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Volatility forecasting of carbon prices using factor models

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Abstract

This article develops a forecasting exercise of the volatility of EUA spot, EUA futures, and CER futures carbon prices (modeled after an AR(1)-GARCH(1,1)) using two dynamic factors as exogenous regressors that were extracted from a Factor Augmented VAR model (Bernanke et al. (2005)). The dataset includes 115 macroeconomic, financial and commodities indicators with daily frequency from April 4, 2008 through January 25, 2010 totalling 463 observations that capture the strong uncertainties emerging on the carbon market. The main result shows that the best forecasting performance for the volatility of carbon prices is achieved for the model including the dynamic factors as exogenous regressors, which can be useful to inform hedging or speculative trading strategies by energy utilities, financial market players and risk managers.

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1 Introduction

Since its creation in January 2005, the European Union Emissions Trading Scheme (EU ETS) has become an intellectual and operational center of gravity around which to organize and deliver effective climate change policy. Among its main features, the EU ETS has contributed to establish a carbon price for CO_2 allowances, which is being used for various purposes: hedging for regulated energy companies, speculation for financial arbitragists, portfolio diversification for investment banks, etc. According to Pointcarbon[1], the volume of transactions of allowances on the European carbon market has grown rapidly from 262 million tons in 2005 to over 5,000 million tons in 2009 which, valued at €20/ton on average, represents currently a market value of €100 billion.

Hence, a growing academic literature has been focusing on forecasting the *returns* of carbon prices which can useful for brokers, energy companies and risk managers. Benz and Trueck (2009) analyze the short-term spot price behavior of CO_2 allowances during 2005-2006. By conducting in-sample and out-of-sample forecasting analysis of the returns of carbon prices, they find that AR-GARCH models capture adequately the characteristics like skewness, excess kurtosis and in particular different phases of volatility behavior in the returns. Chevallier (2009) examines the empirical relationship between the returns on carbon futures and changes in macroeconomic conditions. By using variables which possess forecast power for equity and commodity returns, the author documents that carbon futures returns may be weakly forecast on the basis of two variables from the stock and bond markets, *i.e.* equity dividend yields and the "junk bond" premium. Finally, Chevallier (2010) analyzes the modeling of risk premia in CO_2 allowances spot and futures prices. The author finds a better forecast performance of futures premia of all maturities for models incorporating the variance of spot prices as an exogenous variable.

Compared to previous literature, this article focuses on *volatility* forecasting of carbon prices. As noted by Daskalakis et al. (2009), the high volatility and the existence of extreme discontinuous variations in carbon prices mean that much caution is needed when dealing with emission allowance derivatives. Uncertainty linked to financial markets and economic growth, as well as to new institutional design features by 2020 (with a linear reduction in allocation from 20 to 30% and the introduction of auctioning), yields to high volatility levels of carbon prices. To tackle this issue, this article extracts information from a large dataset of macroeconomic, financial and commodities

[1] Available at *http://www.pointcarbon.com/*

markets based on Bernanke et al. (2005)'s Factor Augmented VAR (FAVAR) approach. The central result shows that the best forecast performance of the volatility of carbon prices (namely the conditional volatility extracted from an AR(1)-GARCH(1,1) model as in Benz and Trueck (2009)) is achieved for models including the dynamic factors as exogenous regressors.

The article is structured as follows. Section 2 presents the data. Section 3 details the FAVAR model. Section 4 contains the volatility forecasting exercise. Section 5 concludes.

2 Data

The dataset covers the period going from April 4, 2008 to January 25, 2010, totalling 463 daily observations for each series. We choose this study period in order to provide a recent analysis of the effect of the financial crisis on carbon markets[2].

Three carbon price series are used: the European Union Allowance (EUA) spot price exchanged on BlueNext (*EUA BNX SPOT*), the EUA futures price of maturity December 2010 exchanged on the European Climate Exchange (*EUA ECX FUT*), and the secondary Certified Emissions Reduction (CER) futures price of maturity December 2010 also exchanged on ECX (*CER ECX FUT*). The former two variables represent the most liquid carbon prices available in the EU ETS for spot and futures prices, respectively (Chevallier (2009)). The latter variable may be seen as a proxy of 'world' carbon prices, as they represent carbon assets exchangeable at a global scale within the Kyoto Protocol (World Bank (2009)). The conditional volatility of carbon prices is modeled from an AR(1)-GARCH(1,1) (Benz and Truek (2009)). Carbon price volatilities used in this article are shown in Figure 1.

Concerning macroeconomic, financial and commodities markets, the data include a large number of time-series related to industrial production, market indices and various monetary aggregates. The dataset also comprises the prices of stocks of major US and European companies (for a broad industrial coverage as well as in the energy sector), and a number of bond and stock indices. Finally, the dataset includes detailed information on the use of all the available energy sources across sectors of the economy, including energy products derived from petroleum and natural gas. The list of the 115 variables, along with the required stationarity transformations and

[2]Note that, due to computational burden, we cannot extend easily the study period from the implementation of the EU ETS in 2005. It is likely that by conducting such an analysis on a longer time period, we can limit the obvious impact of the financial crisis on the volatility of carbon prices. We thank a referee for highlighting this point.

'slow' *vs.* 'fast' identification codes (as in Bernanke et al. (2005)), may be found in Table 1. All time-series were downloaded from Thomson Financial Datastream.

