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Forecasting Volatility of UK natural gas futures

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Outline

1. Motivation
2. Background
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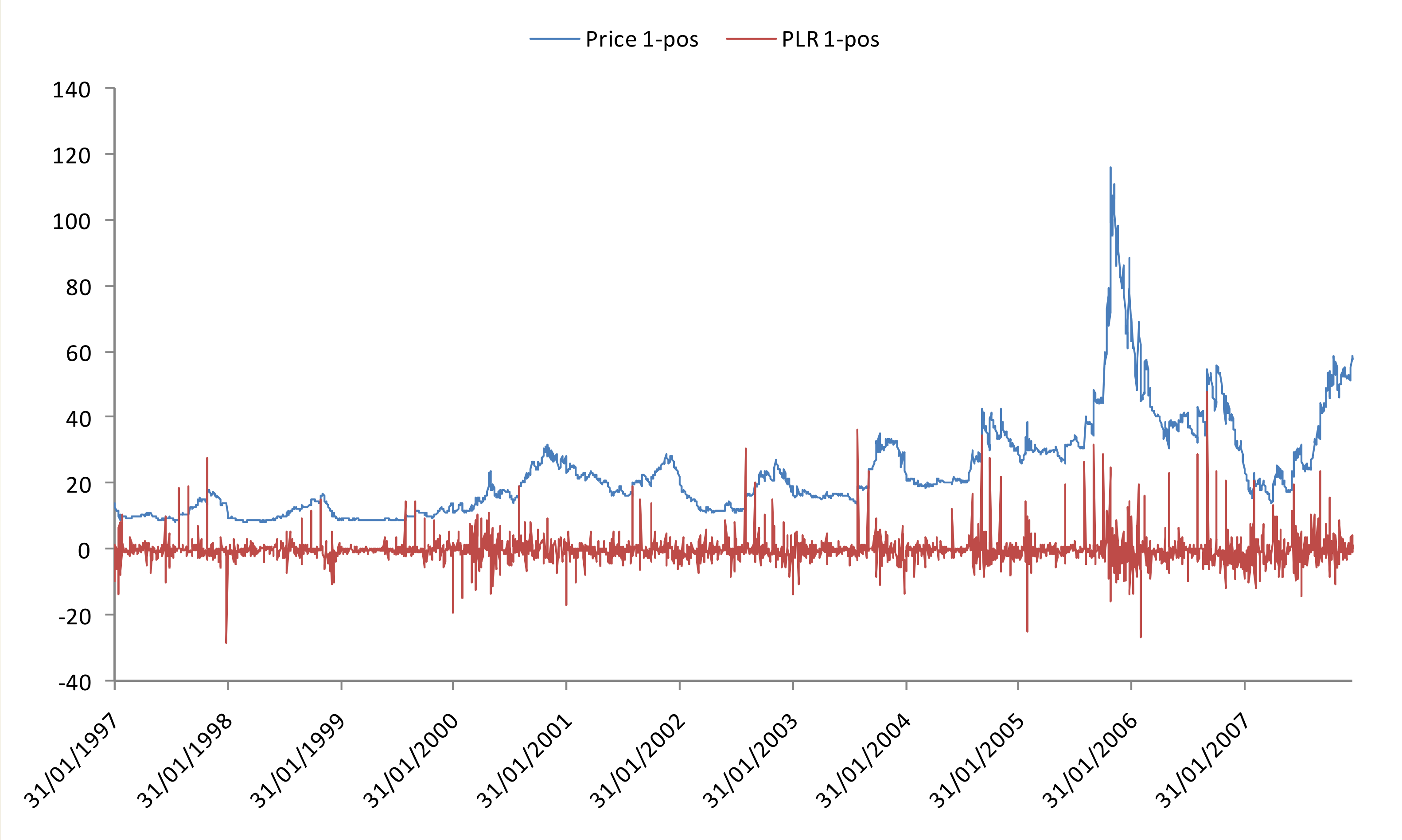
Motivation

- Previous research has focused on US natural gas futures
- There is reason to believe that the UK situation is different from that of the US
- There have been very few attempts to model, much less, forecast UK natural gas futures
- We apply new techniques for this particular geographical area.
- We try to fill the knowledge gap

Motivation continued

- Why this is important?
  - There is insecurity in resource supply during the winter.
  - Volatility estimation and forecasting is necessary for reserve requirement planning.
  - Volatility estimation and forecasting is necessary for defining Value-at-Risk (VaR) quantiles, VaR accuracy, and expected shortfall.
  - VaR is now a standard means of assessing risk.

