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Working Paper

Multivariate volatility modeling of electricity futures

SFB 649 Discussion Paper, No. 2011-063

Provided in Cooperation with:

Collaborative Research Center 649: Economic Risk, Humboldt University Berlin

Suggested Citation: Bauwens, Luc; Hafner, Christian M.; Pierret, Diane (2011) : Multivariate volatility modeling of electricity futures, SFB 649 Discussion Paper, No. 2011-063, Humboldt University of Berlin, Collaborative Research Center 649 - Economic Risk, Berlin

This Version is available at:

<https://hdl.handle.net/10419/56746>

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MULTIVARIATE VOLATILITY MODELING OF ELECTRICITY FUTURES: ONLINE APPENDIX

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October 13, 2011

1 Phelix spot and futures returns: descriptive statistics

Descriptive statistics for the percentage returns of Phelix Base monthly index and Phelix Base futures prices are presented in the Table 1. Phelix Base monthly index is the arithmetic mean of Phelix Base indices for the delivery month. Futures prices series are continuous series composed of successive front contracts and futures returns series are adjusted for contract switches. The month futures price series is constructed such that the nearest contract month forms the first values for the continuous series until the first business day of the actual contract month. The quarter and year futures series are also composed of nearest contracts but the contract switch-over is made on the cascading day.

	Phelix Base	Month Future	Quarter Future	Year Future
Phelix Base	1			
Month Future	-0.005	1		
Quarter Future	-0.032	0.791	1	
Year Future	-0.051	0.559	0.773	1
Mean	-0.014	-0.118	-0.008	0.025
St. Deviation	7.871	2.383	1.462	1.098
Skewness	-1.773	-0.131	-0.149	-0.176
Excess Kurtosis	32.841	4.467	3.541	6.952

Table 1: Descriptive statistics of spot and futures returns (1962 observations). The upper panel shows the sample correlation matrix.

2 Vector-error correction model for Phelix futures

To filter the the log-price series from possible co-movements in the conditional means, we use a vector error correction model (VECM). Based on a lag-structure analysis of log prices, we specify the following VECM:

$$\Delta y_t = \Pi y_{t-1} + \Gamma \Delta y_{t-1} + u_t,$$

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where $y_t = (y_{Mt} \ y_{Qt} \ y_{Yt})'$ is the vector of log prices for different maturities.¹ The long-run matrix Π can be factorized into $\alpha\beta'$ where α (of dimension $3 \times r$) contains the speed of adjustment to disequilibrium coefficients and β (of dimension $3 \times r$) contains the coefficients of the r cointegration relationships such that $\beta'y_t$ is stationary. The vector Γ contains the autocorrelation parameters. We estimate the model by QML under the assumption of homoskedastic errors, even if we know that conditional heteroskedasticity exists in our data. This allows us to separate the estimation of the VECM conditional mean parameters from the parameters of the multivariate GARCH model we assume later for the error vector. This approach does not invalidate the consistency of the estimator of the parameters of the conditional mean.

The trace rank test of Johansen (1991) indicates the presence of two cointegration vectors.² The matrices α and β are identified by imposing $\beta = (I_2 \ B)'$. Their maximum likelihood estimates are:

$$\hat{\beta} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \\ -0.898 & -0.960 \end{pmatrix} \quad \hat{\alpha} = \begin{pmatrix} -0.010 & 0.016 \\ -0.004 & 0.009 \\ 0.000 & 0.001 \end{pmatrix}.$$

Given the p-value of 64% for the likelihood ratio test, we conclude that the last row of the alpha matrix ($\alpha_{31} \ \alpha_{32}$) is not rejected to be null. Year futures returns are therefore not subject to error-correction, and can be interpreted as the common trend of the system. Integrating the restriction that the last row of α is equal to zero, we get $\hat{\beta}_1 = (1 \ 0 \ -0.91)$ and $\hat{\beta}_2 = (0 \ 1 \ -0.968)$ as estimated cointegration vectors.