Next, we detail the procedure to extract factors from such a large dataset in a FAVAR model.

3 Factor-Augmented VAR

In a seminal article, Bernanke et al. (2005) pointed out that macroeconomic aggregates such as output and inflation might not be perfectly observable neither to the policy-maker nor to the econometrician. Instead, they argued that the observed macroeconomic time series should be thought of as "noisy" measures of economic concepts. Accordingly, these concepts should be treated as unobservable in empirical work, so as to avoid confounding measurement error or idiosyncratic dynamics with fundamental economic shocks.

Therefore, they suggested to extract a few common factors from a large number of macroeconomic time-series, and to study the mutual dynamics of the key economic aggregates by estimating a joint VAR of the factors and the policy instrument, an approach which they labelled "Factor-Augmented VAR". This approach can be summarized by the following equations:

$$X_t = \Lambda_F F_t + \Lambda_r r_t + e_t \tag{1}$$

$$\begin{pmatrix} F_t \\ r_t \end{pmatrix} = \mu + \Phi(L) \begin{pmatrix} F_{t-1} \\ r_{t-1} \end{pmatrix} + \omega_t \tag{2}$$

where X_t denotes a Mx1 vector of period-t observations of the observed macroeconomic variables, Λ_F and Λ_r are the Mxk and Mx1 matrices of factor loadings, r_t denotes the carbon prices, F_t is the kx1 vector of period-t observations of the common factors, and e_t is an Mx1 vector of idiosyncratic components, $\mu = (\mu'_f, \mu_r)'$ is a $(k+1)$x1 vector of constants, $\Phi(L)$ denotes the $(k+1)$x$(k+1)$ matrix of order-p lag polynomials and ω_t is a $(k+1)$x1 vector of reduced form shocks with variance covariance matrix Ω. Standard initial conditions in this context can be found in Koop (2003).

Consequently, our FAVAR is the tri-variate VAR of carbon prices augmented with factors f_t. Two factors were extracted using standard static Principal Components methods (Stock and Watson (2002a,b)), with $p = 2$ the order of the FAVAR model based on standard lag length structure criteria. Figure 2 pictures the dynamic factors extracted from the dataset. Factor 1 contains macroeconomic and financial time-series, while Factor 2 accounts for commodities time-series (see Table 1 for the list of variables). Visually, we observe a high degree of variability in macroeconomic and financial variables. Commodities variables also exhibit a high degree of variability, but with a more pronounced adjustment to the financial crisis towards the end of the period. Descriptive statistics for the two factors, as well as for the carbon prices, are given in Table 2. Next, we develop our volatility forecasting exercise of carbon prices by using the factors obtained from the dynamic FAVAR analysis.

4 Volatility Forecasting

Before proceeding with the formal volatility forecasting exercise, we compute first the correlations between factors and carbon price volatilities. As shown in Table 3, the correlations are comprised between -0.02 and -0.287, which does not indicate potential multicolinearity problems between the endogenous and exogenous variables in our model.

Second, we present in Table 4 the results of pairwise Granger causality F-tests between factor and carbon price volatilities. We are able to detect potential causality links (in the Granger sense) between factors and the $EUAECXFUTVOL$ variable: Factor 2 causes $EUAECXFUTVOL$ at the 5.7% significance level, while Factor 1 is not significant at the 10% level but very close (11.6%). This information appears useful to infer that statistical relationships exist between variables in our model.

Table 5 presents regression results of carbon price volatilities on factors estimated from the FAVAR(2) model. Here, the modeling differs from Benz and Trueck (2009) on two points: *(i)* in the variance equation, we specify an ARCH(1) model instead of a GARCH(1,1) since the GARCH coefficient was not significant, and *(ii)* in the mean equation, we replace the endogenous variable by carbon price *volatilities* (as explained in Section 2) and we introduce the two dynamic factors as exogenous variables.

This specification yields to interesting results[3]. Indeed, we are able to observe that dynamic factors impact significantly (at the 1% level) and *negatively* carbon price volatilities across all regressions. The negative sign may be explained by the fact that factors constitute a proxy for the depressive effect of the financial crisis embedded within macroeconomic, financial and commodities markets indicators. The FAVAR(2) model therefore appears to capture adequately the "unobservable" information contained in large datasets, as posited by Bernanke et al. (2005). Besides, these first results document

[3]Note the introduction of various level of lags for the exogenous and endogenous variables did not change qualitatively the results obtained. To conserve space, we present only here results in contemporaneous form.

the effect of the financial crisis on carbon price volatilities which - to our best knowledge - is new. In the variance equation, we verify that all the coefficients are positive and statistically significant in order to validate the ARCH modeling. Diagnostic tests which are provided at the bottom of Table 5 confirm that the residuals are not autocorrelated (based on the Ljung-Box test), and that the ARCH effects are correctly captured by the model (based on the Engle ARCH test).

The next step consists in assessing the forecasting power of our model compared to a model without factors. We first need to compute m-step-ahead forecasts of carbon price volatilities based on the following expression (Bollerslev et al. (1994)):

$$\sigma^2_{(t+m)} = \alpha_0 + \sum_{i=1}^{q} \alpha_i \epsilon^2_{(t+m-i)} \tag{3}$$

This standard formulation is convenient to obtain the volatility estimate over the m-day horizon. In our forecasting exercice, we typically compute one-day forecasts. The forecast error is simply the difference between the actual and forecasted values.