Background



Price 1-pos
PLR 1-pos
140
120
100
80
60
40
20
0
-20
-40
31/01/1997
31/01/1998
31/01/1999
31/01/2000
31/01/2001
31/01/2002
31/01/2003
31/01/2004
31/01/2005
31/01/2006
31/01/2007

Background

- Deregulation has led to calls for redefinition of risk in the 1990s in this market.
- Linkage to the European Interconnector and North Sea pipelines distinguishes this market from that of the U.S. situation where most of the previous research on volatility was focused.
- Insecurity of supply during winter months has increased volatility.
- Volatility increases reserve requirements and general demand.
- 45% of UK electricity in 2007 came from natural gas supplies, so this is an important factor of production and consideration in the cost of living in the U.K.

Research problems

1. Can we model UK natural gas futures with GARCH models?
2. What are the best models for all positions?
3. How valid are these models?
4. How stable are these models?
5. How does volatility affect percentage log returns?
6. Which models forecast best for each of 9 positions over 1, 5, 10 and 20 trading days?

Data

- Time frame: 1997 thru 2007
- Unit for analysis of price: GBPence/therm
- Daily percentage log returns: $100*(\ln(P)_t/P_{t-1}))$
- 9 months positions (postponed 1 through 9 months)
- Data from Inter-Continental Exchange (ICE)

Methods 1

- Preliminary Analysis
  - ACF, PACF of PLR suggest occasionally AR(1) or AR(1/2)
  - ADF tests suggest mean (not necessarily variance) stationarity of PLR.
  - Geweke Porter Hudak tests suggest no long memory
  - Sign-bias tests generally indicate no asymmetry
- GARCH mining
  - Based on lowest Schwartz Criterion

Methods 2

- Residual diagnostics
  - Portmanteau tests of standardized residuals
  - Portmanteau tests of squared residuals
  - Tse’s Residual Based Diagnostics test

$$E(z_t^2 - 1) = \alpha_1 z_{t-1}^2 + \alpha_2 z_{t-2}^2 + \ldots + \alpha_{t-p}^p$$

- Nyblom stability tests
  - Individual and joint tests were run.

RiskMetrics Model

mean model :

$$plr_t = c + \sum_{i=1}^{p} \phi_i plr_{t-i} - \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \delta_1 \sigma_t^2 + \delta_2 R_t + \varepsilon_t$$

RiskMetrics variance model :

$$\sigma_t^2 = \omega + (1-\lambda)\varepsilon_{t-1}^2 + \lambda \sigma_{t-1}^2 + bR_t$$

where

$c = constant$

$\varepsilon_t = z_t \sigma_t$

$z_t \sim i.i.d.t(0,1,v)$

$R_t = contract\ rollover\ dummy\,(last\ working\ day\ /\ month)$

$\lambda = 0.94$

RiskMetrics Forecasting Model

$$mean\ \ forecasting\ \ model:$$

$$plr_{t+h|t} = c + \sum_{i=1}^{p} \phi_i plr_{t+h-i|t} - \sum_{j=1}^{q} \theta_j \varepsilon_{t+h-j|t} + \delta_1 \sigma^2_{t+h|t} + \delta_2 R_{t+h|t} + \varepsilon_t$$

$$RiskMetrics\ variance\ \ forecasting\ \ model:$$

$$\sigma^2_{t+h|t} = \omega + (1-\lambda)\varepsilon^2_{t+h-1|t} + \lambda\sigma^2_{t+h-1|t} + bR_{t+h|t}$$

$$where\ h = \ forecast\ \ horizon\ of\ \ 1,5,10, and\ 20\ leads$$

APGARCH variance Model

APGARCH variance model :

$$\sigma_t^{\delta} = \omega + \sum_{i=1}^{q} \alpha_i (| \varepsilon_{t-i} | - \gamma_i \varepsilon_{t-i})^{\delta} + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^{\delta} + bR_t$$

γ measures the leverage (asymmetry) in the response of conditional variance to positive and negative shocks.