Conditional on the parameter estimates $\hat{\beta}$, a parsimonious VECM model (after removing non significant variables at the 5% level) is estimated by maximum likelihood (assuming Gaussian errors) as

$$\begin{aligned} \Delta y_{Mt} &= 0.066 + 0.121 \Delta y_{Mt-1} - 0.010 \hat{\beta}'_1 y_{t-1} + 0.014 \hat{\beta}'_2 y_{t-1} + \epsilon_{Mt} \\ &\quad (0.096) \quad (0.029) \quad (0.004) \quad (0.005) \\ \Delta y_{Qt} &= 0.028 + 0.15 \Delta y_{Qt-1} - 0.003 \hat{\beta}'_1 y_{t-1} + 0.006 \hat{\beta}'_2 y_{t-1} + \epsilon_{Qt} \\ &\quad (0.056) \quad (0.025) \quad (0.002) \quad (0.002) \\ \Delta y_{Yt} &= 0.026 + 0.071 \Delta y_{Qt-1} + \epsilon_{Yt} \\ &\quad (0.025) \quad (0.020) \end{aligned}$$

where Newey-West autocorrelation- and heteroskedasticity-consistent (HAC) standard errors are reported in parentheses. Note that we keep the non-significant constants in the equations to obtain zero-mean residuals for the next step devoted to multivariate volatility modeling.

3 Comparison of multivariate GARCH models for Phelix futures

Table 2 provides a ranking of different multivariate GARCH models applied to Phelix futures according to the log-likelihood, Bayesian and Akaike information criteria.³

¹Note that y_{t-1} , like the returns, is adjusted for contract switches.

²The estimation results of this section are obtained using the PcGive module of OxMetrics version 6.10 (see Doornik and Hendry (2009)).

³These estimation results are obtained using the G@RCH module of OxMetrics version 6.10 (see Laurent (2009)).

	# parameters	Log-likelihood	BIC	AIC
cDCC, Aielli (2009)	14	-7716.403	7.924	7.884
DCC, Engle (2002)	14	-7721.455	7.929	7.889
DCC, Tse and Tsui (2002)	14	-7734.057	7.942	7.902
CCC, Bollerslev (1990)	12	-7803.046	8.005	7.971
BEKK, Engle and Kroner (1995)	24	-7864.649	8.114	8.046
GO-GARCH (NLS), van der Weide (2002)	12	-7940.692	8.145	8.111
O-GARCH, Alexander (2002)	9	-8244.385	8.443	8.418

Table 2: Ranking of multivariate GARCH models for Phelix futures (GARCH variances, Gaussian distribution). Sample period: 07.03.2002-04.14.2010 (1961 observations)

4 DCC and mDCC estimation results for VECM residuals

The conditional variance h_{iit} following a standard GJR process is defined as

$$h_{iit} = \omega_i + \alpha_i \epsilon_{it-1}^2 + \beta_i h_{iit-1} + \gamma_i \epsilon_{it-1}^2 I_{\{\epsilon_{it-1} < 0\}}$$

where $I_{\{\epsilon_{it} < 0\}}$ is a dummy variable equal to one when the past shock is negative, $\alpha_i, \beta_i \geq 0$, and $\alpha_i + \beta_i + 0.5\gamma_i < 1$.

	standard GJR		multiplicative GJR	
Month Baseload Future	Coefficient	Std. error	Coefficient	Std. error
Cst (ω)	0.068	0.028	-	-
ARCH (α)	0.232	0.037	0.296	0.032
GARCH (β)	0.836	0.024	0.724	0.034
GJR (γ)	-0.126	0.032	-0.164	0.033
Log-likelihood:	-3862.30		-2293.23	
	standard GJR		multiplicative GJR	
Quarter Baseload Future	Coefficient	Std. error	Coefficient	Std. error
Cst (ω)	0.020	0.008	-	-
ARCH (α)	0.215	0.030	0.211	0.027
GARCH (β)	0.838	0.020	0.755	0.029
GJR (γ)	-0.087	0.029	-0.093	0.032
Log-likelihood:	-3019.41		-2420.46	
	standard GJR		multiplicative GJR	
Year Baseload Future	Coefficient	Std. error	Coefficient	Std. error
Cst (ω)	0.006	0.004	-	-
ARCH (α)	0.159	0.024	0.136	0.013
GARCH (β)	0.856	0.023	0.823	0.018
Log-likelihood:	-2393.37		-2303.15	

Table 3: Conditional variance parameter estimates for VECM residuals ϵ_t (standard GJR, left part) and standardized residuals ξ_t (multiplicative GJR, right part). Sample period: 01.09.2003-04.14.2010 (1831 observations)

NOTE: The estimates and likelihood values of the previous table are not directly comparable with those of Table 1 in the paper because the estimation sample size is equal to 1831 observations above, whereas it is equal to 1467 in Table 1 of the paper. This difference is due to the lack of availability of the Powernext baseload index series before 06.23.2004. Notice that the GJR results in Table 1 of the paper and the multiplicative GJR results in the table above are for the same type specification and estimation (i.e. second stage QML of the multiplicative DCC model), but for a different sample period.

