-1}}\left[\frac{\xi_t}{\xi_{t-1}}\frac{S_t}{S_{t-1}}\Big/\frac{B_t}{B_{t-1}}\right] \\ &= \mathbb{E}^{\mathbb{P}}_{\text{t-1}}\left[\exp\{-\eta_t\varepsilon_t - \Psi^{\varepsilon}_t(\eta_t)\}\exp\left\{\lambda_t\sqrt{h_t} - \tfrac{1}{2}h_t + \sqrt{h_t}\varepsilon_t\right\}\right] \\ \Leftrightarrow 0 &= \Psi^{\varepsilon}_t\left(\eta_t - \sqrt{h_t}\right) - \Psi^{\varepsilon}_t(\eta_t) + \lambda_t\sqrt{h_t} - \tfrac{1}{2}h_t\,, \end{aligned}$$

which implies that $\eta_t = \lambda_t, \forall t$. For equations (B-4) and (B-10) to describe the same Radon-Nikodym derivative, it must be that

$$\text{(B-12)} \qquad \begin{aligned} \xi_\tau &= \exp\left\{-\sum_{t=1}^{\tau}\left(\lambda_t\varepsilon_t + \tfrac{1}{2}\lambda_t^2\right)\right\} \\ &= \exp\left\{-\sum_{t=1}^{\tau}\left(\lambda_t\rho u_t + \lambda_t\sqrt{1-\rho^2}z_t + \tfrac{1}{2}\overbrace{\left(\rho^2\eta_{u,t}^2 + 2\rho\sqrt{1-\rho^2}\eta_{u,t}\eta_{z,t} + (1-\rho^2)\eta_{z,t}^2\right)}^{\text{Using equation (B-8)}}\right)\right\} \\ &= \exp\left\{-\sum_{t=1}^{\tau}\left(\eta_{u,t}u_t + \eta_{z,t}z_t + \Psi^{u,z}_t(\eta_{u,t},\eta_{z,t})\right)\right\} \end{aligned}$$

where the last equality holds if and only if for all t,

$$\text{(B-13)} \qquad \eta_{u,t} = \rho\lambda_t \quad \text{and} \quad \eta_{z,t} = \sqrt{1-\rho^2}\lambda_t\,.$$

I thus have

$$\text{(B-14)} \qquad u_t^* = u_t + \rho\lambda_t$$

$$\text{(B-15)} \qquad z_t^* = z_t + \sqrt{1-\rho^2}\lambda_t\,,$$

that is, the mean shift on each process is proportional to the correlation of that process with total market innovations. Notably, if ρ=0, that is if market shocks and macroeconomic shocks were uncorrelated, the latter would be unaffected by the risk neutralization.

Finally, observing that both processes u_t^* and z_t^* are standard normal under $\mathbb{Q}$, I end with the familiar risk-neutralization from Duan (1995)

$$\varepsilon_t^* = \varepsilon_t + \lambda_t = \rho u_t^* + \sqrt{1-\rho^2} z_t^* \,. \tag{B-16}$$

The risk-neutral form of the MacroGARCH model is thus a straightforward extension of that typically used for the NGARCH(C) model (Appendix A.2). This leads to the risk-neutral form of the model in Equations (21) to (23).

To simulate this risk-neutral form of the model, the question remains as to how to forecast the future values of the ADS business conditions index. First, by construction, $\rho = \mathrm{Corr}(\varepsilon_t, u_t)$ is the correlation between market returns and macroeconomic innovations. In the estimation of my model, the dynamics of x_t, and thus the u_ts, are assumed to be exogenous. Therefore, an estimate of ρ may be obtained simply by measuring the correlation between the filtered ε_ts and the u_ts. Filtering the ε_ts using the MacroGARCH model and the u_ts assuming that the index follows an AR(1), as in ADS (2009), the correlation that I obtain is 1.99% with a p-value of 6.3%. The correlation is thus not statistically significant, and more importantly not economically significant. Second, the estimate of the autoregressive coefficient is 0.9992 and is not significantly different from 1 at the 5% level. Based on these two observations, I simply assume that the best forecast for future fundamental volatility is its current value; that is, I set $\tau_{t+k} = \tau_t$ when forecasting at time t. I do the same for the RP-based version of the model. For the VIX-based model, I fit an

AR(1) process to the natural logarithm of the VIX over the estimation period. This model is used to simulate the VIX in the Monte Carlo pricing. As expected, the (log-) VIX model's innovations are highly correlated with return innovations as $\mathrm{Corr}(\varepsilon_t, u_t) = -0.649$.

Table IA.1: Option-Pricing Results: IVRMSE for the Alternative Specifications (Estimation Period, 1990/05–2007/11)

Table IA.1 reports the IVRMSE results corresponding to the results in Table 7. More specifically, this table reports, in percentage points, the average IVRMSE for various subsamples of options during the estimation period. For each subsample, I also report t-stats (in parentheses) on the average of $\text{IVRMSE}_w^{\mathcal{M}} - \text{IVRMSE}_w^{\text{AMG(C)}}$, to assess whether model $\mathcal{M}$ is significantly outperformed by the asymmetric MacroGARCH(C) model (AMG(C)); negative t-stats arise when $\mathcal{M}$ dominates. The t-stats are computed using Newey-West standard errors with a lag of 12 weeks and are bold whenever their magnitude is larger than 1.96. Additionally, I report the ratio [in square brackets] of the model's pricing error to that of the ADS-based asymmetric MacroGARCH(C) model.