Thus, we take our analysis one step further by evaluating how the dynamic factors estimated from the FAVAR(2) model improve the forecast performance of carbon price volatilities. To do so, we regress the carbon price volatilities in Table 5 without/with incorporating the two dynamic factors and compare in-sample forecasts based on the Root Mean Squared Error (RMSE), the Mean Absolute Error (MAE), and the Mean Absolute Percentage Error (MAPE).

Suppose the forecast sample is $j = T+1, T+2, \ldots, T+h$, and denote the actual and forecasted value in period t as y_t and $\hat{y}_t$, respectively. The reported forecast error statistics are computed as follows:

$$RMSE = \sqrt{\sum_{t=T+1}^{T+h} \frac{(\hat{y}_t - y_t)^2}{h}} \tag{4}$$

$$MAE = \sum_{t=T+1}^{T+h} \frac{\mid \hat{y}_t - y_t \mid}{h} \tag{5}$$

$$MAPE = 100 \sum_{t=T+1}^{T+h} \frac{\frac{\mid \hat{y}_t - y_t \mid}{y_t}}{h} \tag{6}$$

In Table 6, all criteria are minimized in the models incorporating the dynamic factors, which suggests that these variables are useful for forecasting in this context. Let us examine visually their forecast performance.

Figure 3 plots the forecasted series together with the actual series in the forecast sample with error bounds. The dashed red-line represents the mean value of corresponding in-sample forecasts. The dashed green-lines represent upper and lower forecast error bounds computed with, respectively, plus and minus two standard error series. We observe that the mean of in-sample forecasts track reasonably well the mean of the dependent variable in the models incorporating the dynamic factors. These comments apply more especially for the variables $EUAECXFUTVOL$ and $CERECXFUTVOL$. The accuracy of volatility forecasts appears higher than for the $EUABNXSPOTVOL$ variable (all volatility forecasts seem to underestimate the actual value but the effects are less pronounced for the former two variables).

This graph confirms that the best insample forecasts are obtained with the dynamic factors estimated from the FAVAR(2) model, as the red dashed-lines provide satisfactory goodness-of-fit to the dependent variable. Also, forecast error bounds fall generally within the actual dependent variable for the model with dynamic factors included as exogenous regressors. These results hold for all carbon price volatilities.

5 Conclusion

The EU ETS was created in 2005 with a "light touch" of regulation in order to allow a liquid allowances market to establish itself. The pilot Phase (2005-2007) showed that the market is subject to strong uncertainties, due to physical, institutional and financial determinants, and that information release has to be done in a particular way (Alberola et al. (2008)).

In contrast with previous literature, we develop in this article a forecasting exercise of the *volatility* of carbon prices which can be useful for brokers, energy regulated companies and financial market players. Against this background of strong uncertainties, we extract "latent" unobservable information from 115 macroeconomic, financial and global commodities time-series into two dynamic factors based on Bernanke et al. (2005)'s Factor Augmented VAR model with daily frequency from April 4, 2008 through January 25, 2010 totalling 463 observations.

Then, we use the dynamic factors in order to forecast the volatility of carbon prices modeled after an AR(1)-GARCH(1,1) model (Benz and Truek (2009)). The highest forecasting accuracy is obtained for the model with the dynamic factors included as exogenous regressors for the volatility of carbon prices, as indicated by standard in-sample forecasts statistics. This result is robust across various categories of carbon prices: EUA spot and futures prices, as well as CER prices.

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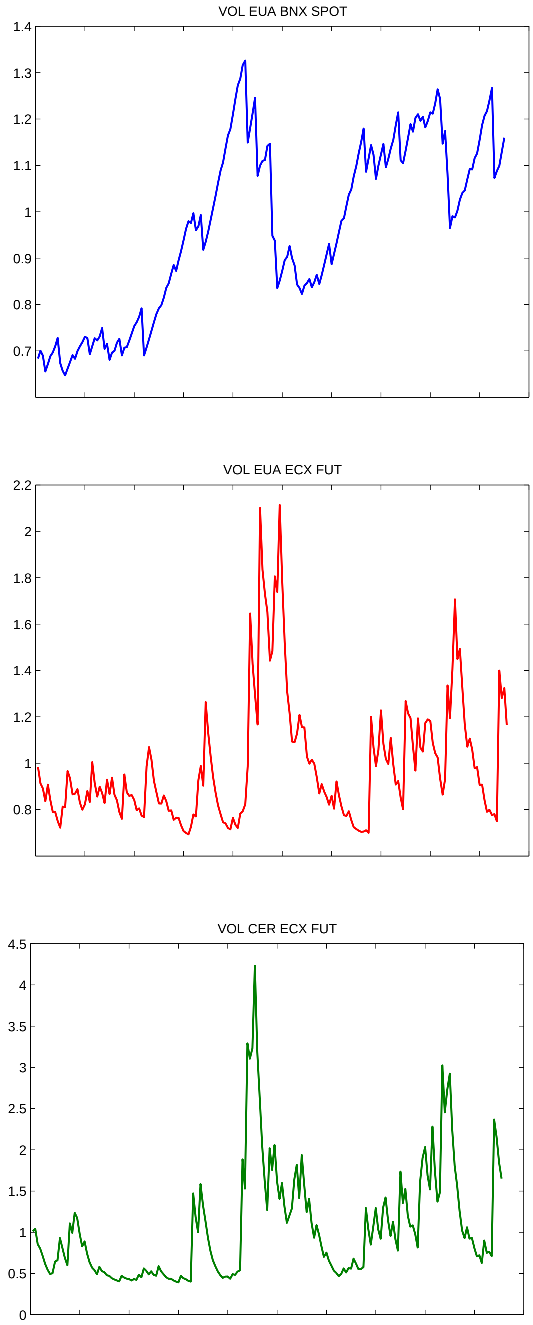