R_t is the rollover dummy,

δ is the power to which the conditional standard deviation is taken, as in a Box-Cox transformation. δ is the power parameter in the variance model

δ_1 is the arch-in-mean conditional variance included in the mean model, which is the same mean model for the RiskMetrics model.

The distribution is Student- t, with the degrees of freedom estimated by the model.

APGARCH complete model

APGARCH mean model :

$$plr_t = c + \sum_{i=1}^{p} \phi_i \, plr_t - \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \delta_1 \sigma_t^2 + \delta_2 R_t + \varepsilon_t$$

APGARCH variance model :

$$\sigma_t^\delta = \omega + \sum_{i=1}^{q} \alpha_i (|\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-i})^\delta + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^\delta + bR_t$$

APGARCH Forecasting model

APGARCH mean forecasting model :

$$plr_{t+h|t} = c + \sum_{i=1}^{p} \phi_i \, plr_{t+h-i|t} + \sum_{j=1}^{q} \theta_j \varepsilon_{t+h-j|t} + \delta_1 \sigma_{t+h|t}^2 + \delta_2 R_{t+h|t} + \varepsilon_{t+h|t}$$

APGARCH variance forecasting model :

$$\sigma_{t+h|t}^{\delta} = \omega + \sum_{i=1}^{q} \alpha_i \left(| \varepsilon_{t+h-i|t} | - \gamma_i \varepsilon_{t+h-i|t} \right)^{\delta} + \sum_{j=1}^{p} \beta_j \sigma_{t+h-j|t}^{\delta} + bR_{t+h|t}$$

Algorithms

- Broyden, Fletcher, Goldfarb, and Shanno (BFGS)
  - Quasi-Newton maximum likelihood
  - Quite fast
  - Only worked with RiskMetrics
- Simulated Annealing (Sa or MaxSa)
  - Worked with both RM and APGARCH
  - Resampling routine escapes local optima
  - Quite slow
  - Generally better fit
- When tied for performance, BFGS wins owing to speed.

Methods 3

1. Forecasting
   1. Mean and variance over four horizons: 1, 5, 10, 20 trading days

2. Forecast evaluation
   1. mean square error
   2. mean absolute error
   3. mean absolute percentage error
   4. logarithmic loss function

Mean Square Forecast Error

$$MSFE(h) = \frac{1}{h}\sum_{j=1}^{h}(\hat{\sigma}_{T+j} - \sigma_{T+j})^2$$

$$where$$

$$h = \ forecast \ horizon \ length$$

$$T = largest \ number \ of \ in - sample \ obs$$

Mean Absolute Error

$$MAE = \frac{1}{h}\sum_{j=1}^{h}|\,\hat{\sigma}_{T+j} - \sigma_{T+j}\,|$$

Mean Absolute Percentage Error

$$MAPE = \frac{100}{h} \sum_{j}^{h} \frac{|\,\hat{\sigma}_{T+j} - \sigma_{T+j}\,|}{\sigma_{T+j}}$$

Logarithmic Loss Function

$$LL = \frac{1}{h} \sum_{j=1}^{h} \left[\ln(\varepsilon_{T+j}^{2}) - \ln(\hat{\sigma}_{T+j}^{2}) \right]^{2}$$

Results

- We tried GARCH, EGARCH, GJRGARCH, IGARCH, RiskMetrics GARCH and APGARCH.
- We find that only RiskMetrics GARCH and APGARCH can model all nine positions and converge.

PARAMETER SIGNIFICANCE RiskMetrics

$$plr_t = c + \sum_{i=1}^{p} \phi_i plr_{t-i} - \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \delta_1 \sigma_t^2 + \delta_2 R_t + \varepsilon_t$$

$$\sigma_t^2 = \omega + (1-\lambda)\varepsilon_{t-1}^2 + \lambda \sigma_{t-1}^2 + bR_t$$

RiskMetrics Parameter significance

	1M	2M	3M	4M	5M	6M	7M	8M	9M
c	-	-	-	-	-	-	-	-	-
ARMA parameters	* to ***	***	- to ***	-	- to ***	- to ***	-	** to ***	** to ***
δ_1	***	***	-	-	-	-	-	**	*
δ_2	-	-	**	*	-	-	-	***	***
ω	NI	NI	NI	NI	NI	NI	NI	NI	NI
λ	Fix	Fix	Fix	Fix	Fix	Fix	Fix	Fix	Fix
b	***	***	***	***	***	***	***	***	***