	IVRMSE				
			MacroGARCH(C)		
	NGARCH(C)	NGARCH(C_3)	Rec. Prob.	VIX	Asym. ADS
All options	3.93	3.84	3.85	3.31	3.71
	(6.94)	**(3.33)**	**(6.68)**	**(-3.31)**	–
	[1.06]	[1.03]	[1.04]	[0.89]	[1.00]
Maturity					
Short-Term	3.71	3.69	3.63	3.34	3.55
	(6.59)	**(4.27)**	**(4.38)**	(-1.98)	–
	[1.04]	[1.04]	[1.02]	[0.94]	[1.00]
Medium-Term	3.80	3.69	3.70	3.17	3.60
	(7.19)	**(2.70)**	**(4.90)**	**(-3.28)**	–
	[1.06]	[1.03]	[1.03]	[0.88]	[1.00]
Long-Term	3.99	3.86	3.93	3.14	3.72
	(6.34)	**(2.75)**	**(8.18)**	**(-3.70)**	–
	[1.07]	[1.04]	[1.06]	[0.85]	[1.00]
Calls					
All	1.96	1.91	1.89	2.27	1.88
	(2.67)	(0.78)	(1.10)	**(3.29)**	–
	[1.04]	[1.02]	[1.01]	[1.21]	[1.00]
ATM	2.13	2.07	2.06	2.08	2.01
	(3.59)	(1.36)	**(2.54)**	(0.62)	–
	[1.06]	[1.03]	[1.02]	[1.03]	[1.00]
OTM	1.88	1.83	1.82	2.37	1.81
	(2.19)	(0.51)	(0.45)	**(4.50)**	–
	[1.04]	[1.01]	[1.00]	[1.31]	[1.00]
Puts					
All	4.63	4.52	4.53	3.68	4.35
	(7.27)	**(3.74)**	**(7.22)**	**(-5.19)**	–
	[1.06]	[1.04]	[1.04]	[0.84]	[1.00]
ATM	2.53	2.46	2.47	2.27	2.40
	(3.98)	(1.67)	**(3.16)**	(-1.07)	–
	[1.06]	[1.03]	[1.03]	[0.95]	[1.00]
OTM	4.99	4.88	4.89	3.91	4.69
	(7.51)	**(3.96)**	**(7.72)**	**(-5.69)**	–
	[1.06]	[1.04]	[1.04]	[0.83]	[1.00]

Table IA.2: Option-Pricing Results: IVRMSE for the Alternative Specifications (Out-of-Sample, 2007/12–2010/10)

Table IA.2 reports the IVRMSE results corresponding to the results in Table 8. More specifically, this table reports, in percentage points, the average IVRMSE for various subsamples of options between Dec. 2007 and Oct. 2010 (out-of-sample). For each subsample, I also report t-stats (in parentheses) on the average of $\text{IVRMSE}_w^{\mathcal{M}} - \text{IVRMSE}_w^{\text{AMG(C)}}$, to assess whether model $\mathcal{M}$ is significantly outperformed by the asymmetric MacroGARCH(C) model (AMG(C)); negative t-stats arise when $\mathcal{M}$ dominates. The t-stats are computed using Newey-West standard errors with a lag of 12 weeks and are bold whenever their magnitude is larger than 1.96. Additionally, I report the ratio [in square brackets] of the model's pricing error to that of the ADS-based asymmetric MacroGARCH(C) model.

	IVRMSE				
			MacroGARCH(C)		
	NGARCH(C)	NGARCH(C_3)	Rec. Prob.	VIX	Asym. ADS
All options	6.07	5.87	5.67	7.35	5.54
	(5.04)	**(4.80)**	**(2.91)**	**(2.49)**	–
	[1.10]	[1.06]	[1.02]	[1.33]	[1.00]
Maturity					
Short-Term	5.51	5.41	5.28	6.52	5.20
	(5.27)	**(4.03)**	**(2.83)**	**(2.52)**	–
	[1.06]	[1.04]	[1.02]	[1.25]	[1.00]
Medium-Term	5.86	5.62	5.50	7.22	5.40
	(4.55)	**(2.94)**	**(2.28)**	**(2.39)**	–
	[1.09]	[1.04]	[1.02]	[1.34]	[1.00]
Long-Term	6.83	6.54	6.24	8.53	6.01
	(4.32)	**(4.15)**	**(2.99)**	**(2.47)**	–
	[1.14]	[1.09]	[1.04]	[1.42]	[1.00]
Calls					
All	3.21	2.98	3.15	4.79	3.19
	(0.08)	(-1.01)	(-0.59)	**(3.51)**	–
	[1.01]	[0.93]	[0.99]	[1.50]	[1.00]
ATM	3.26	3.03	2.94	5.12	2.96
	(1.92)	(0.48)	(-0.31)	**(3.82)**	–
	[1.10]	[1.02]	[0.99]	[1.73]	[1.00]
OTM	3.07	2.84	3.05	4.70	3.10
	(-0.15)	(-1.19)	(-0.64)	**(3.40)**	–
	[0.99]	[0.92]	[0.98]	[1.52]	[1.00]
Puts					
All	7.01	6.80	6.39	8.57	6.14
	(6.70)	**(4.64)**	**(4.07)**	**(2.31)**	–
	[1.14]	[1.11]	[1.04]	[1.40]	[1.00]
ATM	3.63	3.42	3.17	5.64	3.15
	(3.83)	**(2.74)**	(0.32)	**(3.17)**	–
	[1.15]	[1.08]	[1.01]	[1.79]	[1.00]
OTM	7.32	7.11	6.68	8.87	6.41
	(6.77)	**(4.60)**	**(4.10)**	**(2.27)**	–
	[1.14]	[1.11]	[1.04]	[1.38]	[1.00]