	DCC		multiplicative DCC	
	Coefficient	Std. error	Coefficient	Std. error
\bar{Q}_{MQ}	0.795	0.020	-	-
\bar{Q}_{MY}	0.621	0.034	-	-
\bar{Q}_{QY}	0.808	0.021	-	-
a	0.044	0.013	0.052	0.008
b	0.915	0.030	0.835	0.029
Log-likelihood:	1949.18		39.08	

Table 4: Standard DCC (left part) and multiplicative DCC (right part) parameter estimates of standardized VECM residuals (conditional on standard GJR, respectively multiplicative GJR estimation for the univariate variances). Sample period: 01.09.2003-04.14.2010 (1831 observations)

NOTE: The same comment about the sample size difference applies to the previous table in relation with Tables 2 and 3 of the paper. Another difference is that in the results of the paper, the estimations use the u_t residuals based on the results in Table 1, whereas in this appendix, the residuals u_t are based on the estimation results reported in the previous table (i.e. without congestion and day-to-delivery variables).

	DCC(M,Q)		DCC(M,Y)		DCC(Q,Y)	
	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error
\bar{Q}_{ij}	0.815	0.011	0.608	0.035	0.797	0.034
a	0.074	0.024	0.055	0.044	0.067	0.018
b	0.582	0.138	0.887	0.116	0.904	0.024
Log-likelihood:	994.22		443.33		964.08	

Table 5: Conditional correlation parameter estimates between standardized VECM residuals of contracts i and j from bivariate standard DCC estimation ($DCC(i, j)$, conditional on standard GJR estimation for the univariate variances). Sample period: 01.09.2003-04.14.2010 (1831 observations)

5 DCC and mDCC estimation results for returns

Month Baseload Future	standard GJR		multiplicative GJR	
	Coefficient	Std. error	Coefficient	Std. error
Cst (ω)	0.079	0.032	-	-
ARCH (α)	0.250	0.040	0.308	0.032
GARCH (β)	0.830	0.026	0.716	0.032
GJR (γ)	-0.141	0.034	-0.179	0.031
Log-likelihood:	-3880.89		-2282.69	

Quarter Baseload Future	standard GJR		multiplicative GJR	
	Coefficient	Std. error	Coefficient	Std. error
Cst (ω)	0.020	0.008	-	-
ARCH (α)	0.215	0.032	0.204	0.026
GARCH (β)	0.838	0.021	0.755	0.030
GJR (γ)	-0.083	0.028	-0.071	0.030
Log-likelihood:	-3042.95		-2416.38	

Year Baseload Future	standard GJR		multiplicative GJR	
	Coefficient	Std. error	Coefficient	Std. error
Cst (ω)	0.007	0.004	-	-
ARCH (α)	0.159	0.023	0.136	0.013
GARCH (β)	0.855	0.023	0.821	0.019
Log-likelihood:	-2406.87		-2306.29	

Table 6: Conditional variance parameter estimates for returns y_t (standard GJR, left part) and standardized returns (multiplicative GJR, right part). Sample period: 01.09.2003-04.14.2010 (1831 observations)

	DCC		multiplicative DCC	
	Coefficient	Std. error	Coefficient	Std. error
\bar{Q}_{MQ}	0.800	0.019	-	-
\bar{Q}_{MY}	0.627	0.032	-	-
\bar{Q}_{QY}	0.811	0.021	-	-
a	0.046	0.015	0.053	0.009
b	0.907	0.034	0.827	0.033
Log-likelihood:	1983.46		39.96	

Table 7: Standard DCC (left part) and multiplicative DCC (right part) parameter estimates of standardized returns (conditional on standard GJR, respectively multiplicative GJR estimation for the univariate variances). Sample period: 01.09.2003-04.14.2010 (1831 observations)

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