Figure 1: Conditional standard deviation extracted from AR(1)-GARCH(1,1) model for EUA BNX spot allowances, EUA ECX and CER ECX futures contracts of maturity December 2010 from April 4, 2008 to January 25, 2010
Source: BlueNext (BNX) and the European Climate Exchange (ECX)

Note: EUA stands for European Union Allowance, and CER for (secondary) Certified Emissions Reduction.

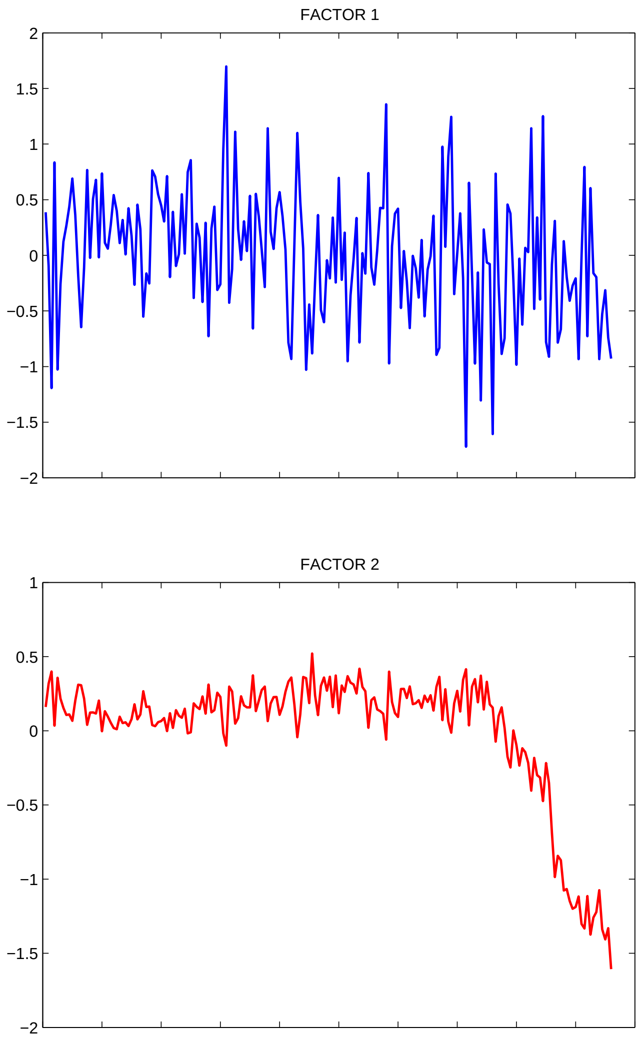

Figure 2: Factors estimated from tri-variate FAVAR(2) model of EUA BNX spot allowances, EUA ECX and CER ECX futures contracts of maturity December 2010 with 115 macroeconomic, financial and commodities variables from April 4, 2008 to January 25, 2010

Note: BNX stands for BlueNext, ECX for European Climate Exchange, EUA for European Union Allownance, and CER for (secondary) Certified Emissions Reduction.