***	Significant at 1% level
**	Significant at 5% level
*	Significant at 10% level
-	Included, but not significant
FIX	Fixed parameter value (=0.94)
NI	Not included in the analysis

PARAMETER SIGNIFICANCE APGARCH

$$lpr_t = c + \sum_{i=1}^{p} \phi_i plr_{t-i} - \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \delta_1 \sigma_t^2 + \delta_2 R_t + \varepsilon_t$$

$$\sigma_t^{\delta} = \omega + \sum_{i=1}^{q} \alpha_i (|\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-i})^{\delta} + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^{\delta} + bR_t$$

APGARCH Parameter significance

	1M	2M	3M	4M	5M	6M	7M	8M	9M
c	***	***	***	***	***	***	***	***	***
ARMA parameters	***	***	***	NI	***	***	***	***	NI
δ_1	***	*	***	***	***	-	-	***	***
δ_2	***	***	***	***	***	***	***	***	***
ω	***	***	***	***	***	***	***	***	***
α's	***	***	***	***	***	***	***	***	***
γ's	***	***	***	***	***	***	***	***	***
δ's	**	***	***	***	***	***	***	***	***
β's	***	***	***	***	***	***	***	***	***
b	***	***	***	***	***	***	***	***	***

***	Significant at 1% level
**	Significant at 5% level
*	Significant at 10% level
-	Included, but not significant
NI	Not included in the analysis

Model Evaluation Results

Table 3 Model Evaluation

position	Best Model	Schwartz Criterion	Temp.	Q-test res	Q-test res²	RBD-test	Joint Nyblom test
1	APGARCH	4.595	7.2760E-11	OK	OK	Ok	25.408***
2	APGARCH	4.951	1.4552E-10	not ok	not ok	Ok	15.455***
3	APGARCH	3.877	5.8208E-10	not ok	not ok	not ok	10.212***
4	APGARCH	3.755	7.2760E-11	not ok	not ok	not ok	25.059***
5	APGARCH	3.612	1.4552E-10	not ok	not ok	not ok	19.533***
6	APGARCH	3.536	7.2760E-11	not ok	not ok	not ok	57.229***
7	APGARCH	3.532	1.8190E-11	not ok	not ok	not ok	26.093***
8	APGARCH	3.431	1.8190E-11	not ok	not ok	not ok	31.649***
9	APGARCH	3.509	3.6380E-11	OK	OK	Ok	18.570***

Temp= temperature. Not ok= significant at .05. Ok = not significant at .05

Volatility affects mean model

Table 4		Model Evaluation					
	Best	Schwartz					
				Parameter			
position	Model	Criterion	Coefficient	estimate	Std error	t-value	t-prob
1	APGARCH	4.595	Arch-in-mean(var)	-0.007	.0002	-32.220	0.000
2	APGARCH	4.951	Arch-in-mean(var)	-0.002	.001	-1.823	0.068
3	APGARCH	3.877	Arch-in-mean(var)	-0.015	0.0002	-69.31	0.000
4	APGARCH	3.755	Arch-in-mean(var)	-0.004	.0008	-4.201	0.000
5	APGARCH	3.612	Arch-in-mean(var)	-0.002	0.004	-0.688	0.491
6	APGARCH	3.536	Arch-in-mean(var)	0.0001	0.002	0.062	0.951
7	APGARCH	3.532	Arch-in-mean(var)	-0.0005	0.003	-0.212	0.832
8	APGARCH	3.431	Arch-in-mean(var)	0.0004	0.002	.1948	0.846
9	APGARCH	3.509	Arch-in-mean(var)	0.004	0.002	1.89	0.059