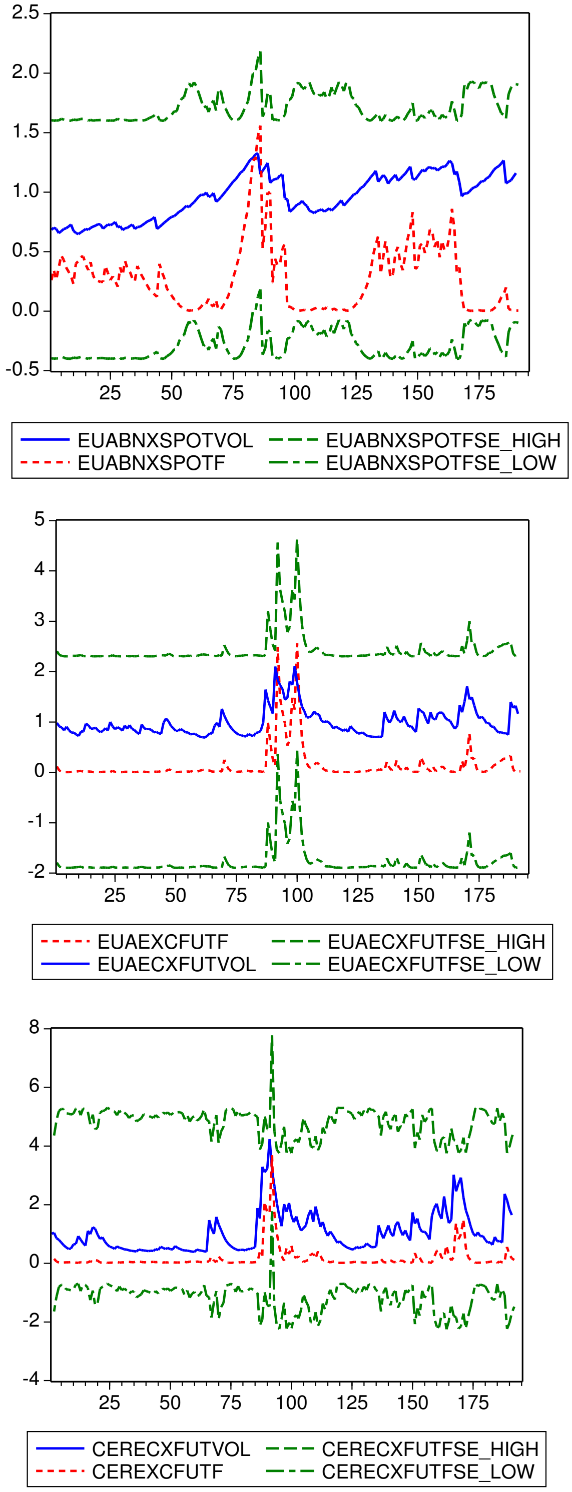

Figure 3: In-sample volatility forecasts of carbon prices with incorporating the factors extracted from the FAVAR(2) model

Note: VOL stands for the conditional volatility extracted from AR(1)-GARCH(1,1) model. F stands for in-sample forecast. FSE stands for forecast standard error, with $HIGH$ and LOW the forecast error bounds computed with, respectively, plus and minues two standard error series.

Table 1: **Macroeconomic, financial and commodities series used in the FAVAR(2) model**

No.	**Series ID**	**Title**	**Tcode**	**SlowCode**
1	CGSYSPT	S&P GSCI Commodity Spot - PRICE INDEX	4	1
2	GSCIEXR	S&P GSCI Commodity Excess Return	4	1
3	GSCITOT	S&P GSCI Commodity Total Return	4	1
4	GSENSPT	S&P GSCI Energy Spot- PRICE INDEX	4	1
5	GSREEXR	S&P GSCI Red. EnergyExcess Return	4	1
6	GSENTOT	S&P GSCI Energy Total Return	4	1
7	RECMDTY	Reuters Commodities Index - PRICE INDEX	4	1
8	MOCMDTY	Moody's Commodities Index - PRICE INDEX	4	1
9	MLCXSPT	MLCX Spot Index - PRICE INDEX	4	1
10	MLCXTOT	MLCX Total Return	4	1
11	MLCXCLE	MLCX Crude Oil (WTI)Excess Return - EXCESS RETURN	4	1
12	MLCXCLS	MLCX Crude Oil (WTI)Spot Index - PRICE INDEX	4	1
13	MLCXCLT	MLCX Crude Oil (WTI)Total Return	4	1
14	MLCXNGE	MLCX Natural Gas Excess Return	4	1
15	MLCXNGS	MLCX Natural Gas Spot Index	4	1
16	MLCXNGT	MLCX Natural Gas Total Return	4	1
17	LCRINDX	London Brent Crude Oil Index U$/BBL - PRICE INDEX	4	1
18	LNGINDX	London Natural Gas Index P/Therm - PRICE INDEX	4	1
19	COALARA	Global Insight Coal Index Basis 6000 - PRICE INDEX	4	1
20	DJUBSSP	DJ UBS-Spot Commodity Index - PRICE INDEX	4	1
21	DJUBEAT	DJ UBS 50/50 Energy&Agri Comdty TR - TOTAL RETURN	4	1
22	DJUBENE	DJ UBS-Energy Index ER - EXCESS RETURN	4	1
23	DJUBEUT	DJ UBS-Commodity Index (Euro) TR - TOTAL RETURN	4	1
24	DJUBHOT	DJ UBS-Heating Oil Sub Index TR - TOTAL RETURN	4	1
25	DJUBNGT	DJ UBS-Natural Gas Sub Index TR - TOTAL RETURN	4	1
26	DJUBPRT	DJ UBS-Petroleum Index TR - TOTAL RETURN	4	1
27	DJUBRBT	DJ UBS-Unleaded Gas Sub Index TR - TOTAL RETURN	4	1
28	DJUBSER	DJ UBS-Future Commodity Ind ER - EXCESS RETURN	4	1
29	CXAGERU	CX Agriculturals Index ER - EXCESS RETURN	4	1
30	CXENERU	CX Energy Index ER -EXCESS RETURN	4	1
31	CYDLOER	CYD Long Only ExcessReturn - EXCESS RETURN	4	1
32	CYDLOTR	CYD Long Only Total Return - TOTAL RETURN	4	1
33	CYDLSER	CYD Long Short Excess Return - EXCESS RETURN	4	1
34	CYDLSTR	CYD Long Short TotalReturn	4	1
35	CRBSPOT	CRB Spot Index (1967=100) - PRICE INDEX	4	1
36	NYFECRB	TR Equal Weight CCI - PRICE INDEX	4	1
37	CRBENGY	TR Equal Weight CCI Energy 1977=100 - PRICE INDEX	4	1
38	WCFINDX	Westpac Commodity Futures Ind - PRICE INDEX	4	1
39	SCINTRE	Seasonal Comm. Index Total EUR - TOTAL RETURN	4	1
40	SCINERE	Seasonal Comm. Index Excess EUR - EXCESS RETURN	4	1
41	CICIERE	China & India Comm. Index Excess EUR - EXCESS RETURN	4	1
42	CICITRE	China & India Comm. Index Total EUR - TOTAL RETURN	4	1
43	FUELOIL	Fuel Oil, No.2 (New York), C/Gallon	4	1
44	OILBREN	Crude Oil-Brent Cur.Month FOB U$/BBL	4	1
45	GASUREG	Gasoline,Unld. Reg. Oxy. NY Cts/Gal	4	1
46	NATLGAS	Natural Gas-Henry Hub $/MMBTU	4	1
47	JETCIFC	Jet Kerosene-Cargos CIF NWE U$/MT	4	1
48	OILGASO	Gas Oil-EEC CIF Cargos NWE U$/MT	4	1
49	LNGINDX	London Natural Gas Index P/Therm - PRICE INDEX	4	1
50	OILBRNP	Crude Oil-Brent Dated FOB U$/BBL	4	1
51	OSCBM1L	Crude Spread Brent M-M+1 UK Close	1	1
52	OSCBM1N	Crude Spread Brent M-M+1 NY Close	1	1
53	LCOEM01	Brent Fut Swap M1 S.Voe U$/BBL	4	1
54	LCOEM06	Brent Fut Swap M6 S.Voe U$/BBL	4	1
55	LCOEQ01	Brent Fut Swap Q1 S.Voe U$/BBL	4	1
56	LCOEQ04	Brent Fut Swap Q4 S.Voe U$/BBL	4	1
57	LCOEY01	Brent Fut Swap Y1 S.Voe U$/BBL	4	1
58	LCOEY02	Brent Fut Swap Y2 S.Voe U$/BBL	4	1
59	LCOEY03	Brent Fut Swap Y3 S.Voe U$/BBL	4	1
60	LCOEY04	Brent Fut Swap Y4 S.Voe U$/BBL	4	1
61	LCOEY05	Brent Fut Swap Y5 S.Voe U$/BBL	4	1
62	POWBASE	Powernext Elec. Baseload E/Mwh	4	1