Table 3: The Forecast Error Measures of the SC-selected model

Table 2

				Forecast horizon							
				1		5		10		20	
Schwartz	Model	Position	Moment:	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance
4.595	APGARCH	1 pos	MSE	0.01686	193.1	7.54	101.9	5.129	245.6	4.64	438.9
			MAE	0.1299	13.9	2.157	8.499	1.71	14.33	1.699	18.72
			MAPE	-	0.9987	-	0.6121	-	0.7567	-	0.8016
			LL	-	43.8	-	11.22	-	10.82	-	+.Inf
4.95119	APGARCH	2 pos	MSE	1.472	26.55	4.601	192.9	8.439	580.1	7.699	1218
			MAE	1.213	5.153	2.044	12.09	2.292	21.28	2.274	26.33
			MAPE	-	0.7818	-	0.4742	-	0.6848	-	0.7207
			LL	-	2.317	-	0.9834	-	6.975	-	5.392
3.87651	APGARCH	3 pos	MSE	0.2989	6.956	5.149	311.7	6.713	348.1	4.949	491.4
			MAE	0.5467	2.637	1.747	16.59	1.939	12.75	1.73	20.93
			MAPE	-	0.8766	-	0.7631	-	0.7118	-	0.823
			LL	-	4.379	-	13.14	-	12.51	-	+.Inf
3.75533	APGARCH	4 pos	MSE	0.4895	0.8437	3.647	8.667	4.734	221	3.606	1048
			MAE	0.6996	0.9185	1.454	2.552	1.724	13.94	1.487	10.63
			MAPE	-	0.6064	-	0.5908	-	0.7718	-	0.7619
			LL	-	0.8692	-	19.47	-	17.91	-	+.Inf
3.61171	APGARCH	5 pos	MSE	1.128	0.015	3.411	294	6.78	94.89	4.174	85.69
			MAE	1.062	0.1225	1.385	17.04	1.944	8.096	1.469	8.4
			MAPE	-	0.1209	-	0.8505	-	0.7136	-	0.7706
			LL	-	0.01302	-	26.61	-	13.87	-	+.Inf
3.53552	APGARCH	6 pos	MSE	1.85	0.06828	1.725	167.2	2.952	154.7	1.829	433.3
			MAE	1.36	0.2613	1.095	12.83	1.409	11.29	1.029	19.19
			MAPE	-	0.1576	-	0.882	-	0.8202	-	0.9285
			LL	-	0.02143	-	14.02	-	12.3	-	+.Inf
3.53224	APGARCH	7 pos	MSE	1.074	4.404	2.445	118	3.01	116.9	1.882	76.26
			MAE	1.037	2.099	1.256	10.74	1.412	9.816	1.048	7.331
			MAPE	-	0.6555	-	0.8327	-	0.7995	-	0.8265
			LL	-	1.136	-	13.39	-	9.69	-	+.Inf
3.43094	APGARCH	8 pos	MSE	1.661	2.74	2.735	48.56	2.246	131.9	1.727	75.36
			MAE	1.289	1.655	1.511	6.662	1.268	7.97	1.068	6.546
			MAPE	-	0.4783	-	0.7163	-	0.7215	-	0.7693
			LL	-	0.4234	-	3.42	-	4.566	-	+.Inf
3.50941	APGARCH	9 pos	MSE	0.05498	258.4	3.248	426.7	19.6	1089	10.29	770.5
			MAE	0.2345	16.07	1.516	20.44	2.551	16.66	1.723	15.7
			MAPE	-	0.9967	-	0.8797	-	0.8809	-	0.9793
			LL	-	32.49	-	11.48	-	5.403	-	+.Inf

Monotonic Patterns:

h=f(horizon)