63	POWPEAK	Powernext Elec. Peakload E/Mwh	4	1
64	APXAVBA	APX-Electricity Avg Price Base Load	4	1
65	APXSUPK	APX-Electricity Avg Super Peak Hours	4	1
66	APXOFPK	APX-Electricity Avg Off Peak Hours	4	1
67	DJCINFP	DJ Cinergy Elec. Firm On Peak - PRICE INDEX	4	1
68	EEXBASE	EEX - Phelix Base Hr.01-24 E/Mwh	4	1
69	NPXAVRF	Nordpool-ElectricityAvg Reference	4	1
70	UKPXSPT	APX Power UK Spot Base Load Index	4	1
71	EIACGPR	Gasoline Conv. US Prod. MBBL/Day - TURNOVER	4	1
72	EIACGST	Gasoline Conv. US Stocks MBBL - INVENTORY VOLUME	4	1
73	EIACODS	Crude Oil US Days of Supply - VALUE	4	1
74	EIACOEX	Crude Oil US Exports MBBL/Day - TURNOVER	4	1
75	EIACOIM	Crude Oil US Imports MBBL/Day - TURNOVER	4	1
76	EIACORI	Crude Oil Refinery Inputs MBBL/Day - TURNOVER	4	1
77	EIACRWT	Crude Oil-WTI FOB Cushing $/BBL	4	1
78	EIADIPR	Distillate Refinery Prod. MBBL/Day - TURNOVER	4	1
79	EIADIST	Distillate US Stocks MBBL - INVENTORY VOLUME	4	1
80	EIADSDS	Distillate US Days ofSupply - VALUE	4	1
81	EIADSIM	Distillate US ImportsMBBL/Day - TURNOVER	4	1
82	EIADSLA	Diesel No.2 LA Low Sulfur FOB C/GAL	4	1
83	EIADSNY	Diesel No.2 NYH Low Sulfur FOB C/GAL	4	1
84	EIAFGPR	Gasoline Finished US Prod. MBBL/Day - TURNOVER	4	1
85	EIAFGST	Gasoline Finished US Stocks MBBL - INVENTORY VOLUME	4	1
86	EIAFOIM	Fuel Oil US Imports MBBL/Day - TURNOVER	4	1
87	EIAFOPR	Fuel Oil Refinery Prod. MBBL/Day - TURNOVER	4	1
88	EIAFOST	Fuel Oil US Stocks MBBL - INVENTORY VOLUME	4	1
89	UKTBT1M	UK TREASURY BILL TENDER 1M - MIDDLE RATE	1	0
90	UKTBTND	UK TREASURY BILL TENDER 3M - MIDDLE RATE	1	0
91	USFDTRG	US FEDERAL FUNDS TARGET RATE - MIDDLE RATE	1	0
92	FRTBS3M	US TREASURY BILL 2NDMARKET 3 MONTH - MIDDLE RATE	1	0
93	EUEONIA	EURO OVERNIGHT INDEX AVERAGE(EONIA) - OFFERED RATE	1	0
94	EURONIA	EURONIA OVERNIGHT AVG. (LDN:WMBA) - MIDDLE RATE	1	0
95	LDNIBON	UK INTERBANK OVERNIGHT - MIDDLE RATE	1	0
96	ECEUR1M	EURO EURO-CURR 1 M (FT/ICAP/TR) - MIDDLE RATE	1	0
97	ECEUR1W	EURO EURO-CURR 1 WK (FT/ICAP/TR) - MIDDLE RATE	1	0
98	ECEUR1Y	EURO EURO-CURR 1 YR (FT/ICAP/TR) - MIDDLE RATE	1	0
99	ECEUR3M	EURO EURO-CURR 3 M (FT/ICAP/TR) - MIDDLE RATE	1	0
100	ECEUR6M	EURO EURO-CURR 6 M (FT/ICAP/TR) - MIDDLE RATE	1	0
101	LCBBASE	UK CLEARING BANKS BASE RATE - MIDDLE RATE	1	0
102	LDNIB7D	UK INTERBANK 7 DAY - MIDDLE RATE	1	0
103	LDNIB1M	UK INTERBANK 1 MONTH - MIDDLE RATE	1	0
104	LDNIB6M	UK INTERBANK 6 MONTH - MIDDLE RATE	1	0
105	LDNIB1Y	UK INTERBANK 1 YEAR -MIDDLE RATE	1	0
106	BBSRB1W	UK REPO BENCHMARK 1 WEEK (LDN:BBA) - MIDDLE RATE	1	0
107	BBSRB2W	UK REPO BENCHMARK 2 WEEK (LDN:BBA) - MIDDLE RATE	1	0
108	BBSRB3W	UK REPO BENCHMARK 3 WEEK (LDN:BBA) - MIDDLE RATE	1	0
109	BBSRB1M	UK REPO BENCHMARK 1 MTH (LDN:BBA) - MIDDLE RATE	1	0
110	BBSRB2M	UK REPO BENCHMARK 2 MTH (LDN:BBA) - MIDDLE RATE	1	0
111	BBSRB3M	UK REPO BENCHMARK 3 MTH (LDN:BBA) - MIDDLE RATE	1	0
112	BBSRBON	UK REPO BENCHMARK O/N(LDN:BBA) - MIDDLE RATE	1	0
113	BBSRB6M	UK REPO BENCHMARK 6 MTH (LDN:BBA) - MIDDLE RATE	1	0
114	BBSRB9M	UK REPO BENCHMARK 9 MTH (LDN:BBA) - MIDDLE RATE	1	0
115	BBSRB1Y	UK REPO BENCHMARK 1 YEAR (LDN:BBA) - MIDDLE RATE	1	0

Source: Thomson Financial Datastream

Note: *Tcode* stands for Transformation code. If z_{it} is the original untransformed series, the transformation codes are: 1. no transformation (levels), $x_{it} = z_{it}$; 2. first difference, $x_{it} = z_{it} - z_{it_{-1}}$; 3. logarithm, $x_{it} = \log z_{it}$; 4. first difference of logarithm, $x_{it} = \log z_{it} - \log z_{it_{-1}}$. *SlowCode* is a dummy variable equal to 1 if the variable is characterized as 'slow', or zero if it characterized as 'fast'. According to Bernanke et al. (2005), the 'fast' moving variables are interest rates, stock returns, exchange rates and commodity prices. The rest of the variables in the dataset are 'slow' moving variables.

Table 2: Descriptive Statistics

	EUABNXSPOTVOL	EUAECXFUTVOL	CERECXFUTVOL	FACTOR1	FACTOR2
Mean	0.963	0.992	1.051	-9.25E-17	1.04E-16
Median	0.972	0.908	0.850	0.013	0.134
Maximum	1.326	2.113	4.232	1.697	0.520
Minimum	0.647	0.693	0.391	-1.720	-1.606
Std. Dev.	0.190	0.271	0.684	0.583	0.445
Skewness	-0.080	1.710	1.677	-0.095	-2.073
Kurtosis	1.687	6.161	6.223	3.097	6.330
Jarque-Bera	13.834	172.708	172.270	0.365	226.323
Observations	462	462	462	462	462

Source: BlueNext, European Climate Exchange, Thomson Financial Datastream

Note: The first three columns are the conditional standard deviations extracted from AR(1)-GARCH(1,1) models with $EUABNXSPOTVOL$ the European Union Allowance spot price from BlueNext, $EUAECXFUTVOL$ the EUA futures price of maturity December 2010 from European Climate Exchange, $CERECXFUTVOL$ the (secondary) Certified Emissions Reduction futures price of maturity December 2010 from ECX. $FACTOR1$ is the first factor extracted from the tri-variate FAVAR(2) model of carbon prices with 115 macroeconomic, financial and commodities variables, and $FACTOR2$ the second factor extracted with the same methodology.

Table 3: Correlations between factors and carbon price volatilities

	EUABNXSPOTVOL	EUAECXFUTVOL	CERECXFUTVOL	FACTOR1	FACTOR2
EUABNXSPOTVOL	1				
EUAECXFUTVOL	0.173	1			
CERECXFUTVOL	0.315	0.806	1		
FACTOR1	-0.219	-0.182	-0.199	1	
FACTOR2	-0.287	-0.023	-0.081	-0.063	1

Note: The first three columns are the conditional standard deviations extracted from AR(1)-GARCH(1,1) models with $EUABNXSPOTVOL$ the European Union Allowance spot price from BlueNext, $EUAECXFUTVOL$ the EUA futures price of maturity December 2010 from European Climate Exchange, $CERECXFUTVOL$ the (secondary) Certified Emissions Reduction futures price of maturity December 2010 from ECX. $FACTOR1$ is the first factor extracted from the tri-variate FAVAR(2) model of carbon prices with 115 macroeconomic, financial and commodities variables, and $FACTOR2$ the second factor extracted with the same methodology.