Model Selection by Forecast Error Measure

Table 4					Preferred Variance Models				
	Forecast		1		5		10		20
	Error	model	value	model	value	model	value	model	value
Position	Measure								
1	MSE	Rmsa RMB	193.1	APG	101.9	Rmsa RMB	245.6	APG	438.9
	MAE	Rmsa RMB	13.9	APG	8.499	Rmsa RMB	14.33	APG	18.72
	MAPE	Rmsa RMB	0.9987	APG	0.6121	Rmsa RMB	0.7567	APG	0.8016
2	MSE	APG	26.55	APG	192.9	Rmsa RMB	580.1	Rmsa	1218
	MAE	APG	5.153	APG	12.09	Rmsa RMB	21.28	APG	26.33
	MAPE	APG	0.7818	RMB	0.4742	Rmsa RMB	0.6848	APG	0.7207
3	MSE	APG	6.956	Rmsa	311.7	APG	348.1	RMB	491.4
	MAE	APG	2.637	RMsa	16.59	APG	12.75	APG	20.93
	MAPE	APG	0.8766	RMsa	0.7631	APG	0.7118	APG	0.823
4	MSE	APG	0.8437	APG	8.667	APG	221	APG	1048
	MAE	APG	0.9185	APG	2.552	APG	13.94	APG	10.63
	MAPE	APG	0.6064	APG	0.5908	APG	0.7718	APG	0.7619
5	MSE	APG	0.015	APG	294	APG	94.89	APG	85.69
	MAE	APG	0.1225	APG	17.04	APG	8.096	APG	8.4
	MAPE	APG	0.1209	APG	0.8505	APG	0.7136	APG	0.7706
6	MSE	APG	0.06828	APG	167.2	APG	154.7	APG	433.3
	MAE	APG	0.2613	APG	12.83	APG	11.29	APG	19.19
	MAPE	APG	0.1576	APG	0.882	APG	0.8202	APG	0.9285
7	MSE	APG	4.404	APG	118	APG	116.9	APG	76.26
	MAE	APG	2.099	APG	10.74	APG	9.816	APG	7.331
	MAPE	APG	0.6555	APG	0.8327	APG	0.7995	APG	0.8265
8	MSE	APG	2.74	APG	48.56	APG	131.9	APG	75.36
	MAE	APG	1.655	APG	6.662	APG	7.97	APG	6.546
	MAPE	APG	0.4783	APG	0.7163	APG	0.7215	APG	0.7693
9	MSE	APG	258.4	APG	426.7	APG	1089	APG	770.5
	MAE	APG	16.07	APG	20.44	APG	16.66	APG	15.7
	MAPE	APG	0.9967	APG	0.8797	APG	0.8809	APG	0.9793

APG=APGARCH

RMB= RiskMetrics BFGS

Rmsa= RiskMetrics simulated annealing

Possible RM preference on positions 1,2, or 3.

Conclusions 1

- Two models can model all nine positions of UK natural gas futures: RiskMetrics GARCH and APGARCH.
- Two algorithms can work with RiskMetrics GARCH and one algorithm can work with APGARCH to perform this task.
  - RM: BFGS and simulated annealing
  - APGARCH: simulated annealing

Conclusions 2

- The best models for all positions are the APGARCH with the simulated annealing algorithm, according to the Schwartz criterion, and passage of residual diagnostic assumptions.

Conclusions 3

- Only the first and nine position models pass all of the residual diagnostics tests and the RBD test.
- However, none of the models passes the joint Nyblom Stability test.

Conclusions 4

- Only the first 4 positions have volatility models significantly negatively impacting the percentage log returns mean models.
- Yet these impacts are small—generally less than 1 percent. Contracts for large volumes would be necessary to obtain substantial returns on these transactions.

Conclusions 5

- None of the models are stable.
- This finding suggests that caution be exercised in forecasting.
  - Forecasting near horizons rather than far horizons might be preferred.
- Only on positions 2, 3, and 4 does the volatility increase monotonically as a function of the forecast horizon.

Conclusions 6

- APGARCH generally outperform the other models in forecasting
- Evaluation is done by MSE, MAE, and MAPE
- APGARCH is generally the optimal model—a useful bit of knowledge for planners, risk managers, and traders in the UK gas futures market.
  - Only in the 1 day ahead and 10 day ahead does the RiskMetrics outperform the APGARCH for position 1
  - For Position 2, RM outperforms 10 trading days out.
  - For Position 3, only 5 days out, does the RM simulated annealing outperform the APGARCH.

Directions for Future Research

1. Replication on more recent data could serve to confirm or disconfirm our findings.
2. Boxing day trading anomaly for 2nd position
3. Exploring the asymmetry anomaly
    1. No sign bias effect in most cases
    2. Significant gamma parameter in the APGARCH
    3. Leverage size versus leverage sign effects
    4. Volatility skew (change over positions)
    5. Volatility smile and smirk graphical analysis
    6. Power analysis for Sign Bias test.

Directions for Future Research 2

4. Do simulations for out-of-sample h step ahead VaR.
5. Replicate methods for analysis of other energy markets (electricity, oil, coal, etc.)
6. Explore dynamic conditional correlation between the U.K. electricity and natural gas markets.

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Thank You!

We’ll be happy to entertain any questions you might have now.