Table 4: Pairwise Granger causality F tests

Null Hypothesis	F-Statistic	Probability
FACTOR1 does not Granger Cause EUABNXSPOTVOL	0.561	0.571
EUABNXSPOTVOL does not Granger Cause FACTOR1	4.075	0.018
FACTOR2 does not Granger Cause EUABNXSPOTVOL	0.534	0.586
EUABNXSPOTVOL does not Granger Cause FACTOR2	1.619	0.200
FACTOR1 does not Granger Cause EUAECXFUTVOL	2.174	0.116
EUAECXFUTVOL does not Granger Cause FACTOR1	3.299	0.039
FACTOR2 does not Granger Cause EUAECXFUTVOL	2.906	0.057
EUAECXFUTVOL does not Granger Cause FACTOR2	1.279	0.280
FACTOR1 does not Granger Cause CERECXFUTVOL	0.710	0.492
CERECXFUTVOL does not Granger Cause FACTOR1	4.675	0.010
FACTOR2 does not Granger Cause CERECXFUTVOL	0.308	0.734
CERECXFUTVOL does not Granger Cause FACTOR2	1.205	0.301

Note: Carbon price variables are the conditional standard deviations extracted from AR(1)-GARCH(1,1) models with $EUABNXSPOTVOL$ the European Union Allowance spot price from BlueNext, $EUAECXFUTVOL$ the EUA futures price of maturity December 2010 from European Climate Exchange, $CERECXFUTVOL$ the (secondary) Certified Emissions Reduction futures price of maturity December 2010 from ECX. $FACTOR1$ is the first factor extracted from the tri-variate FAVAR(2) model of carbon prices with 115 macroeconomic, financial and commodities variables, and $FACTOR2$ the second factor extracted with the same methodology. This table reports pairwise F statistics and their p-values.

Table 5: Regressions of carbon price volatilities on factors estimated from the FAVAR(2) model

	EUABNXSPOTVOL (1)	EUAECXFUTVOL (2)	CERECXFUTVOL (3)
Mean Equation			
Constant	0.922*** (0.004)	0.907*** (0.004)	0.773*** (0.026)
Factor 1	-0.029*** (0.007)	-0.062*** (0.008)	-0.104*** (0.037)
Factor 2	-0.151*** (0.007)	-0.230*** (0.017)	-0.208*** (0.032)
Variance Equation			
Constant	0.001* (0.001)	0.005*** (0.001)	0.062*** (0.012)
ARCH(1)	0.937*** (0.381)	0.942*** (0.178)	0.987*** (0.172)
Diagnostic Tests			
Adjusted R-squared	0.139	0.144	0.147
AIC	-1.400	-0.526	-1.404
SC	-1.314	-0.441	-1.489
Log likelihood	138.013	55.282	128.422
LB Test	0.186	0.200	0.172
ARCH Test	0.963	0.991	0.986
F-Stat.	0.000	0.000	0.000

Note: Carbon price variables are the conditional standard deviations extracted from AR(1)-GARCH(1,1) models with $EUABNXSPOTVOL$ the European Union Allowance spot price from BlueNext, $EUAECXFUTVOL$ the EUA futures price of maturity December 2010 from European Climate Exchange, $CERECXFUTVOL$ the (secondary) Certified Emissions Reduction futures price of maturity December 2010 from ECX. $FACTOR1$ is the first factor extracted from the tri-variate FAVAR(2) model of carbon prices with 115 macroeconomic, financial and commodities variables, and $FACTOR2$ the second factor extracted with the same methodology. $ARCH(1)$ is the ARCH(p) coefficient of order 1. Standard error in parenthesis. *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level. AIC is the Akaike Information, SC the Schwarz information criterion, LB Test is the Ljung-Box test, $ARCH$ test is the Engle ARCH test, and $F - Stat.$ the p-value of the F-Statistic.

Table 6: In-sample volatility forecasts of carbon prices with/without factors estimated from the FAVAR(2) model

Variable	RMSE	MAE	MAPE
EUABNXSPOTVOL without factors	0.200	0.177	19.836
EUABNXSPOTVOL with factors	0.183	0.152	16.173
EUACERFUTVOL without factors	0.311	0.203	18.375
EUACERFUTVOL with factors	0.293	0.187	16.479
CERECXFUTVOL without factors	0.788	0.494	47.003
CERECXFUTVOL with factors	0.733	0.455	43.122

Note: Carbon price variables are the conditional standard deviations extracted from AR(1)-GARCH(1,1) models with $EUABNXSPOTVOL$ the European Union Allowance spot price from BlueNext, $EUAECXFUTVOL$ the EUA futures price of maturity December 2010 from European Climate Exchange, $CERECXFUTVOL$ the (secondary) Certified Emissions Reduction futures price of maturity December 2010 from ECX. $FACTOR1$ is the first factor extracted from the tri-variate FAVAR(2) model of carbon prices with 115 macroeconomic, financial and commodities variables, and $FACTOR2$ the second factor extracted with the same methodology. $RMSE$ refers to the Root Mean Squared Error, MAE to the Mean Absolute Error, and $MAPE$ to the Mean Absolute Percent Error.